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Research Article

Comparing Bayesian and Maximum Likelihood Methods in Structural Equation Modelling of University Student Satisfaction: An Empirical Analysis

Killian Asampana Asosega,[1,2] **Wahab Abdul Iddrisu**,[1,3] **Kassim Tawiah**,[1,2] **Alex Akwasi Opoku**,[1] **and Eric Okyere**[1]

[1]*Department of Mathematics and Statistics, University of Energy and Natural Resources, Sunyani, Ghana*
[2]*Department of Statistics and Actuarial Science, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana*
[3]*Department of Mathematics and Statistics, Ghana Communication Technology University (GCTU), Accra, Ghana*

Correspondence should be addressed to Killian Asampana Asosega; killian.asosega@uenr.edu.gh

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Students' satisfaction in the university environment is essential to both the student (customer) and management of the university. Satisfied students are determined to succeed in their academics, and this sustains their loyalty and trust, which results in an improved image and esteem of the university. This study examined the level of students' satisfaction with campus facilities and infrastructure, campus social life, student support services, and the quality of academics in the University of Energy and Natural Resources (UENR) in Ghana and further investigated how students' satisfaction with the above four areas of the university environment affect each other. A questionnaire was administered to continuous students in UENR, and the collected data were analysed using structural equation modelling within the maximum likelihood and Bayesian frameworks whose results and performance were compared. Results showed that students' satisfaction levels with available campus facilities, campus social life, and student support services were low but were fairly satisfied with the quality of academics. Both maximum likelihood and Bayesian techniques showed positive significant effects of students' satisfaction with campus facilities and infrastructure on satisfaction with campus social life, students' support services, and academics. Moreover, students' satisfaction with social life was positively associated with their satisfaction with academics and student support services. Although both estimation methods obtained similar estimates and inferences, the Bayesian SEM outperformed the ML-SEM based on the recommended fit indices. Findings of the study highlight the significant effects of satisfaction with campus facilities and student support services on students' satisfaction with academics and the university environment at large. The study further underpins the important role of the availability of adequate facilities and quality students' services in improving and sustaining satisfaction.

1. Introduction

In recent times, higher education across the world has experienced fierce competition among local and international institutions of higher learning [1]. Higher institutions of learning are therefore faced with the challenge of how to ensure the sustainability of their educational programs by improving the quality of services (teaching and learning, students, support systems, and conditions of infrastructure/facilities on campus among others) to students to enhance their satisfaction. According to [2], students' satisfaction is a complex concept, consisting of several dimensions. Authors of [3] defined student satisfaction as the favourability of a student's subjective assessment of the numerous outcomes and experiences associated with the education received. Moreover, [4] also described the satisfaction of students as the overall sum of students' attitudinal and behavioural beliefs that result from accumulating all benefits obtained from an educational system by students. According to [5], the life of students in the university environment is a web of interconnected social and academic experiences for the duration of their studies. Universities worldwide have and will continue to put in place strategic and rigorous processes to achieve and sustain high-quality standards with students' satisfaction as the main focus towards achieving academic excellence.

Student satisfaction is therefore an important tool for ensuring the sustainability of universities and most especially very young ones like the University of Energy and Natural Resources. Moreover, students' satisfaction, when well harnessed, results in high students' retention and attraction of potential new students and profitability of the institutions [6–8]. Again, all organizations, especially universities, need to provide the best of services to their students (customers), since these services are also rendered by competitors in the education space and must be regularly assessed and evaluated to help maintain and improve these services to enhance students' satisfaction [9].

Due to rapid modernization and globalization across the world, higher education has become customer-oriented with a focus on students. These growing trends have necessitated the incorporation of some measure of students' satisfaction in their marketing strategies, planning policies, and recruitment drives [10]. According to [9, 11–14], higher educational institutions must regularly conduct students' satisfaction evaluations of their internal performance to help identify areas that make them distinct and unique among other higher educational institutions and help discover areas that need improvement to meet the expectations of students.

Findings in [15] established that students' satisfaction in any higher educational institution is attained when their initial expected experience and performance are met or exceeded. A study by [16] assessed students' satisfaction by two groupings. The first focused on teaching and learning evaluations, while the second facet mainly concentrated on the comprehensive student experience of the entire institution.

For this present study, students' satisfaction refers to the overall students' score of happiness with the university environment based on campus facilities, support systems for students, social life, and teaching and learning evaluations in the university. This study investigates how the satisfaction levels of continuing students (level 200 to level 400) in UENR, one of the young universities in Ghana, are influenced by the four areas of the university environment, and how they are connected with the overall satisfaction level of students in the university. Several studies have established and elaborated on the importance of student satisfaction to institutions of higher learning such as universities, polytechnics, and colleges [5, 7, 9, 17, 18]. However, most of these studies aggregated all four areas considered, which therefore creates a gap with respect to how students' satisfaction with each of these aspects of the university are interconnected and how the respective satisfaction levels feed into the overall satisfaction of students in university. The outcome of the study could be leveraged upon to identify areas demanding improvement to further enhance the quality of services provided to students by management of the university. For this study, only students who have spent at least one academic year on campus were eligible to be administered a questionnaire. Continuous students of the university were considered because they have experienced the university environment and are familiar with life on the university campus. They study excluded the first years who might be trying to cope with the new environment in the university since most of them are coming from senior high school.

