

Research Article

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Unlocking Success: Validation of the Motivated Strategies

Reginald Govender , Sarah Bansilal 

Abstract

Background/purpose. This study examined the validity of Paul Pintrich's Motivated Strategies for Learning Questionnaire (MSLQ) in a South African online university setting. With the rise of digital education, understanding student motivation in virtual environments has become critical. The research aimed to determine whether the MSLQ's motivation scales—developed initially in a different context—remain valid and reliable for assessing South African students' motivational constructs in online learning.

Materials/methods. A total of 276 university students participated, completing a 31-item questionnaire on a 7-point Likert scale. The study focused on six latent motivational variables: Intrinsic Goal Orientation, Extrinsic Goal Orientation, Task Value, Control of Learning Beliefs, Self-efficacy for Learning and Performance, and Test Anxiety. Covariance-based Structural Equation Modeling (CB-SEM) was used to assess the construct validity of the MSLQ in this context.

Results. The initial model did not fit well. However, after removing latent variables with poor statistical properties, the revised model demonstrated a significant fit. This indicated that a modified version of the MSLQ is valid for use in South African online learning environments.

Conclusion. The study concluded that a refined MSLQ model is applicable and useful for monitoring student motivation in South African online education. This tool can support course sustainability by helping instructors track and respond to motivational trends across different course offerings.

1. Introduction

Education around the world has changed due to the quick growth of online learning environments (Scherer et al., 2021), which gives students more freedom and flexibility. However, this change has also brought challenges (Kilag et al., 2024), especially when encouraging academic motivation and self-regulated learning. Understanding the dynamics of student motivation in online contexts is particularly important in South Africa, where socioeconomic disparities and infrastructure limitations still exist (Mabasa, 2024). The Motivated Strategies for Learning Questionnaire (MSLQ) is widely used in Western educational settings, but little is known about its structural validity and applicability in an African online learning environment.

The purpose of this study is to evaluate the suitability of the proposed model and its correspondence with empirical data obtained from South African students in an online learning environment. The results offer insights into how motivational constructs appear in digitally mediated learning environments and support the validity and reliability of the MSLQ in this setting. The significance of this study is that it has the potential to influence student support tactics, policy creation, and instructional design that are specific to the online education systems in South Africa. The majority of students at the university in question are first-generation in their families to attend university and come from poor socio-economic backgrounds, and can register with government financial aid (Sabi et al., 2020). By placing a well-established tool in a non-Western, technologically advanced yet socioeconomically marginalized educational context, the study fills a crucial gap. It promotes greater inclusivity in global research on academic motivation in online learning. The main finding is that although the MSLQ exhibits satisfactory psychometric properties, certain contextual modifications enhance its applicability and efficacy for South African students. These results highlight how crucial culturally sensitive assessment instruments are to advancing fair and successful online learning. This study aimed to investigate the hypothesised structure of the motivation section of the MSLQ among a group of South African University students in an online environment and provide reliable evidence of the academic motivation of the MSLQ. Hence, Covariance-based Structural Equation Modeling, which will include Confirmatory Factor Analysis (CFA), will be conducted to assess the adequacy of the proposed model and the extent to which the data align with the model. A revised model is presented, offering a model that better fits the empirical measurements in the given context.

2. Literature Review

The self-report tool, MSLQ, is intended to evaluate students' motivational orientations and their application of various learning strategies within a university course or module. The MSLQ is based on a broad understanding of how people learn and what motivates them, which was initially designed by Wilbert McKeachie (McKeachie et al., 1986). The MSLQ comprises two scales, namely the (i) motivation section and the (ii) learning strategy section. The motivation section focuses on students' goals, values, and beliefs about a course, which include their confidence in their ability to succeed and anxiety about tests. The learning strategy section includes items about students' usage of various cognitive and metacognitive methods. This study focuses on the first section of the motivation scales, determining students' motivation in an online learning environment.

Online learning has become increasingly prevalent in recent years, and understanding the factors contributing to successful learning outcomes within this context is paramount. This research paper investigates the validity and reliability of Paul Pintrich's Motivated Strategies for Learning Questionnaire (MSLQ) against an online learning environment. The MSLQ, developed by Paul Pintrich, has delivered valuable insights into the interplay between motivation and learning strategies, establishing itself as a significant tool in educational research. The significance of the MSLQ is underscored by its comprehensive structure and robustness, highlighting the important relationships

of student motivation and learning strategies. The questionnaire facilitates an in-depth exploration of students' motivational beliefs and self-regulation strategies (Pintrich et al., 1993; Yousefi & Rezaei, 2022). The multifaceted nature of the MSLQ enables researchers and educators to gain a nuanced understanding of how motivation influences academic behavior and performance (Credé & Phillips, 2011; Rad, 2021). Unlike many other tools that may only measure single dimensions of motivation or strategy use, the MSLQ encompasses a holistic view of student engagement, thus offering a more nuanced and intricate framework for analyzing educational results. The questionnaire's significance is demonstrated by its global impact, as it has been translated and adapted into multiple languages and contexts worldwide (Duncan et al., 2005; Huang et al., 2008), while its reliability is supported by robust factor analyses and good predictive validity for course performance (García et al., 1995).

