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Exploring Students' Perceptions of Academic Integrity in the Digital Classroom through Exploratory Factor Analysis (EFA)

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Abstract

Objectives: The research aims to develop a reliable tool for thoroughly understanding the multifaceted concept of academic integrity and establish a foundational model that can serve as a cornerstone for subsequent investigations into academic integrity within digital classrooms. **Methods:** A cross-sectional survey method was employed, involving 196 students from the College of Education of a state university in the Visayas region of the Philippines. The participants were students across year levels from the following programs: Bachelor of Secondary Education and Bachelor of Elementary Education. The data underwent thematic analysis to identify initial factors, which were then developed into a questionnaire. The questionnaire was validated through face and content validation by a panel of experts. Data were analyzed using SPSS. **Findings:** The analysis revealed nine factors influencing academic integrity: learning environment, ethical concerns, cheating, academic anxiety, educational impact, mental health, external pressures, technology challenges, and motivation. These factors highlight the multifaceted nature of academic integrity in online learning. This research informs interventions and policies to promote integrity and student success, advocating for continued exploration in this evolving field. **Novelty:** This study used Exploratory Factor Analysis (EFA) to create a research-based framework of students' perceptions of academic integrity in the digital classroom. By presenting a framework, future studies can build upon this model to further explore and refine our understanding of academic integrity dynamics in the digital age. Ultimately, the culmination of these efforts aims to foster a culture of honesty, trust, and intellectual integrity within the academic community.

Keywords: Academic integrity; Digital classroom; Exploratory Factor Analysis (EFA); Students' perception; Crosssectional survey

1 Introduction

Over the years, learning has played a significant role in human history. Humans have always sought to increase their knowledge, comprehend the world more thoroughly, and simplify their lives. The finest place to learn is in a classroom[1]. For many years, most schools conducted face-to-face, teacher-led instruction. The introduction of Coronavirus Disease 2019 (COVID-19) and the consequent quarantine measures abruptly changed the way that education was delivered, moving it to an online, modular, and flexible format.

Online learning can be considered a remarkable innovation in Philippine Education. It allows students to learn anywhere. All they need is a device and a good internet connection. With online learning, students can open the online learning platform whenever they find time on their hands[2]. Hence, students who have loaded schedules in school and have chores in their homes may be able to better manage their study time.

The internet, as a major component of online learning, allows students to easily access material online. In the twenty-first century, the internet has become an essential component of both life and education. Its development has a lot of advantageous effects. With the help of technology and mobile devices, learners in the current century have access to a vast amount of knowledge that can be used to complete projects and organize research. Our current environment's access to information is something that people from past generations can only imagine[3]. Yet, as the saying goes, "With great power comes great responsibility". Alongside this newfound access to information comes the risk of ignoring academic integrity.

Academic integrity encompasses the core principles of honesty, trust, fairness, respect, responsibility, and courage [4]. These principles serve as the foundation for the definition of ethical academic behavior, which is the development of a community centered on knowledge sharing. In a post-secondary institution, students and employees who always work with academic integrity strengthen an institution's reputation. This is so that an academic transcript, degree, or certificate from an institution maintains its essence, and the corresponding knowledge and skills can be expected from its holder. Individual students gain from this reputation, and the conclusions drawn about them are based on their academic achievements[5]. A common framework for professional work is established by knowing the core principles of academic integrity that are held within a community and acting accordingly. This makes the importance of the mastery of information, skills, and skills clear.

With this, the duty of highlighting academic integrity falls on educators. Some students believe that they own the knowledge they get online. Yet this idea has to be refuted and rejected. The availability of so much information makes it simple for students to become engrossed in it, which can result in unintended consequences. Poor notetaking, in which students may forget to cite the work they have found through online sources, is one factor that can aggravate this problem[3]. Teachers must help students learn how to be responsible 21st-century digital citizens in light of this access to information. Teachers must educate students with the abilities necessary to traverse the potentially treacherous waters of the digital world. In light of this, a range of tools and procedures are available to improve the integrity and security of the online learning environment[6].

In addition, there are a variety of new ways to cheat. Some are in online learning environments and others are in classroom settings. These include, but are not limited to, downloading essays from the internet and submitting them as one's work; inappropriately using materials during an online exam without permission; contacting other students online to get answers; or having someone else complete an online exam or assignment in place of the student[7]. In particular, both faculty and students perceive online testing to offer more cheating opportunities than in traditional, live-proctored classroom environments[8,9], with the main concerns being students collaborating to cheat and using forbidden resources during the exam[10].

In recent years, research on academic integrity and/or dishonesty has been done. For example, researchers such as Holden et al.[5], Perkins, et al.[11], Benson et al.[12], Perera-Gonzalez et al.[13], Çelik et al.[14], Garg et al.[15], and Peled et al.[16] have delved into various aspects of academic integrity in online courses, exploring challenges, technological solutions, educational interventions, student perceptions, cultural influences, and institutional roles.

In exploring academic integrity in online courses, Holden et al.[5] delved into the unique challenges of maintaining honesty and preventing cheating in digital classrooms. Perkins et al.[11] investigated plagiarism among students and discussed the intervention called academic misconduct education, Benson et al.[12] studied interventions like honor codes and tutorials on citation practices to promote integrity. Perera-Gonzalez et al.[13] explored student perceptions and attitudes towards integrity in digital classrooms, analyzing factors influencing dishonest behaviors and strategies for fostering honesty. Çelik et al.[14] discussed the role of faculty and institutions in fostering integrity, examining attitudes towards cheating and support mechanisms. Garg et al.[15] explored technological solutions such as plagiarism detection software to deter cheating and promote honesty. Peled et al.[16] examined cultural variations in attitudes towards integrity and globalization's impact on academic honesty in digital classrooms. These various research works have studied academic dishonesty. Despite that, there is no known literature or study on utilizing empirical data on academic dishonesty to establish a useful tool or model for establishing a thorough concept of academic integrity. To manage or mitigate the emerging culture of academic dishonesty among learners, there is a need to develop a governing model for academic integrity so its different elements can be broken down and studied further. Hence, this research provides a new and recent tool for studying academic dishonesty and academic integrity.

