Using Data Analytics to understand student support in STEM for Nontraditional Students.

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ABSTRACT

Co-curricular supports have been practice bias, which makes it difficult to understand need-based support for nontraditional students in STEM. Thus, the aim of this study was to use data analytics to understand student support in STEM for Nontraditional Students. Quantitative research method approach was adopted with a longitudinal survey of 366 students in Fall and 218 students in Spring. In order to understand the support system for nontraditional students, structural equation modeling was used. RStudio was used to screen and analyze the initial data, and the lavaan package in R was used to conduct latent variable analyses. To examine the latent correlations, all constructs were concurrently integrated in a single Confirmatory Factor Analysis model. Subsequently, the data analysis process moved on to robust full information maximum likelihood (RFIML) estimation of SEM and the non-significant pathways were removed until the final model was developed. The study found that though the omnibus support model, as well as the support model for traditional, were not confirmed in both Fall and Spring semesters, it was confirmed for nontraditional students in the Fall semester. The significant loadings for the nontraditional students in the Fall semester include academic integration, university integration, academic advisory support, faculty support, stem faculty support, student affairs support, and cos-of-attendance support training. However, it was found that the support model for nontraditional students in Spring semesters, was not confirmed. Therefore, using structural equation modeling, this study provides important insights for understanding support for nontraditional students.

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1 Introduction

Science, technology, engineering, and mathematics (STEM) education has become increasingly popular in recent years, focusing on equipping students with the skills they need to succeed in the workforce. However, nontraditional students, such as first-generation college students, individuals from underrepresented groups, and those who are older, have families, work full-time, or have other obligations, often face unique challenges when pursuing STEM education. Nontraditional students are characterized by factors like delayed enrollment by a year or more after high school, attending school part-time, having dependents, being a single parent, working full time while enrolled, being financially independent of parents, and not receiving a standard high school diploma. These students may require additional support and resources to succeed in their studies, given the challenges they face, such as balancing work and family responsibilities, financial concerns, and prior academic experience (Sánchez-Gelabert, 2020).

Understanding the level of support these students receive and the factors that contribute to their success can help institutions better serve this population. Data analytics can be an effective tool in this regard, as it allows for the collection and analysis of large amounts of data related to these students. In recent years, there has been a growing focus on increasing diversity, equity, and inclusion in STEM fields. As nontraditional students have unique challenges, understanding their needs and providing adequate support is crucial for enhancing diversity in STEM and improving the success of all students. This study aims to use data analytics to understand the support needs of nontraditional students in STEM education, integrating data on student demographics, academic performance, and engagement to identify patterns and trends in their support needs. The findings of this study will inform the development of targeted support interventions to help nontraditional students succeed in their STEM studies.

1.1 Background

STEM education has become increasingly important in recent years, as the demand for skilled workers in STEM fields continues to grow. However, nontraditional students, such as those who are older, have families, work full-time, or have other obligations, often face unique challenges when it comes to pursuing STEM education. These students may require additional support and resources to succeed in their studies. Research has shown that nontraditional students are more likely to face academic and social challenges compared to traditional students (Pascarella & Terenzini, 2005). These challenges can include difficulty adjusting to academic demands, balancing work and family obligations, and feeling isolated or disconnected from the campus community (Lisciandro, 2022). These challenges can have a negative impact on academic performance and persistence in STEM fields.

The academic performance refers to the degree to which a student, instructor, or an institution has achieved their short or long-term educational goals (Talib & Sansgiry, 2012), which is assessed by continuous assessment or cumulative grade point average (CGPA). Experts frown on poor academic performance due to it linkage with unemployment, poverty, promiscuity, drug use, homelessness, illegal activity, social isolation, insufficient health insurance, and high dependency (Yigermal, 2017). According to them, good academic performers enjoy greater incomes, better work perks, and more prospects for promotion (Tentama & Abdillah, 2019). Thus, students are expected to devote a significant amount of their time to studying if they hope to graduate with high academic standing. Yet, acquiring knowledge, attitudes, values, and skills via education is not easy, but rather a lengthy and difficult journey through life.

In order to manage those challenges, higher education institutions play a crucial role in developing skilled labor that may help solve a community's actual challenges (Idris, Hassan, Yaâacob, Gill, & Awal, 2012). The higher education institutions serve as potent transformation agent that enhance livelihoods and health and promotes social stability (Dhankhar, Solanki, & Dalal, 2021). That notwithstanding, studentsâ access to higher education institutions, depends on academic performance, which is in turn vital for access to economic and social possibilities that are linked to higher living standards for people via increased productivity (Poursafar & Shabahang, 2021) Thus, academic performance measures talented human capital at the macro level, which has been seen as an engine of economic growth and favorably affects economic development (Tadese, Yeshaneh, & Mulu, 2022).

However, the thesis of this research is that data analytics can be used to understand the needs of nontraditional students and provide targeted support to help them succeed. This viewpoint is underpinned by the Model of Co-Curricular Support (MCCS) (Lee & Matusovich, 2016), which argues that academic performance is an output produced from studentsâ participation in support systems needed for academic, university, social, and professional integration into the educational systems. Data analytics can be used to identify patterns and trends in the support needs of nontraditional students. By analyzing data on the studentsâ demographics, academic performance, and engagement, institutions can identify factors that contribute to success or barriers to success for nontraditional students. For example, data may reveal that nontraditional students who work full-time are more likely to struggle with time management and need additional support in this area.