1.1. Literature Review. Students' satisfaction, as a multidimensional phenomenon, is influenced, by several factors [19–22]. Among these factors are the availability of adequate campus facilities. In [23–25], findings showed that students' overall satisfaction and improved performance depended on the availability of adequate facilities inside and outside the lecture room. Moreover, the study in [11] observed that higher institutions of learning with appropriate campus facilities were more likely to score higher satisfaction levels as well as higher graduate output. It is therefore important to assess and evaluate the impact of adequate campus facilities and their subsequent utilization on the overall satisfaction levels of students in the university environment.

The social life of students in the university environment refers to the feeling of being part of the university environment and commitment towards a part or entire university environment as a whole [4, 5]. Moreover, [5, 26] opined that the social component of the university student is derived from the perceptions with respect to the feeling of connectedness, social support from affiliations, and the expression of being respected, valued and accepted by the groups, affiliations, and the entire university. The social life of students has a direct effect on the overall satisfaction scores of students in the university environment as observed and confirmed in findings of [27–29].

The quality of student support systems and services provided in the university environment has a strong impact on the satisfaction level of students [9, 30–32]. The importance of support services for students, as observed in [9, 12], further highlights the need for higher educational institutions to enhance the quality of support systems or services in place for their core consumers (students). The student support services in this study constitute the various student tailored activities put in place by the university towards the comprehensive and holistic well-being of the students during the duration of their studies in the university. The study will help identify any possible gaps and areas that require the needed interventions to improve the overall students' satisfaction level in the university environment.

The teaching quality and competence component of the university environment is also a key determinant of students' satisfaction. Higher educational institutional including universities are primarily mandated to train, develop, and enhance the skills of human capital for economic growth and development. According to [33], the quality of teaching and learning in the university is a key factor considered by students prior to entering the institution and has a direct effect on the students' overall satisfaction. Also, work in [34] observed and confirmed the significant impact of the quality of teaching of lecturers on students' satisfaction scores and further suggested measures to improve the teaching quality of university lecturers for enhanced satisfaction levels of students. In a related study,

[35] identified the competence of university lecturers as an important factor affecting the satisfaction levels of students. They also emphasized that lecturers with personal, pedagogical, social, and professional competence demonstrate high quality of teaching which directly affects students' satisfaction. In addition, [36], observed a positive association between students' satisfaction and competence of faculty. Again, the competence of university teachers has significant positive effects on the quality of teaching, which directly feeds into the satisfaction scores of students in the university [32, 37, 38].

2. Materials and Methods

2.1. Research Design. This study examined the influence and impact of campus facilities, students' support systems, social life, and academics and the quality of lecturers on the overall satisfaction of continuous students. The study employed structural equation modelling (SEM) in the frequentist (maximum likelihood estimation) and Bayesian frameworks to explore the relationships between some variables (constructs) and the overall students' satisfaction.

2.2. Participants. A students' satisfaction questionnaire was designed and administered to a random sample of continuous students of the University of Energy and Natural Resources (UENR) between September 2020 and February 2021. Out of the initial 700 questionnaires distributed to students who were eligible and willing to participate in the survey, 650 were completed and returned, representing a response rate of 92.85%.

2.3. Data Collection Procedure. All continuing students on the main UENR campus were eligible to participate in the survey across all programs. Permissions were sorted from lecturers before questionnaires were administered to students to respond to the survey during the last 15 to 20 minutes of the lecture period. Students' participation in the satisfaction survey was voluntary, and also students were clearly informed and assured of the confidential treatment of their responses. Moreover, every student could complete only one questionnaire. The survey questionnaires were administered and completed in English language and returned to the researchers after the class. The questionnaire consists of two parts. The first part collected information on the demographic characteristics of respondents such as sex, age, level or year of study, religion, and program of study. The second part obtained information relating to student's satisfaction with (1) campus facilities and infrastructure with 13 items, (2) social life with 8 items, (3) student support systems with 11 items, and (4) academics and attributes of teaching staff (lecturers) with 24 items. Students' responses were identified on a 5-point Likert-type scale as follows: 1: very dissatisfied, 2: dissatisfied, 3: neutral, 4: satisfied, and 5: very satisfied.

2.4. Methods. Structural equation modelling (SEM) is a powerful multivariate statistical tool that has gained great application and usage in scientific investigations to assess and evaluate proposed multivariate casual relationships [39–41]. SEM is a multivariate technique which incorporates concepts and ideas from regression, factor analysis, and path analysis. SEMs have extensively been utilized in behavioural and educational sciences, which grants researchers the opportunity to postulate hypotheses as well as investigate relationships among variables including observed and latent variables [42].