Despite the research conducted, a gap exists in understanding student's perceptions and a research-based framework of academic integrity in the digital classroom. Thus, the primary aim of this research is to develop a strong and dependable tool for thoroughly understanding the multifaceted concept of academic integrity in higher education, with a particular emphasis on its connection with online learning environments. By delving into the diverse forms and underlying factors cultivating academic dishonesty, this study hopes to reveal effective techniques for promoting academic integrity.

Furthermore, this research endeavors to establish a foundational model that can serve as a cornerstone for subsequent investigations into academic integrity within digital classrooms. By laying out a systematic framework, future studies can build upon this model to further explore and refine our understanding of academic integrity dynamics in the digital age. Ultimately, the culmination of these efforts aims to foster a culture of honesty, trust, and intellectual integrity within the academic community. The following are the objectives of the study:

1. What are the fundamental dimensions that comprise academic integrity within the digital classroom environment?
2. To what extent does the academic integrity questionnaire designed for the digital classroom demonstrate satisfactory internal consistency?
3. What overarching model on academic integrity within the digital classroom can be derived from the outcomes of the study?

The next part of the paper delved into the research design and methodology employed in the study. It provided a comprehensive overview of the approach taken to investigate the research questions. This section described the particular procedures utilized to gather, analyze, and evaluate data, ensuring that the study findings were rigorous and valid.

2 Methodology

This study employed a survey method, specifically adopting a cross-sectional research design. Cross-sectional research is instrumental in gathering data and providing numerical insights into trends, attitudes, or opinions within the studied population[17]. Given the research objectives, a survey approach was deemed most suitable[17]. Notably, no existing measure comprehensively addressed academic integrity in the digital classroom, necessitating the development of a new instrument and the analysis of the construct of "academic integrity." In a cross-sectional survey, characteristics and potential differences among multiple samples or populations are examined simultaneously at a single point in time.

To achieve a comprehensive understanding of academic integrity in the digital classroom, exploratory factor analysis (EFA) was employed to unveil the underlying structure of observed variables. EFA serves as a valuable tool for summarizing and interpreting underlying relationships and patterns within the data[18]. It was deemed the most appropriate method because of its nature of identifying the common factors that explain the order and structure among measured variables without having a pre-determined set of resulting factors in mind[19]. Similarly, this study starts the analysis without predetermined expectations regarding the number of common factors or which measured variables will be influenced by the same factors[20]. In essence, EFA aims to reveal the underlying dimensions associated with academic integrity. EFA, in general, allows researchers to identify the structure of the relationships between the variables and the respondents; consequently, providing opportunities for sound development of theoretical models.

2.1 Respondents

Statisticians generally recommend that a sample size of at least 100 be used to ensure that survey research yields statistically significant results. Two distinct categories of respondents were included in the present study. The first set comprised 134 third-year students selectively chosen from the College of Education of a public state university in the Visayas region of the Philippines. This selection was purposeful, aiming to include individuals who started their college journey during the pandemic, undergoing online admissions and classes. Furthermore, the College of Education's selection is important since its students are being prepared to become future educators, thereby assuming roles of influence and responsibility. Hence, emphasizing academic integrity among these students is important, as it serves as a cornerstone for their ethical and professional development.

The data from the students' responses formed the foundation for constructing initial items related to academic integrity within digital classrooms.

The second set consisted of 196 students, who were not a part of the first set but were also from the College of Education. Comparable selection criteria were used to guarantee consistency across both groups. These students completed a questionnaire about academic integrity in digital learning environments, which was then subjected to factor analysis.

To facilitate the emergence of an interpretable factor structure, established research recommends a minimum of 5 to 10 participants per survey variable/item. Considering that the questionnaire consists of 32 items related to academic integrity, approximately 160 participants were deemed necessary. Employing a statistical power analysis for Exploratory Factor Analysis (EFA), the targeted sample size was set at a minimum of 160 participants. With an actual sample size of 196, the requirement for exploratory factor analysis was adequately met[21].

2.2 Data Gathering Instruments

The item development phase commenced with the crafting of a 10-item open-ended questionnaire. Open-ended questions allow respondents to freely express their thoughts and opinions on various topics, which provides researchers with qualitative and non-numerical data that can offer deep insights. Unlike closed-ended questions with predetermined responses, open-ended inquiries often yield unexpected and enlightening insights that might otherwise be overlooked.

Given the aim of understanding student perspectives on academic integrity, an open-ended questionnaire was deemed the most suitable tool for data collection. Five questions were designed to explore students' perceptions regarding the underlying reasons for academic dishonesty in digital classrooms, while another five focused on eliciting potential strategies to enhance academic integrity. The questionnaire was developed using Google Forms for ease of administration and data management.

Since the data collected were qualitative in nature, a thematic analysis was conducted. The analysis of students' opinions on academic integrity led to the development of the questionnaire items, resulting in the identification of eight key dimensions, namely: academic anxiety and pressure (AAP), interest and motivation (IM), external pressure (EP), technological-related challenges (TC), cheating and academic misconduct (CAM), learning environment issues (LEI), psychological and mental health (PMH), and ethical concerns (EC). These dimensions were used in the item development phase. The preliminary instrument consisted of 32 items with 3 items reflecting academic anxiety and pressure, 3 items in interest and motivation, 4 items in external pressure, 3 items in technological-related challenges, 5 items in cheating and academic misconduct, 3 items in learning environment issues, 7 items in psychological and mental health, and 4 items ethical concerns. It can be noticed that there is uneven item distribution per factor because the initial factors were derived from students' perceptions, which were then categorized into themes. This thematic grouping naturally resulted in varying numbers of items under each factor, depending on the importance or emphasis of the themes in the students' responses.