This information can inform the development of targeted interventions to address this specific need. One of the key challenges faced by nontraditional students in STEM is a lack of access to resources and support systems. In to address this, universities and colleges can use data analytics to identify students who are at risk of dropping out and provide targeted support, such as mentorship programs and academic tutoring, which is relevant for student support. Student support alludes to the aggregate expected advantages of the assets implied for helping the students pursuing degree programs (Lei, Cui, & Chiu, 2018). Relatedly, the MCCS contends that students who are knowledgeable about and have access to resources that help them succeed will integrate into the university environment more readily than those who are not knowledgeable about and do not have access to those resources (Rowe, Charles, & DuBose, 2020).

(Peixoto et al., 2018)characterized academic integration as students' academic performance, level of scholarly advancement, and impression of having a positive involvement in the academic settings. On the other hand, university integration is intended to make efficiencies that can make advanced education more affordable for families, and this usually calls for one initiative group, a solitary workforce and staff to bring together program exhibit and a solitary consolidated spending plan (Asad, Hussain, Wadho, Khand, & Churi, 2021). Similarly, social integration deals with participation in extracurricular activities and the presence of positive associations with peers (Stasiūnaitienė, Nedzinskaitė-Mačiūnienė, & Mazlaveckiene, 2020).

Relatedly, professional integration is portrayed as the changes made to the way to deal with professional work and professional personality during the time spent at school (Ramdhony, Mooneeapen, Dooshila, & Kokil, 2021), which incorporates both the widespread and the socially unambiguous parts of being a professional, and embedding professional personality with more extensive social standards and belief systems (Kamel, 2020). Therefore, student support alludes to the aggregate expected advantages of the assets implied for helping the students pursuing engineering degree programs and non-engineering degree programs (Los Santos, Bain, Kupczynski, & Mundy, 2019). This happens where undergraduate programs are to increase enrolment in the face of confronted maintenance issues, and students who face severe connectivity limits in the school system due to their characters (Lei et al., 2018).

Accordingly, the complicated and steady difficulties to further developing variety and increasing the number of degrees granted, have brought about student-support drives at higher education institutions ((Rowe et al., 2020)). As observed by Raaper, Brown and Llewellyn (2022), these include student clubs, undergrad research, temporary jobs, centers, service projects, and different exercises that can give growth opportunities to students. Proxies for student support incorporate student commitment, sense of belongingness as well as campus environment, and advanced education learning conditions. Some of the factors evaluated with these instruments in literature incorporate personnel and staff rehearses, nature of relational connections, hierarchical capabilities, and security (Holahan & Batey, 2019), dynamic and cooperative learning, test, enhanced instruction, student-workforce communication, and supportive grounds issues (Said et al., 2020).

Such information is valuable for individual office responsibility and for evaluating student commitment and environment at an organizational level as well as distinguishing needs for institutional enhancements ((Maerten-Rivera et al., 2021). Nonetheless, discoveries from these instruments can be restricting when the reason for the estimation is to reinforce support at the scholarly unit level on the grounds that the input is focused on the quality and sources of support an establishment offers and does not guarantee helpful feedback for the kinds and nature of support that scholastic level projects plan to give like proficient systems service opportunities.

The relevance of co-curriculum support has already been established in the literature. (Knight & Novoselich, 2017) as well as (Lattuca, Knight, Ro, & Novoselich, 2017) have shown how co-curricular support relates with students' initiative, employability, scholarly achievement, steadiness, viable learning, moral turn of events of students, and interdisciplinary skill. (Krause et al., 2015) also investigated how day camps gave an environment for students to bond with their friends and with the workforce while fostering their expert abilities and found that co-curricular support significantly affects students' diligence and accomplishment.

The study by (Stiltz, Buettner, Kennedy, Zundl, & White, 2013) is another co-curricular support built on the provision of tutoring and growth opportunities for female students at Douglass Residential School, which found that students showed better trust in finishing their engineering program as well as more noteworthy feeling of belongingness and scholastic accomplishment ensuing to encountering these sorts of co-curricular supports. However, a weakness in our ongoing comprehension of these endeavors is that co-curricular support is practice-oriented. A related gap in the literature is that a large portion of the current studies about models of co-curriculum support and mediations centre around enrollment and maintenance of numbers or measures like understudy satisfaction. These actions are significant, but how the co-curricular support given by student support centres is expected to work or the ways the support professionals intend to further develop studentsâ insight were omitted.

Though (Lee & Matusovich, 2016) integrated understudy maintenance hypothesis with understudy support practice and found that understudy's interactions with the academic, social, and professional frameworks in a school and the entire college frameworks impacted their outcome in a college degree program, both traditional and non-traditional engineering students were not studied concurrently. Thus, little is known about how the various support systems could be integrated to produce an omnibus and need-based model of co-curriculum support for non-traditional students in STEM. In order to address the challenges of non-traditional students in STEM, institutions have implemented various support interventions, such as academic tutoring, mentorship programs, and student organizations. However, the effectiveness of these interventions may vary depending on the needs of nontraditional students. Understanding the specific support needs of nontraditional students in STEM education is essential to developing targeted and effective support interventions. Based on these research gaps identified in the literature, the aims of this project were to:

1. Find out which constructs of the Model of Co-curriculum support (MCCS) are statistically significant for traditional and nontraditional students?

