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Learners' self-directed learning readiness factors towards online learning in Universities: An exploratory factor analysis

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ABSTRACT

Self-directed learning is an essential skill to be possessed by learners for them to comfortably study online besides harnessing their scientific reasoning, critical appraisal, information literacy, and life-long learning. The purpose of this study was to explore factors attributed to self-directed learning readiness towards online learning among university learners. The study adopted the design science world view, quantitative research design and survey research method. This study used a sample size of 398 learners who were randomly selected to take part in the study. Proportional allocation method was used to get the exact number of learners per university who were randomly selected. Quality was ensured through both validity and reliability tests. Exploratory Factor Analysis was used to extract principal components and indicators mapping onto them. Based on the indicators' themes that were converging on the constructs, the constructs were named: Self-Management with 13 indicators; Self- Control with 11 indicators and Urge to Learn with 6 indicators. This study will be beneficial to policy makers in universities for assessing the state of self-directed learning readiness of learners towards online learning.

Introduction

Self-directed learning is one of the methods used to develop learners' capabilities in terms of scientific reasoning, critical appraisal, information literacy and life-long learning (Bhat & Dahal, 2023). According to Luu, (2022) Self-directed learning is an essential attribute that learners need to possess for them to comfortably study online. The outbreak of COVID-19 acted as a catalyst towards online learning adoption as universities put in place measures to ensure that they remain afloat by reaching out to their students through different online learning platforms during the lockdown periods

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(Maphalala *et al.*, 2021). Self-directed learning calls for the learners to be actively involved in their studies and decision making as they prepare for life-long learning.

Self-directed learning has unique attributes which have to be present for learning to occur. Self-directed learners use different cognitive capabilities to control their learning experiences which makes them participate actively in their learning process (Loeng, 2020). It generally involves the amount of responsibility a learner invests in their own learning process. Some of the attributes associated with self-directed learners are: self-management, independent learning, having self-regulation skills, having control over their own learning, evaluating personal learning process and correctly defining learning targets (Brandt, 2020). Learners who are self-directed in their learning process as Morris *et al*. (2023) compares, take full responsibility for their learning requirements and goals, an attribute which helps them to achieve professional competencies.

Self-directed learning calls for the learners to be proactive and actively participate in self-evaluation, self-assessment and peer-assessment by shifting the learning responsibility from the lecturer to the learner (Bhandari *et al.*, 2020). Self-directed learning is essential for learners as they prepare for their future. The learner requires self-drive which solely depends on their personal attributes. This covers self-motivation, self-management, self-monitoring, and self-control (Cronin-Golomb & Bauer, 2023). Self-drive affects how students control their own studies.

Self-directed learning calls for learners to take full responsibility of their learning and possess a range of transferable cognitive skills which will make them able to nature their lifelong learning skills. In line with this, Tekkol and Demirel (2018) postulate that for self-directed learning to take place, students have the responsibility of spelling out their personal learning goals, pinpointing and addressing loopholes within their studies, identifying resources, selecting and carrying out learning strategies, monitor their learning process, evaluate their learning, be autonomous, self-motivated, open to learn, curious, willing to learn, value learning, have self-control and take the initiative to learn. Learners need to have control over the process of conceptualization, design, and implementation of their learning.

Hawkins (2018) explains that despite any learner having the ability to turn into a self-directed learner, the level of self-directed learning may vary depending on personal attributes like motivation to learn, self-confidence, conscience, experience, and intelligence which are collectively called *learner readiness for self-directed learning*. Self-directed learning readiness is the extent to which learners have the attributes, talents and personality features required for self-directed learning and thus control the process of learning (Alfaifi, 2016). This is echoed by Madhavi and Madhavi (2017) who state that it is the degree to which an individual possesses attitudes and abilities necessary for self-directed learning.

Different learners' features according to Karimi (2016) such as age, gender, previous experience and attributes like curiosity, critical thinking, decision-making abilities, self-motivation, diligence, independence, self-discipline, self-confidence, and goal-oriented may affect the self-directed learning readiness level. This is in agreement with Cadorin *et al.* (2015) who studied that the more work experience a person has, the more self directed their learning becomes. Promoting worker self-directed learning readiness enhances their self-confidence, learning capacity, accountability, and independent learning ability (Chikeme *et al.*, 2024).