Research has highlighted the complex interplay between student motivation, self-regulation, and learning outcomes in online settings (Elshareif et al., 2021; Govender & Khoza, 2022; Roy, 2023). Students' academic motivation can positively impact their social ability, sense of community, and learning satisfaction. In addition, self-regulation has been shown to play a central role in mediating the relationship between students' perceptions of learning tools and their online learning experiences (Govender & Khoza, 2022; Govender, 2023). Self-regulated learning (SRL), which emphasizes motivational components such as self-efficacy, task value, and goal orientation, remains foundational in understanding student engagement in online contexts (Pintrich, 2004). In online learning environments, students with higher self-efficacy and intrinsic motivation- core elements of Pintrich's framework usually demonstrate greater persistence and academic achievement (Broadbent & Poon, 2015). The value component, which reflects the perceived importance and usefulness of learning tasks, has been shown to predict student satisfaction and performance in virtual classrooms significantly (Kizilcec et al., 2017), while goal orientation was found to correlate positively with deep learning strategies and reduced dropout rates in online courses (Sun & Rueda, 2012). Thus, integrating Pintrich's motivational constructs into an online environment may provide nuance in understanding student autonomy, engagement, and success.

Through the MSLQ motivation section, we understand motivation stems from innate drives and personal needs, guiding and sustaining students' academic behaviors. Self-regulation plays an important role in the motivation process as it involves actively monitoring and controlling one's thoughts, feelings, and actions in pursuing and achieving one's goals (Zimmerman, 2008; Cheng et al., 2013; Tabak et al., 2013). By understanding how these motivational processes unfold within online learning, teachers and policymakers can work to promote effective learning strategies and improved student outcomes. Fostering students' academic motivation should be a key priority for online instructors since it plays a crucial role in shaping students' learning experiences in digital environments. (Govender, 2023). Online learning has been growing for over a decade, and the COVID-19 pandemic has significantly accelerated this trend (Mollenkopf et al., 2020). Learning effectively in online environments is crucial for students to thrive in this evolving educational landscape. Furthermore, the prevalence of online information means that students must be able to navigate, find, and integrate online information into their understanding. Online learning environments grant students greater autonomy and flexibility in accessing and engaging with learning materials, adding to the need for robust self-regulation and motivation (Hartnett & Hartnett, 2016).

The lack of a facilitator in an online setting can pose unique challenges for cultivating student motivation, which must be carefully addressed. The growing prominence of online education and the unique attributes of online learning contexts highlight the pressing need for students to develop strong academic motivation skills. Online learning has been lauded for its ability to provide students with greater flexibility and convenience compared to traditional F2F (face-to-face) education (Serdyukov, 2017). As noted, students can access learning materials and engage with instructors remotely, allowing them to fit their studies around other commitments. Additionally, online learning

provides opportunities for students to develop digital competencies that are increasingly valuable in today's job market, giving them a competitive edge. In this sense, online learning can empower students to take greater control over their educational journeys (Kulikowski et al., 2022). However, online learning environments also present unique challenges. Students can struggle with comprehension, retention, and concentration, likely due to lower motivation, reduced interaction, and inadequate support (Govender, 2023). These difficulties can be exacerbated by the socioeconomic statuses of students, teachers, and institutions, further compounding the barriers faced in an online learning environment. There is also evidence that the rapid, large-scale transition to remote learning during the COVID-19 pandemic was marked by significant challenges, as both teachers and students were not fully prepared for this modality (Cutri et al., 2020; Hassan et al., 2020; Wong, 2023; Hathaway et al., 2024; Kilag et al., 2024; Scherer et al., 2021). Additionally, online education has been met with skepticism from stakeholders who question the legitimacy and value of this mode of study, particularly in light of high attrition rates and low student attainment (Garg & Goel, 2022).

This ambivalence towards online learning may stem, in part, from concerns that deep learning and meaningful social connections are more difficult to foster in digital environments. Overall, the existing literature suggests that the advantages of online learning must be carefully weighed against its potential drawbacks, particularly in relation to students' academic motivation (Goodsett, 2020; Wieland & Kollias, 2020; Xie et al., 2020). There is likely to be little to no research that investigated the hypothesized model of the MSLQ model among South African university students in an online environment. There is a possibility that the era and context of the MSLQ might affect how it performs in an African online climate as compared to a Western non-online environment. If this is the case, it grants a revised model to be presented.

3. Methodology

3.1. Data Collection Tool

The Motivation Strategies for Learning Questionnaire (MSLQ) is a self-report instrument that examines the motivational orientations of tertiary students and their utilization of various learning strategies in a course (Duncan et al., 2015). The theoretical frameworks underpinning the MSLQ tool are the cognitive view of motivation and learning strategies (McKeachie et al., 1986). The original MSLQ study was conducted during the Winter of 1990 with 380 students, the majority being White students, during an era without online learning (Pintrich et al., 1993).

