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Relating Student Engagement Indicators to Academic Performance Using Multiple Correspondence Analysis

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Abstract**:** *Student engagement is an essential device for deepening learning, achieving learning outcomes, developing competencies, and improving academic performance in education settings. It is widely receiving increased attention among various scholars and higher education leaders. However, there are increasing concerns about the academic performance of students in higher education settings. The application of statistical data analytics for mining student engagement datasets is a candidate strategy for discovering essential indicators associated with academic performance. However, widely used data analytic methods like principal component analysis are ineffective when most of the indicators captured are categorical, making them inappropriate for establishing the weighty academic performance indicators. This study's objective was to investigate the application of multiple correspondence analysis to establish weighty student engagement indicators of academic performance. This study's findings have indicated that higher-order learning and student-staff interaction are weighty indicators that relate student engagement to academic performance.*

Keywords**:** *Academic performance, correspondence analysis, national survey, student behaviour, student engagement.*

1. Introduction

Student engagement encompasses students' positive behaviors and experiences and is receiving more awareness among researchers, higher education authorities, and the public in recent years [1]. It is required because students acquire more skills when engaged; it is key to student satisfaction with learning and an essential ingredient of higher-order learning and student success [2]. It has become a more prominent phenomenon in studies on education quality because of its association with personal development and learning [3-6]. Student engagement has been recognized as a significant factor in understanding student dropout and improving throughput and retention rates. Its disengagement antonym is presupposed to be a gradual deviant behavior of students by becoming less committed to learning activities [7-9]. In addition, it has been directly linked to enhancing academic performance, which was explicated to be a strong predictor of student success and good behavior in schools [10]. Moreover, student engagement can be correlated with both health-compromising and health-promoting behaviors [11]. Student engagement and academic performance are of prime importance to managers of education institutions as institutional productiveness is mostly assessed by academic achievement.

It is presumed that an understanding of student engagement indicators might help educators prevent adverse consequences due to the exhibited associations with the heterogeneity of outcomes. However, scientific methods and statistical data analytic tools have not yet gained prominent usage for learning about student engagement. This study seeks to broaden the scope of extant studies on student engagement and address a gap in the literature by applying Multiple Correspondence Analysis (MCA) as an Exploratory Data Analysis (EDA) method to relate student engagement indicators to academic performance. The South African Survey of Student Engagement (SASSE) tool has provided the 2018 dataset for this study. The SASSE is a customized archetype of the National Survey of Student Engagement (NSSE) that was initially developed in the United States of America. The NSSE was offered as a barometer for evaluating best practices in institutions of higher learning. It is one of the most famous resources on student engagement for assessing student participation in various educational activities [4]. The NSSE tool has been utilized by many countries across the world, including South Africa, the United States of America, Canada, Australia, the United Kingdom, and Switzerland.

This study's outcome can practically benefit managers of educational institutions and policymakers as both groups seek to understand better and address the inherent challenges of enhancing student development. This study has major significant contributions in two prominent areas. Firstly, identifying weighty indicators that might improve students' academic performance in a higher institution of learning is a unique contribution. The identified indicators can help higher education institutions' authorities be useful in assisting students to succeed. Secondly, MCA's application for the first time to mine a large and complex student engagement dataset is an essential contribution to data mining research. The paper is succinctly organized after providing the introductory message as follows. In Section 2, we provide details about related studies on student engagement and the MCA method. In Section 3, we present details of participants, the study dataset, and statistical analysis. In Section 4, we present study results, while Section 5 is a discussion of the results. Section 6 features concluding remarks with possible future research.

