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RESEARCH ARTICLE

A Learning Analytic Approach to Modelling Student-Staff Interaction From Students' Perception of Engagement Practices

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by Covenant University Research Ethics Commitee (CHREC) under Registration No. NHREC/25/10/2021, and performed in line with the US Department of Health and Human Services.

ABSTRACT The connection between student-staff interaction, students' positive outcomes, and institutions has been widely studied as a key focus of research on student engagement and quality learning in higher education. In this study, a learning analytic approach is taken to establish a model for student-staff interaction. Two African institutions are engaged in the analysis for data acquisition. The two student engagement datasets used in this study are acquired by survey approach using National Survey of Student Engagement Instrument from the student perspectives. An association rule mining technique with Frequent Pattern Growth algorithm is implemented to discover interesting associative patterns among the student engagement indicators in relation to two student engagement datasets. Structural equation modelling was then employed to investigate the discovered interesting associative relationships. This study evaluated 16 different student-staff interaction models using various fit indices to identify the most accurate predictor of student-staff interaction (SSI). The results suggest that poor quality interactions (QI), reflective and integrated learning (RI), and quantitative reasoning (QR) are key factors that influence the quality of SSI. The methodology and resulting validated models offer a unique contribution to the field and can inform the development of policies and best practices to enhance student engagement and improve learning outcomes in higher education.

INDEX TERMS Learning analytics, student engagement, student-staff interaction model.

I. INTRODUCTION

In higher education institutions, students are critical stakeholders, and their outcomes are of paramount importance. As a result, there has been a significant amount of research focused on students, utilizing various analytical methods such as descriptive, predictive, diagnostic, and prescriptive analyses. One area of interest is student engagement, which has been widely described in the literature as a determinant of various student outcomes [1], [2]. These outcomes generally include student achievement, perseverance, motivation, and satisfaction [3]. Most of these studies are concerned with identifying and assisting at-risk students in their academic success [4], [5], by understanding their learning patterns and suggesting strategies for improvement [6], [7], [8].

In the late 1970s, there was an increased interest in promoting student success, which led researchers, policymakers, and higher education administrators to emphasize student engagement [9]. In response to this trend, national-level engagement surveys such as the College Student Experience Questionnaire (CSEQ) and the US National Survey of Student Engagement (NSSE) were introduced in the early 2000s [9]. Other countries also implemented similar surveys, including the United Kingdom National Students Survey, South Africa Student Survey of Student Engagement, Canada National Students Survey of Engagement, Ireland Student Survey of Engagement, and Australia Survey of Student Engagement. These surveys were mainly adapted versions

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of the NSSE and were used for cross-institutional data collection [3]. Despite the growing popularity of student engagement research and surveys in many countries over the past two decades, it remains a relatively new research area in some nations, especially in those still developing their higher education systems.

Numerous studies have explored the multifaceted construct of student engagement, and among its various dimensions, student-staff interaction activity has shown a correlation with several positive student outcomes including student retention, academic success, active learning through solving of real-world problems, soft skills such as group work, cross-curriculum skills, and improved communication with their peers [10], [11], [12]. The concept of student-staff interaction encompasses formal and informal relationships, as well as the many responsibilities faculty members play in educational institutions as role models, advisors, instructors, sources of advice, mentors and support systems. Since these interactions are not spontaneous, they are influenced by a variety of variables.

Learning analytics provides the capability to investigate the growing tide of learner data to understand the activities and behaviours associated with practical learning and leverage this knowledge to optimise the educational system or environment [13]. The literature indicates a variety of strategies, approaches, perspectives, and tools used by scholars to analyse and comprehend student engagement [14], [15]. These methods for student engagement data collection include self-report surveys or questionnaires [16], [17], interviews or focus groups [18], and Learning Management System Log Data [19] among others. These data are then analysed using insightful approaches such as Frequency Analysis [20], Content analysis [21], Descriptive analysis, Prediction analysis [4] and other data mining approaches [22].

Despite ongoing advancements in higher education research, the persistent challenge of creating learning environments that foster student engagement remains a central focus in higher education, as highlighted in the literature [21], [23], and [24]. Unfortunately, students' viewpoints on this matter have received comparatively limited attention. Numerous studies have revealed a compelling connection between increased student performance and engagement initiatives, underscoring the pivotal role of engagement as a predictive factor for learning outcomes [25]. Furthermore, the impact of student-staff interactions on various aspects of student engagement has been widely acknowledged [10], [11]. Nevertheless, the academic discourse reflects a divergence of opinions concerning the determinants of student-staff interaction, with no established model to date. Additionally, there is a lack of consistency in how student-staff interaction is conceptualized and measured across the existing body of literature [26]. Intriguingly, our research has not identified any previous studies that have constructed a model for student-staff interaction based on students' perspectives of engagement practices. Several of the previous researches primarily focused on using statistical analysis to perform sophisticated analytical tasks on students' information, learning behaviours, skills, and attitudes without explicitly considering students' perceptions [27], [28]. As noted by [29] and [30], an exclusive focus on easily quantifiable indicators of student engagement and the use of correlation-based methods or standard regression analysis may not yield accurate results. Instead, a more comprehensive investigation is necessary, with additional data points and perspectives to uncover and explore the underlying indicators [31]. In light of these considerations, this study aims to build student-staff interaction models from students' perceptions of engagement practices using learning analytics approaches. This model will be instrumental in promoting student success and enhancing the quality of higher education institutions' learning experiences. The following objectives will help to attain this research's overarching aim:

i. to survey students' perceptions of engagement practices for student engagement dataset acquisition;
ii. to pre-process the acquired dataset in (1) and conduct descriptive analysis on the dataset;
iii. to discover interesting associative patterns among the student engagement indicators in relation to the pre-processed dataset in (ii); and
iv to investigate the prevalent interesting patterns in (iii) with structural equation modelling and establish interesting inferences.

The structure of the article is arranged as follows: Section II provides a comprehensive review of related literature, which is divided into three main sections. Section III, outlines the research methodology employed in this study. Subsequently, section IV details the research data analysis, findings and discussion. In section V, the study's conclusion and recommendations are presented, along with the limitations encountered during the research process, as well as suggestions for future research directions.

II. LITERATURE REVIEW

To demonstrate the relevance and originality of our study and to support the suitability of our chosen methodology, we have divided the review of related literature into three main sections. These sections are focused on learning analytics, student engagement, and student-staff interaction. By exploring these areas, we aim to establish the currency and relatedness of our research to previous studies.

A. LEARNING ANALYTICS

The scope and significance of learning analytics (LA) research have expanded significantly over the last decade due to its conceivable likelihood to meaningfully improve how well students and teachers learn and teach by demonstrating how educational innovations work [32]. LA is a phrase that is frequently used to refer to "the process of measuring, collecting, analysing, and reporting data on learners and their settings to better understand and optimize learning and its contexts" [33]. Ranjeeth et al. [34] define learning analytics as the "use of intelligent data, analytical models, and data generated by learners to discover knowledge and social connections, as well as to make predictions and offer guidance on learning''. It provides researchers with a plethora of fascinating methods for better understanding teaching and learning; and improves data infrastructure: beginning with data collection and processing and ending with visualization and suggestion. Learners benefit from closing the feedback loop, which allows for more rapid, precise, and actionable responses. Additionally, instructors, instructional designers, and institutional leaders can acquire new perspectives on their students' performance by observing and tracking the learning process [35].

Learning analytics encompasses a diverse set of analytical techniques, including descriptive, predictive, diagnostic, and prescriptive analyses, all aimed at enhancing students' self-awareness, fostering self-reflection, and cultivating lifelong learning skills and strategies. Additionally, it plays a pivotal role in elevating the quality of teaching and learning through the demonstration of the effectiveness of pedagogical innovations.

The application of learning analytics in higher education has become increasingly important for optimizing strategic outcomes. According to Leitner et al. [36], higher education institutions collect and analyse data to gain insights and make predictions based on critical questions identified. The literature highlights various strategic objectives that are achieved through the use of learning analytics, such as administrative and resource planning [37], identifying at-risk students [4], [5], [38], understanding institutional successes and challenges [38], altering academic and pedagogical models [19], [39] identifying data and risk challenges [38], [40], analysing what-if scenarios and experimenting with different approaches [41], [42], increasing productivity and effectiveness [43], [44], measuring faculty activity [45], and helping learners understand their learning style [6], [7], [8], [46]. By leveraging learning analytics, higher education institutions can make data-driven decisions to improve their operations and enhance student success.

A recent literature review conducted by Oladipupo et al. [47] identified six key objectives of incorporating learning analytics into the analysis of student engagement. These objectives include enhancing students' learning experiences, improving teaching and curriculum design, providing personalized learning support to students, promoting self-directed learning, predicting and enhancing student outcomes, and identifying optimal analytical methods and techniques. By using learning analytics to achieve these objectives, institutions can gain valuable insights into student engagement and tailor their strategies to meet the unique needs of individual learners.

In this research, two distinct learning analytics approaches were engaged in succession to achieve the research objectives. These approaches, Association Rules Mining and Structural Equation Modelling will be explained in detail in the following sections.

1) ASSOCIATION RULE MINING

Association rule mining is a data mining technique used to uncover previously unknown associative relationships that match a set of user-defined criteria. The goal is to uncover relationships between variables within a huge dataset. This may consist of determining which factors are most strongly associatively correlated with a single variable of interest [48].