SEM is comprised of two statistical techniques, namely, path analysis and confirmatory factor analysis. Path analysis was proposed to find the causal relationships among a number of variables by creating path diagrams [43]. Confirmatory factor analysis (CFA) on the other hand is aimed at estimating and measuring latent variables or constructs [44–47]. CFA extracts latent constructs from other variables and shares the most variance with related variables. The latent estimates are based on the correlated variations of the data and can reduce the dimensions of the data, standardize the scale of multiple indicators, and explain the correlations inherent in a given data [47].

Related to CFA is another kind of factor analysis called exploratory factor analysis (EFA) with the same estimation procedure as CFA. However, CFA is adopted and applied when the indicator for each latent variables is correctly specified in accordance with theory or prior knowledge and or experiences [39, 48]. The EFA is used to estimate the underlying latent variables. In practice, the EPA is often carried out to choose useful underlying constructs for CFA when there is little or no prior knowledge concerning the latent constructs [49, 50].

A standard SEM model comprises of the structural model and measurement model. The measurement model evaluates the latent variables or composite variables, whereas the structural model examines the hypothetical dependencies based on path analysis [45, 46]. SEM involves the following five key logical steps: model specification, identification of the model, model parameter estimation, evaluation of the model, and model modification [39, 45–47]. Model specification deals with specifying the hypothesized relationship among the variables of interest in the SEM according to one's prior knowledge or beliefs. The model identification checks the model for whether it is underidentified, just identified, or overidentified. Parameter estimates of the identified model can only be estimated if such a model is either just identified or overidentified. The model evaluation step deals with the assessment of model performance or fit indicators through computed indices for the overall goodness of fit. And the final step, model modification, adjusts the model for improvements in model fit measures, usually by means of post hoc model modifications [47, 51].

The SEM methodology is a more robust statistical tool capable of hypothesizing any kind of relationships and interactions among research variables in a single causal framework [52]. Moreover, the SEM procedure helps researchers to appreciate the concepts of latent variables and their role within the SEM domain. According to [53], latent variables present a form of abstraction that affords researchers the opportunity to appropriately describe associations among a collection of variables or events which share a common characteristic. This property of latent variables in SEM allows the combination of items (indicators) which are associated with the student's satisfaction with campus facilities and buildings on the university campus labelled as (campus facilities and infrastructure). In addition, SEM also has the ability to determine the interconnections between latent variables and their impact on other latent variables. For prediction and estimation of research parameters of interest in SEM, the following measurement and structural models are, respectively, used [54, 55]:

$$y = \mu + \Lambda\omega + \varepsilon, \tag{1}$$

$$\eta = \Gamma\xi + \delta, \tag{2}$$

where y is a $(p \times 1)$ random vector of manifest variables, μ is a vector of measurement intercepts, Λ is a $p \times q$ factor loadings matrix, Γ is an unknown matrix of regression coefficients, and ε and δ are $p \times 1$ and $q \times 1$ random vectors of measurement residuals, respectively. The interpretations of μ and Λ are the same as the interpretations of the intercept and regression coefficients in the classical regression model [54].

2.5. Maximum Likelihood Approach. The maximum likelihood (ML) estimation is one of the most utilized frequentist parameter estimation approaches in SEM. The ML technique employs an iterative procedure to minimize the discrepancy between the sample covariance matrix and the reproduced covariance matrix, evaluated by a fit function. According to [56, 57], the approach is based on the minimization of the following multivariate log-likelihood ratio fit function with the assumption of multivariate normality:

$$F_{\mathrm{ML}} = \log\left|\sum(\theta)\right| + tr\left(S\Sigma^{-1}(\theta)\right) - \log|S| - p, \tag{3}$$

where Σ is the covariance matrix based on p measured variables, S is the sample covariance matrix, and $\Sigma(\theta)$ is the model-implied covariance matrix, in which each element is a function of model parameter θ. The implied matrix $\Sigma(\theta)$ for a CFA model can further be expanded as

$$\sum(\theta) = \Lambda\Phi\Lambda^T + \Psi, \tag{4}$$

where Φ is the covariance matrix of factors and Ψ is the covariance matrix of residuals. In practice, parameters are estimated based on the sample covariance matrix S. When a model fits the data well, the model-implied covariance matrix $\sum(\theta)$ gets close to the sample covariance matrix S and consequently, the ML fit function $F_{\mathrm{ML}}(\theta)$ approaches 0.

The ML computational algorithm for SEM is based on the covariance matrix of the sample and further assumes that the sample observations are identically and independently distributed according to multivariate normal distribution [55]. However, when this assumption is not satisfied, the sample covariance matrix cannot be determined in the usual way as it becomes very difficult to obtain. Therefore, several earlier studies [42, 58] have proposed the adaptation of an attractive and flexible Bayesian technique as a means of overcoming such problems. In addition, according to [39], the traditional SEM analysis, which often uses the maximum likelihood estimation (MLE) and likelihood ratio test (LRT), results in the rejection of substantive theory and rather utilizes model modifications randomly to improve model fit. The Bayesian structural equation modelling (BSEM) therefore leverages on the weakness of the classical SEM framework due to its flexibility and better improved representation of theories or experiences into the model [41, 59].