In contrast, this cross-sectional study was conducted at a South African university that embraces democracy and has a diverse ethnic group of students. This context was used to investigate the hypothesized model of the motivation section of the MSLQ in an online learning environment. Participants were made to complete the adapted motivation scales of the MSLQ. This part of the questionnaire consisted of 31 items based on a 7-point Likert scale with a range from 1 to 7 representing *not at all very true for me* to *true of me* (Appendix A). The motivation scales are based on six subscales (constructs), namely: Intrinsic Goal Orientation (IGO), consisting of four items; Extrinsic Goal Orientation (EGO), consisting of four items; Task Value (TV) composed of six items; Control of Learning Beliefs (CLB) consisting of four items; Self-efficacy for Learning and Performance (SLP) composed of eight items and Test Anxiety (TA) consisting of five items.

IGO refers to the degree to which students engage in learning for personal interest, enjoyment, or inherent satisfaction. Students with high intrinsic motivation are likely to adopt deep learning strategies and persist through academic challenges (Pintrich, 2004). This shift has been shown to have a positive association with self-regulated learning and academic achievement in both face-to-face and online educational settings (Artino, 2009). EGO reflects the extent to which students are motivated by external rewards such as grades, recognition, or approval from others. While it can

influence performance, it is often linked to surface-level learning strategies and short-term engagement (McClintic-Gilbert et al., 2013). Hence, it is important to balance extrinsic incentives with intrinsic motivators to sustain meaningful learning. TV encompasses students' perceptions of the importance, usefulness, and interest in a learning task. High task value is a strong predictor of engagement, persistence, and academic success, particularly in self-directed environments like online learning (Kizilcec et al., 2017). When students perceive tasks as meaningful, they are more likely to invest effort and adopt effective learning strategies. CLB refers to students' perceptions of their ability to influence learning outcomes through effort and strategy use. Students with strong control beliefs are more likely to take responsibility for their learning and persist in the face of difficulty or challenges (Pintrich, 2004). In an online learning environment, these beliefs are crucial for self-regulation, as students must effectively manage their own time and resources. SLP reflects students' confidence in their ability to complete academic tasks successfully. High self-efficacy is associated with greater effort, persistence, and use of cognitive strategies (Broadbent & Poon, 2015). In online environments, enhancing self-efficacy through feedback and scaffolding can improve learning outcomes. TA refers to the emotional and physiological responses that interfere with academic performance during assessments. High levels of test anxiety can impair concentration, reduce working memory capacity, and negatively affect academic achievement (Putwain et al., 2016).

3.2. Study Population and Sampling Technique

To investigate the validity of the MSLQ, data were collected from undergraduate students studying towards a four-year Bachelor of Education degree enrolled in an online module/course at a University in South Africa. All necessary permissions from the ethics review board and registrar's office were obtained. Participation in this study was voluntary, and participants could withdraw from the study at any time. The confidentiality and anonymity of participants were maintained to safeguard their privacy. An invite was sent to students in the researcher's course, and the survey questionnaire was completed online. The model fit indices are generally very sensitive to sample size in covariance-based (CB) analysis. It is recommended that the minimum sample size for CB-SEM (covariance-based structural equation modeling) analysis is 150 (Bentler & Chou, 1987). The cohort of undergraduate students was easily accessible to the researchers because they were based on the same campus, and invitations were sent to students. A total of 276 participants responded based on convenience and simple random sampling. Wolf et al. (2013) point out that sample size requirements for SEMs vary greatly from model to model. A one-size-fits-all approach should be cautioned, as sample sizes have been found to be valid from 30 to over 400 cases through running a series of Monte Carlo simulations, while also finding that more is not always better. However, the study meets the requirements of seminal work by Anne Boomsma, who established the minimum sample size of 200 (Boomsma, 1982; Boomsma, 1985).

3.3. Process

The study falls within the confirmatory research or hypothesis-confirming domain since MSLQ is an established questionnaire in which hypotheses/relationships between each construct will be tested to determine if they hold (Nilsen et al., 2020). In general, Confirmatory Factor Analysis (CFA) or Exploratory Factor Analysis (EFA) aims to test a theoretical model using empirical data by measuring latent variables and their indicators (Fan et al., 2016; Hair et al., 2018). EFA is carried out when the factors are unknown, whereby the phenomenon is not established through theoretical underpinning and is to be discovered. In contrast, CFA is carried out when there is an established theory about the phenomenon (Orçan, 2018). While both factor analyses belong to the family of multivariate techniques associated with structural equation modeling (Fan et al., 2016; Raunig et al., 2023), in this study, the data set was best examined to fit a CFA model.