The respondents were asked to express their responses on a 5-point Likert Scale. The 5-points are: strongly disagree (1), disagree (2), uncertain/unsure (3), agree (4), and strongly agree (5). The instrument underwent a rigorous process of face and content validation, involving inputs from three esteemed experts in the field. These experts brought diverse perspectives and specialized knowledge to ensure the thoroughness and appropriateness of the instrument.

Firstly, a university psychometrician, renowned for expertise in measurement theory and assessment design, contributed valuable insights into the instrument's validity and reliability. Drawing on their deep understanding of psychometrics, they assessed the instrument's alignment with established measurement principles, ensuring its capacity to accurately capture the intended constructs.

Additionally, two university-level experts—a guidance counselor and an educator—played important roles in the validation procedure. Their extensive experience working directly with students provided crucial perspectives on the instrument's relevance, clarity, and sensitivity to the target population's needs and experiences. The guidance counselor offered insights into students' behavioral and emotional dynamics, while the educator provided valuable inputs on instructional strategies and pedagogical considerations relevant to academic integrity.

Together, these experts collaborated to scrutinize the instrument's face validity, ensuring that it was appropriate and comprehensible to respondents. They also evaluated its content validity, assessing the thoroughness and relevance of the items in capturing the multifaceted dimensions of academic integrity in the digital classroom.

By engaging a diverse panel of experts encompassing psychometricians, counselors, and educators, the validation process ensured that the instrument met rigorous standards of quality and comprehensiveness, enhancing confidence in its effectiveness as a research tool for exploring academic integrity in the digital learning environment.

2.3 Data Collection Procedure

The researchers sent a letter to the University president for permission to conduct a survey among students of the College of Education. It was clearly stated in the letter that responses from students will be treated as highly confidential and will not be taken against them or the faculty. It will only be the perception of the students on what they believe caused academic dishonesty during an assessment conducted online, whether it is a synchronous or asynchronous session.

After permission was secured, the researchers conducted the study in the first semester of the Academic year 2022-2023. It takes quite a bit longer to gather the results since it was sent via Google Forms due to health protocols. Constant follow-up through email and group chat was done to gather substantial data. To maintain confidentiality and anonymity, the Google forms were set not to collect personal information from the students. The researchers stopped accepting responses from the students when the data was saturated; that is, no unique answer was found after reviewing the responses.

Since the data were from open-ended questions, the response was qualitative in nature. Thus, the researchers used thematic analysis by Braun and Clarke[22]. A technique for assessing qualitative data called thematic analysis involves looking through data collection to find, examine, and report recurring themes[22]. The following steps were observed: (1) familiarizing yourself with the data: This entails repeated and active reading through the data. Responses from the Google Forms were downloaded to an Excel file and were read repeatedly by the researcher; (2) generating initial codes: As the first truly analytic step in the process, coding helps to organize data at a granular, specific level. After the first step in the analysis (i.e., familiarization work), the researchers began to take notes on potential data items of interest, questions, connections between data items, and other preliminary ideas. Moreover, the data were collated in a paper to form initial codes; (3) searching for themes: The third step involves an examination of the coded and collated data extracts to look for potential themes of broader significance. By examining, combining, contrasting, and even visually mapping how codes connect to one another, the researchers have now created themes based on the initial code; (4) reviewing themes: This step provides a clear example of the recursive nature of the entire process of thematic analysis. Re-reading and revising codes and themes are expected parts of the analytic process. While this iterative process could theoretically continue indefinitely. Some themes are broad and need to be reviewed if these answer the research question. Re-reading and refining the themes were done in this stage; (5) defining and naming themes: Once the thematic map has been refined, this step finds the researcher creating a definition and narrative description of each theme, including why it is important to the broader study question. The researchers then construct a clear narrative explaining how and why each theme's coded data offers distinctive insights, advances understanding of more general issues, and interacts with other themes. The themes derived were considered as the initial factors and became the basis for developing the survey questionnaire for academic integrity in digital classrooms.

Another permission to conduct the study was secured from the office of the president to collect data regarding academic integrity in the digital classroom. After permission was granted, the researchers gave out a hard copy of the questionnaires to 196 students from the College of Education enrolled in the 1st semester of AY 2023-2024. After which, these were gathered and analyzed as presented in the next stage.

2.4 Data Analyses

All the data gathered were analyzed using the Statistical Package for the Social Sciences (SPSS) software, Version 26. With its extensive collection of statistical capabilities, the software made it easier to handle and analyze the data effectively. The analysis was guaranteed to be accurate, and dependable, and to produce significant insights that were in line with the objectives of the study.

2.4.1. Screening and Data Cleaning

Initially, all "negatively worded" items were recoded in the positive direction (i.e., a score of 1 became a 5, a score of 2 was recoded as a 4, and so on). Participant responses were checked to ensure they all were within the range on the Likert scale (minimum of 1 and maximum of 5). All the data inputting errors were corrected. Additionally, the recoded items were relabeled for clarification purposes and were scanned for missing responses. Descriptive statistics were computed to check the normality of the item distributions. Based on the descriptive statistics, valid responses were identified.

2.4.2. Inspection of Parametric Properties of Questionnaire Items

The parametric nature of each item was also inspected. Histograms, box plots, and QQ plots were viewed to identify outliers and any other irregularities in the data distribution. Items with skewness and kurtosis values of less than an absolute value of 1 can be considered normally distributed for statistical analyses[23].