2. Determine how can survey data be best visualized using an interactive system.

2 Review of Related Literature

This section reviews literature related to the usage of data analytics to understand studentâs support in STEM for nontraditional students. The process of conducting a literature review is critical to the development of high-quality research studies. This was done to provide a comprehensive and systematic examination of all available research and publications related to student support in STEM for nontraditional students. Thus, the goal of this literature review is to identify gaps in knowledge, synthesize existing research, and provide a foundation for this current research. In the literature review process, citations are important because they are used to track the use of information and ideas from other sources in scholarly publications. This provides insight into the impact and influence of individual publications, as well as the evolution of research in this particular field.

Literature reviews can be time-consuming and tedious, especially when dealing with large volumes of literature. Therefore, the need for a reliable and efficient tool to manage literature review is critical. In recent years, there has been an increasing focus on the use of technology to aid in the literature review process. One such technology is Cortext manager, a software tool designed to facilitate citation analysis and literature review. The Cortext manager is a web-based tool that allows researchers to import, organize, and analyze research data efficiently. The Cortext manager has been designed to work with a wide range of file formats, including Endnote, RefWorks, and BibTeX, among others. The tool also allows researchers to export their data in various formats, making it easy to share with colleagues or other researchers.

One of the key features of the Cortext manager is its ability to perform automated text analysis. The tool uses natural language processing techniques to identify key concepts and themes in research papers. This feature makes it easy for researchers to identify patterns and trends in research literature, which can inform their research design. In this paper Cortext manager is used to identify the key concepts that are used in the discussion section of journal papers related to support system in STEM for nontraditional students.

2.1 Computational Literature Review Using Cortext Manager

As the literature review process involves several steps, including searching for relevant literature, screening, and evaluating the quality of the identified studies, the Cortext manager can assist researchers in all these steps, making the literature review process more efficient and reliable. The first step in the literature review process is searching for relevant literature. The Cortext manager provides several options for importing research data, including importing data from reference management software or uploading PDF files directly. The tool also allows researchers to search for relevant literature using specific keywords, authors, or publication dates. The Cortext manager then automatically imports the identified studies and stores them in the researcher's account.

The next step in the literature review process is screening the identified studies to determine their relevance to the research question. The Cortext manager provides an easy-to-use screening tool that allows researchers to screen their literature based on specific inclusion and exclusion criteria. The tool allows researchers to screen their literature in batches, making the process more efficient. The final step in the literature review process is evaluating the quality of the identified studies. The Cortext manager provides a range of tools to assist researchers in evaluating the quality of their literature. For instance, the tool can generate a summary of the key findings of the studies reviewed.

We conducted a thorough analysis of approximately 80 research journal articles with titles related to "Nontraditional students" or "Support systems". Upon reviewing the discussion sections, we ascertained that the majority of these articles did not focus on the intended topics. Nonetheless, we identified 25 relevant papers that met our criteria. We subsequently extracted the discussions from these 25 articles and utilized Cortext Manager to identify recurring words, appearing at least three times, in order to construct a network map.

In this study a map generated by Cortext might show clusters of related terms based on their co-occurrence in a corpus of text data, which provide insights into the key concepts or themes present in the data. The Cortext manager map explores support systems for nontraditional students in science, technology, engineering, and mathematics. It is based on desk review of 25 related journal papers on support systems for nontraditional students in the fields of science, technology engineering, and mathematics (STEM) and thus highlights the various clusters on nontraditional students in these fields.

The Cortext manager map is interactive and allows users to explore different types of support systems available to the nontraditional student. It reveals clusters of terms related to different types of support systems, such as college success and inter-role conflict, education environment and educational goals, individual differences and student retention, study groups and academic success as well as student engagement and campus environment. Each type of cluster associated with these support systems are represented by a different colored icon on the Cortext manager map, and clicking on the icon reveals more information about the related clusters or issues within that particular support system.