According to Gallagher and Brown (2013), researchers use Structural Equation Modeling (SEM) to analyze or test relationships between observable and latent variables. The linear, causal, direct, or indirect correlations can be identified between common components through SEM. Also, SEM evaluates the measurement model with CFA (Hayes et al., 2017; Hair et al., 2020). CB-SEM is a broader technique that encompasses CFA. In addition to testing measurement models like CFA, CB-SEM can also test the structural model. Covariance-based Structural Equation Modeling (CB-SEM) was performed on the data, measuring the construct validity of the MSLQ in terms of online learning and testing the fit of the hypothesized model. In the case of confirmatory testing, CB-SEM is preferred over PLS-SEM since it uses chi-square to assess the difference between the observed and suggested covariance matrix. CB-SEM employs an advanced statistical model to estimate and evaluate correlations between dependent and independent variables and the hidden structures in between (Rigdon et al., 2017; Hair et al., 2018). CB-SEM will conduct a chi-square test to test the null hypothesis that the anticipated model (predicted) and actual data (observed) are equal. Therefore, the null hypothesis (H₀): The model fits perfectly. Usually, one does not favour rejecting the null hypothesis since the predictions should align closely with the actual data. When conducting SEM, researchers often first evaluate the measurement model (whether the measured variables accurately reflect the desired constructs or factors) before assessing the structural model. Hence, reporting will be done on the measurement model (including model fit) and the structural model (discriminant validity). The structural model will only be considered if the desired results are found in the measurement model (Jackson et al., 2009).

4. Results

The sample size of this study was n=276 undergraduate students studying towards their Bachelor of Education. In assessing students' motivation for online learning, data was collected from 31 items, using a 7-point Likert scale with 1 referring to not true of me and 7 referring to very true of me, and was analyzed. The Composite Reliability (CR) and Cronbach's Alpha (CA) were used to ascertain the reliability of each construct, which was way over the recommendation of (>0.7) (Hair et al., 2018).

The hypothesized six-construct (latent variable) model of motivation of learning online: IGO, EGO, TV, CLB, SLP, and TA, with their indicators, is graphically represented in Figure 1. The large circles represent the six constructs (the values represent the CR), and the rectangles represent the indicators (values represent the factor loadings). The bidirectional arrows refer to the factor correlations depicting the relationship between constructs. In contrast, the one-way direction arrows indicate the factor loadings, and the small circles show the error variance.

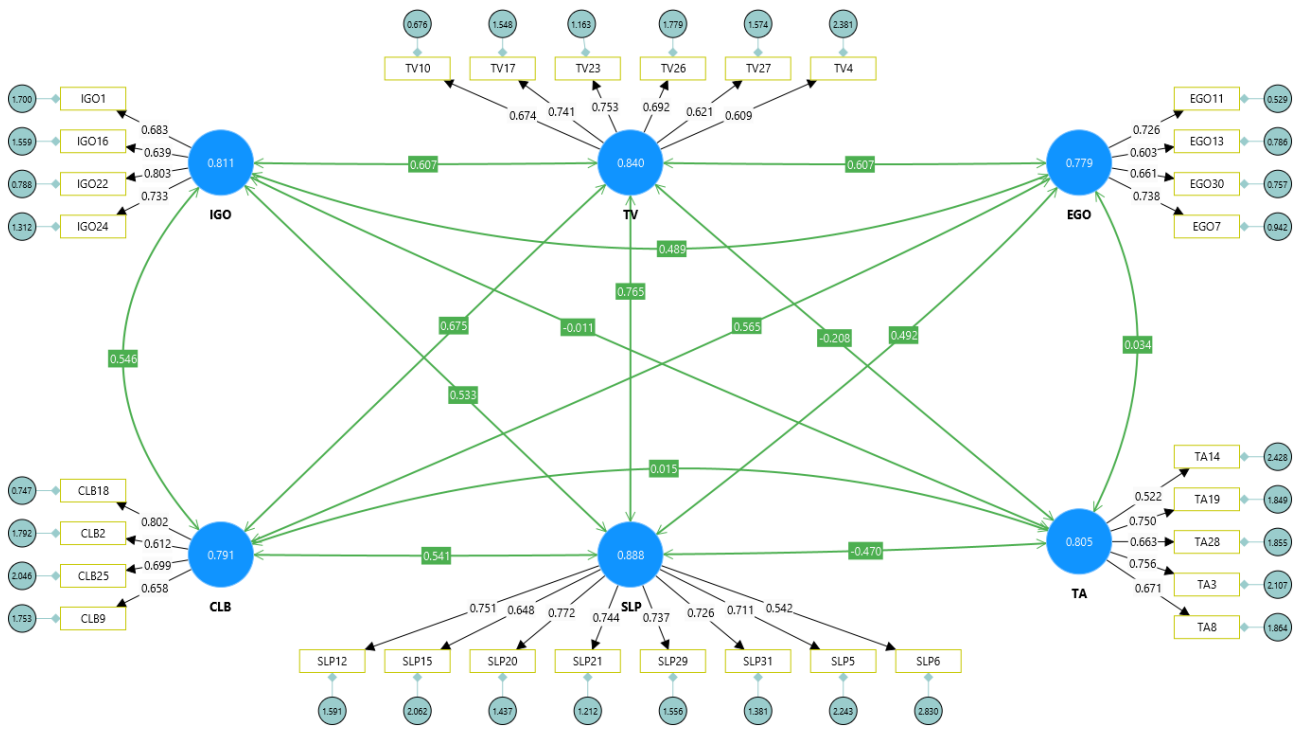


Figure 1. The six-construct model of the MSLQ motivation section based on online learning.