Abd-El-Fattah (2010) carried out a study about Garrison's model of Self-directed learning validation and its relationship to academic achievement. The model had three constructs attributed to it: self-management; self-monitoring, and motivation. This study highlighted that motivation mediates the relationship between self-management and self-monitoring.

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A study carried out by Karataş *et al.* (2021) used a Self-Directed Learning Readiness scale to determine the readiness levels of pre-service teachers participating in the research for self-directed learning. The scale, originally developed by Fisher *et al.* (2001) had three sub-dimensions: self-management with 20 items; Willingness to learn with 16 items and self-control with 16 items. It was further repoted that the three factors explained 42.5 % of the total variance.

Methodology

This research was based on design science world view which advocates for knowledge generation through smart observation and measurement of what actually exists in the real world (Brocke *et al.*, 2020). Quantitative research design was adopted for this study to enable the researcher collect discrete data values (Asenahabi *et al.*, 2019). Survey method was adopted in collecting quantitative data using questionnaires. According to Regmi *et al.* (2016) questionnaires are used for capturing a lot of data on a statistical form from many people in a relatively short time.

Simple random sampling technique was used to collect data about self-directed learning factors for online learning. There were 64 universities in Kenya as at 2024 as Mutua (2024) pointed out and Singh (2006) reiterated that a sample size of 10% to 20% of the accessible population is appropriate for survey research. This study used a sample size of 15% of 61 universities in Kenya (as at 2020) forming a sample size of 10 institutions. The 10 institutions had a total number of 74235 learners enrolled and studying using the online learning platforms which represented the study population. To get the exact number of respondents who took part in the study (sample size), the study adopted a formula by Yamane (1973). A confidence level of 95% was assumed.

$$n = \frac{N}{[1+N(e)^2]} = \frac{74235}{1+74235\ (0.05)^2} = 398 \text{ learners}$$

where n = Sample size; N is the population size and e is the level of precision - 0.05

Stratified proportional allocation method was used to ensure equality in representation with respect to the number of learners enrolled on the online learning platforms for each university. Simple random sampling technique was adopted in the study to pick out the respondents to ensure that the sampled entities are a representative of the entire population.

The questionnaire for self-directed learning factors was adapted from Fisher and King (2010) and intricately designed to bring out self-directed learning factors for online learning. Questions in the questionnaire were presented in the form of closed questions organized by 5-point Likert scale: Scale 1 = Strongly disagree; Scale 2 = disagree; Scale 3 = neutral; Scale 4 = agree and Scale 5 = Strongly agree.

To ensure quality of the data collection tool, validity was attained through both internal validity and external validity. Reliability was ensured by carrying out a pilot study and performing an internal consistency reliability test. The internal consistency of the data collection instrument was analyzed using Cronbach's alpha where the Cronbach's alpha value for Self-Directed Learning construct was .988 with 39 items. A Cronbach's alpha value of 0.90 and above is considered as excellent reliability (Taber, 2018). Exploratory factor analysis was used to extract constructs and indicators that converge in them.

Data Analysis and Discussion

Gender of respondents

Data analysis based on gender of the respondents pointed out that of the 398 learners who took part in the study, 229 which represents 57.5% were male while 169 which represents 42.5% were female.

Level of education

The study revealed that of the 398 respondents, 120 which represents 30.15% were postgraduate students while 278 which represents 69.85% were undergraduate students.

Exploratory Factor Analysis

This section aimed at analyzing the self-directed learning of university students and extracting principal components to be used as constructs. The respondents were tasked with rating their level of agreement of 39 different indicators with respect to self-directed learning on a scale ranging from Strongly agree (1); Agree (2); Undecided (3); Disagree (4) to Strongly disagree (5). The responses were summarized and analyzed to extract constructs and their correlating indicators using exploratory factor analysis.

Construct Extraction

The number of components to be extracted were determined using three different methods: Kaisen criteria; Scree plot and Parallel analysis. Table 1 – Self-directed learning total variance explained displays the analyzed data using kaisen criteria.