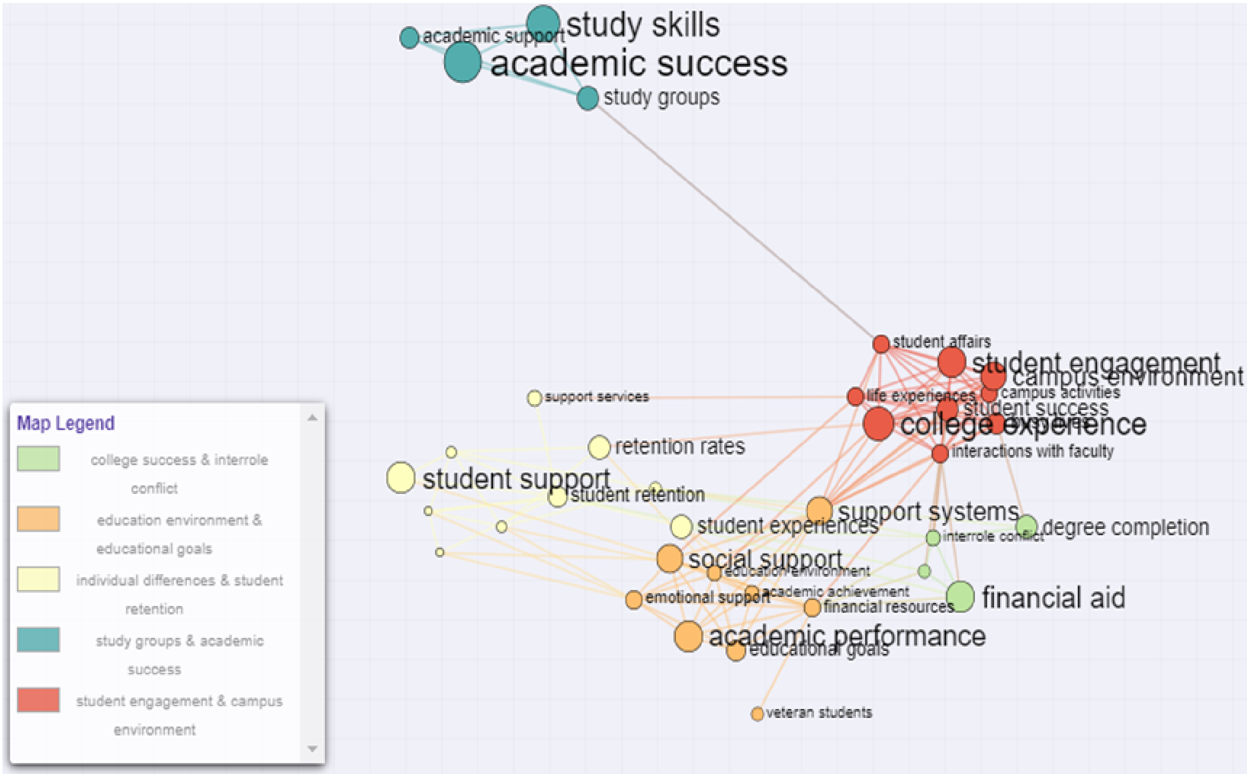

Figure 1: Cluster of Support Systems Available to Nontraditional Students in STEM

Moreover, out of the five different types of support systems available to nontraditional students, the concept of inter-role conflict appeared in all of them, except that it does not appear in student engagement and campus environment support systems. On the other hand, interactions with faculty, education environment as well as college success appeared in three types of the total five support systems. Relatedly, financial aid, and academic achievement appeared in two out of the five types of support systems, while the rests of the concepts appeared in one of the five types of support systems.

The Cortext manager map was constructed based on links to additional resources for nontraditional students, such as online communities and professional organizations to different types of nontraditional students, such as those who are older, have families, or work while attending school. The Cortext manager map is a useful tool for nontraditional students, educators, and administrators who are looking to support and promote success for all students, regardless of their backgrounds or circumstances. The map generated by Cortext provide insights into the relationships and connections between different types supports for nontraditional students.

For instance, from the Cortext manager map, the cluster of college success and inter-role conflict support systems for nontraditional students is related closely to student experiences, interactions with faculty, and financial resources.

Figure 2: Cluster of College Success and Inter-Role Conflict

On the other hand, the cluster of education environment and educational goals support systems related strictly with academic performance, financial aid, social support, student experiences, educational goals, academic achievement, interactions with faculty, emotional support, inter-role conflict veteran students, and college success.

Figure 3: Cluster of Education Environment and Educational Goals

Moreover, the cluster of individual differences and student retention related to support systems for nontraditional students involves financial aid, academic achievement, inter-role conflict, and financial resources.

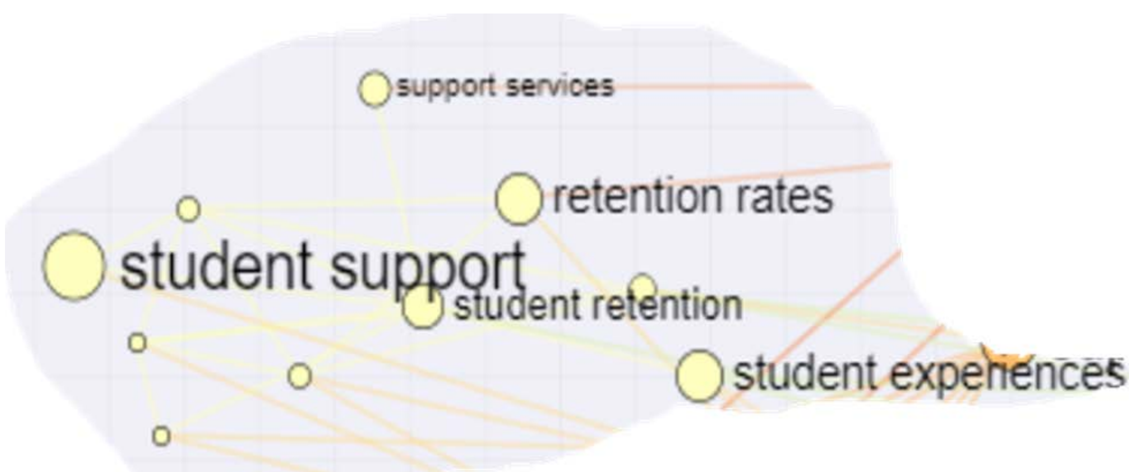

Figure 4: Cluster of Individual Differences and Student Retention

In relation to the study groups and academic success, the clusters related to the support systems available to nontraditional students, include the concepts of study skills, and academic support.

Figure 5: Cluster of Individual Differences and Student Retention

Finally, clusters that form student engagement and campus environment type of support systems available to nontraditional students are support systems in general, student success, retention rates, busy lives, student affairs, campus activities, interactions with faculty, education environment, and life experiences.