The formal definition of an association rule, as stated in [49], is as follows: Let $A = \{s_1, s_2, \ldots, s_x\}$ be a set of d attributes referred to as items, and $B = \{t_1, t_2, \ldots, t_y\}$ be a set of y transactions known as the database. Each transaction t_s in B consists of a subset of the items in A. A rule is represented as $C \Longrightarrow D$, where $C, D \subseteq A$ are mutually exclusive items, i.e., $C \cap D = \emptyset$. Rules can also be considered as predictable transactions within a database. C and D are referred to as the antecedent and consequent of the rule, respectively.

Application of the association rule in the analysis of student engagement can be useful for identifying knowledge that can be used to increase student engagement, such as recognising the linkages between factors that influence student engagement. Association rule mining may help us uncover how students view their level of engagement, which can lead to the adoption of methods that effectively promote higher education. To determine a rule's significance and interest, several metrics are existing but the following have been widely employed:

i. Support: The support of an item within a database is a measure of its frequency. Alternatively, it can be defined as the proportion of transactions that contain the itemset. To compute the support of an itemset C in a transaction set B, equation (1) is used.

$$Support\ (C) = \frac{|t \in B; C \subseteq t|}{|B|} \tag{1}$$

ii. Confidence: The confidence of a rule is determined by its frequency in the database. As per the standard definition, it is measured as the proportion of transactions that contain both itemset C and D, where C is the antecedent and D is the consequent, relative to transactions that include only itemset C as shown in equation (2).

$$Confidence\ (C \Longrightarrow D) = \frac{Support\ \left(C \bigcup D\right)}{Support\ (C)} \tag{2}$$

iii. Lift: To measure the significance of an association rule, the lift is commonly used. When the lift value is 1, it suggests that the two item sets are independent, and the rule that connects them is inconsequential. However, if the lift value is greater than 1, it implies that the two item sets are correlated, and the rule may help predict future instances of the consequent given the antecedent. The lift's importance is determined by analysing the entire transaction database, as well as the confidence of the rule as shown in equation (3).

$$Lift\ (C \Longrightarrow D) = \frac{Support\ \left(C \bigcup D\right)}{Support\ (C) \times Support\ (D)} \tag{3}$$

Association rules are generally utilized with categorical datasets and have a range of applications such as examining patterns of student engagement, analysing behavioural data, and detecting network intrusions, among others [50], [51], [52]. There have been a variety of algorithms proposed for association rule mining, with the Apriori algorithm and Frequent-Pattern Growth Algorithm being the most widely used [53].

2) STRUCTURAL EQUATION MODELLING

The Structural Equation Modelling (SEM) approach is defined as a robust, general, versatile, and multi-variable analysis method used to evaluate the validity of hypotheses based on empirical data [54]. Additionally, multiple dependency relationships can be estimated, as path analysis and latent growth models [55]. SEM is frequently used to validate hypotheses in a variety of student-related studies, including those examining the causes of low retention rates for first-year undergraduates [56], validating the construct describing the critical factor influencing collaborative learning in an online environment [17], and examining the relationship between student engagement and success in an abstract algebra course [57].

Rather than analysing measurement models, this research will examine structural models derived via the inferences of the association rule mining result in this study. In practice, these relationships should ideally correspond to theories about student engagement in literature or suggest new hypotheses to be considered. As a result, this research focuses on the development and validation of structural models. This study considers the theoretical direction of causality between each identified structural model, analyses the interchangeability of the latent variables, assesses the presence of covariation among the latent variables, and uses the Root Mean Square Error of Approximation (RMSEA), Confirmatory Factor Index (CFI), and Tucker-Lewis Index (TLI) to corroborate the suitability of the chosen structural model for theorising.

B. STUDENT ENGAGEMENT

Student engagement, according to the literature, is more of an umbrella word for a collection of ideas based on a study on students and the impact that their school experiences have on their learning and development. It encompasses students' engagement in educationally helpful activities and their evaluations of the institutional aspects that promote their learning and progress [58]. McCarrell and Selznick [59] concur with Kuh [58], claiming that student engagement is the result of a dynamic relationship between what students do and what the institution does. It is not something students do or experience, but a reality that is co-created in the classroom by students and faculty members in a setting that is both particular and broad at the same time, rather than a theoretical idea. Student engagement is a notion that incorporates components of psychology, sociology, cognitive development, and learning theory. Its historical origins may be traced back to the following theories: Astin's Student Involvement, Pace's Student Effort, and Tinto's Academic and Social Integration theory [25], [60].

While it is commonly understood that no single definition can satisfy all stakeholders, due to the multi-construct nature of student engagement, numerous diverse definitions exist [61]. The most cited in the literature is the definition by Kuh [58] which describes student engagement as the "quality of effort and involvement in productive learning activities". In other words, engagement aids in the establishment of mental and emotional habits that increase an individual's ability for continual learning and personal development. Bond et al. [30] define it as the "energy and effort that students employ within their learning community, observable via any number of behavioural, cognitive or affective indicators across a continuum. Drawing from literature, the research of Bowden et al. [24] describes student engagement as "A student's positive social, cognitive, emotional, and behavioural investments made when interacting with their tertiary institution and its focal agents (such as peers, employees and the institution itself)".

The evaluation of student engagement serves as a valuable instrument for educational institutions in assessing their alignment with student expectations, gaining profound insights into activities and behaviours intricately connected to effective learning, and, ultimately, enhancing the overall quality of their educational systems and environments. This proactive approach is geared towards elevating student engagement levels, a critical determinant as evidence from prior research has demonstrated that engaged students tend to acquire a more comprehensive set of skills [13], [31]. The academic literature offers a plethora of indicators related to student engagement, and Figure 1 furnishes a comprehensive overview of these indicators per the framework established by the National Survey of Student Engagement (NSSE).

C. STUDENT-STAFF INTERACTION

In academic research, student-staff interaction has long been a motivating area of investigation. Silvola et al. [21] established the critical role of student-staff interaction in determining the intellectual and personal outcomes of college, as well as student satisfaction with their educational experience. A variety of student outcomes, including student retention, academic success, active learning through the solution of real-world problems, soft skills such as group work, cross-curriculum skills, and improved communication with their peers, have been established in the literature to be influenced by student-staff interaction [10], [11], [62].

It is portrayed as a kind of academic engagement in both informal and formal contexts in the literature with a variety of terms, including staff-student interaction, staff-student relationship, teacher-student interaction, teacher-student relationship, faculty-student interaction, and faculty-student relationship, among many others.

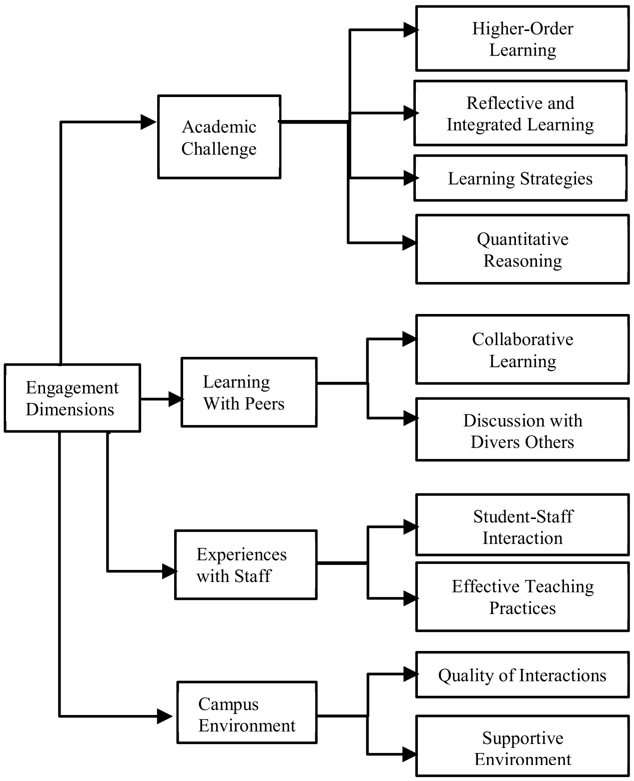

FIGURE 1. Student engagement indicators [63].

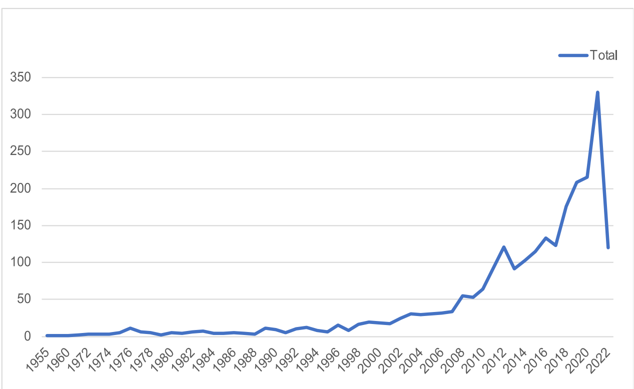

FIGURE 2. The trend of student-staff interaction research (source: scopus).

The concept of student-staff interaction encompasses multiple roles staff members play in educational institutions such as role models, instructors, mentors, advisors, and sources of support. As these interactions are not spontaneous, they are influenced by a variety of variables. Informal and formal student-staff interactions in educational institutions are influenced by the type of institution, the faculty member's personality, interpersonal skills, gender, race, and social standing, as well as the workload and institutional culture [64], [65].

Additionally, evidence reveals that student-staff interaction research continues to catch the interest of researchers, with evidence pointing to exponential rises in publications pertaining to linked research, as seen in Figure 2. This trend mirrors insights suggesting positive links between SSI and improved academic outcomes, including intellectual, social, and civic ability; academic satisfaction; and political engagement [31], [66], positive normalising effect on students' socialisation to the attitudes and values of their institution [56], and cognitive skills for learners [67]. Soltani et al. [68] report that SSI offers notable benefits not only to learners but to educational institutions as well. These positive results include increased retention of students and reputation, among others. However, very little is known of the possible determinants of SSI. The most significant attempt that directly exploring the determinants of SSI was the qualitative study by Cohen [69], which attempted to explore the determinants of SSI using focused groups.