2. Related literature

There is substantial literature about student engagement, which has become a principal focus for institutional scholars in academic performance studies. Student engagement is frequently used to describe interest and enthusiasm for school, and it impacts on academic performance and behavior of a student [12]. The impact of student engagement on student achievement is no longer interrogated [13], but it is understood in different ways [14]. Student engagement involves the participation of students in school activities as well as student recognition and appreciation of school. Students who demonstrate active involvement in school activities are said to have high academic performance [12, 14] and positive attitudes [12]. However, disengaged students usually face the opposite situation, such as demonstrating low academic performance and showing negative behaviors. Besides, student engagement in the context of online learning is particularly challenging because online students seem to have fewer chances to be involved physically with their institutions, indicating the absence of institutional factors. Nevertheless, technology usage nurtures engagement policies based on active learning prospects that include partaking in collaborative study, easing student discussions, distributing resources energetically, and forming coursework with practical mechanisms [12]. Three elements of student engagement are behavioral engagement, cognitive engagement, and emotional engagement, which are defined by a multitude of factors associated with institutions, students, families, teachers, curricula, and learning resources [15]. Behavioral engagement is often defined as an engagement based on individuals' involvement in an institution's academic, social, and extracurricular activities.

Meanwhile, students' behavioral engagement behavior has been identified as a motivating factor that enhances more excellent academic performance and school retention. Cognitive engagement is an aspect of engagement that is focused on student investment in school and learning activities. The study on cognitive engagement is often concerned with how much students invest in learning and whether they are willing to work extra to better academic performance. The emotional engagement was identified as an engagement that focuses on how students identify with their institution. Identification with the institution means belonging, valuing, or feeling essential to the institution and appreciating academic performance in an institution's related outcomes.

In recent times, research has significantly advanced the understanding of student engagement that most scholars have conceptualized it as multi-dimensional [16]. Besides, a substantial quantity of studies has affirmed that educational technology can practically support online students' engagement [17]. In another development, Mayer [18] established that students acquire better knowledge from computer-based teaching, comprising words, graphics, and metaphors compared to words alone in orthodox learning. The incorporation of active learning in curricula can enable student engagement irrespective of the learning environment's conditions. In fact, active learning has been recognized as an instructional approach that involves students' active engagement with course materials through discussions, problem-solving, case studies, and other pragmatic teaching methods [19]. The NSSE tool has been used in many studies that link student engagement to positive student outcomes such as higher grades, retention, persistence, and completion [20, 21]. However, despite the increased interest in student engagement, the various statistical tools previously employed to analyze datasets associated with student engagement have been identified to present inherent limitations [16, 22, 23].

2.1. Student engagement methods

Many education scholars have viewed student engagement from different perspectives of student actions, teacher activities, and institution efforts. Different methods have been proposed in the literature for facilitating student engagement, and a typical example is flipped learning [24]. The method of NSSE has provided data to gain intuitive insight into the levels of student engagement [25]. The canon of literature has mentioned different methods that have been previously employed by researchers to investigate student engagement from a theoretical perspective and analyzed datasets associated with student engagement [26, 27]. More details about some of these methods have been covered by other authors [7, 17, 25, 28]. Based on the literature search, some of the methods previously employed to analyze student engagement datasets have some shortcomings and, as such, cannot bring forth the potential information that is needed for enhancing the academic performance of students. Consequently, there is a need to deploy more data analytic methods with an excellent capability to divulge confidential information contained in student engagement datasets.

2.2. Multiple correspondence analysis

The present study is focused on the application of Multiple Correspondence Analysis (MCA) to analyze a dataset associated with student engagement, even though there is no substantial literature on statistical methods in student engagement research. Although other disciplines such as health sciences, engineering, political science, and sociology [29-31] have extensively used the MCA method, it is rare in student engagement literature. For instance, Das and Sun [32] used MCA to explore the contributing factors regarding fatal run-off-road crashes in Louisiana. Kim and Yamashita [33] used the MCA method to investigate the characteristics of pedestrian-involved collisions in Hawaii. Although we have acknowledged that there are a considerable number of studies on student engagement [24, 35], none of these studies have used graphical EDA techniques for the analysis of the South African Survey of Student Engagement (SASSE) to the best of our knowledge. MCA achieves coherent analysis by grouping indicators according to their similarity. Accurate results cannot easily be achieved by merely using a correlation-based method or classical regression analysis scheme.