2.6. Model Evaluation Measures. SEMs are often evaluated based on model fit indices for individual path analysis coefficients (p value and standard error) and the overall model fit indicators such as Root Mean Square Error Approximation (RMSEA) and Standardized Root Mean Square Residual (SRMR). The RMSEA is the model badness of fit test index where the value of zero (0) signifies perfect fit while higher values indicate lack of fit [60, 61]. RMSEA is important for identifying misspecified models and is less sensitive to sample size compared to the chi-square test. Acceptable RMSEA values should be less than 0.06 [39, 60, 62]. SRMR is similar to RMSEA and should be less than 0.09 for a good fitting SEM model [60]. Another fit measure is the Comparative Fit Index (CFI), which measures the amount of variance accounted for in the covariance matrix structure. CFI values range from 0.0 to 1. According to [60], CFI values of at least 0.95 are desirable for a better model fit. CFI is less sensitive to sample size than the chi-square test [62, 63]. Related to the CFI is the Tucker-Lewis Index (TLI), and this is a nonnormal fit index (NNFI) which overcomes the pit falls of the normed fit index (NFI) and is independent of the sample size [64, 65]. A TLI of 0.90 and above is considered acceptable for a given SEM [60].

2.7. Bayesian Structural Equation Modelling. The Bayesian structural equation modelling (BSEM) proposed in [59] has gained popularity in recent times for analysing complex factor structures as a result of its ability to incorporate exploratory features into traditional structural equation models (SEMs). The Bayesian SEM which is fundamentally based on the Bayes' theorem and has practically demonstrated a better representation of substantive theory [59]. The BSEM is applied mostly on the assumption that prior knowledge or experience of researchers is strong and has significant effects on the parameter estimates [39]. The BSEM can assign informative priors to some selected small-sized parameters and allow for the free estimation of these parameters. These informative priors are also known as shrinkage priors and are aimed at shrinking trivial parameter estimates to zero (0) with the goal of yielding a parsimonious factor structure that retains the reasonable parameter estimation of nontrivial effects [66]. The shrinkage priors can assume several distribution forms such as Laplace and normal distributions [67–69].

The Bayesian method of estimation incorporates prior information which represents relevant previous knowledge or experiences into the data likelihood to form the posterior [55, 70, 71], specifically expressed as

$$P(\theta \mid y) = \frac{P(\theta)P(y|\theta)}{\int_{-\infty}^{\infty} P(\theta)P(y \mid \theta)d\theta} \propto P(\theta)P(y \mid \theta), \tag{5}$$

where y is a vector of observed data (items) from a survey and θ is a vector of population parameters, $P(\theta)$ is the prior distribution, and $\mathrm{P}(\theta \mid \mathrm{y})$ is the data likelihood conditioned on the model parameters [42, 59]. The posterior, $\mathrm{P}(\theta \mid \mathrm{y})$, can be expressed as proportional to the product of the

Table 1: Sociodemographic profile of the respondents.

Sociodemographic variables		Frequency	Percent
Total	All respondents	650	100
Gender	Male	510	78.5
	Female	140	21.5
Age	15-19	149	22.9
	20-24	421	64.8
	25-29	59	9.1
	30-34	9	1.4
	35-39	8	1.2
	40+	4	0.6
Religious affiliation	Christian	585	90
	Muslim	50	7.7
	Traditional	8	1.2
	Other	7	1.1
Father's highest level of education	Basic	117	18
	Secondary	161	24.8
	Tertiary	372	57.2
Mother's highest level of education	Basic	230	35.4
	Secondary	240	36.9
	Tertiary	180	27.7

conditional data likelihood and prior distribution. The denominator of (5) is the normalizing constant and computing it is often intensive [42].

The choice of priors is essential in the Bayesian estimation technique. Priors can therefore range from informative (strong prior knowledge or belief) to noninformative priors (no or little prior knowledge) [66, 72]. Informative priors denote strong belief of parameters and often have small variances. Choosing meaningful informative priors helps in moving the posterior far away from the likelihood of improper data as a result of small sample sizes and or nonnormal data. Noninformative priors have large prior variances and therefore have little or no impact on the posterior distribution unlike informative priors [66, 73].

The Bayesian parameter estimation approach is usually accomplished by an iterative sampling of a large number of observations from the posterior distributions of unknown parameters employing the Markov Chain Monte Carlo (MCMC) algorithm through the Gibbs sampler [74]. MCMC is usually employed to obtain a set of observations from a specific multivariate probability distribution. The Gibbs sampler randomly samples the data iteratively from a conditional distribution and then integrates over a joint distribution. At the $(k + 1)$ th iteration, the Gibbs sampler updates the posterior distribution in accordance with the kth iterated values [55] as follows:

(a) Generate $\Omega^{(k+1)}$ from $P(\Omega \mid \Psi^{(k)}, \Lambda^{(k)}, \Phi^{(k)}, Y)$