2.4.3 Exploratory Factor Analysis (EFA)

2.4.3.1 Prerotation item and factor analyses. In this section, the steps that were taken prior to rotating the factor matrix are summarized. These included an analysis of the initial reliability, intercorrelations, and assumptions underlying principal axis factoring (PAF or principal factor analysis) and oblique rotations.

2.4.3.2 Initial reliability analysis. To determine whether the 32 items represented an internally consistent measure, the researcher computed an overall Cronbach alpha (α) coefficient.

2.4.3.3 Correlational analysis. An analysis of the inter-item Pearson Product correlations was conducted. Items with consistently low (approximately < .20) or high (> .80) inter-item correlations were deleted.

2.4.3.4 Verifying assumptions. In verifying assumptions prior to rotation, the researcher computed Bartlett's Test of Sphericity and a Kaiser-Meyer-Olkin Measure of Sampling Adequacy[23]. A significant sphericity (p < .05) suggests that the data set, and thus, the correlation matrix is factorable. In addition, the researcher is looking for a KMO ranging between 0.60 and 0.90. These results will indicate whether it is an identity matrix. Bartlett's Test compares the correlation matrix to the identity matrix (i.e., it checks whether there is a certain redundancy between the variables that we can summarize with a smaller number of factors). Therefore, if the items are highly correlated, only one factor is most likely sufficient.

2.4.3.5 Extraction methods. Initially, both principal component analysis (PCA) and principal (factor) axis analysis (PAF or PFA) were computed on the data set. The items were examined for high and low factor loadings. The minimum acceptable factor loading was set at 0.35[24] .

2.4.3.6 Factor rotation. To determine the number of factors to rotate, the following criteria were used: the amount of the explained variance for each derived factor (over 10%), factor eigenvalues greater than 1 [24], and from the results of the scree test. In addition, a parallel analysis was computed given that it is a more rigorous method for determining the number of factors to rotate[23]. Orthogonal and oblique rotations were compared.

More specifically, varimax rotations (i.e., a form of orthogonal rotation that rotates in 90° angles) for both PCA and PAF were examined for simple structure. The similarity between the PCA and PAF results suggested that both approaches represent a coherent and interpretable factor structure. However, PAF is especially well-suited for determining potential latent constructs in the data set and provides a more accurate estimate of the item correlations. Therefore, the researcher was mainly interested in analyzing the data using PAF.

In addition, according to Seijas-Macaias[23], oblimin rotation (i.e., a form of oblique rotation that rotates the eigenvectors in less than 90°angles) should be used when there is an expected correlation between factors. Since the items were developed based on the three dimensions (i.e., physical and sexual safety, social and emotional safety, and learning environment and academic support), the researcher expected some correlation between factors. Furthermore, oblimin rotation was conducted as it is appropriate for the current data set because it is logical to assume that factors are correlated given the subjective nature of participants' perceptions and experiences.

2.4.3.7 Post-rotation. Post-rotation initial factors were extracted from the matrix, that is, the common or shared variance of each variable is partitioned from its unique variance and error variance to identify the underlying factor structure and to determine simple structure. The communalities (h2) and explained variance for each item were examined. The percentage of total variance explained is crucial in determining factors and 60% serves as the acceptable minimum[24]. Items that have crossloadings (i.e., items that load substantially on two or more factors) were deleted if the loadings were weak (< .30). The researcher redid the analysis without those items to establish a simple structure. Lastly, the factors were named based on the content of the factor items.

2.4.3.8 Reliability of factors. Once the simple structure was determined, alpha coefficients were computed on the specific items comprising each derived factor. It was hoped that each factor as well as the overall scale would yield alpha values of at least 0.70.

To create a thorough model of academic integrity in the digital classroom, the gathered data was subjected to the stated procedure.

2.5 Ethical considerations

Ethics was properly observed in the conduct of the present study based on the standards of the American Psychological Association (APA). This study ensured that no form of harm would happen to the participants during the conduct of the study. Furthermore, ethical guidelines such as privacy and confidentiality in conducting ethical research were observed. The following ethical principles were observed by the researcher in the conduct of the study: (1) health protocols were strictly observed; (1) permission to conduct the study was sought first through consent forms; (2) the researcher informed the participants that no harm would come to them in relation to the study; (3) in case the participants would not like to answer the questions or he/she felt uncomfortable, the researcher assured the participants that their right to self-determination is assured; (4) participants' anonymity was reserved and their confidentiality was respected.

3 Results and Discussion

3.1 Data Cleaning and Inspection of Parametric Properties of Questionnaire Items

The initial phase of the data analysis process involved meticulously screening the data for usability, reliability, and validity. This is to ensure its suitability for statistical analyses. A total of 196 respondents completed the survey, prompting the researchers to meticulously review the questionnaires to identify incomplete responses or missing entries. Any items with missing values were replaced with the mean scores of their respective items.

Descriptive statistics were then computed to assess the normality of the item distributions and to ascertain whether the items met the parametric assumptions necessary for factor analysis. Alongside scrutinizing means, standard deviations, minimum/maximum values, skewness, and kurtosis indices, various visual aids (e.g., item histograms, box plots, and QQ plots) were utilized for thorough analysis[19].

Items displaying skewness and kurtosis values within an absolute range of 1 were considered to be normally distributed for statistical purposes[23]. Upon reviewing the parametric properties of each item, as documented in Table 1, it was determined that no items necessitated removal. This indicates that all items met the requisite assumption of normal distribution, essential for conducting factor analysis.