A common finding from the literature has indicated different tools that researchers have utilized to assess student engagement. However, student engagement is always challenging to explain, which is not the focus of this study because it is a complex construct prejudiced by multilevel factors. Moreover, it remains fuzzy from the literature on student engagement factors that directly impact academic performance. This study focuses on relating student engagement indicators of NSSE to academic performance using the method of MCA. The research introduced in this paper serves as the first reference point to demonstrate MCA's useful application to determine the weighty engagement indicators that contribute to students' academic performance from a higher education institution.

3. Materials and methods

3.1. Participants

The present study has utilized 1201 participating students from the Durban University of Technology (DUT) in South Africa. The student responses were drawn from the 2018 SASSE dataset at DUT. The descriptive statistics of participants based on faculty were obtained with the highest proportion of students from faculty of Accounting and Informatics (30.7%), Management Sciences (24.2%), Engineering and the Built Environment (16.5%), Applied Sciences (10.2%), Arts and Design (9.4%) and Health Sciences (9.0%). The student demography in terms of races is approximately 53.0% of sample were female students, 87.8% Black, 9.7% Indian, 1.4% White, and 1.1% Colored students.

3.2. Dataset

This study has been conducted with 2018 SASSE data collected by DUT, one of the participating universities in the Siyaphumelela Network project (**https://www.siyaphumelela.org.za/about.php**). The project is being funded by the Kresge Foundation to improve data analysis at South African universities. The Siyaphumelela Network 2.0 version was recently launched on August 2020 through webinar due to the COVID-19 hiatus (**https://www.saide.org.za/article.php?id=83**). The participating universities are expected to develop capability in data analytics to harvest student data, create South African models of universities using data analytics to improve student learning outcomes, enlarge cadre of experienced professional data analytics and offer services, tools, and systems to foster student success based on scientific evidence from data.
SASSE dataset is an architype of NSSE dataset that reflects student participation in educationally purposeful activities, how students interact with lecturers, peers, and engage with diversity, how students perceive university environment, and demographic information about students. The NSSE instrument is among the most popular survey tools of student engagement. It has been used by many colleges and with four NSSE themes that were sub-divided into ten different indicators. The engagement indicators provide a summary of detailed information contained in student responses.

Each indicator is based on several levels of measurements that were organized coherently into four broad themes, as shown in Table 1. In the current study, we have defined academic performance as measuring student achievement across various modules. It is customarily measured using the average score, high school graduation rate, annual standardized tests, and college entrance examinations. Meanwhile, the average score, which is a measure of academic performance in this study, is typically measured on a scale of zero to four, with a higher average score representing a higher academic performance.

Table 1. Student engagement themes, indicators, and measures of SASSE

Theme	Indicator	Measure
Academic challenge	Higher-order learning	Amount of academic work that emphasized challenging learning tasks, including applying learned information to practical problems, identifying ideas and experiences, evaluating information from other sources, and forming new ideas
	Quantitative reasoning	How often students engaged with numerical and statistical information across curricula and used such information to examine real-world problems, reach conclusions, and evaluate others' concluded learning with peers
	Reflective and integrative learning	How often students connected prior knowledge, other modules or subjects, and societal issues, considered diverse perspectives, reflected on their views while examining others' views
	Learning strategies	How often students enacted basic academic success strategies, for example, identifying important information in readings, reviewing notes after classes, and summarizing subject material
Learning with peers	Collaborative learning	How often students collaborate with others when mastering difficult materials, such as explaining materials to others, preparing for examinations, working on group projects, and asking for help
	Discussion with diverse others	How often students discussed with people who differ in terms of economic background, religious belief, ethnicity, or political views experienced with staff
Experiences with staffs	Student-staff interaction	How often students had meaningful and substantive interactions with advisors and lecturers, such as discussing career plans, subject material outside class or discussing their academic performance, and working on student groups or committees
	Effective teaching practices	The amount that lecturers emphasized student comprehension and learning through clear explanations and organization, using illustrative examples, and providing formative and useful feedback
Campus environment	Quality of interaction	How students rated their interactions with influential people in the learning environment, such as academic staff, student support services, peer learning support, and other students
	Supportive environment	The institution's amount emphasized students' help to persist and learn through academic support programs, encouraged diverse interactions, and provided social opportunities, campus activities, wellness, health, and support for non-academic responsibilities

