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Identification of Autonomous Learning Constraints: Development and Validation of a Scale

Qandeela M Bilal[1], Rafaqat Ali Akbar[2], Muhammad Shahid Farooq[3]

[1]Ph.D Scholar, Institute of Education and Research, University of the Punjab, Lahore, Pakistan.
[2]Dean, Faculty of Humanities and Social Sciences, Lahore Leads University, Pakistan.
[3]Professor, Department of Advanced Studies in Education (DASE), Institute of Education and Research, University of the Punjab, Lahore, Pakistan.
Correspondence: qandeela.bilal@gmail.com[1]

ABSTRACT

Aim of the Study: The study aimed to create a psychometrically sound instrument and a scale that investigates the constraints of undergraduate learners who learn autonomously. The items were produced following a careful revision of the relevant literature.

Methodology: A group of 200 students was chosen for the exploratory factor analysis using the 72-item scale, and a group of 186 students underwent the confirmatory factor analysis.

Findings: The results showed that by using factor analysis processes, the items were adequately put into the components identified by the study Analysis of the data has also revealed that the scale contains three variables that make up its structure and comprises 59 items. It is also showed that scale is a valid and reliable instrument.

Conclusion: It is concluded from this study that the scale development achieved the appropriate values. As a result, this scale is applicable to other research. Furthermore, to extend the scale's application, more research can be done to modify it for use at other educational levels. It will be helpful to combine this scale with additional learner autonomy data collection instruments and can be used in other disciplines of education.

Keywords: Autonomous Learning, Constraints, Scale Development, Undergraduate Students.

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Introduction

One of the biggest challenges facing the global education community today is to maintain learning in the context of global change while remaining supportive of students' well-being (Huang et al., 2020). Autonomous learning is becoming more and more popular in the educational system, and it has become especially popular in the context of teaching and learning. The degree to which learners are in charge of their obligations and choose how to carry them out has significantly changed in recent years due to the rise in autonomy in learning. Autonomous learning is no more an alien teaching approach particularly in modern times. The institutions tend to emphasize the value of the five Cs:

collaboration, communication, creativity, critical thinking, and characteristics. It is consistent with the fundamental ideas underlying autonomous learning. The core concepts of autonomous learning, according to Hasim & Zakaria (2016), include ownership, self-direction, and accountability for gained skills, social construction, and cooperation. It gives students the freedom to take risks and accept accountability for their learning.

Autonomous learning has expedited the shift from instructor-led instruction to student-led learning. With this notion, the teacher will no longer be the "dominant chalk and talk provider" but rather a "facilitator of the teaching-learning process," allowing students to take ownership of their education (Hamza, 2019). Limited attention has been given to the obstacles that impede the large-scale adoption of autonomous learning in the literature on the nature and potential applications of its principles. As a result, the adoption of this approach has been delayed due to a lack of emphasis on autonomous learning's feasibility (Yasmin et al., 2019).

A significant amount of studies on the constraints placed on learners' roles have been done (Saar et al. 2014). The majority of this researches explored psychological issues (Blair et al., 1995); some looked at social elements (Babchuk and Courtney, 1995; Gooderham, 1993); still others assessed the institution's function (Jung & Cervero, 2002; Saar et al., 2014). A combination of these elements was also examined in the majority of research studies (Borg & Al-Busaidi 2012; Nga 2014). The majority of them revealed a number of constraints included teachers who lacked confidence in their students' abilities, a lack of autonomy on the part of the teachers, students who had never learned independently, a lack of incentives for the students, a reliance on the teacher, minimal exposure to English outside of the classroom, a concentration on passing exams, a fixed curriculum (Borg & Al-Busaidi 2012), interactions between teachers and students, and an examination system (Jing, 2005).

The purpose of the current study was to develop scale on constraints of autonomous learning scale (CALS) and, more importantly, to examine the validity and reliability of the CALS among undergraduates students. For two reasons, researchers and instructors or lecturers can use the CALS right away. In order to determine if validity and reliability patterns—particularly the model fit—remain consistent across different populations, we therefore implore upcoming researchers to do as many validations as they can. Second, so that teachers and students can evaluate themselves and their own learning processes, the CALS may provide insightful results for their learning processes.

Therefore, the following have been the main objectives of this research to: (a) create a autonomous learning constraints' identification scale (CALS) and (b) analyze the validity and reliability of the aforementioned scale.