Table 1. Pre-factor Analysis Descriptive Statistics for Survey Items (n=196)

Item Number	Mean	Std. Deviation	Skewness	Kurtosis
AAP1	3.74	0.886	-0.368	-0.111
AAP2	3.8	1.081	-0.668	-0.452
AAP3	3.27	1.16	-0.094	-1.004
IM1	3.34	1.081	-0.113	-0.684
IM2	2.83	1.265	0.239	-0.936
IM3	3.33	1.222	-0.273	-0.918
EP1	3.08	1.178	-0.274	-0.869
EP2	3.51	1.015	-0.325	-0.603
EP3	3.15	1.354	-0.231	-1.165
EP4	3.44	1.11	-0.435	-0.613
TC1	3.48	1.148	-0.361	-0.868
TC2	3.57	1.023	-0.573	-0.274
TC3	4.06	0.892	-0.646	-0.392
CAM1	3.34	1.071	-0.352	-0.59
CAM2	3.46	1.044	-0.245	-0.578
CAM3	2.99	1.15	-0.184	-0.896
CAM4	3.48	1.234	-0.614	-0.553
CAM5	3.59	1.296	-0.662	-0.649
LE1	3.89	1.022	-0.647	-0.198
LE2	3.58	0.949	-0.382	-0.481
LE3	3.51	0.931	-0.261	-0.499
PFMH1	3.93	0.974	-0.663	-0.212
PFMH2	4.07	0.897	-0.916	0.655
PFHM3	3.53	0.908	-0.175	-0.384
PFHM4	3.87	0.946	-0.759	0.423
PFHM5	3.83	1.082	-0.681	-0.244
PFHM6	3.88	0.92	-0.313	-0.847
PFHM7	3.65	1.044	-0.359	-0.611
EC1	3.71	0.928	-0.644	0.279
EC2	3.69	0.91	-0.508	-0.115
EC3	3.48	1.166	-0.421	-0.671
EC4	3.62	1.086	-0.416	-0.775

Note: The SE of skew = 0.174; SE kurtosis = 0.346

3.2 Preliminary Analyses of the Underlying Dimensions of Academic Integrity in the Digital Classroom

In this section, the steps taken prior to rotating the factor matrix are summarized. These included an analysis of the initial reliability, intercorrelations, and assumptions underlying SPSS's principal axis factoring (i.e., principal factor analysis) to determine the underlying dimensions of academic integrity in the digital classroom.

3.2.1 Initial reliability analysis

In order to assess whether the 32 items collectively constituted a reliable and internally consistent measure, a reliability statistic for the overall scale was computed. This involved the calculation of Cronbach's alpha coefficient, a widely used metric in psychometrics for evaluating the internal consistency of a scale or test. The resulting Cronbach's alpha value (α=0.91) indicated a high level of internal consistency among the items comprising the scale. This value, ranging from 0 to 1, suggested that the items exhibited strong interrelatedness and coherence, reinforcing the reliability of the measurement tool employed in the study. A Cronbach's alpha value of 0.91 signifies a strong level of reliability. This affirms the researchers' confidence in the consistency and dependability of the scale in capturing the intended constructs related to academic integrity.

3.2.2 Correlational analyses

An assessment of the inter-item Pearson Product correlations found a variety of relationships from low to high, with values ranging from 0.20 to 0.62 for the majority of the items. While a few correlations fell short of the 0.20 criteria, the researchers decided to include them in the initial rotation to assess their suitability for component analysis. Overall, the correlations between the items were substantial enough to support factor analysis, providing a solid foundation for investigating underlying dimensions or structures in the data.

3.2.3 Verifying assumptions

Before proceeding with the rotated solution, several assumptions were verified. Bartlett's Test of Sphericity yielded a significant result, B (496) = 3056.699, with $p < 0.000$, indicating substantial differences between the correlation matrix and an identity matrix. This test evaluates whether there is redundancy among the variables; high correlations among items suggest that a single factor might suffice. However, Bartlett's Test rejected the null hypothesis of non-significant differences between items, implying the potential for measuring multiple constructs within the model.

Additionally, the Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) provided further insight, yielding a value of 0.80. This value, along with a very low determinant (5.829E-8) for the identity matrix, indicated a favorable correlation matrix. A KMO value above 0.80 is typically deemed meritorious, signifying significant common variance among the variables[23]. Collectively, these findings suggest that the dataset is suitable for factor analysis and supports the exploration of multiple constructs within the model.

3.2.4 Unrotated solution

The Kaiser[24] criterion and the identified factors greater than 1 were examined. A total of 67.72% of the variance was explained by 9 factors with eigenvalues that were greater than one. To further identify potential meaningful factors, the scree plot was examined. Inspection of Cattell's scree test (see Figure 1) supported the appropriateness of rotating these four factors, (i.e. the bend in the elbow occurred after nine factors).

Researchers also conducted parallel analysis (see Figure 2) in which each eigenvalue (which represents the size of the factor) was compared against an eigenvalue for the corresponding factor in many randomly generated data sets that have the same characteristics as the data being analyzed[23]. In doing so, each eigenvalue is compared to an eigenvalue from a data set that has no underlying factors. Thus, eigenvalues from the factor analysis were compared with the eigenvalues from the parallel analysis. Eigenvalues for the 5th and subsequent components (factors) were nearly equal, indicating that eigenvalues of this magnitude could have been derived from a random sample of data. Therefore, only nine factors were retained for further analysis. Cattell's scree test matched the above results, while Kaiser's rule would have retained nine. Thus, the researcher decided to rotate these nine factors based on the results of the visual inspection of Cattell's scree test, the accounted percentage of variance, and the results from the parallel analysis.

Initially, both principal component analysis (PCA) and principal (factor) axis analysis (PAF or PFA) were conducted on the data set with the 32 items that met the normal distribution standard for EFA. The items were examined for high and low factor loadings, and .30 was set as the minimum acceptable factor loading[21].