3.3. Analysis

Multiple Correspondence Analysis (MCA) has been applied in this study to analyze the student engagement dataset. MCA is a descriptive method designed to analyze simple two-way and multiway tables containing some measures of correspondence between rows and columns. It is a useful data analysis method and graphical demonstration of categorical data in massive and multifaceted datasets [32]. The graphical capability of MCA synopses the expression of associations among indicators without any underlying assumptions, which makes interpretation easier [32]. Moreover, MCA can look at multiple types of data and dimensions concomitantly, resulting in a sharp divergence to running innumerable bivariate investigations [32]. It is performed on an $N \times K$ indicator matrix in which N is the number of data samples, and K is the number of features describing the samples. The element in the cell (n, k) of the indicator matrix consists of an individual information n and category k [36]. Related categories in MCA are to be found close together in Euclidean space, leading to clouds of data points that have comparable distributions [32]. Remarkably, MCA's output generates two-point clouds that are typically represented by a 2-dimensional graph [32]. The cloud of individuals is constructed on distances between individual information for an indicator, for which diverse categories of indicators have been selected [29]. Meanwhile, the squared distance between individuals related to each category is obtained in the case of each indicator [32, 36]. An initial descriptive statistical analysis was performed to report the modalities of each indicator in the same direction. MCA method has been used in this study to explore indicators that associate student engagement to academic performance. On each of the factorial axes, we have obtained a discrimination measure to represent the intensity with which an indicator explained the axis. Moreover, we have analyzed the relative contributions of indicators and assessed which modalities are represented on the axes. The name of each MCA dimension was arbitrarily attributed according to the interpretation of its list of indicators. The proximities and locations of indicators, according to the axes, show their interdependences. A shorter distance between two indicators is an indication of a higher correspondence. In this study, MCA was performed using the R package FactoMineR included in the R software to benefit from the efficient implementation of the method.

4. Results

In this study, all the student engagement indicators captured by the SASSE dataset were utilized to perform MCA based on the explanation given in Section 3. The dataset contains 1201 rows (students) and ten columns (indicators) as proposed by NSSE. The graphical representations of MCA have helped to simplify the process of interpreting the associations among student engagement indicators. The indicator levels that share similar characteristics are located close together and well indicated in a 2-dimensional plot forming clouds of points. The associations among indicators in the first two dimensions are shown in Fig. 1 for all the engagement indicators. The individual information is compared to interpret the MCA plot and categories within the indicators by gauging the distances of map points. The closer the engagement indicators are to each other, the more they are related. The engagement indicators are colored, and lines show the distribution of each indicator along with the map. This result signifies that many of the engagement indicators possess a rough contribution to the MCA. However, it should be acknowledged that the closer an indicator is to the center of the map, the lesser its contribution to the eigenvalue of the respective dimension. This study's findings reveal that the engagement indicators that have contributed most to the first two dimensions are higher-order learning, supportive environment, student-staff interaction, and reflective and integrative learning because they are farthest from the center of the map.