Literature Review

Autonomous Learning

Autonomous learning was initially defined by Holec (1981). He described autonomous learning as "the ability to take charge of one's own learning". He continued by expanding on this fundamental definition as: establishing the goals, outlining the subject matter, choosing the approaches and strategies to be applied, keeping an eye on the acquisition process (rhythm, time, location, etc.), and assessing the knowledge gained.

Gardner (1981) also defined it as the ability to take charge of one's learning. As per Gardner's further remarks, formal systematic learning is the source of this ability, which cannot be acquired naturally. Furthermore, to him, ability refers to the ability or capacity to perform something rather than the ability to conduct behavior. Thus, the capacity to control behavior in a particular setting is known as autonomy and the capacity to direct learners' behavior during the learning process is known as autonomous learning.

According to several studies (Benson, 2011; Dogan & Mirici, 2017; Little, 1995, 2007; Smith, 2008), autonomous learners are recognized for their ability to take initiative, understand why they are learning, set reasonable and achievable goals, demonstrate responsibility, act independently, and monitor their progress in learning. Furthermore, Dogan and Mirici (2017) clarified that independent learners acquire knowledge both inside and outside of the classroom; they understand that learning happens everywhere, at any time, and is not limited to the confines of the classroom.

Constraints

One of the most significant areas of educational research is autonomous learning, which the present education reform desperately needs (Hui, 2008). Education reformers of today argue that teachers should adopt a more flexible approach to teaching and encourage student initiative. Autonomous learning has the potential to enhance conventional teaching methods and promote the holistic growth of students. One of the goals of teaching to students is to foster their capacity for learning (Liu, 2016).

The degree of autonomous learning among students varies. This is due to various factors that impact the autonomy of students. The implementation of an autonomous learning process may be hampered in any given educational situation by institutional and student's personal constraints. The constraints of autonomous learning are related to human thought processes and actions (Tran & Duong, 2020).

There are limitations on the growth of the autonomous learner in any given learning environment. Developing autonomy is still possible, nevertheless, despite this. Many elements, including intelligence, motivation, anxiety, and attitude, can impact the process of autonomous learning (Shams, 2008). According to Tram and Kha (2021), a student's attitude has an impact on how well he learns. A learner who believes he is incapable of learning might not put in enough effort, which would prevent the learner from making progress toward autonomous learning.

Students in universities are among those who are more susceptible to stress and anxiety (Deng et al., 2021). Personal, social, and academic factors are the three categories of stress-causing factors that can be studied in university life (Iturriozet al., 2018; Menon & Thattil, 2018). The factors such as psychological issues, personality and developmental issues, and economic issues lead to stress in the personal sphere of a student (Cleary et al., 2012). Motivated people learn better, and this is a key factor in student achievement. As their academic performance is often viewed as a sign of their thriving, motivated learners have a clear advantage (Brown et al., 2017). Arici-Ozcan et al. (2021) identified the beneficial impact of motivation on students' academic performance, corroborating the findings of Brown et al. (2017).

External factors are the primary source of most constraints faced by learners. The majority of the difficulties that students encounter are caused by their institutions. Educational hurdles are defined by Yasmin et al. (2019) as outdated and rigid syllabuses that do not meet the requirements of the lifelong learning paradigm. A shortage of resources, opportunities for professional growth, exposure, and training of teachers was the most identified constraints in many publications (Almusharraf, 2020; Borg & Alshumaimeri, 2019; Lin & Reinders, 2019; Yavuz et al., 2020). As a result, a barrier to this learner-centered approach is students' passive attitude throughout class.

It is difficult to fully integrate learner autonomy when teachers are personally attached to using traditional teaching methods (Alonazi, 2017; Lin & Reinders, 2019; Liu et al., 2018; Shamir-Inbal & Blau, 2021; Yasmin & Sohail, 2018a). Furthermore, the primary teaching profession suffers from the overwhelming workload of teachers, which includes administrative tasks, co-curriculum responsibilities, and ad hoc meetings. Teachers find it challenging to modify their instruction to meet the requirements of their students due to the power and influence of legislators (Alonazi, 2017; Borg & Alshumaimeri, 2019; Dogan & Mirici, 2017; Liu et al., 2018; Yasmin et al., 2019).