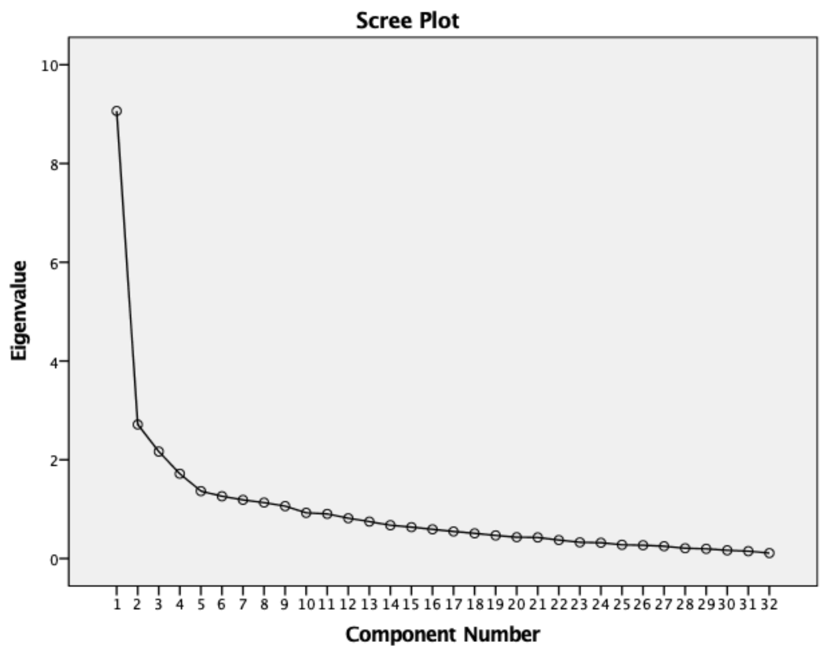

Fig 1. Scree Plot based on Principal Component Analysis (PCA) with 32 items

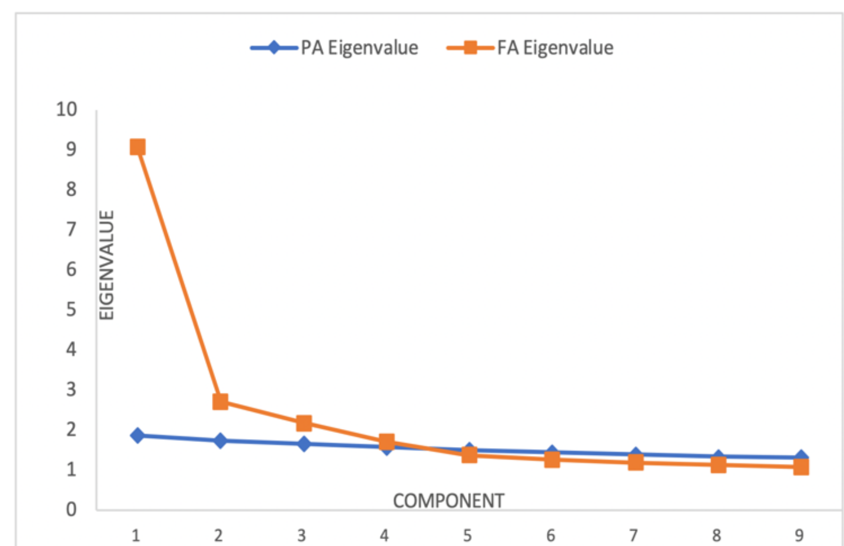

Fig 2. Eigenvalue Comparison between Factor Analysis (FA) and Parallel Analysis (PA)

3.2.5 Rotation results

Researchers compared varimax rotations (i.e., a form of orthogonal rotation that rotates in 90° angles) for both PCA and PFA and found similar variance in the models. This similarity between the PCA and PFA results suggests that both approaches represent a coherent and interpretable factor structure. However, PFA is especially well-suited for determining potential latent constructs in the data set and provides a more accurate estimate of the item correlations.

According to Seijas-Macias et al.,[23] oblimin rotation (i.e., a form of oblique rotation that rotates the eigenvectors in less than 90°angles) should be used when there is an expected correlation between factors. Since the items were developed based on the 9 factors the researcher expected some correlation between factors. Furthermore, oblimin rotation was conducted as it is appropriate for the current data set. This is because it is logical to assume that factors are correlated, given the subjective nature of participants' perceptions and experiences.

Based on a visual inspection of the oblimin rotation matrices using a PFA nine-factor structure, the researcher selected the pattern rotation matrix because it provided the best interpretation of the factor structure with the least evidence of cross-loadings. Communalities were reasonably strong, ranging from about 0.42 to 0.84. With 32 items, a reasonably clear factor pattern, and the loadings were interpretable. Each of the 32 items representing the nine factors and their factor loadings are presented in Table 2. Factor 1 was represented by 7 items, labeled as learning environment and system issues, with loadings ranging from 0.43 to 0.70. Factor 2 was represented by 4 items, labeled as ethical concerns, with loadings ranging from 0.65 to 0.82. Factor 3 was represented by 4 items, labeled as cheating and academic misconduct, with loadings ranging from 0.68 to 0.78. Factor 4 was represented by 4 items, labeled as academic anxiety, with loadings ranging from 0.44 to 0.84. Factor 5 was represented by 3 items, labeled as educational impact, with loadings ranging from 0.59 to 0.67. Factor 6 was represented by 3 items, labeled as psychological and mental health, with loadings ranging from 0.46 to 0.82. Factor 7 was represented by 3 items, labeled as external pressures, with factor loading ranging from 0.42 to 0.84. Factor 8 was represented by 2 items, labeled as technology-related challenges, with loadings ranging from 0.56 to 0.76. Factor 9 was represented by 2 items, labeled as interest and motivation, with loadings ranging from 0.55 to 0.75. In summary, the resulting factor structure demonstrated both acceptable internal consistency and factorial validity.