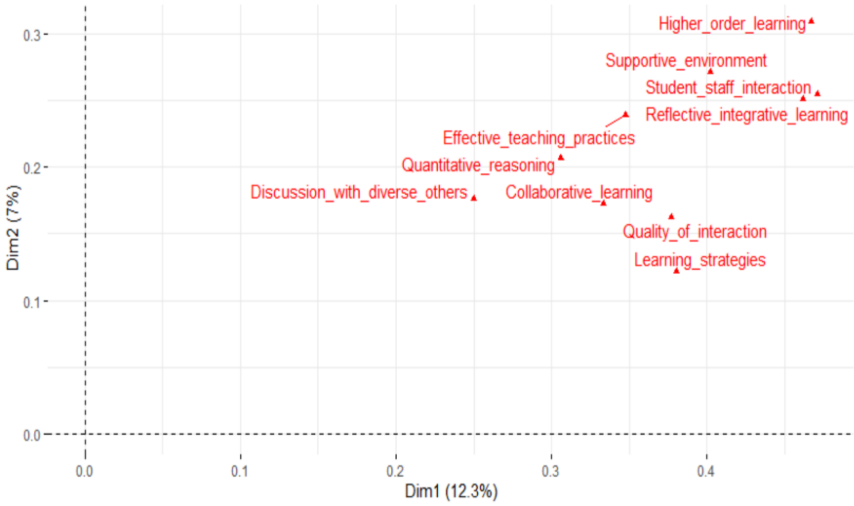

Fig 1. Plot of all engagement indicators

The magnitude of information related to each dimension is termed eigenvalue [37], with 0 or 1 indicating the total variance among indicators. Every point on the plot has its contribution to all dimensions, and the scale of the plot depends heavily on the volume of contributions of each dimension. In this study, we have observed that the first and second dimensions exhibited a greater eigenvalue than the other dimensions. The first and second dimensions have eigenvalues of 0.380 and 0.216, respectively, as presented in Table 2. Together, these two dimensions explain about 19% of the data variability. The low eigenvalues calculated for our dataset have demonstrated that the engagement indicators are heterogeneous. This heterogeneity may be a result of the random nature of the SASSE measures.

Table 2. Eigenvalue, percentage variance and cumulative percentage variance of top five dimensions

Eigenvalues	Dimension				
	1	2	3	4	5
Eigenvalue	0.380	0.216	0.147	0.122	0.117
Percentage of variance	12.250	6.978	4.727	3.950	3.789
Cumulative percentage of variance	12.250	19.228	23.956	27.906	31.695

The model estimation has resulted in the formation of 10 principal dimensions, as shown in Fig. 2. The number of dimensions to be formed was estimated by the MCA method, and each dimension explains a certain amount of variance within the SASSE dataset. For instance, dimension 1 explains 12.3% of the dataset's total variance, while dimension 2 explains 7.0% of the dataset's total variance.

In Table 3, considering the coefficient of determination (R^2) and p-value, all the indicators contributing to this study were identified. The order of presentation indicates the importance of each indicator. An association's strength is indicated by R2 parameter, with the value of 0 indicating no interrelation, and 1 indicates an extremely strong interrelation between the qualitative and MCA dimensions. The engagement indicators that were identified as contributing mostly to dimension 1 is "student-staff interaction", "higher-order learning", "reflective and integrative learning", and "supportive environment". In addition, these four indicators were consistently identified as mostly contributing to the second dimension.

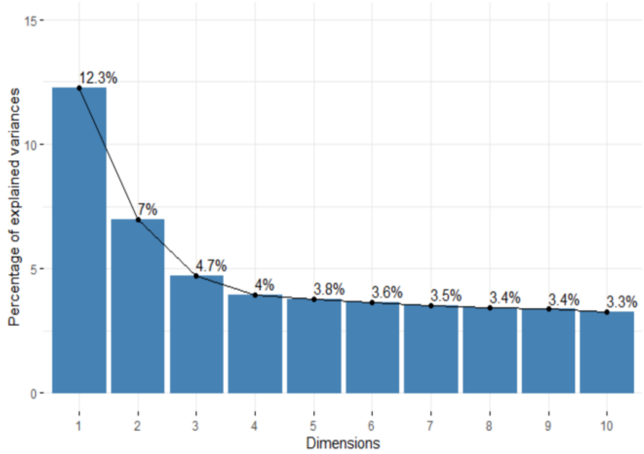

Fig 2. Indicator decomposition per dimension

Table 3. Statistical significance test for weighty indicators contributing to student engagement in the top 2 dimensions