IGO= Intrinsic Goal Orientation; EGO= Extrinsic Goal Orientation; TV= Task Value; CLB= Control of Learning Beliefs; SLP= Self-efficacy for Learning and Performance and TA= Test Anxiety

The findings (Table 1) suggest that all constructs achieved the recommended level of acceptable factor loadings in accordance with CB-SEM (>0.50; unlike PLS-SEM >0.7) (Hulland, 1999; Truong & McColl, 2011).

Table 1. Factor Loadings and Reliability

Constructs	Indicators	Loading	Cronbach's alpha (standardized)	Composite reliability (rho_c)	Average variance extracted (AVE)
CLB	CLB18	0.802	0.791	0.780	0.484
	CLB2	0.612			
	CLB25	0.699			
	CLB9	0.658			
EGO	EGO11	0.726	0.779	0.780	0.468
	EGO13	0.603			
	EGO30	0.661			
	EGO7	0.738			
IGO	IGO1	0.683	0.811	0.804	0.514
	IGO16	0.639			

Constructs	Indicators	Loading	Cronbach's alpha (standardized)	Composite reliability (rho_c)	Average variance extracted (AVE)
	IGO22	0.803			
	IGO24	0.733			
SLP	SLP12	0.751	0.888	0.886	0.500
	SLP15	0.648			
	SLP20	0.772			
	SLP21	0.744			
	SLP29	0.737			
	SLP31	0.726			
	SLP5	0.711			
	SLP6	0.542			
TA	TA14	0.522	0.805	0.812	0.459
	TA19	0.750			
	TA28	0.663			
	TA3	0.756			
	TA8	0.671			
TV	TV10	0.674	0.840	0.836	0.468
	TV17	0.741			
	TV23	0.753			
	TV26	0.692			
	TV27	0.621			
	TV4	0.609			

Note. n=276

Construct Reliability was assessed using Cronbach's Alpha and Composite Reliability. The Cronbach Alpha and Composite Reliability (CR) for each construct were measured in the range from .77 to .88, surpassing the acceptable level of .70 (Hair et al., 2018; Nunnally & Bernstein, 1994). Therefore, each construct meets construct reliability in this study. The convergent validity of the constructs was assessed using the Average Variance Extracted (AVE), with a recommended threshold

of 0.50 (Fornell & Larcker, 1981). The AVE values exceeded 0.50 for IGO and SLP, whereas CLB, EGO, TA, and TV did not meet the recommended threshold. However, the latter constructs do approach 0.5. AVE is considered a conservative measure representing the amount of variance in the indicators accounted for by the latent constructs (Fornell & Larcker, 1981). If the CR is greater than 0.6 while the AVE is less than 0.5, the convergent validity of the construct is tolerable (Fornell & Larcker, 1981; Malholtra, 2010; Lam, 2012). Hence, the use of CR alone is adequate for establishing convergent validity; therefore, the scales in the present study have achieved convergent validity (Table 1).

The model fit assessment reflects the degree to which the data fit the model. The model fit indices reported in Table 2 are the recommended reporting standards found among 194 factor analysis studies (Jackson et al., 2009). There is clear evidence that the indicators do not adequately measure their intended concept. The model fit measure is insignificant, $\chi^2 (n = 276) = 801.648, p < 0.05$. Hence, the model does not fit the dataset since H_0 is violated (rejected), and we will not proceed to test discriminant validity under the structural model.

Table 2. Results on the Six-Model Fit

Model fit	Index	Estimate value	Desired value
Absolute fit	Chi-square	0.000	$p > 0.05$
	RMSEA	0.058*	RMSEA < 0.08
	SRMSR	0.068	SRMSR < 0.05
	GFI	0.840	GFI > 0.90
Incremental fit	AGFI	0.810	AGFI > 0.90
	CFI	0.897	CFI > 0.90
	TLI	0.885	TLI > 0.90
	NFI	0.808	NFI > 0.90
Parsimonious fit	Chi-square/df	1.913*	Chi-square/df < 3.0

Note. *Statistical significance

n = 276

4.1. A Restructure of the Model

Although CB-SEM requires a minimum indicator factor loading of 0.50 (Mohamad et al., 2019), it is recommended that all indicators have factor loadings greater than 0.6 (Dash & Paul, 2021). On the other hand, some scholars apply even stricter criteria, such as a cut-off of 0.7 (Rahn, 2008). Since the Pintrich Motivation Strategies for Learning Questionnaire (MSLQ) motivation scales were superimposed to evaluate student motivation in an online learning environment, the researchers dropped each indicator one at a time to improve the model. The factor loadings closer to 0.5 were dropped first until the desired model indices were reached. Hence, this results in a model that best fits the data given the context (Figure 2).