The efficiency of the autonomous learning approach being used in the classroom can be manipulated and influenced by external circumstances such as cultural barrier (Abdulkader, 2016; Lin & Reinders, 2019; Sidhu et al., 2018; Yasmin et al., 2019). Many researchers have highlighted the impact of culture on behavior, cognition, and education (Hofstede, 2011). Scholars have highlighted the close relationship between learner autonomy and culture (Palfreyman, 2003; Oxford, 2003; Benson, 2007).

According to Smith (2003), learner autonomy can be applied in a variety of cultural contexts. It also determines the roles that teachers and students can play in educational settings, including who gets to do what, when, and how. The assumption made by teachers is that it is best to accomplish tasks correctly the first time around. Committing errors is considered a source of shame. Students' thoughtful, receptive input is rarely appreciated in activities that require pair or group work. Students from the Middle East and Asia tend to respond in a passive manner. This is because it is culturally understood to follow elders' instructions and to give the most regard to people with the greatest level of seniority (Nii & Yunus, 2022).

A research gap was identified by the literature review. The majority of the researches were founded on an exploratory study that employed field notes, observations, and interviews as its instruments. Therefore, it may be claimed that different study designs or instruments may reveal distinct parts of the constraints of autonomous learning that need further investigation.

Methodology

In order to develop a scale for exploring constraints of autonomous learning, this descriptive study is being conducted. Researcher also looked into the development process and the psychometric qualities (validity-reliability) of the scale.

Participants

Regarding the minimum sample size needed for factor analysis, various recommendations have been made in the relevant literature. While Gorsuch (1983) asserts that 5 people would be sufficient for the analysis, Nunnaly (1978) recommends 10 or 15 participants for each item. The study was carried out using the participant count recommended by Gorsuch (1983); however, some forms were not included in the analysis because the participants failed to return them or filled them out in an erroneous or incomplete manner. To facilitate exploratory factor analysis, the current study's sampling sizes were intended to range from 200 to 300. To facilitate exploratory factor analysis, sample sizes in the current study were intended to be 250 students who were chosen from department of mathematics, University of the Punjab. The students who were enrolled in 1st, 3rd, 5th, and 7th semester of BS mathematics were selected as participants. A total of 30 students from one classroom failed to return the scale in form of scales, and another 20 students either completed some questions on the scale inaccurately or not at all. These 50 scales were therefore excluded from the analysis. The data gathered from 200 students was subjected to exploratory factor analysis.

Confirmatory factor analysis cannot be used without a sufficient sample size. For confirmatory factor analysis, a minimum sample size of 100 is recommended by the relevant literature (Brown, 2006; Marsh et al., (1999); Sapnas & Zeller, 2002). It was intended to use the data collected from 200 students for the confirmatory factor analysis of the scale, which was completed following the exploratory factor analysis. The students involved in the confirmatory analysis are not the same as the ones in the exploratory analysis. The selected sample for confirmatory analysis was from institute of education and research (IER), university of the Punjab, Lahore. The students who were enrolled in 1st, 3rd, 5th, and 7th semester of BS education were selected as participants. However, the analysis was conducted using the information gathered from 186 students out of 200, as 14 of them either completed the scale incorrectly or failed to respond to certain items.

Development Process

The literature (Cohen & Swerdlik, 2013; Crocker & Algina, 1986; DeVellis, 2014; seker & Gencdogan, 2014) has emphasized that scale process of development needs to consist of specific steps. The steps involved in developing the scale in this study are: 1) Identifying the purpose of the scale (exploring the constraints in autonomous learning process); 2) Specifying the participants to whom the scale will be applied; 3) Identifying the characteristics (autonomous learning constraints) that should be included in the scale and their range; 4) selecting the scale's item types in relation to the elements that are meant to be defined (constraints); 5) creating test items based on the selected item types; 6) reviewing the items and creating a scale in form of questionnaire; 7) seeking feedback from field experts regarding the scale's legibility; 8) finalizing the scale's design prior to the pilot application based on the feedback from the field experts; 9) Calculating the items' scores and analyses; 10) Summarizing scale's psychometric qualities (validity and reliability) at the final stage of the pilot testing; 11) developing actual scale in light of the findings.

A comprehensive review of the literature on constraints of autonomous learning was conducted, with a focus on the description of the notion of constraints of autonomous learning. Following that, researcher worked separately to develop statements that reflected what is believed to be the essential elements of constraints of autonomous learning as shown in the body of current literature.