Dimension 1	R^2	*p*-value
Student-staff interaction	0.471	<0.001
Higher order learning	0.467	<0.001
Reflective integrative learning	0.462	<0.001
Supportive environment	0.402	<0.001
Learning strategies	0.380	<0.001
Quality of interaction	0.377	<0.001
Effective teaching practices	0.347	<0.001
Collaborative learning	0.333	<0.001
Quantitative reasoning	0.306	<0.001
Discuss with diverse others	0.249	<0.001
Dimension 2	R^2	*p*-value
Higher order learning	0.309	<0.001
Supportive environment	0.271	<0.001
Student-staff interaction	0.253	<0.001
Reflective integrative learning	0.251	<0.001
Effective teaching practices	0.239	<0.001
Quantitative reasoning	0.206	<0.001
Discussion with diverse others	0.175	<0.001
Collaborative learning	0.171	<0.001
Quality of interaction	0.162	<0.001
Learning strategies	0.121	<0.001

Fig. 3 shows the categories of engagement indicators in the top 2 dimensions in descending order of importance. The figure illustrates the levels with the most contributions, and a critical look at this table indicates that levels of very much Higher-Order Learning (HOL1) and very much Supportive Environment (SE2) are significantly linked to both dimensions. This result means a robust association between these two indicators in enhancing the academic performance of students.

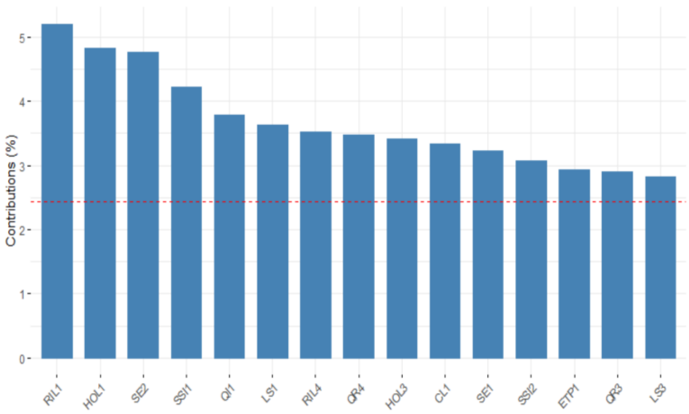

Fig 3. Contributions of levels in the first two dimensions

Furthermore, to substantiate whether the levels of a nominal indicator diverge significantly [37], we have created a 95% confidence ellipse for each engagement indicator. Some of the graphical outputs are shown in Fig. 4. The confidence ellipse provides a strong level of uncertainty correlated with the point location. It was observed based on this figure that all levels of indicators of never Collaborative Learning (CL4), very much Higher-Order Learning (HOL4), sometimes Reflective and Integrative Learning (RIL3), and very often Student-Staff Interaction (SSI4) imply no convergence of confidence ellipses. This finding implies that these indicators are fundamental to student engagement, and for students to improve their academic performance, they must be encouraged to participate in higher-order learning interventions. Besides, we have observed that various engagement indicators differ significantly based on the 95% confidence ellipses overlapping. Hence, we can faithfully conclude based on this finding that they have contributed equally to students' academic performance at the Durban University of Technology.