Table 2. Summaryof PFA Pattern Matrix (Direct Oblimin Rotation) for 32-Item Inventory

Item	Factors								
	1	2	3	4	5	6	7	8	9
Learning Environment and System Issues									
PFHM4	**0.70**		0.34						
PFHM7	**0.68**								
LE3	**0.61**							0.36	
LE2	**0.60**				0.38			0.32	
PFHM6	**0.56**				0.35	0.44			
PFHM3	**0.56**	0.32					0.31		
PFMH1	**0.43**				0.33	0.33			
Ethical Concerns									
EC2		**0.82**							
EC4		**0.73**							
EC1		**0.73**							
EC3		**0.65**							
Cheating and Academic Misconduct									
CAM4			**0.78**						
CAM3			**0.74**						
CAM5			**0.69**						
CAM2			**0.68**						
Academic Anxiety									
AAP1				**0.84**					
AAP2				**0.74**					
AAP3	0.51			**0.56**					
EP4		0.33		**0.44**			0.40		
Educational Impact									
LE1		0.40			**0.67**				
IM1				0.33	**0.60**				
EP2					**0.59**		0.39		

Continued on next page

Table 2 continued

Psychological and Mental Health									
PFHM5						**0.82**			
PFMH2	0.43					**0.67**			
TC2					0.36	**0.46**		0.44	
External Pressures									
EP3							**0.84**		
EP1					0.36		**0.62**		
IM3					0.34		**0.42**	0.31	
Technology-related Challenge									
CAM1								**0.76**	
TC1								**0.56**	
Interest and Motivation									
TC3									**0.75**
IM2			0.32					0.40	**-0.55**

Note. Factors are denoted by bolded items; empty cells within the matrix signify a factor loading below 0.30

3.3 Factor Analysis Model

Analysis of the data was carried out through SPSS and AMOS. After conducting factor analysis on the provided subconstructs within each category, the resulting factors may indicate the underlying dimensions that explain the relationships among the observed variables.

Learning Environment and System Issues: The factor derived from the subconstructs suggests that challenges related to the digital learning environment and system issues contribute to compromised academic integrity online. This factor encompasses issues such as stress, time management struggles, ineffective study habits, and other difficulties with online learning systems. Students may find it challenging to maintain academic integrity when they encounter obstacles or inefficiencies within the digital learning environment.

Ethical Concerns: The factor derived from the ethical concerns subconstructs indicates that a lack of awareness or understanding of academic integrity principles and policies contributes to breaches in academic integrity in the digital realm. This factor highlights the importance of educating students about academic integrity and fostering a culture of ethical behavior in digital learning environments.

Cheating and Academic Misconduct: The factor derived from the cheating and academic misconduct subconstructs suggests that factors such as anonymity, normalization of cheating, lack of understanding, and viewing cheating as assistance contribute to academic integrity breaches online. This factor underscores the need for interventions to address attitudes and perceptions toward cheating in digital environments.

Academic Anxiety: The factor derived from the academic anxiety subconstructs indicates that psychological factors such as fear of failure, lack of self-trust, and high expectations from teachers and institutions influence students' academic integrity online. This factor highlights the importance of addressing academic anxiety and promoting resilience to maintain academic integrity in digital spaces.

Educational Impact: The factor derived from the educational impact subconstructs suggests that issues such as teaching quality, lack of interest in the subject, and peers influence students' commitment to academic integrity online. This factor emphasizes the need for engaging teaching methods, promoting student interest, and fostering a supportive peer environment to uphold academic integrity in digital learning.

Psychological and Mental Health: The factor derived from the psychological and mental health subconstructs indicates that factors such as laziness, procrastination, and dependence on technology contribute to disregarding academic integrity in digital spaces. This factor underscores the importance of addressing psychological well-being and promoting effective study habits to prevent academic integrity breaches online.

External Pressures: The factor derived from the external pressures subconstructs suggests that social pressure, family pressure, and lack of motivation influence students' commitment to academic integrity in the digital world. This factor highlights the need for supporting students in managing external pressures and fostering intrinsic motivation to uphold academic integrity online.

Technology-related Challenge: The factor derived from the technology-related challenge subconstructs indicates that challenges such as the temptation of multiple submissions and limited internet access impact students' ability to maintain academic integrity online. This factor underscores the importance of addressing technological barriers and promoting the ethical use of technology in digital learning environments.

Interest and Motivation: The factor derived from the interest and motivation subconstructs suggests that opportunities for collaboration and the desire for higher grades influence students' commitment to academic integrity online. This factor emphasizes the importance of fostering intrinsic motivation and creating collaborative learning opportunities to promote academic integrity in digital spaces.

In summary, the factors derived from factor analysis provide insights into the underlying dimensions that contribute to academic integrity in the digital classroom. Understanding these factors can inform the development of targeted interventions and strategies to promote ethical behavior and uphold academic integrity in online learning environments. The model is depicted in Figure 3.