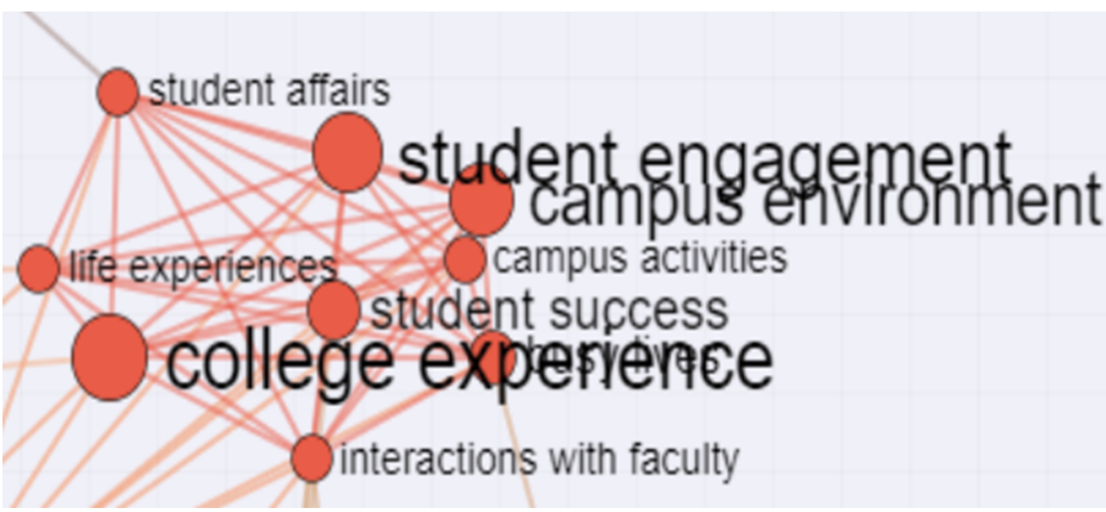

Figure 6: Cluster of Student Engagement and Campus Environment

Additionally, as the Cortext manager map reveals only five types of support systems for nontraditional students in STEM, it is a hint to key stakeholders involved in supporting nontraditional students in STEM that there are gaps in other areas where additional support is needed or other types of support systems that were not captured by Cortext manager map. This information can be helpful for researchers, educators, and policymakers in identifying areas for improving and developing strategies to better support nontraditional students in STEM fields.

The Cortext manager has several benefits for researchers. First, the tool is web-based, making it accessible from anywhere with an internet connection. This feature makes it easy for researchers to collaborate with others, even if they are not in the same physical location. Second, the tool is easy to use, even for researchers who are not familiar with natural language processing techniques. The Cortext manager provides a user-friendly interface that makes it easy to import, organize, and analyze research data. Third, the tool saves time and effort in the literature review process. The Cortext manager automates several tasks, such as text analysis and screening, making the process more efficient.

Despite the benefits of the Cortext manager, there are several limitations to the tool. For instance, interpreting a map generated by Cortext can be complex and requires some background knowledge about the analysis technique used and the specific research question being investigated. Secondly, the tool relies on natural language processing techniques, which may not be accurate in identifying key concepts and themes in the research literature. Thirdly, the tool is limited to the data available in the research literature. Therefore, it may not be suitable for research questions that require data from other sources, such as surveys or interviews.

Thus, a Structural Equation Model (SEM) analysis was used to explore the relationships between these different types of support and the outcomes for nontraditional students, such as academic success. The map generated by Cortext was used to help identify the key concepts or themes that are most relevant to the research question and guide the development of the SEM model. The next section presents conceptual and empirical works related to the study.

2.1.1 The Concept of Nontraditional Students

Nontraditional students are sorted as students who fall outside the commonplace lifecycle of a postsecondary student. Generally, they are grown-up students hoping to get back to school to either begin another profession or get a promotion in their vocation. Despite the fact that there are many scopes of manners by which nontraditional students are characterized (Rozvadská & Novotnỳ, 2019) proposed a thorough definition that incorporates enlistment rules, monetary and family status, and secondary school graduation status. Generally, the seven qualities explicitly connected with nontraditional students, and their relating rate circulation of students across all institutional sorts in enclosures (Singh, 2019). These include deferred enlistment by a year or more after secondary school, went to part-time, having wards, being a solitary parent, working all day while selected, being monetarily free from guardians, and did not get standard secondary school recognition. As noted by (Brozina, 2022), nontraditional students who sign up for school to get a degree are more uncertain than traditional students to finish a degree or remain enlisted following four years, because nontraditional students are searching for various elements in a school than traditional students.

Nontraditional students view advanced education with greater interest in their professions, while traditional students have a greater amount of profound association with the school they decide to go to postsecondary school (Webb, 2018). More often than not, nontraditional students return to school to get the vocation they need or to make progressions in their ongoing profession (Bourque, 2019). Along these lines, most nontraditional students are searching for a method for completing school earlier and whether this is by getting a degree, more limited courses, or utilizing move credits to graduation, nontraditional students usually see the end goal when they sign up for a program and they find out if the program will be compatible with their timetable (Tieben, 2020). As most nontraditional students have outside commitments such as work or a family to really focus on, realizing that a school has choices that will make learning adaptable, as an online school, is significant.