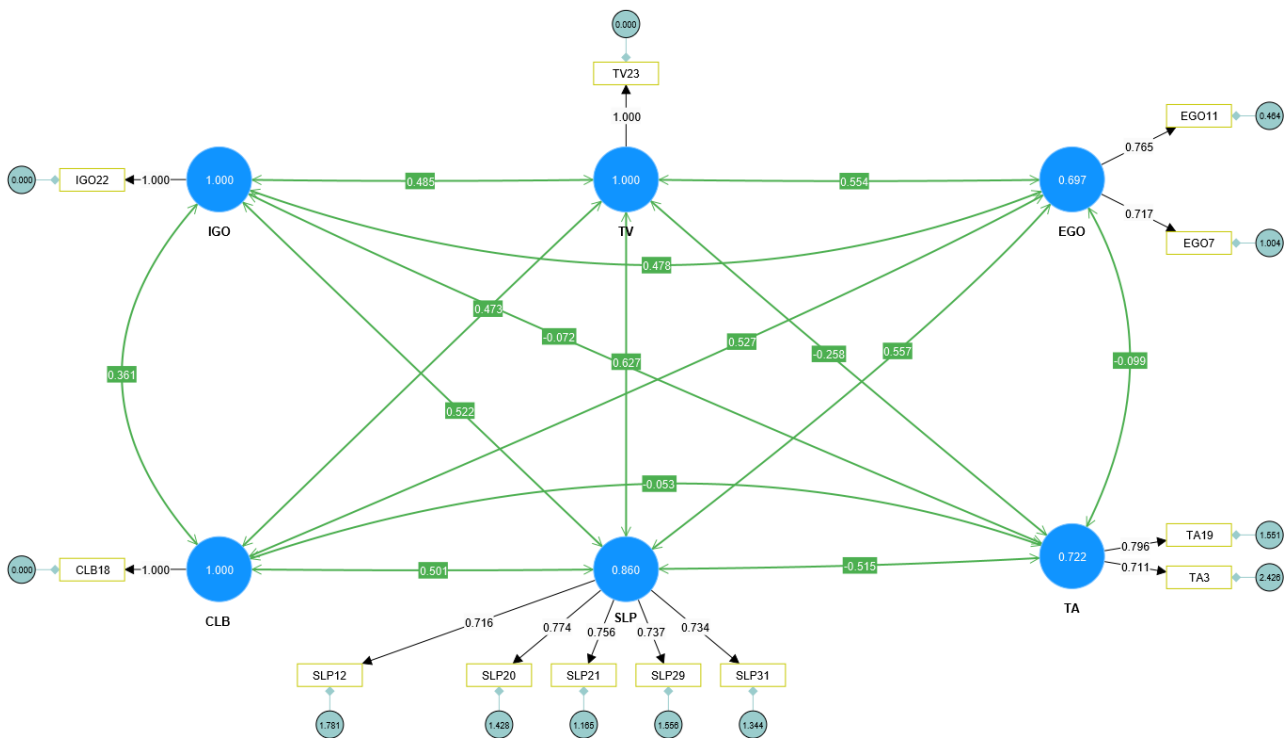


Figure 2. Restructured Model of the MSLQ Motivation Section Based On Online Learning

Single-indicator latent variables or single-indicator constructs are depicted (Figure 2), as they are latent variables CLB, IGO, and TV, which have one indicator. Negative correlations, as indicated by the path coefficients, were observed between TV and TA, EGO and TA, SLP and TA, CLB and TA, and IGO and TA. Therefore, the TA constructs have negative relationships with all the other constructs. This trend is easy to understand since students with high test anxiety often feel less confident about their abilities, and it can reduce their perceived control and intrinsic interest and dampen their perceived enjoyment of tasks.

The findings of the restructured model (Table 3) suggest that all constructs exceeded the recommended acceptable factor loading threshold of > 0.50 (Hulland, 1999; Truong & McColl, 2011), with values ranging from 0.7 to 1.0. The Cronbach's Alpha and Composite Reliability (CR) for each construct were measured to range from 0.70 to 1.0, in line with established thresholds (Nunnally & Bernstein, 1994; Hair et al., 2018). In addition to meeting construct reliability, each construct met convergent validity, as all AVEs exceeded the recommended threshold of 0.50 (Fornell & Larcker, 1981).