Following its creation, the survey was refined through talks with experts whose input, observations, and debates were highly beneficial and greatly aided in the scale's development. To help the participants understand the questionnaire, the translation method was employed (Sousa & Rojjanasrirat, 2011). The purpose of translating the scale into English to Urdu was to increase the validity of the data by enabling all respondents to comprehend all of its contents. After being translated by two specialists, it was revised once again and assessed by experts. It was noted that there were no comprehension issues with the finished version.

Data Collection

The researchers visited the selected institutions personally to speak with the students about the study's goals, importance, procedures, and most importantly ethical issues after receiving ethical approval from the Institutional Review Board and permission from the university. It is also informed that their participation was voluntary and that their information would be kept anonymous to ensure appropriate execution of the research and careful completion of the questionnaires. The chosen students received the questionnaires in their hands. Enough time was allotted to the responders to finish the questionnaire. In order to evaluate the exploratory factor analysis in the first part of this study, 250 scales were shared; in the second phase, 200 were used for the confirmatory factor analysis. There were 200 valid surveys for exploratory analysis and 186 for confirmatory analysis after the invalid scales, such as incomplete ones, were sorted out.

Examining Data through Statistics

The statistical software programs SPSS was used for all analyses. To gain insight into the draft scale's structure, factor analysis was done. The data was evaluated for suitability for factor analysis using the Bartlett's Test of Sphericity and the Kaiser-Olkin Measure of Sampling Adequacy (Dziuban & Shirkey, 1974). First, eigenvalues > 1 and Principal axis factoring analysis were used in exploratory factor analysis (EFA). Maximum likelihood estimation was then used to carry out confirmatory factor analysis (CFA). The scale's reliability level and item heterogeneity were assessed using the Cronbach Alpha internal consistency coefficient.

Results and Discussion

The results of the draft's validity and reliability tests are presented in this section. In the context of validity concerns, construct validity was investigated, and reliability was assessed using Cronbach Alpha.

In order to determine whether the data are normally distributed and move forward with parametric testing, exploratory data analysis (EDA) was used to examine the data prior to the normality test. The goal was to identify outliers, missing values, and errors in the data input. There were no missing values, according to the descriptive statistics produced by the SPSS program. Outliers were evaluated, both univariate and multivariate. Boxplots were used to evaluate the univariate outliers. Two different types of outliers can be found in the boxplots. In boxplots, the moderate outliers are represented by open dots, and the extreme outliers are indicated by asterisks. Univariate outliers are not present in this investigation. The Mahalanobis Distance for the multivariate outliers was computed and the findings indicated that there were no multivariate outliers in this data set. Not a single example was removed in order to return the study to normal.

Exploratory Factor Analysis of Scale for Constraints of Autonomous Learning

An exploratory factor analysis was performed to look at construct validity. The scale items concerning the constraints of autonomous learning were rewritten and clarified following extensive literature review. Consequently, EFA was needed to review the respondents' answers.

Principal axis factoring analysis was used to assess the construct validity of constraints of autonomous learning. Kaiser-Meyer-Oklin values of .864 (Kaiser,1974) and the Bartlett's Test of Sphericity (Bartlett, 1954) χ_2 =5.465 and *df*= 1711 both demonstrated that the sample size was sufficient and that it was statistically significant as required as illustrated in table 1.1. The correlation matrix also showed a large number of coefficients that were equal to or greater than.3, as advised by Tabachnik and Fidell (2001).

Table 1: *Results of KMO and Bartlett's Test*

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.864
Bartlett's Test of Sphericity	Approx. Chi-Square	5.465
	Df	1711
	Sig.	.000

A correlation exists between allowable factor loadings and sample size as well. Stevens (2012) states that factor loadings are significant at the 0.01 level for a sample size of 100 when they are more than 0.512 and significant at the 0.31 level for a sample size of 200 when they are larger than 0.364. As the rule of thumb suggested by Hair et al. (2006), the significant loading should be .50 or higher. The factor loading of each item described below.