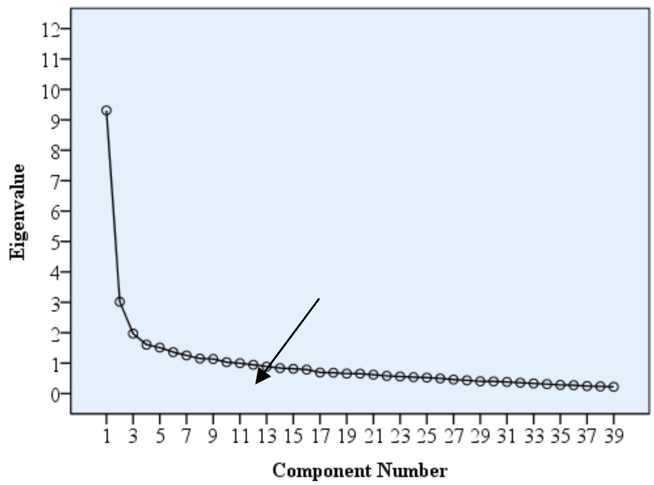
Table1: Self-directed learning Total Variance Explained

Component	Initial Eigenvalues		
	Total	% of Variance	Cumulative %
1	9.309	23.870	23.870
2	3.018	7.739	31.609
3	1.971	5.054	36.664
4	1.508	4.122	40.786
5	1.457	3.874	44.660
6	1.362	3.493	48.153
7	1.255	3.218	51.371
8	1.152	2.953	54.325
9	1.137	2.914	57.239
10	1.033	2.648	59.887
11	.998	2.559	62.446
12	.946	2.425	64.871

Kaisen criteria was used to determine the eigenvalues greater than 1. Table 1 summarizes the analyzed data and pointed out that the first 10 components had eigen values greater than 1.

The second method used was scree plot where the researcher looked for a change in direction (kink) in the line graph. The components above the elbow were retained. Figure 1 – Self-directed learning scree plot graphically indicates the analyzed data.

Figure 1: Self-directed learning Scree plot



According to Figure 1 – self-directed learning scree plot, the kink appeared after the third component. The researcher further used parallel analysis. Table 2 – Self-directed learning parallel analysis displays the generated values.

Table 2: Self-directed learning parallel analysis

Eigen value #	Random Eigen value	Standard Deviation
1	1.7110	0.0561
2	1.6232	0.0416
3	1.5629	0.0315
4	1.5092	0.0305
5	1.4617	0.0251
6	1.4207	0.0252
7	1.3801	0.0218
8	1.3373	0.0209

The researcher systematically compared the Eigen values generated through the kaisen criteria (Table 1) and PCA parallel analysis (Table 2). The first three component values from kaisen criteria were larger compared to the values generated through parallel analysis. It was further noted that the fourth component value of kaisen criteria was lower than the fourth PCA parallel analysis value. Based on the three different comparisons, the researcher retained 3 constructs.

Factorability of the correlation matrix

Communalities analysis elaborates how much variance is explained in each indicator. Based on this analysis, nine indicators: I am confident in my ability to search for new information; I enjoy learning challenges; When presented with a problem I cannot solve I seek for help; I am able to focus on a problem; I prefer to set my own criteria to evaluate my learning performance; I evaluate my own learning performance; I am logical; I enjoy learning new information and I prioritize my work had an extraction value less than 0.3. This implies that the nine indicators did not fit well with the other indicators in their components.

To refine the scale and make it efficient, the researcher eliminated the 9 indicators by virtue of having low communality extraction coefficients and fixed the principal components to 3 by virtue of comparing the Kaisen criteria values, parallel analysis values and the scree plot.

Suitability of Data for Factor Analysis

To determine if the sampled data is suitable for factor analysis, the Kaiser-Meyer-Olkin Measure of sampling adequacy should be greater than 0.60 while the Bartlett's test of Sphericity significant (p) value should be less than 0.05. Table 3 – Self-directed learning KMO and Bartlett's Test illustrates the results of the analyzed data for this study.