Table 3. Factor Loadings and Reliability of the Restructured Model

	Loadings	Cronbach's alpha (standardized)	Composite reliability (rho_c)	Average variance extracted (AVE)
CLB18	1.000	1.000	1.000	1.000
EGO11	0.765	0.708	0.701	0.550
EGO7	0.717			
IGO22	1.000	1.000	1.000	1.000
SLP12	0.716	0.860	0.860	0.553
SLP20	0.774			

	Loadings	Cronbach's alpha (standardized)	Composite reliability (rho_c)	Average variance extracted (AVE)
SLP21	0.756			
SLP29	0.737			
SLP31	0.734			
TA19	0.796	0.723	0.722	0.570
TA3	0.711			
TV23	1.000	1.000	1.000	1.000

Note. n= 276

As part of the covariance-based structural equation modelling, factor loadings were assessed for each item, items (IGO1, IGO16, IGO24, EGO13, EGO30, TV4, TV10, TV17, TV26, TV26, CLB2, CLB9, CLB25, SLP5, SLP6, SLP15, TA3, TA8, TA14, TA19 and TA28) was removed due to low factor loadings, improving reliability and validity hence improving the model fit. The model-fit measures were used to assess the model's overall goodness of fit (Chi-square/df, NFI, TLI, CFI, AGFI, GFI, SRMSR, RMSEA, and Chi-square), and all values were within their respective common acceptance levels (Bentler, 1990; Hu & Bentler, 1999; Ullman, 2001). The factor model (IGO, EGO, TV, CLB, SLP, and TA) yielded a good fit to the data (Table 4): Chi-square/df = 1.027, GFI = 0.975, CFI = 0.999, TLI = 0.999, SRMSR = 0.029, and RMSEA = 0.010.

Table 4. Restructured Results on the Model Fit

Model fit	Index	Estimate value	Desired value
Absolute fit	Chi-square	0.423*	p>0.05
	RMSEA	0.010*	RMSEA<0.08
	SRMSR	0.029	SRMSR<0.05
	GFI	0.975*	GFI>0.90
Incremental fit	AGFI	0.954*	AGFI>0.90
	CFI	0.999*	CFI>0.90
	TLI	0.999*	TFI>0.90
	NFI	0.967*	NFI>0.90
Parsimonious fit	Chi-square/df	1.027*	Chi-square/df < 3.0

Note. *Statistically significant

n= 276

The chi-square test evaluates the overall model. The measure of model fit is significant, χ^2 (n = 276) = 43.116, $p > 0.05$. Hence, the model fits the dataset, since H_0 was not rejected. The Root Mean Squared Error of Approximation (RMSEA) is achieved since this model fit index should be 0.07 or less

(Browne & Cudeck, 1993; Shi & Maydeu-Olivares, 2020). The adopted threshold for the Goodness of Fit (GFI) was >0.90 (Schumacker & Lomax, 2010); however, the GFI in this model met a more stringent threshold of >0.95 (Hu & Bentler, 1999; Hair et al., 2017). The adjusted goodness-of-fit index (AGFI) is a GFI adjusted for degrees of freedom, with a suggested benchmark of >0.90 , which was met (Jöreskog & Sörbom, 1993). The Comparative fit index (CFI) focuses on latent variables (constructs) rather than indicators, and the model met the favored threshold of >0.90 (Hair et al., 2020). Tucker-Likewise, the index (TLI) is usually found to be less than the GFI index value and has a recommended value of 0.90 and above (Bentler, 1990; Hair et al., 2020). The Normed fit index (NFI) is calculated by comparing the chi-square values of the model and the null model, and the recommended threshold is >0.90 , indicating good model fit (Bentler & Bonett, 1980; Hu & Bentler, 1999). The chi-square index value is sensitive to sample size and the number of indicators. As a result, Chi-square, considering the degrees of freedom (Chi-square/df), presents clarity and should ideally be <5 , whereas in this model, a stringent recommendation of <3 was applied (Marsh & Hocevar, 1985; Hooper et al., 2008).

Since the model meets the goodness-of-fit criteria in the measurement model, we will proceed to the structural model to assess discriminant validity. Discriminant validity in the study was evaluated using the Fornell and Larcker Criterion (Table 5) and the Heterotrait-Monotrait (HTMT) Ratio (Table 6).

Table 5. Fornell & Larcker Criterion

	CLB	EGO	IGO	SLP	TA	TV
CLB	1.000					
EGO	0.527	0.741				
IGO	0.361	0.478	1.000			
SLP	0.501	0.557	0.522	0.744		
TA	-0.053	-0.099	-0.072	-0.515	0.755	
TV	0.473	0.554	0.485	0.627	-0.258	1.000

Note. Bold values are the square root of AVE.

Table 6. HTMT Ratio

	CLB	EGO	IGO	SLP	TA	TV
CLB						
EGO	0.526					
IGO	0.361	0.478				
SLP	0.502	0.559	0.522			
TA	0.054	0.093	0.066	0.516		
TV	0.473	0.555	0.485	0.630	0.254	

According to the Fornell and Larcker criterion, discriminant validity is established when the square root of AVE for a construct is greater than its correlation with the other constructs in the

study. Nonetheless, the Fornell and Larcker criteria have been criticized, and the HTMT ratio is increasingly used as a novel technique to assess discriminant validity.

The study demonstrated discriminant validity using the Fornell and Larcker criterion. In addition, the HTMT ratio was evaluated, noting that all ratios fell below the maximum threshold of .85 (Henseler et al., 2015). Therefore, discriminant validity was confirmed by applying both criteria, indicating that the constructs measured are distinct from one another. The results for discriminant validity are presented in Table 5 (Fornell and Larcker Criterion) and Table 6 (HTMT ratio).