Table 2: *Explanatory Factor Analysis Results of the Scale*

Factors **Item**	**1** **Factor Loadings**	**2** **Factor Loadings**	**3** **Factor Loadings**
Item 42	.649		
Item 41	.628		
Item 40	.614		
Item 49	.597		
Item 52	.591		
Item 48	.588		
Item 32	.571		
Item 21	.569		
Item 39	.566		
Item 45	.556		
Item 46	.553		
Item 16	.550		
Item 47	.528		
Item 44	.525		
Item 53	.527		
Item 54	.522		
Item 34	.519		

Item 51	.511		
Item 43	.510		
Item 58	.506		
Item 50	.504		
Item 33	.501		
Item 3		.731	
Item 2		.670	
Item 22		.616	
Item 20		.614	
Item 5		.613	
Item 38		.607	
Item 1		.607	
Item 36		.598	
Item 30		.594	
Item 57		.581	
Item 4		.552	
Item 31		.530	
Item 19		.526	
Item 13			.653
Item 15			.619
Item 11			.596
Item 25			.591
Item 26			.590
Item 23			.580
Item 10			.579
Item 14			.573
Item 9			.571
Item 29			.563
Item 55			.549
Item 28			.548
Item 56			.546
Item 59			.541
Item 37			.539
Item 17			.534
Item 24			.527
Item 7			.524
Item 18			.523
Item 12			.521
Item 27			.520
Item 6			.514
Item 8			.504
Item 35			.501

Screen plot is also used to show the factors. In a screen plot, the number of significant variables is shown by the factor that rapidly and sharply declines (Buyukozturk, 2010). Horizontal lines indicate that additional variances resulting from various causes are in close proximity to one another (Buyukozturk, 2010; Cokluket al., 2012). The inclusion of three components in the scale is confirmed by the scree plot graph presented in Figure 1.