Across literature, better student-staff interaction is determined by different factors such as behavioural traits, psychological factors like stress, academic skills, health conditions, financial or socioeconomic status, institutional conditions, leadership styles, teaching variables, and relationships with peers and parents. These factors were summarised and thematically presented in Kim et al. [70].

III. RESEARCH METHODOLOGY

This study aims to propose a model for student-staff interaction from students' perception of engagement practices. To achieve this, this study followed a learning analytical methodological workflow shown in Figure 3. The key processes are Data collection, Data Pre-processing, Exploratory Data Analysis, Association Rule Mining and Structural Equation Modelling.

A. DATA COLLECTION

This research primarily utilized two datasets obtained from a survey of students' perception of engagement from two African universities. One from a Nigerian university collected (hereafter referred to as Institution ''), between April and May 2022 as part of the objectives of this research, as well as a secondary dataset from the 2016 student engagement survey conducted on a South African university (hereafter referred to as Institution''). Both surveys utilized an adapted version of the NSSE survey instrument, which surveys firs-year and senior students to assess their levels of engagement and related information about their experience at their respective institutions using four key dimensions: staff experience, campus environment, academic challenge, and peer learning. These four dimensions are further subdivided into ten engagement indicators (EI), which are listed in Figure 1. To ensure that each engagement activity is properly evaluated, the ten engagement practices are quantified using 47 activities (measures). Also, both surveys collected additional information on student' sociodemographic traits to help situate the study appropriately, although the variables of interest to this study are those of the 47 NSSE measures.

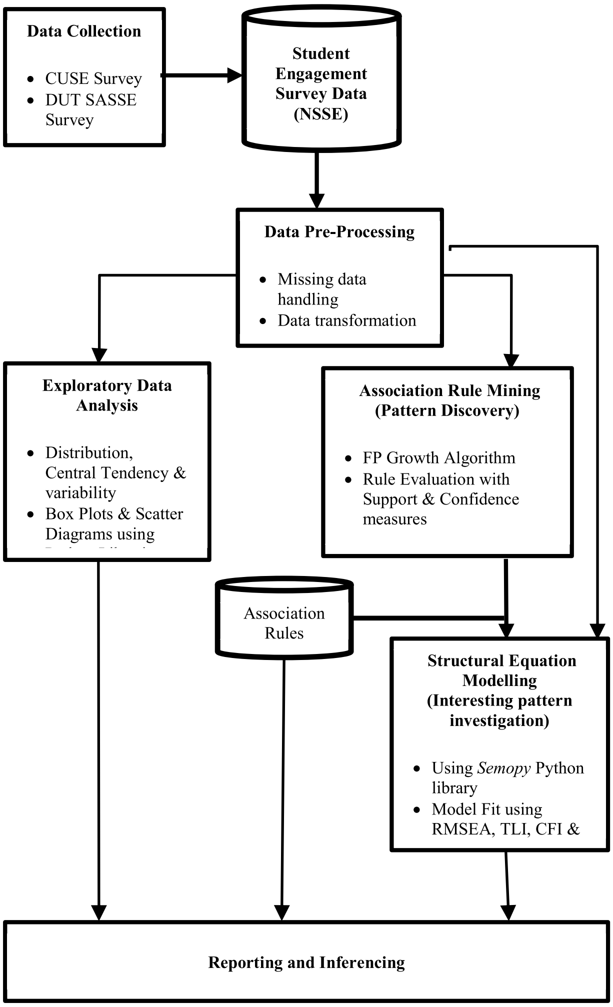

FIGURE 3. The research methodology workflow diagram.

The dataset from institution 'A' used in this study contained a total of 462 variables, including 47 NSSE measures, with the additional variables describing socio-demographic information about the students. The dataset contains 1,399 records that represent the perspectives of the students that institution regarding the institution students' engagement practices. Multiple records in the dataset were missing, leading to the elimination of records with incomplete data. 987 records were used for the analysis in the study after the missing entries in the dataset were removed. On the other hand, the 1320 records from institution 'B' respondents contained no missing values for the engagement indicators. In both datasets, all fields consist of numeric data, which simplifies data pre-processing and processing.

To ensure the quality of survey data, certain measures such as the number of completed surveys, the percentage of respondents who accurately represent the sample population, and the response rates are crucial indicators. These measures serve as essential factors in building trust and confidence in the survey outcomes. Following approval by the institution ethics board, a variety of promotional techniques were used to increase response rates across the various student groups, including collaborating with the student affairs division and course lecturers to communicate and encourage student participation. Students at institution 'A' were given printed copies of the survey during one of their general classes to collect their perceptions of engagement practices. They were informed of the purpose and intent of the survey, and their consent and participation were solicited. 2989 copies of the survey were distributed, and 2752 were returned, with several of the returned surveys unfinished and others uncompleted, indicating that some students chose not to participate. However, 1320 of the returned survey responses contained complete responses for each of the measures of the engagement indicators, which were entered into an Excel sheet. The representative sampling size for this survey, which consists of categorical variables, was determined to be 613. This is based on the statistical estimation theory of Bartlett et al. [71] and the level of confidence associated with this type of research, which focuses on the institution 8601 Full-Time enrolment population. Snapshot of instances of dataset from Institution A and B is shown in Figure 4 and 5 respectively.

B. DATA PRE-PROCESSING

The two datasets were in raw comma-separated version (CSV) form and required no deduplication as each contained unique entries with unique identifiers corresponding to a unique student. However, the dataset 'A' was cleaned by removing all records with one or more missing values using the Pandas Python library, therefore reducing the sample from 1399 to 987 records. Given that the NSSE instrument measures student engagement through a set of 47 Likert Measures, each Engagement Measure (EM) score was transformed into a 60-point scale as part of the transformation process. To generate an EM score, each response set for an item is first converted to a scale with 60 points, with "Never" assigned 0 points, "Sometimes" assigned 20 points, "Often" assigned 40 points, and "Very often" assigned 60 points. Then, the average of the rescaled items is calculated to generate the EM score. A score of zero indicates that a student responded to each item in the EI at the lowest end of the scale, while a score of sixty indicates that the student responded at the highest end of the scale for every item. The snapshot of an instance of dataset 'A' and 'B' is shown in Figure 4 for an example. The pre-processed rescaled EIs are used as input during the next phase of descriptive statistics and association rules mining.

C. EXPLORATORY aNALYSIS

For the Exploratory Data analysis, the untransformed dataset in CSV format for both institutions were explored to describe their student's perception of engagement using various Python libraries such as NumPy, matplotlib, pandas and seaborn. Visualisations using box plots and bar charts were presented to observe the statistical inference of the data by gender and academic major, based on each institution.

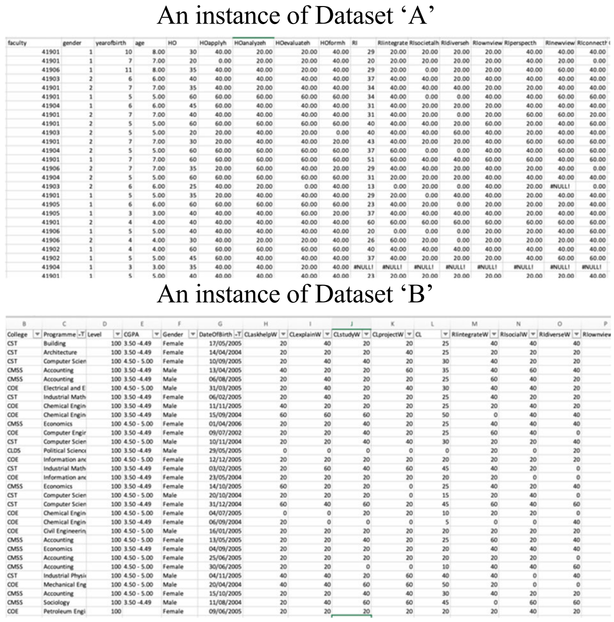

FIGURE 4. An instance of datasets.

D. ASSOCIATION RULE MINING

To examine associative relationship between the student engagement indicators, a data mining method called Association Rule Mining (ARM) was adopted. To discover the interesting associative patterns, FP-Growth association rules mining algorithm was implemented using python programming language. In order to transform the dataset into a binomial structure that is compactible for the adopted FP-Growth Association rule mining algorithm each EI score was transformed into one of the following categories: poor (0-29), good (30-44) or excellent (45-60) depending on the EI score on the rescaled 60-point scale. This representation is consistent with the student academic performance grading system of both universities, with fails (0-49), passes (50-74) and distinction (75-100). This approach inherently allows an engagement indicator to be ultimately transformed into a binary variable for effective quantitative association rule mining. Figure 5 shows the snapshot of the transformed binary dataset 'B'. For mining the frequent itemset, a minimum support of 10% (0.1) was specified to accommodate most EI in the rule generation while for the generation of rules from the frequent itemset, the minimum threshold for association rule confidence is 90%, this is in tandem with 0.1 p-value statistical significance. A rule is referred to as a "valid interesting rule" if the confidence is greater or equal to the minimum threshold value. The valid interesting rules were further subjected to structural equation modelling for investigation. The Python's *mlxtend* library was used to implement the FP-Growth Association rules mining.