2.2 Empirical Review on Support Systems for Non-traditional Students in STEM

(Griffith, 2010) examined the factors that influence all students' persistence in STEM field majors, and in particular the persistence of women and minorities, using restricted-use data from the National Longitudinal Survey of Freshmen (NLSF) and the National Education Longitudinal Study of 1988 (NELS:88). The persistence of female students is favorably impacted by a higher proportion of female STEM graduate students. The results of the logistic regression indicated that the distribution of women and minorities into various undergraduate programs and the variations in their underlying backgrounds have a substantial influence on persistence rates.

(Zeiser & Berger, 2012) looked at various student traits and college experiences that may be associated with time to completion and that may assist to explain these discrepancies in this short. In order to determine whether significant racial/ethnic discrepancies in TTC in 2009 still exist after accounting for differences in other background factors and college experiences, ordinary least squares (OLS) regressions were performed. According to the report, there are still racial and ethnic differences in the median time to PhD completion in a STEM field, with African Americans having a longer median TTC than Hispanics, who in turn had a longer median time to completion than students who did not attend a URM. Therefore, it is necessary to provide a support structure for kids who are underrepresented.

(Williams-McCorvey, 2019) also used a similar approach and reported that support services such as tutoring, mentoring, and financial aid can have a significant impact on the success of nontraditional STEM students and that prior academic experiences, such as prior coursework and prior degrees, have been found to be significant predictors of success in STEM fields.

(Wladis, Hachey, & Conway, 2015) examined how non-traditional student risk characteristics connect to the support system of online course enrollment patterns using data from more than 2,000 community college STEM majors in the National Postsecondary Student Aid Study. Online course enrolment served as the binary dependent variable in the analysis, while non-traditional student characteristics served as the independent variable. Multivariate binary logistic regression models were used. Online enrollment was found to be much more common among students with non-traditional student risk characteristics like postponed enrollment, lack of a high school diploma, part-time enrollment, financial independence, dependents, single parent status, and full-time employment than traditional students. The National Science Foundation carried out a study and found that one major challenge faced by nontraditional students is a lack of confidence in their ability to succeed in STEM. The study found that students who received feedback on their progress were more likely to persist in STEM majors compared to those who did not receive feedback. Thus, the paper concluded that data-driven interventions, such as tracking student progress and providing regular feedback help them stay on track and build their confidence.

The goal of the study by (Webb, 2018) was to acquire understanding of the reasons for these nontraditional students' pursuit of a four-year degree, the difficulties they encounter, and the elements that contribute to their success. At a mid-sized university in the Midwest, the researcher interviewed six undergraduate students as part of this phenomenological study. One semi-structured interview with the participants was conducted to get information about their experiences as non-traditional undergraduate students. The results support an earlier study that revealed non-traditional students have distinctive experiences due to their non-traditional status, but they also show that more needs to be done to support their integration into college culture.

(McCall, Western, & Petrakis, 2020) looked at the evolution of non-traditional student enrollment over the past fifty years, the impact of the Widening Participation agenda on enrollment, and how students perceived the factors that contributed to their enrollment after completing an enabling program. According to the study, the idea of a "traditional" student in higher education is out of date and "non-traditional" students now make up the majority.

(Ghazzawi, Pattison, & Horn, 2021) explored the potential effects of STEM intervention program participation on first-generation, under-represented minority students' long-term persistence and graduation rates. Results from a discrete-time competing risks analysis showed that support system participants had a lower probability of dropping out and a higher probability of staying in a STEM field of study than support system non-participants. Additionally, descriptive results showed that participation in the support system was not a significant predictor of six-year graduation but that participants had greater rates of graduating in any field compared to non-participants of the STEM intervention program. Through a problematization of the academic and well-being support services provided to non-traditional students, (Raaper, Brown, & Llewellyn, 2022) investigated student experiences. To learn more about the type of student support they received, the study spoke with 10 non-traditional students from a UK institution. According to the research, informal support networks for non-traditional students are more likely to avoid formal services and focus instead on family (for well-being support) and other students (for academic and well-being support). The study's findings raise concerns about the institutional support that student networks lack, which is likely to further disadvantage these students, but it also calls into question the prevalent deficit perceptions of non-traditional students.

The first-year retention and academic outcomes of nontraditional students who entered Murdoch University between 2014 and 2016 and successfully completed its enabling program, OnTrack, were analyzed and compared by (Lisciandro, 2022). Regression modelling with several variables was done. Despite having lower academic performance, nontraditional students admitted via the OnTrack pathway were retained at a rate that was comparable to or better than those admitted via all other admission pathways, suggesting that the enabling programs have been successful in enabling access and participation for students who are capable but lack opportunity, including those from disadvantaged backgrounds. But the study came to the conclusion that nontraditional students on enabling pathways can have persistent difficulties that affect their academic achievement, thus future equality and access policies should take adequate measures to enhance these students' broader transition experiences. In order to increase perseverance and retention, (Brozina, 2022) also evaluated unconventional engineering students based on support and success experiences. According to the survey, nontraditional students are less likely than traditional students to finish their degrees or stay enrolled after five years.