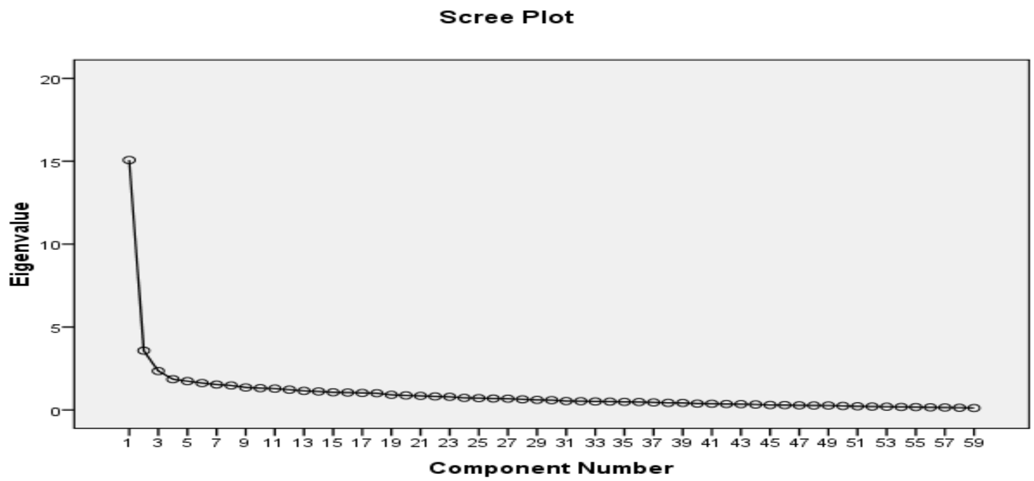


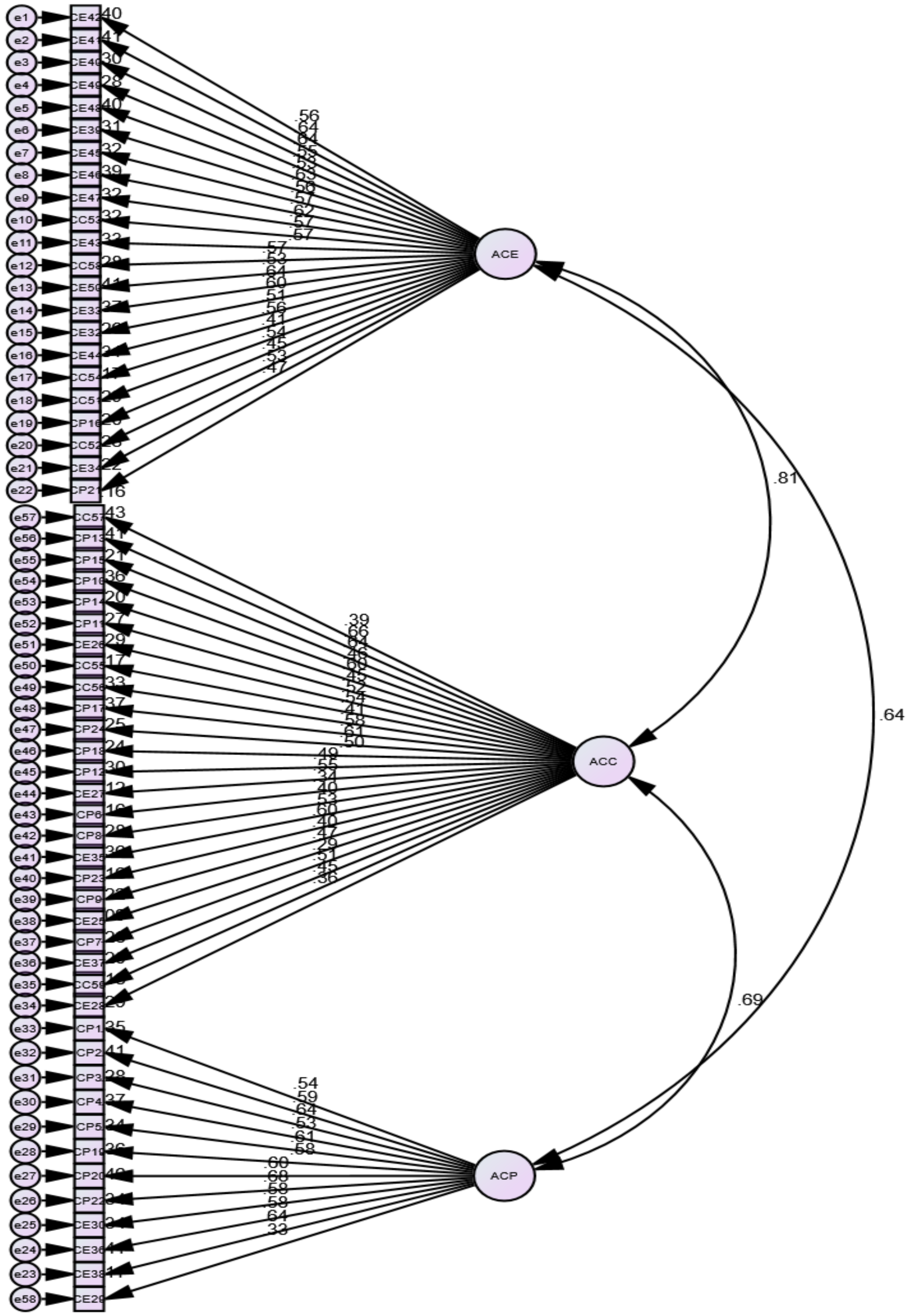
Figure 1. The eigenvalue analysis of constraints of autonomous learning scale obtained from screen plot

It was established that twenty two (22) were loaded on factor one, thirteen (13) were in factor two and twenty four (24) were in factor three above (.50). Five of the deleted items had factor loadings below (.40), whereas eight (8) of the removed items have multiple factor loadings. Out of the 72 items, 59 were included in the final version, which explained 71.637% of the variance.

Confirmatory Factor Analysis for Constraints of Autonomous Learning

Confirmatory factor analysis was carried out using the data from the second group of selected sample using AMOS program, based on the factors discovered as a result of the exploratory factor analysis (EFA). Figure 2 showed the model derived from the analysis.

Figure 2: *Confirmatory factor analysis model for constraints of autonomous learning*



As showed in above figure, it is evident that the degree of freedom and chi-square derived from confirmatory factor analysis (CFA) are χ_2= 620.596, (*df*=373, p<.01), and the ratio is χ_2 /sd =1.659. Joreskog and Sorbom, (1993); Kline, (2005) and Sumer, (2000) stated that perfect consistency is shown when the ratio derived from the chosen samples is less than 3. Therefore, it may be said that there is perfect consistency between the data set and the CFA model. Table 1.3 summarized the additional confirmed goodness of fit values acquired by CFA.