E. STRUCTURAL EQUATION MODELLING

In this study, the valid interesting rules from association rule mining were further investigated with structural equation

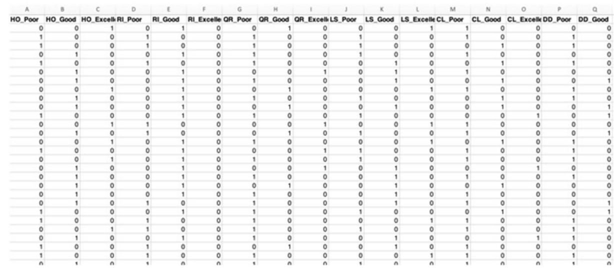

FIGURE 5. Snapshot of a binary form of dataset "B".

modelling to infer a model for SSI. To implement and evaluate the structural models, the *semopy* python library was used to evaluate the direction of causality between each EI in the identified structural models, analyse the interchangeability of the EIs, and assess the presence of covariation among the EIs. To evaluate the appropriateness of each model, and corroborate the suitability of the chosen structural model for predicting student-staff interaction, the following fit indices are used Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), Goodness of Fit Index, and Root Mean Square Error of Approximation (RMSEA). Typically, these four indices are utilised to evaluate SEM models. As generally reflected in the literature and numerous studies of student engagement, indicators of good and excellent model fit are marked by CFI and TLI values greater than 0.90 and 0.95, RMSEA values less than 0.80 and 0.60, and GFI values greater than 0.90 [24], [72], [73].

IV. ANALYSIS AND RESULTS

In this section, the results of the exploratory analysis, association rule mining and interesting rule modelling and investigation using structural equation modelling analysis were presented. These findings align with the core objective and purpose of this study, which is to construct a model for Student-Staff Interaction from students' perceptions of engagement practices. Below, we provide an overview of the outcomes yielded by these methodologies.

A. EXPLORATORY ANALYSIS RESULT

1) DESCRIPTIVE ANALYSIS OF INSTITUTION 'A' STUDENT RESPONSES

In Figures 6 and 7, the exploratory data analysis of Institution 'A's students' perception of engagement were presented. These figures shed light on intriguing patterns of students' assessment of various engagement practices. From Figure 5, those who rated the Collaborative Learning (CL), Higher-Order Learning (HO), Effective Teaching (ET), Discussion with Diverse others (DD), and Learning Strategies (LS) practises as excellent vastly outnumber those who rated them as either good or poor. In addition, the number of students who gave the Reflective and Integrated Learning (RI) and Quality of Interactions (QI) practices good grades exceeds the number of students who gave these practises excellent or poor grades. Conversely, the number of students who rated

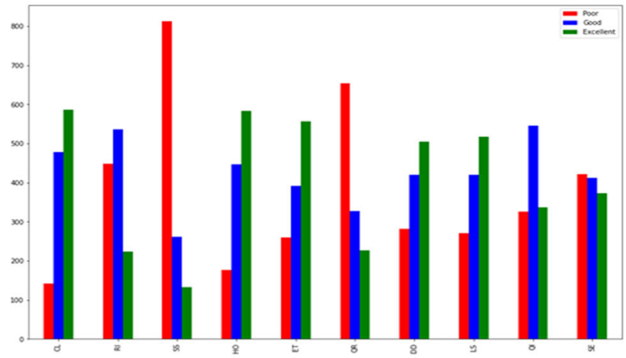

FIGURE 6. The classification of students' responses from institution 'a' based on engagement indicators.

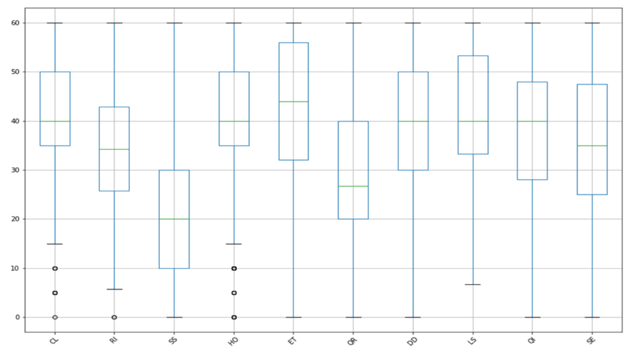

FIGURE 7. The distribution of students' responses from Institution 'A' based on engagement indicators rating.

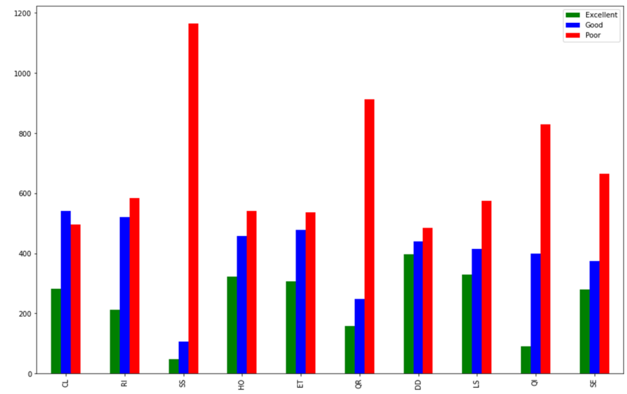

FIGURE 8. The classification of students' responses from Institution 'B' based on engagement indicators.

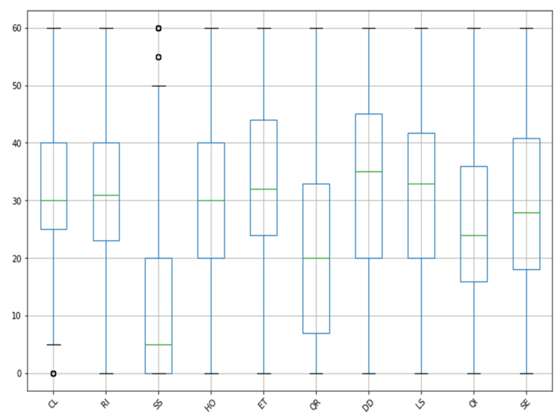

FIGURE 9. The distribution of students' responses from Institution 'B' based on engagement indicators rating.

Quantitative Reasoning (QR), Student Staff Interaction (SS), and Supportive Environment (SE) poorly is significantly greater than the number of students who rated these practices as excellent or good. This is supported from Figure 7, the mean value for the SS practice was only 21.7, while the mean value for the ET practice was 42.2. The low mean scores for QR and SS by students indicate that these practices have been perceived poorly by students. The diversity in the student's perception of the engagement indicator is also observed in Figure 7, except for collaborative learning and Higher-order learning with the shortest boxplots which shows a level of agreement in the student's perception of the two indicators. Due to the limitations of descriptive statistics, it is difficult to determine whether the results are correlated or connected via a chain of cause and effect. A more thorough investigation technique such as association rule mining and structural equation modelling could reveal the relationships among the student engagement practices and all the intricate details of challenging practices.

2) DESCRIPTIVE ANALYSIS OF INSTITUTION 'B' STUDENT RESPONSES

Figures 8 and 9 reveal that the students have given a generally lower rating to their overall educational experience in institution 'B' across all indicators, except for Collaborative Learning (CL), where a larger number of students expressed positive sentiments. Among these indicators, Student-Staff Interaction (SS) received the lowest mean score at 10.5, while Learning Strategies (LS) garnered the highest mean score at 33.9. This same pattern emerged in the responses from students at institution 'A.' It is noteworthy that none of the indicators from Institution 'B' received a higher mean score than those in Institution 'A.' Although the primary focus of this study does not encompass investigating the factors behind this trend, it underscores the need for further examination and appropriate actions. Figure 9 supplements this insight by visually depicting the data's distribution and skewness, presenting data medians and quartiles (or percentiles) through a boxplot. The boxplot shows that the students' perceptions for all indicators are diversely expressed, except for collaborative learning with a shortest boxplot which indicates the students' agreement in perception.

B. ASSOCIATION RULE MINING RESULT

The third objective in this study is to discover interesting associations within the student engagement practices

TABLE 1. Top frequent items observed in the dataset from Institution 'A'.

S/N	Itemset	Support
A1	SS_Poor	0.661
A2	QR_Poor	0.534
A3	HO_Excellent	0.484
A4	CL_Excellent	0.483
A5	ET_Excellent	0.468
A6	QI_Good	0.451
A7	RI_Good	0.436
A8	LS_Excellent	0.431
A9	SS_Poor, QR_Poor	0.408
A10	DD_Excellent	0.403

based on students' perceptions of engagement. These interesting patterns can then be further investigated by structural equation modelling to suggest the determinant factors for predicting SSI in higher education institutions. To accomplish this objective, the FP-growth association rule mining technique was used. The subsequent sections explain the results obtained from each institution's dataset.

1) RESULTS OF INSTITUTION 'A' ASSOCIATION RULE MINING

The top 10 frequent items among a pool of 415, identified with a support threshold of 10% is presented in Table 1. Meanwhile, Table 2 presents nine rules generated with an impressive minimum confidence level of 90%. This high confidence underscores the reliability of these rules and significantly boosts the trustworthiness of any recommendations derived from them.

Of particular significance is the consistent implication across all nine rules: poor student-staff interaction (SSI) is a prevailing concern. This aligns with the student's perception of SSI as the most critical aspect of student engagement, as corroborated by descriptive statistical analysis that indicates a significant proportion of low ratings from Figures 6 and 7.

The highest confidence level was obtained by Rule number A1 at an impressive 95.6%. Rule number A1, not only emphasizes the significance of SSI but also identifies three other critical engagement practices: quantitative reasoning (QR), reflective and integrated learning (RI), and quality of interaction (QI) as determinant factors for SSI. With a confidence level of 95.6%, this rule signifies that deficiencies in QR, RI, and QI practices contribute to the observed issues in SSI, as perceived by students at the case study university.