5. Discussion

The study tested the validity of the MSLQ motivation scales in an online context by proposing the null hypothesis (H0): the model fits perfectly. Structural equation modeling was carried out, in which the measurement model is evaluated first, followed by the structural model. Specifically, covariance-based structural Equation Modeling was performed on the data to assess the construct validity of the MSLQ in the context of online learning and to test the fit of the hypothesized model. The null hypothesis was violated as the measurement model did not meet the required thresholds. The MSLQ did not fit the sample data (Dunn et al., 2012), likely due to the more diverse population than in the original study and the context of the online learning environment (Rao & Sach, 1999; Jackson, 2018). Pintrich and Zusho (2002) reported that the relationship between motivation beliefs and academic achievement may be complex in an online setting.

As a result, the model was redefined by removing indicators with factor loadings closer to 0.5 until the model improved. Subsequently, many indicators related to CLB, IGO, and TV were removed. SLP retained most of its loadings, followed by TA and EGO. All factor loadings were > 0.7 , and the reliability levels were in the range of 0.70 to 1.0. The measurement model was found to be significant, $\chi^2 (n = 276) = 43.116, p > 0.05$, as the Goodness of Fit (GFI), Comparative fit index (CFI), Tucker-Lewis index (TLI), and Normed fit index (NFI) all meet the relevant thresholds. The structured model was assessed for discriminant validity using the Fornell and Larcker criterion and the HTMT ratio, with all thresholds met.

As Skinner (2016) points out, motivational beliefs differ across the developing educational timeline among students, considering cultural variations in motivation. While Pintrich's motivational model provides a framework for understanding students' motivation, there are potential limitations in fully explaining motivational processes across diverse educational settings. It may not fully account for factors like academic entitlement. Further development may be needed to address the complexity of motivational constructs in various educational contexts (Pintrich & Zusho, 2002), given that this study was based on a South African online environment.

The study found that some of the original indicators from the model were not relevant. For example, most TA and CLB indicators did not perform as expected and were removed from the final model. This finding can be explained by the online context within which the students were studying. Many studies (Bansilal, 2024; Comas-Forgas et al., 2021) found that pass rates in the online environment brought about by the COVID-19 pandemic were inflated, and there was concern about the extent of answer sharing possible in that setting. Hence, test anxiety may not have been as significant an issue in that online assessment environment as it normally is. This may also hold true for the CLB indicators, since students may perceive it was easier to pass without extreme effort in the online setting.

Furthermore, it was found that most of the SLP, IGO, EGO, and TV indicators did not work well. Considering that most students in the institution have attended no-fee schools and were only able to attend university because of the government financial aid program, and that only 7% of adults in South Africa have a degree (DHET, 2024), passing the degree is of utmost importance. Hence, intrinsic

and extrinsic goals, as well as interest in and appreciation of the learning content, may be less relevant for these participants compared to those for whom attending university is a matter of personal choice.

A multifaceted approach is required to address online learning and support students' motivation. Online course design should prioritize opportunities for meaningful interaction with both instructors and peers (Huang & Wang, 2022; Govender, 2023). This can include features such as discussion forums, collaborative projects, and regular virtual check-ins, all of which help foster a sense of community and belonging, which is crucial for maintaining motivation. Motivated students tend to exhibit more self-regulatory behaviors, such as planning, monitoring, and reflecting on their learning, which is associated with higher academic achievement (Shroff et al., 2007). Therefore, cultivating motivation should be a key priority for online education stakeholders.

The findings of this study provide a promising foundation for improving the design and delivery of online environments. However, further research is needed to more fully elucidate the complex relationships among the constructs of the Pintrich model. The study has some limitations, as most participants are second-language English speakers. This may have influenced their interpretation of the indicators and results, since the instrument was administered in English, the language of teaching and learning at the institution. In addition, future research is required to enhance the validity of the revised model presented in a South African online context. Research should go beyond validity and aim to unpack the underlying causes and factors that contribute to students' online motivation.

6. Conclusion

The study investigated the hypothesized structure of Pintrich's Motivated Strategies for Learning Questionnaire among a group of South African University students in an online environment. Covariance-based Structural Equation Modeling was carried out, revealing that the statements in the MSLQ are dependable and reliable. However, the model did not fit the sample data and could not accurately predict relevant outcomes. This study evaluates a commonly used instrument in a population that differs from the population on which it was originally developed. A revised model of Pintrich's motivation scales in a South African online environment was presented. By understanding the factors that drive and sustain online learning, stakeholders can better support students in thriving in this evolving educational landscape. The factor structure of the revised model indicates it would be a better fit to the empirical measurements.

Declarations

Author Contributions. R.G. and S.B.: Literature review, conceptualization. R.G.: methodology, data analysis. R.G: review-editing and writing, original manuscript preparation. All authors have read and approved the published version of the article.

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