(b) Generate $\psi^{(k+1)}$ from $P(\Psi \mid \Omega^{(k+1)}, \Lambda^{(k)}, \Phi^{(k)}, Y)$

(c) Generate $\Lambda^{(k+1)}$ from $P(\Lambda \mid \Omega^{(k+1)}, \Psi^{(k+1)}, \Phi^{(k)}, Y)$

(d) Generate $\Phi^{(k+1)}$ from $P(\Phi \mid \Omega^{(k+1)}, \Psi^{(k+1)}, \Lambda^{(k+1)}, Y)$

where $Y = (y_1, y_2, \cdots, y_n)$ is a matrix of observed variables, $\Omega = (\omega_1, \omega_2, \cdots, \omega_n)$ is a matrix of latent variables, and Λ, θ, and Ψ are the matrices of unknown parameters for factor loading, factor covariances, and error distances, respectively. The Gibbs sampling algorithm usually takes random walks within the state space based on the largest posterior distribution. As k increases, the MCMC chains may converge to the posterior distribution of interest with previous iterations discarded as burn-in before reaching the stationary distribution [55, 74]. Moreover, the comparison of the classical (maximum likelihood) SEM to the Bayesian-based SEM model results is based on the recommended model performance indices of mean absolute percentage error (MAPE), mean absolute error (MAE), coefficient of determination (R^2), and the root mean squared error (RMSE) [75, 76].

Table 2: Mean satisfaction scores.

Satisfaction areas	Mean (SD)
Campus facilities and infrastructure	2.3554 (0.6487)
Student support services	2.8983 (0.7872)
Campus social life	2.5602 (0.6959)
Academics	3.3816 (0.7425)
Overall	2.9130 (0.5822)

Table 3: Construct description and factor loadings.

Construct description	Code	Factor loading
Satisfaction with campus facilities and infrastructure (SCFI)		
Satisfaction with campus environment	SCFI6	.695
Satisfaction with computer availability	SCFI7	.653
Satisfaction with internet access on campus	SCFI8	.593
Satisfaction with library resources	SCFI1	.556
Satisfaction with places to study on campus	SCFI2	.544
Satisfaction with hygiene and sanitation conditions on campus	SCFI3	.540
Satisfaction with sports facilities on campus	SCFI4	.540
Satisfaction with lecture rooms	SCFI5	.509
Satisfaction with campus social life (SCSL)		
Satisfaction with opportunities to make friends	SCSL3	.724
Satisfaction with opportunities to develop close friendships	SCSL4	.714
Satisfaction with chances to pursue social interests	SCSL5	.707
Satisfaction with chances to spend enjoyable time with other people	SCSL6	.682
Satisfaction with recreation and events	SCSL7	.663
Satisfaction with social activities and events on campus	SCSL1	.659
Satisfaction with campus entertainment and events	SCSL2	.641
Satisfaction with student support services (SSSS)		
Satisfaction with career guidance and counseling services	SSSS1	.577
Satisfaction with IT help and support for students	SSSS5	.543
Satisfaction with campus signposting (i.e., finding your way around)	SSSS3	.519
Satisfaction with flexible terms for payment of school fees	SSSS4	.515
Satisfaction with helpfulness of staff	SSSS2	.514
Satisfaction with academics (SA)		
Satisfaction with professionalism of lecturers and tutors.	SA1	.781
Satisfaction with the level of knowledge of lecturers	SA2	.780
Satisfaction with the quality of teaching in the university	SA3	.772
Satisfaction with the quality of lecturers	SA4	.771
Satisfaction with flexibility of study options	SA5	.755
Satisfaction with the availability of course materials	SA6	.754
Satisfaction with teaching skills of lecturers	SA7	.741
Satisfaction with the conduct of examinations	SA8	.734

2.8. Empirical Findings. Table 1 shows the demographic make-up of the respondents. Majority of the respondents were male (78.5%) and below 25 years (87.7%) which is not surprising since all respondents were undergraduate students. Moreover, 90% of the respondents belonged to the Christian faith, which is the dominant religion in the country. For parental characteristics, it was observed that fathers were more educated than mothers. More than half (57.2%) of the fathers had tertiary education while only 27.7% of the mothers had tertiary education (Table 1).

The summary results on the mean satisfaction scores for the four areas of the university environment under study are presented in Table 2. From the items in the respective aspects of the university environment, a mean of 3 or more for a given aspect indicates satisfaction and dissatisfaction mean scores under 3. Academics recorded the highest mean satisfaction of 3.382 (0.7425), whereas campus facilities and infrastructure had the least satisfaction score of 2.355 (0.6487). The mean satisfaction scores for campus social life and students' support services are 2.56 (0.6959) and 2.8983 (0.7872), respectively. The results show that students are relatively satisfied with academics than campus facilities and infrastructure, students' support services, and social life on campus. Moreover, the overall mean satisfaction score of

Table 4: Reliability measures.