This explanatory pattern extends across the remaining rules, collectively shedding light on a complex relationship. In the pursuit of enhancing SSI at the case institution, this study investigates further into these associative patterns, leveraging Structural Equation Modelling (SEM) to identify

TABLE 2. Association Rule Mining Results for Institution 'A' Data.

No	Rules	AS	CS	RS	CO	LI	LV	CV
A1	QI_Poor, QR_Poor, RI_Poor → *SS_Poor*	0.116	0.661	0.110	0.956	1.447	0.034	7.739
A2	QI_Poor, RI_Poor → SS_Poor	0.143	0.661	0.135	0.943	1.428	0.040	5.982
A3	SE_Poor, QR_Poor, QI_Poor → SS_Poor	0.119	0.661	0.110	0.932	1.410	0.032	4.964
A4	SE_Poor, QI_Poor → SS_Poor	0.169	0.661	0.157	0.928	1.405	0.045	4.723
A5	HO_Poor, QR_Poor → SS_Poor	0.110	0.661	0.102	0.927	1.403	0.029	4.624
A6	SE_Poor, QR_Poor, RI_Poor → SS_Poor	0.130	0.661	0.119	0.914	1.384	0.033	3.950
A7	QR_Poor, QI_Poor → SS_Poor	0.188	0.661	0.171	0.909	1.375	0.047	3.714
A8	SE_Poor, RI_Poor → SS_Poor	0.171	0.661	0.155	0.905	1.370	0.042	3.585
A9	DD_Poor, QR_Poor, RI_Poor → SS_Poor	0.114	0.661	0.103	0.903	1.366	0.028	3.487

AS = Antecedent Support, CS = Consequent Support, RS = Rule Support, CO = Confidence, LI = Lift, LV= Leverage, CV = Conviction

the most compelling pair for constructing a robust model to bolster Student-Staff Interaction practice in higher institutions.

2) RESULTS OF INSTITUTION 'B' ASSOCIATION RULE MINING

Table 3 presents a selection of the top 10 frequent items out of a total of 867, derived from a dataset comprising 1,320 records from Institution 'B'. These findings echo the trends observed in Institution 'A,' where "Poor Student-Staff Interaction (SS)" emerged as the most prevalent item.

Moving to Table 4 which showcases the top 7 rules from a pool of 448 that met the research's stringent minimum confidence criterion of 90%. Unlike the results from Institution 'A,' which yielded only 9 rules, our selection process in this case employed expert judgment to selecting the top 7 rules that adhered to the criteria, all boasting an impressive minimum confidence level of 99%.

Remarkably, all seven rules consistently underscore the challenge of "Poor Student-Staff Interaction (SS)," reaffirming students' perception of SSI as the most demanding aspect of student engagement. This observation aligns seamlessly

TABLE 3. Top frequent items observed in the dataset from Institution 'B'.

No.	Itemset	Support
B1	SS_Poor	0.883
B2	QR_Poor	0.691
B3	QR_Poor, SS_Poor	0.632
B4	QI_Poor	0.629
B5	QI_Poor, SS_Poor	0.591
B6	SE_Poor	0.504
B7	QR_Poor, QI_Poor	0.469
B8	SE_Poor, SS_Poor	0.464
B9	QR_Poor, QI_Poor, SS_Poor	0.445
B10	RI_Poor	0.443

TABLE 4. Association Rule Mining Results for Institution 'B' Data.

No.	Rules	AS	CS	SU	CO	LI	LV	CV
B1	QR_Poor, CL_Poor, QI_Poor, HO_Poor → SS_Poor	0.138	0.883	0.137	0.995	1.126	0.015	21.233
B2	QR_Poor, CL_Poor, HO_Poor, DD_Poor → SS_Poor	0.111	0.883	0.111	0.993	1.124	0.012	17.150
B3	QI_Poor, CL_Poor, QR_Poor, RI_Poor, HO_Poor → SS_Poor	0.111	0.883	0.110	0.993	1.124	0.012	17.033
B4	DD_Poor, HO_Poor, QR_Poor, RI_Poor, LS_Poor → SS_Poor	0.107	0.883	0.106	0.993	1.124	0.012	16.450
B5	CL_Poor, QI_Poor, HO_Poor, SE_Poor → SS_Poor	0.106	0.883	0.105	0.993	1.124	0.012	16.333
B6	QI_Poor, HO_Poor, RI_Poor, ET_Poor, LS_Poor → SS_Poor	0.102	0.883	0.101	0.993	1.124	0.011	15.633
B7	CL_Poor, QI_Poor, HO_Poor → SS_Poor	0.152	0.883	0.151	0.990	1.121	0.016	11.725

AS = Antecedent Support, CS = Consequent, LI = Lift, Support, SU = Support, CO = Confidence, LV= Leverage, CV = Conviction

with the descriptive statistical analysis, which illuminates the highest proportion of low ratings (refer to Figures 8 and 9). Rule number B1 stands out with the highest confidence at a remarkable 99.5%. Additionally, Rule number B1 elucidates that "Poor Quantitative Reasoning (QR)," "Poor Collaborative Learning (CL)," "Poor Quality of Interactions (QI)," and "Poor Higher-Order Learning (HO)" practices are determinant factors to the challenges in SSI at Institution B. The remaining six rules follow a similar explanatory pattern.

TABLE 5. Overview of Fitness of Structural Models for Institution 'A'.

Model	Rules	RMSEA	CFI	TLI	GFI
A1	QI, QR, RI → SS	0.046	0.944	0.935	0.927
A2	QI, RI → SS	0.051	0.939	0.927	0.923
A3	SE, QR, QI → SS	0.062	0.916	0.903	0.903
A4	SE, QI → SS	0.073	0.904	0.888	0.893
A5	**HO, QR → SS**	**0.036**	**0.985**	**0.979**	**0.976**
A6	SE, QR, RI → SS	0.059	0.909	0.896	0.892
A7	QR, QI → SS	0.044	0.974	0.966	0.964
A8	SE, RI → SS	0.067	0.898	0.883	0.884
A9	DD, QR, RI → SS	0.047	0.0950	0.941	0.935

TABLE 6. Overview of Fitness of Structural Models for Institution 'B'.

Model	Rules	RMSEA	CFI	TLI	GFI
B1	QR, CL, QI, HO → SS	0.062	0.919	0.904	0.905
B2	QR, CL, HO, DD → SS	**0.050**	**0.950**	**0.940**	**0.937**
B3	QI CL, QR, RI, HO → SS	0.056	0.902	0.889	0.882
B4	DD, HO, QR, RI, LS → SS	0.055	0.918	0.905	0.900
B5	CL, QI, HO, SE → SS	0.068	0.880	0.865	0.864
B6	QI, HO, RI, ET, LS → SS	0.060	0.887	0.873	0.867
B7	CL, QI, HO → SS	0.070	0.911	0.893	0.899

3) RESULTS OF STRUCTURAL EQUATION MODELLING ANALYSIS

A one-step structural equation modelling analysis was conducted to investigate the interesting associative relationship discovered between Engagement practices by the association rule mining algorithm in this study. First, a measurement model was specified using the NSSE measures for each engagement indicator. The relationships specified by the association rules were then modelled as testable and interpretable structural models. To evaluate the appropriateness of each model, the following fit indices results are presented in this section: Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), Goodness of Fit Index, and Root Mean Square Error of Approximation (RMSEA). The subsequent section summarises the analyses' findings.

4) RESULTS OF INSTITUTION 'A' STRUCTURAL EQUATION MODELLING ANALYSIS

The nine association rules derived from Institution 'A''s association rule mining process were represented as one-step structural models, with each antecedent having a direct effect on SSI according to the rule on Table 2. The results of each model's fit indices are tabulated in Table 5, while the models and their standardised factor weights are plotted in Figures 10-18. Using the RMSEA, six of the nine models, A1, A2, A5, A6, A7, and A9, demonstrated excellent model fitness. With RMSEA = 0.036, Cfi = 0.985, TLI = 0.966, and GFI = 0.976, Model A5, which includes higher-order learning (HO) and quantitative reasoning (QR), received the highest fitness evaluation.

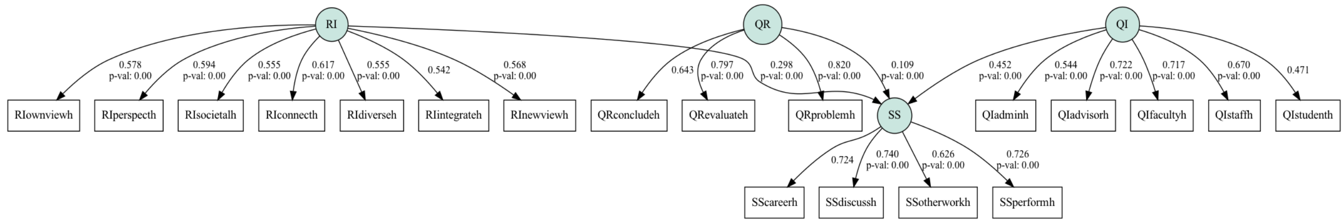

FIGURE 10. Result of the SEM analysis of model A1.