Table 3: *Results of confirmatory factor analysis via fit parameters values.*

Fit Parameter	**GFI**	**AGFI**	**PGFI**	**CFI**	**RMSEA**	**RMR**	**sd**	χ_2	χ_2**/sd**
Values	.906	.898	.890	. 895	.064	.078	373	620.596	1.659

RMSEA is arguably one of the goodness of fit indices that CFA uses the most frequently. A model-data fit in a CFA analysis is indicated by an RMSEA score of 0.05 or less. However, it is also mentioned that this number is reasonable up to 0.08 (Browne & Cudeck, 1993; Hu & Bentler, 1999; Simsek, 2007; Vieira, 2011). It seems acceptable that the RMSEA score is 0.064. According to Anderson and Gerbing (1984) and Marsh et al. (1988), values that show an adequate model-data fit are those with an AGFI value greater than 0.80 and an RMR value less than 0.10. AGFI is determined by CFA to be 0.898 which is close to minimum criteria and RMR to be 0.078. It can concluded that the model-data fit is reasonable based on these findings. CFA's primary goal is to determine how well a model fits data from the past (Sumbuloglu & Akdag, 2009). It might be inferred that the three-factor structure of constraints of autonomous learning was validated in this regard.

Reliability of Constraints of Autonomous Learning

Test item reliability and score consistency were assessed using Cronbach's Alpha (Agbo, 2010; Tan, 2009). In order to determine reliability, the researcher entered the gathered pilot data into SPSS. The scale for constraints of autonomous learning had .948 Alpha values. The results of factor-wise reliability are listed below:

Table 4: *Statistics of reliability in relation to constraints of autonomous learning factors*

Sr. No	**Name of factors**	**Cronbach's Alpha**
1	Personal Constraints	.88
2	Institutional Constraints	.91
3	Cultural Constraints	.74

The constraints of autonomous learning scale's Cronbach alpha value was .948, over a minimum point of .70. Additionally, the factor reliability was computed. Three factors had alpha values of.884, .913, and .741, all of which were greater than.70.

To sum up, fifty nine (59) questions on constraints of autonomous learning scale was made ready for the preliminary test application under the scope of the study. The final form of the scale was translated by two language experts into English to Urdu and certified that the same meanings were conveyed by specific items in the English and in the Urdu versions of the scale.

Conclusion

The purpose of this study was to create a scale that would help undergraduate students determine the constraints of their own learning and more importantly, to examine the validity and reliability of the constraints of autonomous learning scale (CALS). First, an exploratory factor analysis was conducted, and then a confirmatory factor analysis was carried out. The scale is composed of three factors: personal, institutional, and cultural constraints. The total variance of the three factors in the scale is 71.631%. Following the completion of the exploratory factor analysis, a confirmatory factor analysis was carried out on the data obtained. The results of the reliability analysis revealed that the internal consistency values were found to be within an acceptable range and the Cronbach Alpha value—the internal consistency coefficient—was calculated as 0.948. It is based on three factors and 59 items.

The scales created or modified by researchers are primarily based on observations and interviews in the literature review. There was no particular scale created in a form of questionnaire. The development of a consistently reliable instrument for gauging the constraints of autonomous learning is the other key feature of the current study. Personal constraints refer to the first scale factor. The majority of the components in this category relate to learning aspects that are personally impacted, such as motivation, self-efficacy, anxiety, attitude and prior education. Stated differently, learner-centeredness pertains to the process of determining learning objectives, implementing strategies to guarantee learning, and assessing learning. Related literature has also stressed the significance of these parameters in autonomous learning.

Determining learning constraints in any educational institution is the second aspect, which is referred to as institutional constraints. These constraints deal with figuring out the amount of time, learning material, teacher's behavior, and availability of learning resource. Culture-related constraints are the third and last component. While most researchers in the literature stress the necessity of identifying autonomous learning constraints, earlier scales did not include any factors pertaining to these constraints. This scale differs from the others in that it provides a more thorough coverage of these factors.

The scale, which was designed based on the study's findings, was determined to be validated and reliable data collection tool that may be utilized in future research aimed at identifying the constraints of undergraduate students' autonomous learning. Research using a variety of participants is recommended to be able to yield useful information about the scale's consistency.

Suggestions

It is concluded from this study that the scale development achieved the appropriate values. As a result, this scale is applicable to other research. Studies or assesses tools that are designed to measure constraints of autonomous learning, however, have not yet been generated. The integrating CALS with additional data gathering instruments will enhance the body of literature. Furthermore, to extend the scale's application, more research can be done to modify it for use at other educational levels.

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Conflict of Interest

Authors have no conflict of interest.

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ORCID iDs

Qandeela M Bilal [1] https://orcid.org/0009-0007-6305-2253
Rafaqat Ali Akbar [2] https://orcid.org/0009-0008-3859-8470
Muhammad Shahid Farooq [3] https://orcid.org/0000-0002-1971-085X

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