	SCFI	SCSL	SSSS	SA	Total
Alpha	0.807759	0.850967	0.735213	0.918846	0.912519
Omega	0.807416	0.854619	0.737126	0.917816	0.932686
omega2	0.807416	0.854619	0.737126	0.917816	0.932686
omega3	0.80164	0.85938	0.739042	0.912425	0.925809
avevar	0.547887	0.559753	0.560034	0.583177	0.562712

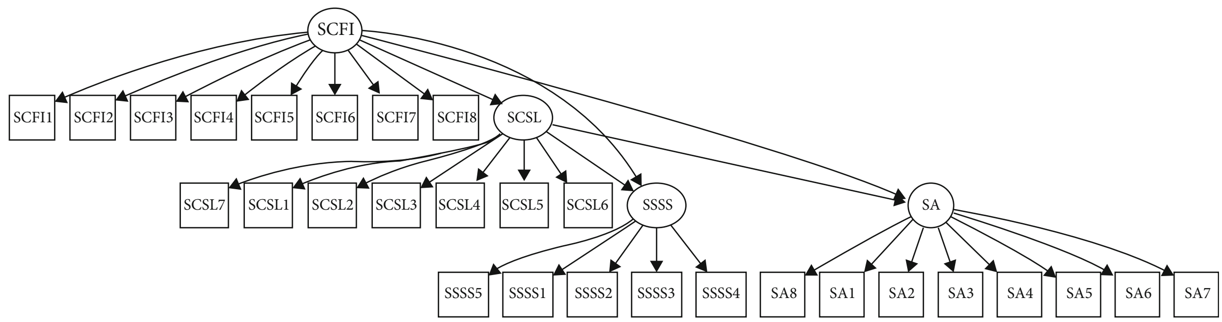

Figure 1: Research model.

2.913 (0.582) < 3 suggesting that students are generally not satisfied with the entire university environment.

Four constructs were considered in the research model based on the hypotheses of the study. The most significant indicators for each construct were identified using the factor loadings presented in Table 3. Based on the recommendation of [77], indicators with factor loadings less than 0.5 were not included in the SEM model.

Validity and reliability of the research instrument were examined using Cronbach's alpha (alpha) and average variance extracted (avevar), respectively. For validity, [78, 79] recommend alpha values greater than 0.7 whereas [80] recommend average variance extracted to be greater than 0.5 for reliability as the case in [81]. As observed in Table 4, all four constructs meet the required threshold for Cronbach's alpha and the average variance extracted. This indicates that the research instrument used for this study was valid and reliable.

The five hypotheses considered in this study include the following:

H_1. Student satisfaction with campus facilities and infrastructure has a significant effect on satisfaction with academics.

H_2. Student satisfaction with campus facilities and infrastructure has a significant effect on satisfaction with campus social life.

H_3. Student satisfaction with campus facilities and infrastructure has a significant effect on satisfaction with student support systems.

H_4. Student satisfaction with campus social life has a significant effect on satisfaction with academics.

H_5. Student satisfaction with campus social life has a significant effect on satisfaction with student support systems.

These hypotheses resulted in the research model in Figure 1.

Results for the research hypotheses concerning the relationships among the various constructs based on the maximum likelihood method of estimation are presented in Table 5. The results indicate a significant positive effect of satisfaction with campus facilities and infrastructure on satisfaction with campus social life (Est = 0.91, p value < 0.001), satisfaction with student support systems (Est = 0.68, p value < 0.001), and satisfaction with academics (Est = 0.34, p value < 0.001). Moreover, a significant positive effect was observed

Table 5: Parameter estimates based on the maximum likelihood estimation.

Relationship	Est.	SE(Est.)	Z	p value
SCFI ⟶ SCSL	0.910443	0.100202	9.086093	0.000011
SCSL ⟶ SSSS	0.270033	0.056465	4.782308	1.73E-06
SCFI ⟶ SSSS	0.683781	0.100028	6.835863	8.15E-12
SCSL ⟶ SA	0.28452	0.066189	4.298627	1.72E-05
SCFI ⟶ SA	0.349615	0.098834	3.537381	0.000404

in the effect of satisfaction with campus social life on satisfaction with student support systems (Est = 0.27, p value < 0.001) and satisfaction with academics (Est = 0.28, p value < 0.001).

The relationships among the various constructs based on the maximum likelihood method of estimation have been summarized in Figure 2.

The observed and acceptable range of values for the fit indices used to evaluate how well the research model fits the collected data based on the maximum likelihood method of estimation are presented in Table 6. All four fit indices considered in this study fall within the acceptable range of values, indicating that the research model fits the collected data well based on the maximum likelihood method.

Results for the research hypotheses concerning the relationships among the various constructs based on the Bayesian method of estimation are presented in Table 7. Weakly informative prior distributions (normal (0, 10)) were selected for parameter estimation. Similar to the results obtained using the maximum likelihood method, the results from the Bayesian estimation indicate a significant positive effect of satisfaction with campus facilities and infrastructure on satisfaction with campus social life (estimate = 0.93, pi.lower = 0.74, and pi.upper = 1.12), satisfaction with student support systems (estimate = 0.85, pi.lower = 0.65, and pi.upper = 1.07), and satisfaction with academics (estimate = 0.35, pi.lower = 0.18, and pi.upper = 0.55). Moreover, a significant positive effect was observed in the effect of satisfaction with campus social life on satisfaction with student support systems (estimate = 0.23, pi.lower = 0.13, and pi.upper = 0.33) and satisfaction with academics (estimate = 0.26, pi.lower = 0.16, and pi.upper = 0.37).