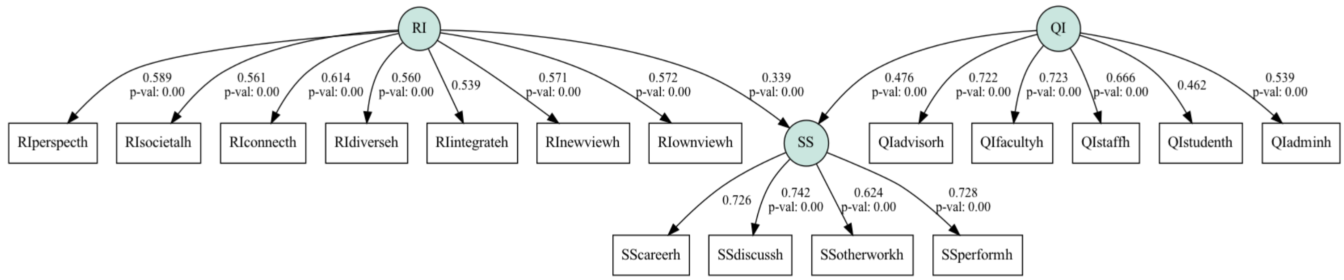

FIGURE 11. Result of the SEM analysis of model A2.

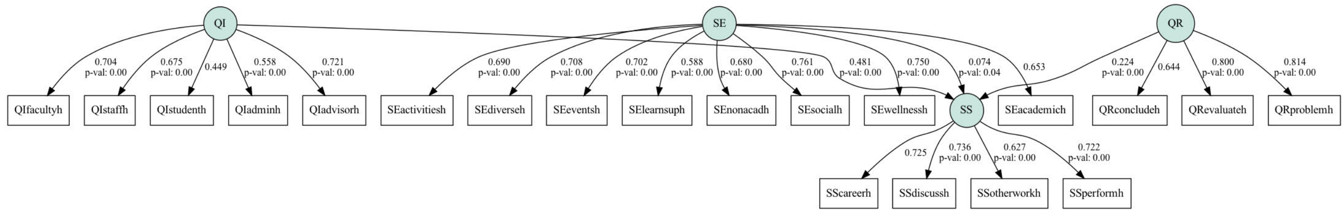

FIGURE 12. Result of the SEM analysis of model A3.

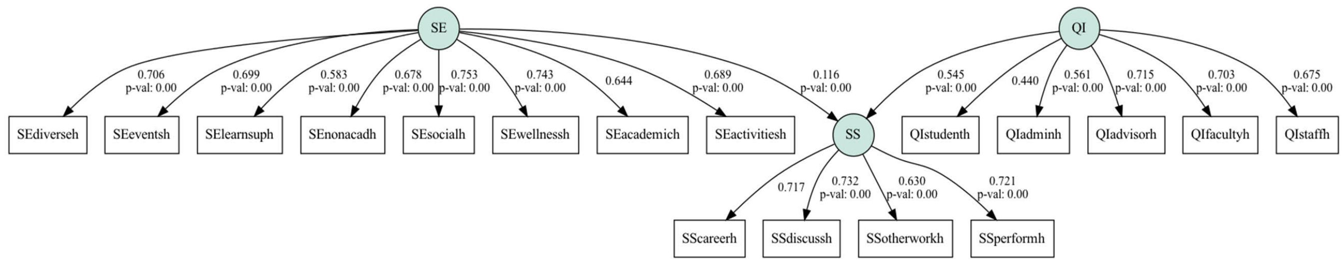

FIGURE 13. Result of the SEM analysis of model A4.

The Higher Order Learning Engagement Indicator is measured by the following four measures, including:

i. Applying facts, theories, or methods to practical problems or new situations
ii. Identifying the different parts of an idea, experience, or argument in detail (analysing)
iii. Evaluating a point of view, decision, or information source
iv. Forming a new idea or understanding by putting together various pieces of information
v. While the Quantitative Reasoning Engagement Indicator is Measured with the following Engagement Indicators:
vi. Reaching conclusions based on your analysis of numerical information (numbers, graphs, statistics, etc.)
vii. Using numerical information (numbers, graphs, statistics, QR etc.) to examine a real-world problem or issue (unemployment, climate change, public health, etc.)
viii. Evaluating what others have concluded when they used numerical information (numbers, graphs, statistics, etc.)

The validated structural equation model concludes, therefore, that the measures or factors influencing student-staff interaction, according to the perceptions of students at Institution ‘A’, include the amount of academic work

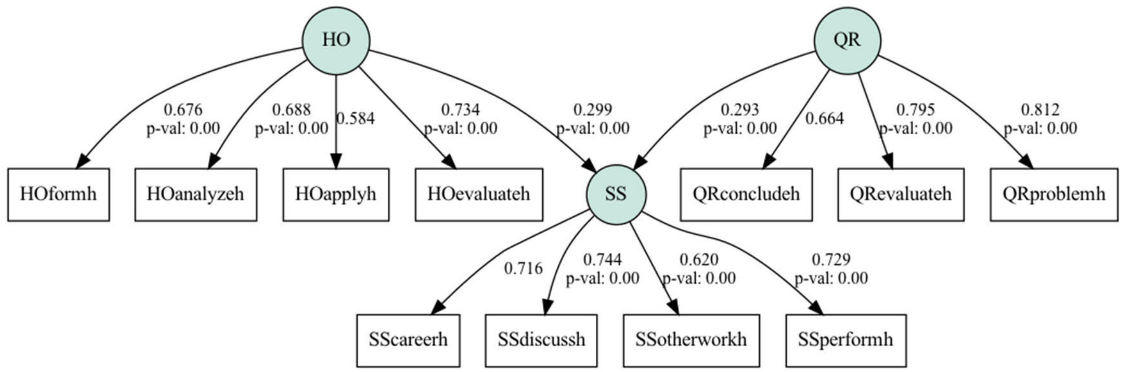

FIGURE 14. Result of the SEM analysis of model A5.

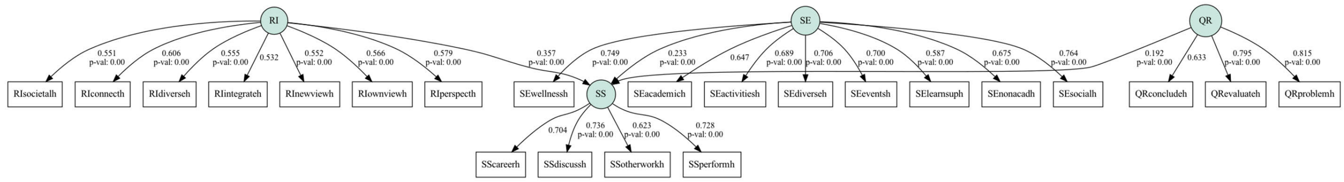

FIGURE 15. Result of the SEM analysis of model A6.

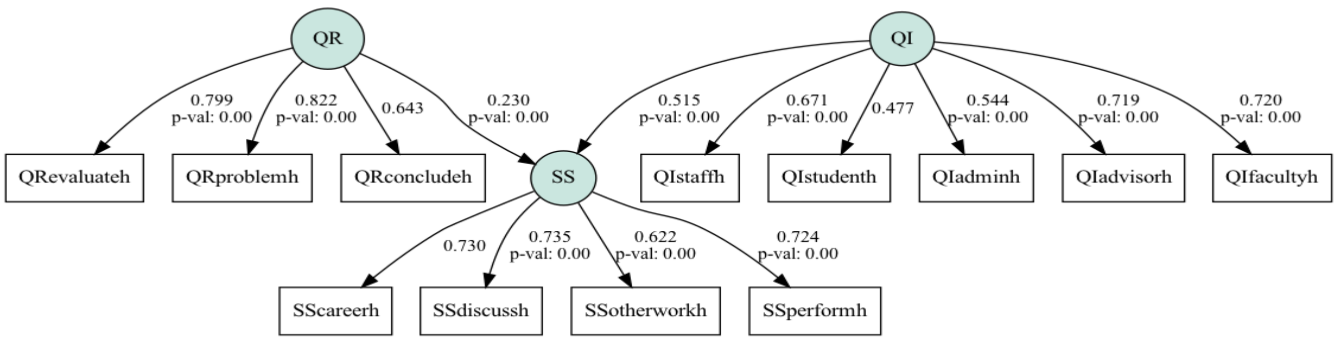

FIGURE 16. Result of the SEM analysis of model A7.

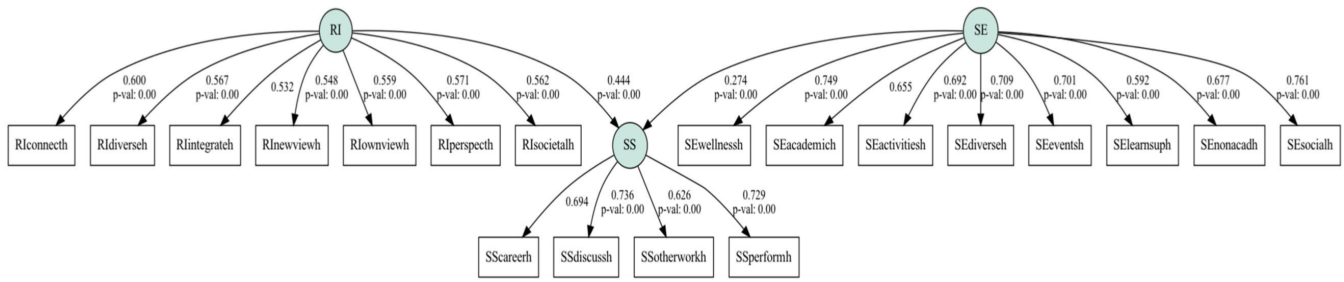

FIGURE 17. Result of the SEM analysis of model A8.

emphasising challenging learning tasks, such as applying learned information to practical problems, identifying ideas and experiences, evaluating information from other sources, and forming new ideas by combining various pieces of information.