Table 3: Self-directed learning KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.873
Bartlett's Test of Sphericity	Approx. Chi-Square	3715.803
	Df	435
	Sig.	.000

Based on the data collected and analyzed, Table 3 – Self-directed learning KMO and Bartlett's Test depicts that the Kaiser-Meyer-Olkin Measure of sampling adequacy value is 0.873. This value is greater than 0.6 and closer to 1. Besides, the Bartlett's test of Sphericity significant (p) value is 0.000, a value much less than 0.05. These imply that factor analysis is appropriate for this data.

Factor Extraction

After rotating the three-factor solution, the Rotated Component Matrix showed how the indicators map on the components. Table 4 – Self-directed learning rotated component matrix used Principal Component analysis extraction method, Varimax with Kaiser Normalization rotation method with the rotation converging in five (5) iterations.

Table 4: Self-directed learning Rotated component matrix

	Component		
	1	2	3
Confidence to rely on SDL skills	.497		
I organize my own studies	.477		
I strategize my solutions to problems	.477		
I possess excellent time management skills	.651		

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I am self-disciplined	.629		
I exercise rigorous time limits	.676		
I plan my learning activities	.743		
I possess excellent management capabilities	.704		
I am methodical	.572		
I am systematic in my learning	.591		
I set aside specific times for my studies	.580		
I trust myself to pursue my studies	.503		
I enjoy learning new things	.474		
I take responsibility for my actions		.605	
I set high standards for myself		.512	
I am in charge of the activities I do		.535	
I have high personal expectations		.629	
I take responsibility for my actions		.691	
I enjoy making personal decisions		.614	
I can research for information on my own		.571	
I like to establish my own learning objectives		.537	
I would rather set my personal life goals		.593	
I am conscious of my learning constraints		.449	
I have great confidence in my capability to learn		.536	
I have to acquire knowledge			.576
I enjoy assessing my work			.411
I am receptive to fresh ideas			.677
I assess novel concepts critically			.553
I learn from the errors I make			.509
I am curious as to why some things happen			.639

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

Based on Table 4, 13 indicators converged in component 1. These indicators were: I am confident enough to rely on my self-directed learning skills with minimum lecturer intervention with a loading coefficient of 0.497; I organize my own studies with a loading coefficient of 0.477; I strategize my solutions to problems with a loading coefficient of 0.477; I possess excellent time management skills with a loading coefficient of 0.651; I am a self disciplined with a loading coefficient of 0.629; I exercise rigorous time limits with a loading coefficient of 0.676; I plan my learning activities with a loading coefficient of 0.743; I possess excellent management capabilities with a loading coefficient of 0.704; I am methodical with a loading coefficient of 0.572; I am systematic in my learning with a loading coefficient of 0.591; I set aside specific times for my studies with a loading coefficient of 0.580; I trust myself to pursue my studies with a loading coefficient of 0.503 and I enjoy learning new things with a loading coefficient of 0.407. These thirteen indicators converge in a construct depicting the ability to manage personal activities. This implied that the first component was renamed 'self-management'.

11 indicators converged in the second component. These indicators were: I take responsibility for my actions with a loading coefficient of 0.605; I set high standards for myself with a loading coefficient of 0

.512; I am in charge of the activities I do with a loading coefficient of 0.535; I have high personal expectations with a loading coefficient of 0.629; I take responsibility for my actions with a loading coefficient of 0.691; I enjoy making personal decisions with a loading coefficient of 0.614; I can research for information on my own with a loading coefficient of 0.571; I like to establish my own learning objectives with a loading coefficient of 0.537; I would rather set my personal life goals with a loading coefficient of 0.593; I am conscious of my learning constraints with a loading coefficient of 0.449 and I have great confidence in my capability to learn with a loading coefficient of 0.536. These indicators converge on a personal attribute related to self-control. This implied that the second component was renamed 'self-control' with 11 indicators.

6 indicators converged in the third component. These indicators were: I have to acquire knowledge with a loading coefficient of 0.576; I enjoy assessing my work with a loading coefficient of 0.411; I am receptive to fresh ideas with a loading coefficient of 0.677; I assess novel concepts critically with a loading coefficient of 0.553; I learn from the errors I make with a loading coefficient of 0.509 and I am curious as to why some things happen with a loading coefficient of 0.639. These indicators converge in a construct related to urge to learn. This implies that the third component was renamed as 'urge to learn' and it has 6 indicators.