The relationships among the various constructs based on the Bayesian method of estimation have been summarized in Figure 3.

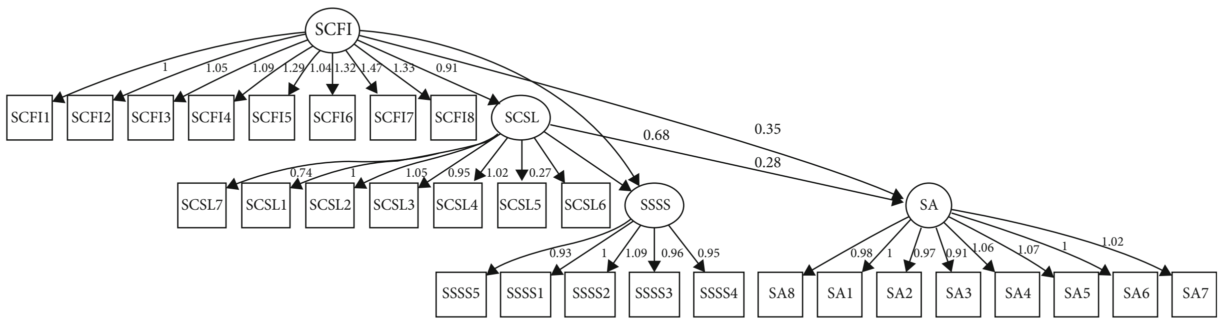

Figure 2: Maximum likelihood estimates for research model.

Table 6: Fit indices for maximum likelihood SEM.

Fit index	Value	Acceptable range
CFI (Comparative Fit Index)	0.9761	>0.90
TLI (Tucker-Lewis Index)	0.9738	>0.90
RMSEA (Root Mean Square Error of Approximation)	0.0430	<0.08
SRMR (Standardized Root Mean Square Residual)	0.05999	<0.08

Table 7: Parameter estimate BSEM.

Relationship	Estimate	Post.SD	pi.lower	pi.upper	Rhat	Prior
SCFI ⟶ SCSL	0.931	0.099	0.741	1.122	1.001	Normal (0, 10)
SCSL ⟶ SSSS	0.232	0.05	0.134	0.332	1	Normal (0, 10)
SCFI ⟶ SSSS	0.854	0.106	0.651	1.065	1.001	Normal (0, 10)
SCSL ⟶ SA	0.269	0.054	0.160	0.373	1	Normal (0, 10)
SCFI ⟶ SA	0.356	0.092	0.182	0.545	1.002	Normal (0, 10)

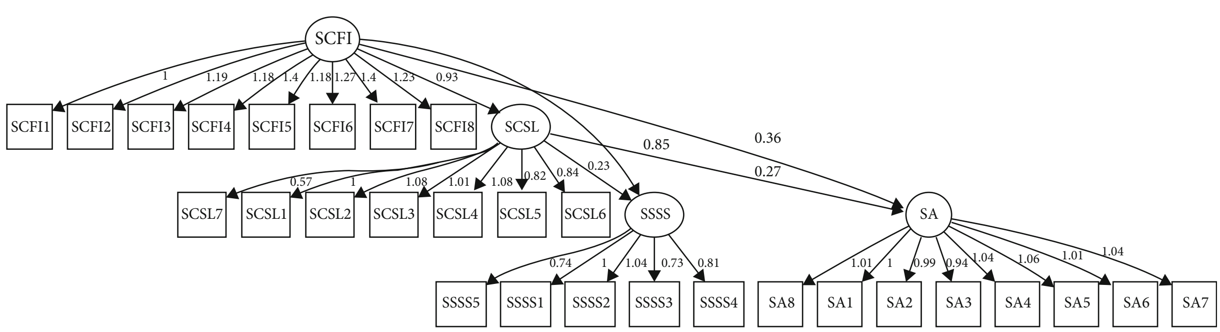

Figure 3: BSEM analysis of research model.

Performances of the SEM models based on the maximum likelihood estimation and the Bayesian estimation were compared, and the results are presented in Table 8. Based on the recommendation of [75], four comparative indices including the coefficient of determination (R-squared), the mean absolute error (MAE), the mean absolute percentage error (MAPE), and the root mean squared error (RMSE) were considered. These indices are used to measure the strength and accuracy of model predictions. Even though both the maximum likelihood method and the Bayesian method performed very well, the values of all four comparative indices suggest that in this application, the Bayesian method performed better than the maximum likelihood method.

3. Discussion

Students' satisfaction has been identified as one of the key factors for ensuring the sustainability and profitability of tertiary institutions across the world. The concept of university students' satisfaction is often aggregated and ignores the

Table 8: Performance of the Bayesian and maximum likelihood methods.