5) RESULTS OF INSTITUTION 'B' STRUCTURAL EQUATION MODELLING ANALYSIS

Table 6 presents the fitness evaluations of the seven models evaluated for institution 'B'. Using the RMSEA, all models are tactically significant, with values indicating good to

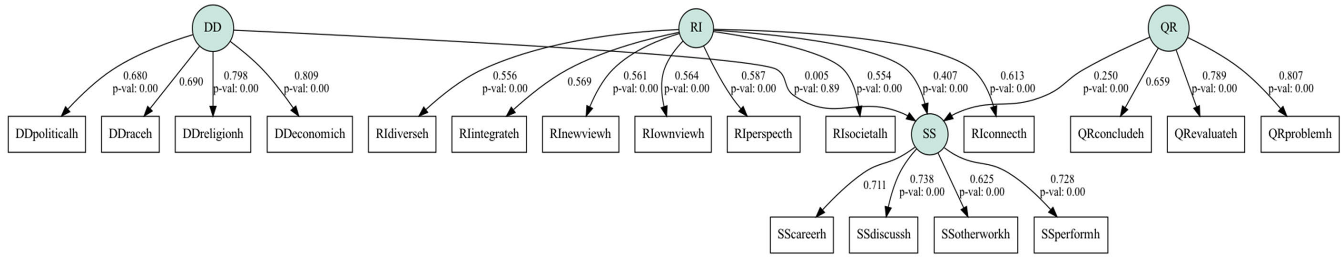

FIGURE 18. Result of the SEM analysis of model A9.

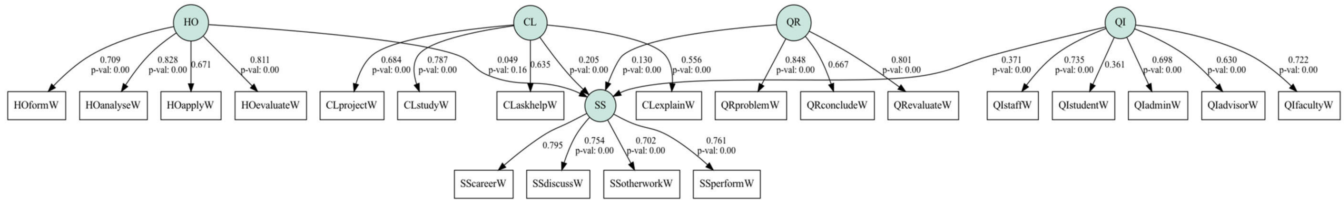

FIGURE 19. Result of the SEM analysis of model B1.

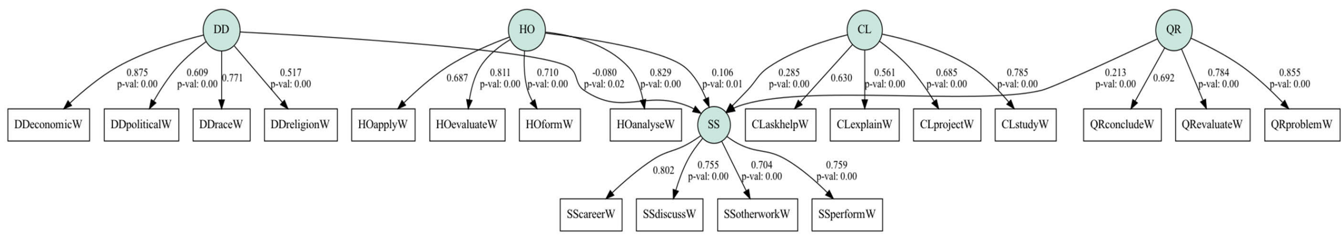

FIGURE 20. Result of the SEM analysis of model B2.

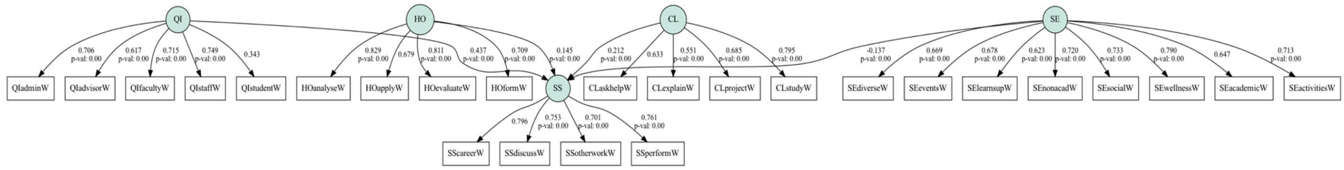

FIGURE 21. Result of the SEM analysis of model B3.

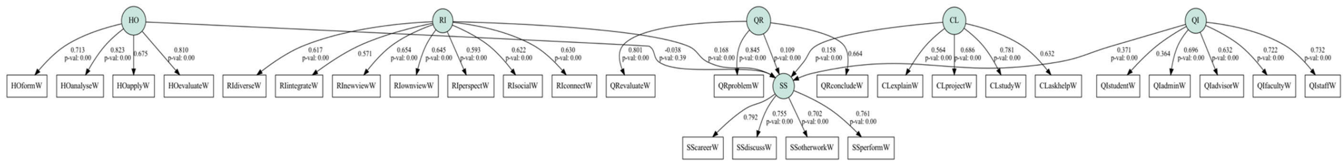

FIGURE 22. Result of the SEM analysis of model B4.

excellent fitness. With an RMSEA of 0.050, a CFI of 0.950, a TLI of 0.940, and a GFI of 0.937, model B2 is the most appropriate. This model suggests that the combination of poor quantitative reasoning (QR), collaborative learning (CL), higher-order learning (HO), and discussion with diverse others (DD) EIs influence SSI at institution 'B' based on students' perceptions of engagement practises. This conclusion is similar to the inferences of students at institution 'A' with the addition of Collaborative Learning and Discussion with Diverse Others as the differentiating indicators. The standardised factor weights for each structural model are depicted in Figures 19- 25. The measures for evaluating these CL and DD engagement indicators are specified below:

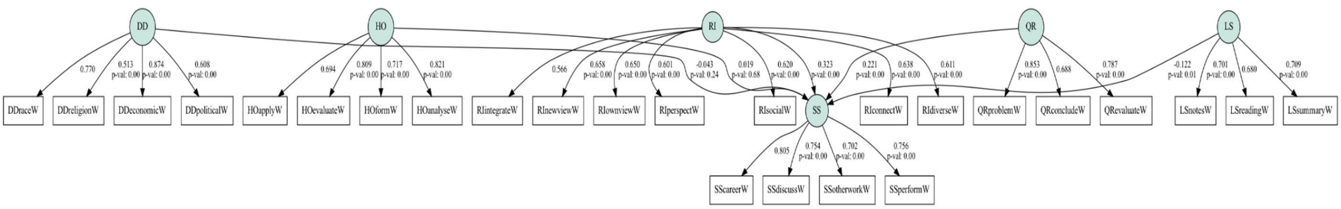

FIGURE 23. Result of the SEM analysis of model B5.

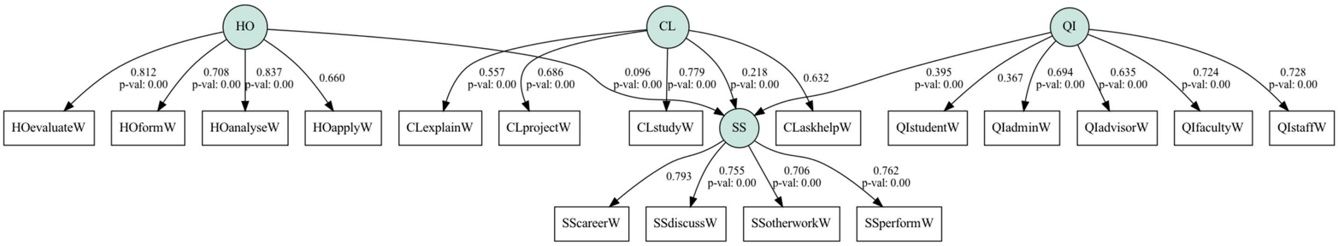

FIGURE 24. Result of the SEM analysis of model B6.

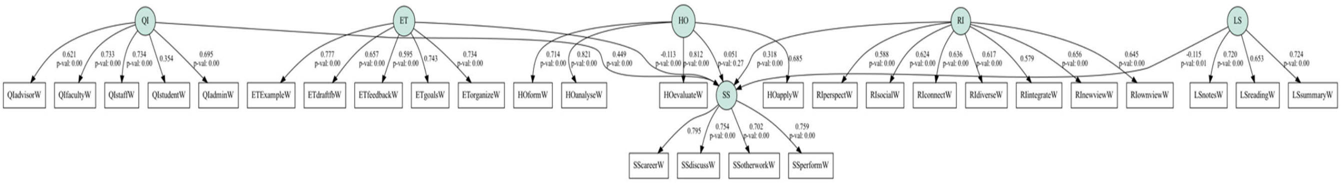

FIGURE 25. Result of the SEM analysis of model B7.

Collaborative Learning Engagement Indicator is Measured with the following four Engagement Indicators:

i. Asking another student to help you understand module/subject material
ii. Explaining a module/subject material to other students
iii. Preparing for exams by discussing or working through module/subject material with other students
iv. Working with other students on projects or assignments

Discussions with Diverse Others Engagement Indicator is Measured with the following four Engagement Indicators:

i. Discussion with People of a race or ethnicity other than your own
ii. Discussions with People from an economic background other than your own
iii. Discussions with People with religious beliefs other than your own
iv. Discussion with People with political views other than your own

6) DISCUSSION OF FINDINGS

This study is driven by the overarching goal of constructing models that depict student-staff interactions, derived from students' perspectives on engagement practices. To attain this primary objective, three distinct analytical approaches were employed. The first revolves around exploratory analysis, setting the foundational context. However, the true innovation of this study lies in the subsequent two analyses, where Learning Analytics (LA) techniques, specifically the FP-Growth association rule mining technique and Structural Equation Modelling, were applied.