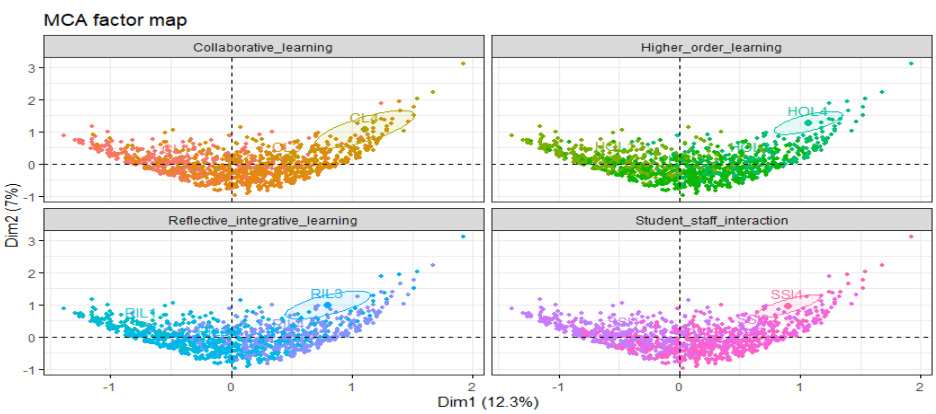

Fig 4. Factor map of indicator levels

Fig. 5 shows the MCA biplot of the dataset under investigation, wherein the projections of row points onto directions defined by indicator vectors give an approximation up to a scaling indicator. The universal presentation of various levels of indicators in each portion of the 2-dimensional plot is given. The plot shows a global behavioral pattern in the student engagement dataset of which rows (students) are indicated by blue points and columns (categories) by red triangles. The distance between any row points or column points on the biplot gives a similarity or dissimilarity of two points. Row points with a similar profile are closed on the factor map, and the same argument holds for column points. The graphical plot provides an overall representation of categories with the highest contributions in each quadrant in the 2-dimensional plot, in which very much higher-order learning and sometimes student-staff interaction are making higher contributions. The result establishes that two major engagement indicators, which have contributed most to students' academic performance at the Durban University of Technology, are higher-order learning and student-staff interaction.

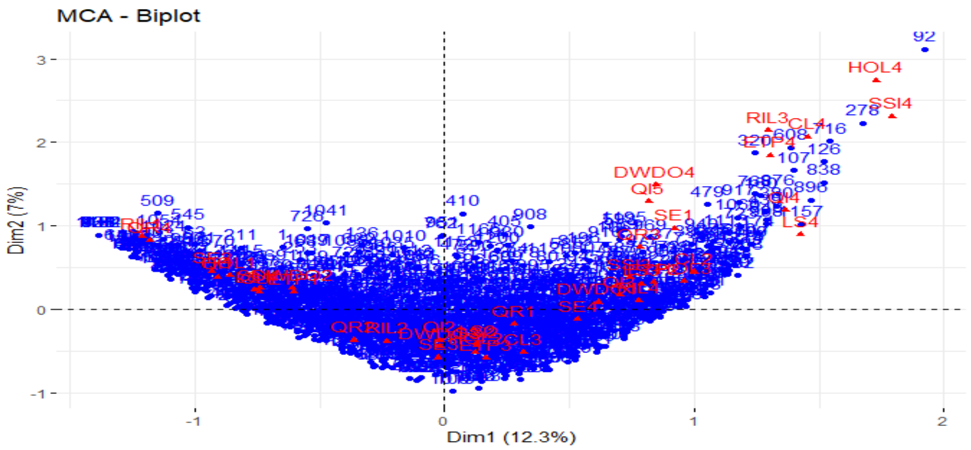

Fig 5. Biplot of student engagement dataset

5. Discussion

This study was designed to investigate student engagement indicators associated with students' academic performance at Durban University of Technology (DUT) and to evaluate whether there are subgroups with different pattern profiles. This study highlighted the engagement indicators that mostly contribute to variance in our MCA analysis and their main correspondences. These indicators could be considered the most relevant factors that can improve students' academic performance at DUT. This study can be replicated easily in other higher institutions of learning to establish a global comparison. For instance, higher-order learning is a concept that resonates with different types of learning activities and the amount of cognitive processing. It is a way to help students think divergently and convergently and not just memorize to improve their cognitive ability. Research has demonstrated that engaging students in the learning process increases their attention and motivates them to acquire higher-level critical thinking skills. Meanwhile, the results presented in this paper have demonstrated that we can use MCA to identify significant indicators that contribute to student academic performance. The total variance explained by the selected indicators is not high, with about 19% of the data dispersion recorded in this study. The eigenvalue correction can be recalculated to increase variances further using the Burt matrix to adjust for data dispersion [30, 37]. MCA's unsupervised method can generate a more exciting combination of clouds with a tidy dataset, that is, a dataset with no missing values.