2.3 Chapter summary

Data analytics can be a powerful tool in understanding the level of support and success of nontraditional STEM students. Previous studies suggest that support services, demographic factors, and prior academic experiences all play a role in the success of these students. By using data analytics to better understand the experiences of nontraditional STEM students, institutions can develop targeted support programs to improve outcomes and increase access to STEM fields for this population. By collecting and analyzing data on student experiences and outcomes, educators can gain insights into challenges faced by these students and develop targeted strategies to support their success. With increased support, nontraditional students can pursue and succeed in STEM fields, leading to a more diverse and inclusive STEM workforce. The next section presents the methodology used to model the support system in the study area.

3 Methodology

In the Fall and Spring semesters of 2021, we administered two sets of surveys to explore various dimensions of student integration and support, encompassing academic, social, professional, and university integration, as well as support from academic advisors, faculty, peers, and other resources. The Fall semester surveys included the Integration Survey, with sections on Academic, Social, Professional, and University Integration, and the Student's Perspective of Support Survey, which covered Academic Advisory Support, Faculty Support, STEM Faculty Connection, Student Affairs support, and Cost-of-Attendance support and Training. Similarly, the Spring semester surveys featured an Integration Survey identical to the Fall version, and a Student's Perspective of Support Survey that focused on Academic Peer Support, STEM Peer Connections, Out-of-Class Engagement, STEM Career Development, and General Career Development.

In the Fall semester, 374 and 366 students participated in the first and second surveys, respectively, with 13 students excluded for not participating in both, resulting in 361 usable responses for analysis. In the Spring semester, 223 and 218 students participated in the first and second surveys, respectively, and five students were excluded for not participating in both surveys, leaving 218 usable responses for analysis.

RStudio was used to screen and analyze initial data, and the lavaan package in R was used to conduct latent variable analyses. We calculated descriptive statistics for all of the indicators that were entered into SEM, as well as internal consistency estimates for the composite scores of the constructs. Prior to the actual evaluation, the data analysis process answered the research questions using a concurrent CFA and SEM. In order to examine the latent correlations, all constructs were concurrently integrated in a single CFA model. The results indicate the degree to which the predicted factor loadings fit the data. A loading of 0.50 is regarded as significant and provides a strong indication of the underlying construct.

Subsequent to confirming the factor structure, the data analysis process moved on to robust full information maximum likelihood (RFIML) estimation of SEM. This was done in order to test the hypothesized relationships between the variables, as illustrated in Figure 1. This method was appropriate because the data contained both non-normality and messiness. SEM analysis is a CFA extension because it incorporates both a measurement model (the model subjected to CFA testing) and a structural model (i.e., predictive relationships among latent variables). The SEM analysis performs significance tests on the regression coefficients that define the structural model's relationships, while the non-significant pathways are removed, and the model is re-specified. The final model is not developed until all significant regression pathways have been determined (Richards, 2018)

3.1 Participant Description (Fall)

Two different surveys were administered in Fall 2021. Eight out of 374 students who responded to the first survey did not participate in the second survey. Also, five out of the 366 students who responded to the second survey did not participate in the first survey making a total of 13 students who did not participate in both surveys. These 13 students were, therefore, eliminated giving a sample size of 631 usable responses for the study analysis. There were more females than males (48% male, 51% female), and one percent of the students did not disclose their identity. The nontraditional status of the participants indicated that 22.4 percent were minimally nontraditional, 10.5 percent were moderately nontraditional, and 1.1 percent were highly nontraditional. However, 65.9 percent of the participants did not have a nontraditional status. Talking about the majors of the participants, Science had the largest share of 46.5 percent, followed by Engineering (39.3%), Technology (10.5%) and the smallest was Mathematics (4%). Lastly, the residential status of the participants also indicated that, there were more commuter students than resident students (60.1% commuters, 39.9 percent resident students.

3.2 Participant Description (Spring)

Two different surveys were administered (SPS and SPS Integration) in spring 2022. Five out of 223 students who responded to the SPS survey did not participate in the SPS Integration survey. These five students were, therefore, eliminated giving a sample size of 218 usable responses for the study analysis. There were fewer females than males (50.5% male, 47.7% female), and 1.8 percent of the students did not disclose their identity. The nontraditional status of the participants indicated that 35.3 percent were minimally nontraditional, 4.6% were moderately nontraditional, and 0.5 percent were highly nontraditional. However, 59.6 percent of the participants did not have a nontraditional status. Talking about the majors of the participants, Science had the largest share of 47.7 percent, followed by Engineering (41.3%), Technology (9.2%), and the smallest was Mathematics (1.8%). Again, the residential status of the participants also indicated that there were more commuter students than resident students (74.3% commuters, and 25.6 percent resident students). Lastly, looking at the year group of the participants, the Junior students had the largest representation of 31.7 percent. This was followed by the Senior students (26.6%), Freshmen (23.4%), and sophomores had the least representation of 18.3 percent.

4 Results and Discussion

The results and discussion section is the key part of any research paper or report, as it presents the key findings of the study and provides an interpretation of those findings. In the case of using data analytics to understand student support in STEM for nontraditional students, this section is crucial to understanding how best to support nontraditional students in STEM education. Specifically, this results and discussion section of a research paper focused on understanding support for non-traditional students in STEM using structural equation modeling, which would be critical to understanding how to best support non-traditional students in higher education. By identifying the factors that influence STEM non-traditional students' success and understanding how they are related, the researcher can provide valuable insights into how support for non-traditional students can be improved.