	R-squared	Mean absolute error	Mean absolute percentage error	Root mean squared error
BSEM	0.767	0.223	0.018	0.041
Maximum likelihood SEM	0.711	0.274	0.021	0.055

interconnections that possibly exist among the different facets of the university environment, which includes campus facilities and infrastructure, students' support services, social life, and academics and quality of lecturers in the university. This present study is aimed at examining how satisfaction with the four facets of the university environment are related based on two statistical estimation techniques. The research instrument for the study is valid and reliable based on the Cronbach's alpha and average variance extracted.

Results show that students are satisfied with the academics' facets of the university environment in UENR but are not satisfied with facilities and infrastructure, support services, and social life. The overall satisfaction of surveyed students in UENR is generally low. This observation underpins the need for universities to take the necessary measures to improve the quality of services rendered to their customers (students) since quality service contributes significantly to students' satisfaction and loyalty [82].

The MLE-SEM approach adequately fits the data collected for the study in accordance with the accepted and recommended fit indices (CFI, TLI, RMSEA, and SRMR) [47, 81]. Based on the MLE approach, satisfaction with campus facilities and infrastructure has a significant positive effect on satisfaction with campus social life, students' support services, and academics. Moreover, satisfaction with social life in UENR is positively associated with satisfaction with academics and student support services. Similar to the MLE approach, the Bayesian-SEM also showed significant positive effects of students' satisfaction with campus facilities and infrastructure on their satisfaction with social life, students, and support services, as well as academics. And students' satisfaction with social life positively affected their satisfaction with academics and student support services. The significant effects of satisfaction with campus facilities and student support services on students' satisfaction with academics further highlight the important role of the availability of adequate, modern facilities and the quality of student-centred services in improving and sustaining overall students' satisfaction in higher institutions of higher learning as observed in [31, 34, 83].

Moreover, the significant effects of available facilities and quality of social life on campus on students' overall satisfactions were identified in [84–86]. The low satisfaction of students with respect to campus social life, available campus facilities, and student support services therefore requires urgent attention by university management to enhance students' satisfaction, which also improves academic performance [9, 27, 29].

Although both the MLE and Bayesian methods observed similar parameter estimates and significant effects and inferences, the BSEM approach outperformed the MLE-based SEM in accordance with the four fit indices for evaluating the two methods within the SEM framework [75, 76]. The preference or better performance of the Bayesian SEM observed in this work supports the findings in [76] that concluded that the Bayesian SEM performed better than the maximum likelihood procedure in examining library user satisfaction. Moreover, the observations of this current study confirm the conclusions made in [71, 87] that the Bayesian method in general affords researchers the ability to manipulate information in both the priors and observed data which results in improved statistics and model fit indices. According to [42, 52, 71], the BSEM framework also performs better and it is more robust than classical ML-SEM even under nonnormal distributions and small sample sizes.

4. Conclusion

Students' satisfaction is an important and evolving area to both students and management of educational institutions including universities. Students' satisfaction is a key determinant of improved students' performance, loyalty as well as sustainability and profitability of the institution. This study investigates the relationships among students' satisfaction with four components of the university environment using the ML- and Bayesian SEM techniques. Empirical results from the survey indicate that students in UENR are generally not satisfied, most especially with student support services, available facilities and infrastructure, and campus social life.

Both the ML and Bayesian versions of SEM identified similar significant positive effects of satisfaction with campus facilities on satisfaction with campus social life and student support services provided. Moreover, a significant positive effect of satisfaction with social life on academics and student support services was observed in both ML-SEM and BSEM. However, the BSEM with weakly informative prior distributions (normal (0, 10)) performed better than the ML-SEM based on the coefficient of determination (R-squared), the mean absolute error (MAE), the mean absolute percentage error (MAPE), and the root mean squared error (RMSE) as observed in [42, 52, 75, 76].

Findings in this study call for urgent measures by university authorities to mobilize the needed resources towards improving facilities on the university campus and the provision of quality students' support services to enhance students' satisfaction. Moreover, students' satisfaction with academics will be significantly improved if the other three environmental factors are improved due to the positive impact these factors have on academics. In line with the recommendations of [9], universities with students who are unsatisfied with the services provided to them must initiate steps to continuously improve student support services to enhance students' overall satisfaction in the university environment which leads to students' loyalty and retention. Satisfied university customers (students) are marketing agents for the university to prospective students, and therefore, their satisfaction must be continuously evaluated to identify gaps and limitations which could be leveraged upon for the overall success and long-term sustainability and profitability of universities in Ghana.

Data Availability

The survey data in support of the findings of this present study are available upon request.

Conflicts of Interest

The authors declare that they do not have any conflicts of interest regarding this study.

Authors' Contributions

KAA, WAI, KT, and EO conceptualized and designed the study. KAA and WAI proposed the statistical methodology. WAI performed the statistical analysis. KAA drafted the manuscript. AAO, KT, and EO reviewed the manuscript. All authors agree to be answerable to all aspects of the work and jointly own the work. All authors read and approved the final manuscript.

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