These advanced methodologies were pivotal in uncovering intricate associations between various indicators of student engagement and the quality of student-staff interactions. This illumination serves as a valuable resource for shaping recommendations aimed at institutional management enhancement. As part of this illumination, the analysis results from these two institutions show a good agreement on the germane factors that predict student-staff interaction and the slight diversity in student perception from one country to the other, which is probably based on the cultural background of the students and the internalization level of the institution. The explorative analysis, as depicted in Figures 6-9, unveiled that Student-Staff Interaction (SS) and Quantitative Reasoning (QR) were the most challenging facets of student engagement across the surveyed institutions. This aligns with findings from Oladipupo and Samuel [74], who also identify these areas as critical but fail to delve into the underlying causes or identify relationships due to limitations in their methodologies.

This limitation underscores the necessity of employing LA techniques capable of unveiling hidden patterns, driven by individual characteristics and robust rules for the inference model [75]. The association rule results, presented in Tables 2 and 4, illuminate the relationships among various student engagement Indicators (EIs) and their influence on the quality of Student-Staff Interaction (SSI). These findings hold significant potential for informing strategic interventions and policy decisions within the higher education of learning.

Notably, the 16 rules collectively highlight that Quantitative Reasoning (QR) and Quality of Interaction (QI) are pivotal EIs, appearing in 10 rules, closely followed by Higher-Order Learning (HO) and Reflective and Integrated Learning (RI) in 8 rules, and Supportive Environment (SE) and Collaborative Learning (CL) in 5 rules.

Leveraging the insights garnered from the Structural Equation Modelling (SEM) analysis, which identified rule 5 as the most suitable model characterizing the relationship with EIs at Institution A, recommendations can be tailored accordingly. Policies and interventions aimed at enhancing Higher-Order Learning and Quantitative Reasoning can be targeted. Encouraging problem-based activities and coursework that emphasize application, analysis, judgment, and synthesis is essential. Such approaches require students to actively integrate new and existing knowledge to solve problems, a practice that has been shown to improve interactions and cognitive outcomes in previous studies [76]. At Institution B, guided by rule number 1, policies promoting Quantitative Reasoning, Collaborative Learning, Higher-Order Learning, and Discussion with Diverse Others should be emphasized and encouraged. However, when we delve into the standardized factor loadings of the model, it becomes apparent that DD has a minimal and negative effect on student-staff interaction (see Figure 22).

7) RECOMMENDATIONS FOR THE APPLICATION OF FINDINGS

The results of this study offer valuable insights into the factors influencing student-staff interaction at the universities under examination. These findings shed light on the significance of understanding the diversity of these factors across different countries. Notably, when examining secondary data from Institution 'A,' we observed that higher-order learning and Qualitative Reasoning (Model A5) had a substantial impact on predicting student-staff interaction. This observation finds strong support in the primary data collected from Institution 'B,' with Higher Order (HO) and Qualitative Reasoning (QR) appearing in models B1 through B7. These insights and recommendations drawn from both institutions are pivotal in fostering improved student outcomes through enhanced student-staff interaction.

In the pursuit of establishing a universally applicable model, out of the 16 models scrutinized in this study, Model A1 emerged as the most preferred in enhancing student engagement practices from the student's perspective. Although all the models demonstrated favourable fitness indices, Model A1 stood out as the only model encompassing the three most frequently occurring indicators among the 16 rules: QI, QR, and RI. These three indicators were also evenly distributed across both institutions, underscoring their pivotal role in influencing student-staff interaction quality.

The model suggests that the quality of interactions (QI), reflective and integrated learning (RI), and quantitative reasoning (QR) are key indicators influencing the quality of student-staff interactions. Quantitative reasoning assesses how frequently students employ numerical and statistical information to solve real-world problems, evaluate others' conclusions, and arrive at their own. Reflective and integrated learning measures the frequency at which students connect their learning with prior knowledge, other modules/subjects, societal issues, and diverse perspectives, while also reflecting on their perspectives and examining those of others.

The quality of interactions measures the level of satisfaction students derive from their interactions with other students, peer learning support, lecturers, academic staff, student support services, and administrative services. These findings underscore the significance of incorporating these engagement indicators into initiatives aimed at enhancing student-staff interaction.

As a result, we propose the following recommendations in light of the established models explored in this study for predicting student-staff interaction. It is imperative to consciously enhance the following Engagement Indicators (EIs) collectively, given the interrelated nature they exhibit.

1. To improve the quantitative reasoning (QR) skills of students, Institutions should:
   a. Foster strategic and metacognitive reasoning via performance task in lecture courses that enables students to use numerical and statistical information to reach conclusions, examine real-world problems, as well as evaluate others' conclusions [77].
   b. Introduce Quantitative Reasoning assessments to pre-admission examinations and general courses to increase the quantitative reasoning skills of students at the institution.

2. To improve the quality of interactions (QI) institutions should:
   a. Build ties with students through highly efficient administrative procedures. This should include fast turnaround times on various administrative functions, promoting the atmosphere and culture of love, and the use of information technology tools to speed up administrative processes and the experience of students.
   b. Introduce standard operating procedures and turnaround times for various institutional services students expect and establish a monitoring mechanism to ensure consistent efficiency.

c. Actively promote the awareness and various student support services available at the institution as well as adopting innovative ways to reach students, such as the use of social media platforms [78], [79].

3. To improve the reflective and integrated learning (RI) skills of students, Institutions should:

a. Encourage students to establish bold and worthwhile academic goals to encourage student outcomes [80].
b. Promote student engagement in active learning via problem-based and community-based learning, and research with faculty [76].
c. Continually evaluate students' learning such as with frequent impromptu assessments.
d. Encourage and train lecturers to connect modules to various societal issues, considering diverse perspectives.

V. CONCLUSION

The primary objective of this study centred around constructing student-staff interaction models based on students' perceptions of engagement practices using learning analytics and structural equation modelling, has been successfully achieved and rigorously validated. To address the initial objective of conducting a student survey on their perceptions of engagement practices, a university in Nigeria was the chosen institution, surpassing anticipated response rates and providing a robust sample size exceeding the predefined minimum threshold.

The second objective, involving data preprocessing and descriptive analysis, was effectively executed using Python libraries. The insightful outcomes of this analysis were visually represented through boxplots and bar charts, shedding light on critical dataset patterns. Objective three, aimed at identifying associative patterns between student engagement indicators and student-staff interactions, was met through the generation of high-confidence rules using the FP-growth association rule mining technique.

Furthermore, the study leveraged these association rules to derive structural models, which were subjected to Structural Equation Modelling (SEM) analysis. This process revealed the most intriguing rules and inferences, providing valuable insights aligned with existing literature. The impetus behind this research was the pressing need to address concerns related to improving student-staff interaction within various educational institutions. This interaction has been closely tied to a range of outcomes spanning from student achievements to institutional and national impact.

This study contributes significantly to the body of knowledge in student engagement by pinpointing the underlying causes of subpar student-staff interaction and constructing an inference rule model for resolution. It is important to note that this study relies on secondary data obtained from an institution in South Africa on student engagement and primary data collected from a private institution in Nigeria, in 2022. Consequently, the limitations regarding generalization beyond these specific contexts and the divergent results obtained from rule analyses and SEM underscore the need for future comprehensive investigations aimed at establishing a globally applicable and consistent model.

This study has evolved and validated several models of student-staff interaction to promote student outcomes and quality of learning, by studying data on students' perception of engagement practices from the two institutions. In summary, this study contributed the following to knowledge: established the hybrid approach of Association Rule Mining Algorithm and Structural Equation Modelling for analysing student engagement dataset; established innovative associative patterns between National Survey of Student Engagement (NSSE) indicators concerning student-staff interaction; and developed a novel student-staff interaction model from student perception of engagement.

The results of this research lay the ground for many recommendations and future work considerations to improve the discoveries of this research. Thus, for future improvements to this research, the following recommendations are made:

1. It is essential to interpret the results of this study cautiously, considering the diverse array of factors influencing student-staff interaction, as elucidated in the second section of this research. Given the distinct models observed across the two institutions in this study, further research is imperative to delve into the impact of institutional factors on student-staff interaction, ultimately striving for a more universally applicable model.
2. Exploring various Learning Analytics (LA) approaches for experimental comparison with the findings of this study would be a judicious step. For example, given the significant strides in elucidating causal relationships through the application of Causal Bayesian Network (CBN) theory, it is now possible to derive causal links directly from data using such methodologies. Thus, the results of this study can be compared with those obtained through CBN analysis, further enriching our understanding.
3. It should be noted that a good-fitting model is not necessarily a valid model. Given the decision-making value of discovered relationships, it is useful to seek to implement and evaluate these models towards improving student-staff interaction at the institutions of this study and beyond.
4. This study only evaluated the discovered relationships using one-level structural equations. Modification of the models can be tested to test the rules based on different causal models such as chaining, conjunction (confluence) and network.
5. Lastly, to generalize this model in the context of Nigerian universities, it is essential to extend this research to some other institutions in Nigeria to be able to capture their students' perceptions of engagement.

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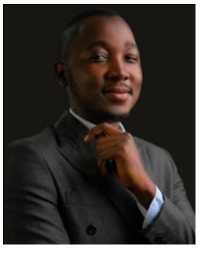

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