A 95% confidence ellipse was constructed for the engagement indicators (Fig. 5) to substantiate whether the nominal indicator levels diverge significantly [38, 39]. The confidence ellipse provides a strong level of uncertainty correlated with point location. It was observed that some levels of higher-order learning and student-staff interaction are all associated with students' academic performance at DUT. Consequently, the two indicators can be regarded as pivotal for student engagement at DUT. Moreover, we have observed that various levels of those indicators differ significantly based on the 95% confidence ellipses overlapping. Thus, we can infer that they have contributed equally to the academic performance of students at DUT. The 15 highest contribution levels have been presented in Fig. 3 for coherency, which revealed various proximities combinations. Concerning the corresponding closeness of points, the classification of various clouds of points can be constructed. For instance, one combination corresponds to higher-order learning quite a bit as the contributing indicator. The dataset's global proximity behavioral patterns are revealed in the biplot with rows and columns representing blue points and red triangles, respectively, for the first two dimensions (Fig. 5). The way the quality of fit of the biplot is measured is exciting. Since it is well-known that regular (crisp) MCA seriously underestimates this measure. This finding is consistent with previous studies that have used MCA in other application areas, indicating that an indicator's contribution depends heavily on its levels. This, in turn, means that the greater the levels of an indicator, the greater its contribution to the variance of a cloud [31, 40]. There are many reasons that MCA is better than other parametric methods and why it is proposed in this study for relating student engagement indicators to academic performance. For instance, the corresponding closeness or disparity between more cases can be investigated concomitantly using MCA layout. In a scenario where more than two cases are to be investigated for interdependence, MCA's characteristics can provide colossal merit. This aspect is not investigated in the current study, but it may be a candidate recipe for future study. Despite other methods that can only pinpoint the weighty contributing indicators, MCA can link any other feasible associations among the contributing indicators. This point becomes the main distinguishing merit of MCA over other statistical methods, especially the parametric ones. Another important reason for using MCA is its ability to apply intuition to a large dataset using a detailed visualization functionality that intrinsically comes with the method [29, 40]. Despite the inability to compute an estimated effect on indicators, MCA is still unique in identifying the significant combinations of desired indicators. For investigating the links between qualitative indicators, that is, the link between student engagement and academic performance, the study objective has been achieved.

Besides, the quantification of categorical data can help further when modeling is possible with MCA in a more straightforward manner. This research's findings are practically useful to higher institutions' authority in determining student engagement's focal issues based on evidence from data. Moreover, they can aid authorities and policymakers in gaining intuition that can help comprehend weighty contributing indicators of student engagement, thereby leading to more astute policymaking. This study's key recommendation for higher education and education policymakers' authority is to promote student engagement, particularly in interventions associated with higher-order learning and student-staff interaction.

6. Conclusion

The present study has indicated that MCA represents an essential addendum to the list of scientifically sound methods that can be used to relate student engagement indicators to academic performance. Existing statistical analysis methods, particularly the parametric ones, have a fundamental underlying assumption and a pre-defined association between the outcome of interest and covariates. Such models could result in unreliable inferences, should one of the underlying assumptions be violated. In MCA's case, with no such underlying assumption, it has shown to be a useful statistical data analytic tool for mining information in a dataset associated with student engagement, as revealed in this study's findings.

The study findings have identified some exciting combinations among indicator levels used in the student engagement dataset. This study found that higher-order learning and student-staff interaction are essential indicators for relating student engagement to academic performance. This may imply that performing students engage in higher-order learning and interact well with staff. Moreover, we have observed that various responses of student engagement indicators differ significantly based on the overlapping of 95% confidence ellipses. Consequently, any education institution interested in enhancing student academic performance should prioritize learning interventions pertaining to higher-order learning and student-staff interaction.

The one apparent limitation derives from this current study is its cross-sectional design, which means that temporal directions of associations between reciprocally connected indicators could not be defined. MCA's limit involves its mainly explorative role, which means further analysis is required to evaluate the key findings' role. Future research should focus on capturing student engagement indicators' cognitive and emotional aspects to inform policymaking on improving student academic performance. A vast shortage of studies focuses on student engagement's cognitive and emotional dimensions and factors influencing these dimensions.

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