Based on this analysis, self-directed learning was attributed to three factors as highlighted in Figure 2 – Self-Directed Learning factors.

Figure 2 –Self-Directed Learning factors.

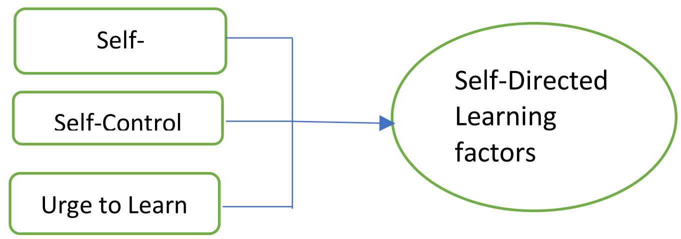

Figure 2 depicts that self-directed learning was attributed to three unique factors: Self-management; Self-control and Urge to learn with each factor having multiple indicators as indicated in Table 5- Self-directed learning indicators

Table 5: Self-directed learning indicators

Self-Management Indicators
I've confidence to rely on my SDL skills with minimum lecturer intervention
I organize my own studies
I strategize my solutions to problems
I possess excellent time management skills
I am self-disciplined
I exercise rigorous time limits
I plan my learning activities
I possess excellent management capabilities
I am methodical
I am systematic in my learning
I set aside specific times for my studies
I trust myself to pursue my studies
I enjoy learning new things

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Self-Control Indicators
I take responsibility for my actions
I set high standards for myself
I am in charge of the activities I do
I have high personal expectations
I take responsibility for my actions
I enjoy making personal decisions
I can research for information on my own
I like to establish my own learning objectives
I would rather set my personal life goals
I am conscious of my learning constraints
I have great confidence in my capability to learn

Urge to Learn Indicators
I have to acquire knowledge
I enjoy assessing my work
I am receptive to fresh ideas
I assess novel concepts critically
I learn from the errors I make
I am curious as to why some things happen

Implication of the Constructs

Self-management is the learner's capacity to organize their own learning activities. It involves planning study schedules, setting goals, managing resources, and maintaining a disciplined approach to tasks. In online learning environments, where the structure of traditional classrooms is absent, learners must rely heavily on their ability to manage their time and commitments effectively. Learners with strong self-management skills are typically able to prioritize tasks, avoid procrastination, and adjust to the flexible nature of online courses. On the other hand, poor self-management can lead to missed deadlines, lack of participation, and reduced learning outcomes due to disorganization and lack of direction.

Self-control refers to the learner's ability to regulate their emotions, behavior, and impulses. It becomes particularly important in online learning settings, which often involve distractions from home environments and the digital world. Unlike in face-to-face classrooms, learners in online settings must resist temptations such as social media, multitasking, or simply disengaging from the learning process. Those with high self-control are more likely to maintain consistent study habits, remain focused on learning objectives, and persevere through challenges. Without adequate self-control, learners may struggle with maintaining attention, managing frustration, or sustaining motivation in the absence of direct supervision.

The **urge to learn** reflects the internal drive a learner has to acquire knowledge and grow intellectually. This motivation can stem from personal curiosity, career aspirations, or a genuine interest in the subject matter. In online learning, where external motivators like teacher presence or peer pressure are less prominent,

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the internal desire to learn becomes a critical driver of engagement and success. Learners with a strong urge to learn are more likely to explore resources independently, actively participate in discussions, and seek help when needed. Conversely, a weak urge to learn may result in disengagement, passive learning, and an overreliance on external prompts to complete tasks.

Conclusion

Self-directed learning readiness is attributed to three construct/factors – self-management, self-control and urge to learn. Self-management has 13 indicators which correlate well with it; self-control has 11 indicators which correlate well with it while urge to learn has 6 indicators which correlate well with it.

Recommendation

This paper recommends that university management should analyze the self-directed learning readiness of learners towards online learning frequently and support the weak students to improve their level as self-directed learning readiness since it is an essential skill for effective online learning.

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