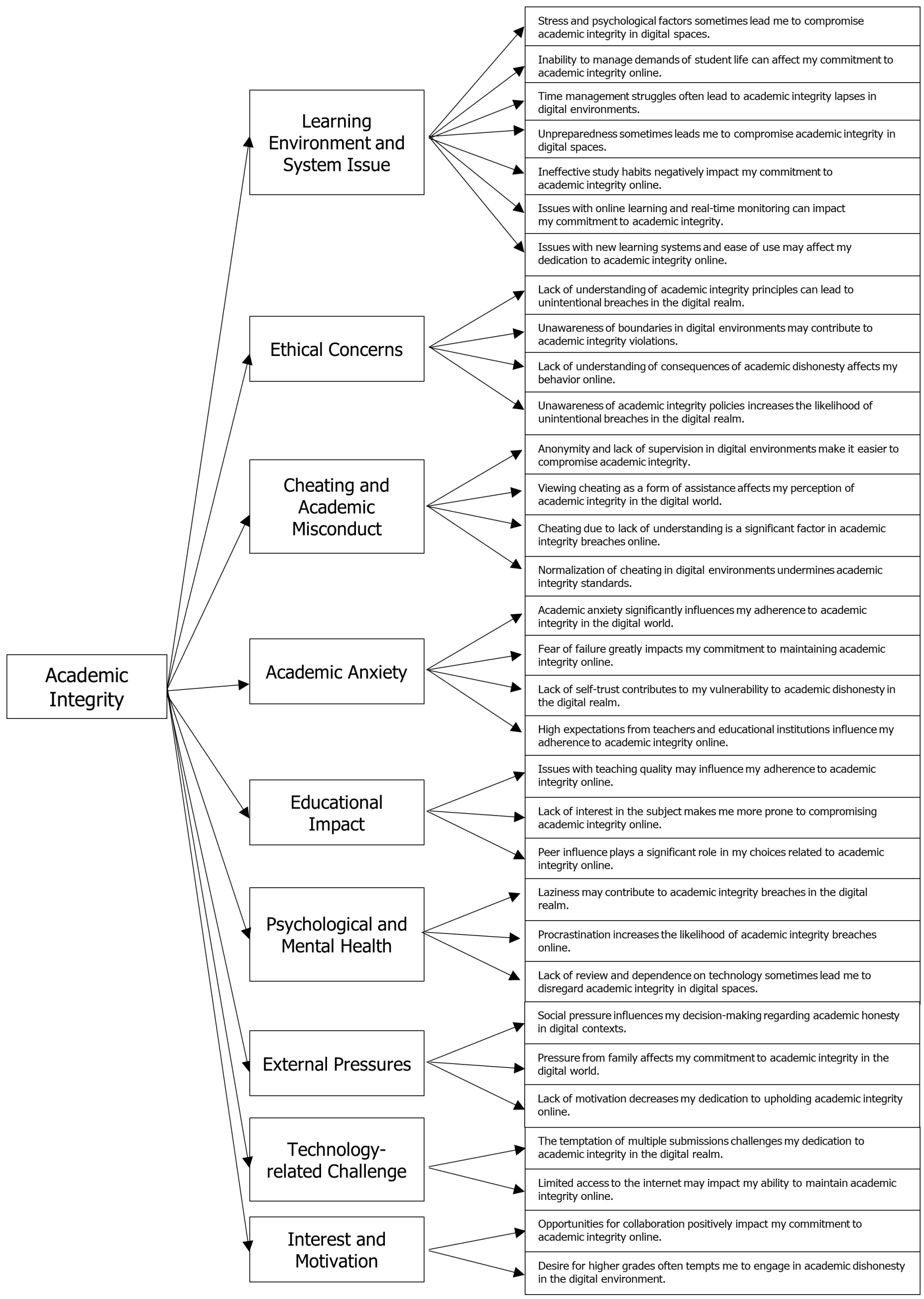

Fig 3. An Exploratory Factor Analysis of Students' Perceptions of Academic Integrity in the Digital Classroom

4 Conclusion

This study explores the subject of academic integrity in online learning. Different from previous research, this paper presents a new approach to digging deeper into the reduced practice of academic integrity among learners in a digital learning world. The study used a survey design and employed exploratory factor analysis (EFA) to get a thorough understanding of the subject. Moreover, this paper is a pioneering work in developing an academic integrity model developed through a rigorous series of data analyses. The developed model hopes to open unlimited opportunities for further research and educational developments.

In conclusion, the rigorous process undertaken prior to rotating the factor matrix has provided valuable insights into the dimensions of academic integrity in the digital classroom. The initial reliability analysis, correlational analyses, and verification of assumptions have all contributed to establishing the strengths of the dataset and its suitability for factor analysis.

The unrotated solution revealed nine factors namely: learning environment and system issues, ethical concerns, cheating and academic misconduct, academic anxiety, educational impact, psychological and mental health, external pressures, technology-related challenges, and interest and motivation. These factors explained a significant portion of the variance, supported by both Cattell's scree test and parallel analysis. These factors represent distinct dimensions of academic integrity, ranging from learning environment and system issues to ethical concerns, academic anxiety, and external pressures, among others.

The decision to employ oblimin rotation was apt given the expected correlation between factors, which aligns with the subjective nature of participants' perceptions and experiences in the digital classroom. The resulting factor structure demonstrated acceptable internal consistency and factorial validity, with strong communalities and interpretable factor loadings.

Despite the rigorous process of analyzing the data to reveal factors surrounding academic integrity, this paper presents data only from students enrolled in an education program (i.e., studying to become a teacher). The nature of the students and their program of study maintains an emphasis on academic integrity and is consistently taught and exercised in their daily classes. Hence, the data may be limited to these types of students. Consequently, the findings may not totally apply to students enrolled in other programs of study (e.g., business, medicine, engineering). Moving forward, it is recommended to further validate the identified factors through additional studies and diverse samples.

Moreover, interventions and policies aimed at promoting academic integrity in the digital classroom should consider the varied nature of the identified dimensions. By addressing factors such as learning environment issues, ethical concerns, and academic anxiety, stakeholders can work towards fostering a culture of academic integrity and supporting students' success in digital learning environments.

Furthermore, ongoing research in this area should explore the dynamic nature of academic integrity in response to evolving digital technologies and educational practices. By staying abreast of emerging trends and challenges, educators, institutions, and policymakers can develop proactive strategies to uphold academic integrity and ensure the integrity of digital learning experiences for all stakeholders.

Finally, in research endeavors focusing on academic integrity in the digital classroom, it is recommended to incorporate confirmatory factor analysis (CFA) as a crucial step to assess and validate the proposed model and the interactions between these factors, which is crucial for understanding the complexity of academic integrity in digital classrooms. By employing CFA, researchers can systematically evaluate the alignment between observed variables and latent factors hypothesized to contribute to academic integrity behaviors within online learning environments.

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