4.1 Data analysis (Fall Data)

RStudio was used to screen and analyze initial data, and the lavaan package in R was used to conduct latent variable analyses. We calculated descriptive statistics for all of the indicators that were entered into SEM, as well as internal consistency estimates for the composite scores of the constructs. With respect to the descriptive statistics of the indicators, Table 1 also shows that the mean Academic Integration (AI) index was 4.89 with a standard deviation of 0.83 (skewness = -0.90, kurtosis = 1.51), while the mean University Integration (UI) index was five with a standard deviation of 0.87 (skewness = -1.09, kurtosis = 1.31). Relatedly, the mean Academic Advisory Support (F1) index was 3.60 with a standard deviation of 1.02 (skewness = -1.71, kurtosis = 1.18), while the mean Faculty Support (F3) index was 3.94 with a standard deviation of 0.70 (skewness = -1.36, kurtosis = 4.5). On the other hand, the mean Stem Faculty Support (F4) index was 2.86 with a standard deviation of 1.11 (skewness = -0.31, kurtosis = -0.24), while the mean Student Affairs Support (F8) index was 3.17 with a standard deviation of 1.10 (skewness = -0.31, kurtosis = -0.06). Finally, the mean Cos-of-attendance Support Training (F11) index was 2.90 with a standard deviation of 0.94 (skewness = -0.11, kurtosis = -0.26).

Table 1: Descriptive Statistics for Fall data set.

Latent Variables	Mean	SD	SE	Skewness	Kurtosis	CA
Academic Integration	4.89	0.83	0.04	-0.90	1.51	0.91
University Integration	5.00	0.87	0.05	-1.09	1.31	0.81
Academic Advisory Support	3.60	1.02	0.05	-1.71	0.18	0.85
Faculty Support	3.94	0.70	0.04	-1.36	4.50	0.88
Stem Faculty Support	2.86	1.11	0.06	-0.31	-0.24	0.92
Student Affairs Support	3.17	1.10	0.06	-0.31	-0.06	0.82
Cost-of-attendance Support & Training	2.90	0.94	0.05	-0.11	-0.26	0.86

Note. SD = Standard Deviation, SE = Standard Error, CA = Cronbachâs alpha. Academic Integration and University Integration were set to a six-point scale ranging from 1-6 and the rest of the latent variables were set to a five-point scale ranging from 1-5.

4.2 Confirmatory factor analysis

Prior to evaluating the conceptual framework depicted in Figure 1, the data analysis process answered the research questions using a concurrent CFA and SEM. To examine latent correlations, we examined all constructs concurrently in a single CFA model. The results indicate the degree to which the predicted factor loadings fit the data. A loading of 0.50 is regarded as significant and provides a strong indication of the underlying construct.

The goodness of fit indices in Table 3 indicates that the a priori measurement model fits the collected data reasonably well based on the RFIML estimation results (e.g., TLI above.90; CFI above.90; SRMR less than 0.08; RMSEA less than 0.08). At the time, all factor loadings were significant. Because all loadings were greater than .50, the results indicated that the measurement model's factors possessed adequate validity. As a result, the measurement model appeared to fit the data well, necessitating no changes.

Table 2: Fit Statistics for Fall data set.

Statistic	χ^2	df	TLI	CFI	SRMR	RMSEA(90% CI)
Measurement model	1073.36	649	0.93	0.94	0.07	0.043(0.038-0.047)

TLI = TuckerâLewis index.

CFI = comparative fit index.

SRMR = standardized root mean squared residual

RMSEA = root-mean-square error of approximation.

4.3 Structural equation modeling (SEM).

After confirming the factor structure, the data analysis process moved on to robust full information maximum likelihood (RFIML) estimation of SEM in order to test the hypothesized relationships between the variables, as illustrated in Figure 1. This method was appropriate because the data contained both non-normality and missingness (Jia Wu, 2019). SEM analysis is a CFA extension in that it incorporates both a measurement model (the model subjected to CFA testing) and a structural model (i.e., predictive relationships among latent variables). The SEM analysis performs significance tests on the regression coefficients that define the structural model's relationships, and non-significant pathways are removed, and the model is respecified. The final model is not developed until all significant regression pathways have been determined (Richards et al., 2018).

4.3.1 SEM Overall Model for Fall Data (Model 1)

The model fit test revealed that the hypothesized model was well-fitting with a Chi square = 1224.12, RMSEA = 0.043 (90 percent confidence interval [0.038, 0.047]), SRMR =0.072, TLI = 0.93, CFI = 0.93. While the model fit was satisfactory, one of the structural model's hypothesized regression pathways (i.e., Cost-of-Attendance Support and Training to University Integration) was associated with a non-significant weight (i.e., t 1.867). Therefore, the model is not confirmed.

Table 3: Fit statistics for the SEM model.

Statistic	χ^2	df	TLI	CFI	SRMR	RMSEA(90% CI)
Measurement model	748.24	423	0.935	0.94	0.078	0.046(0.041-0.051)

TLI = TuckerâLewis index.

CFI = comparative fit index.

SRMR = standardized root mean squared residual

RMSEA = root-mean-square error of approximation.

4.3.2 Multi Group Analysis.

We compared our model for students who identified themselves as either traditional students or Nontraditional student in the survey. The model invariance tests, based on the modification indexes, revealed paths that were significantly different between traditional and nontraditional students. We conducted a chi-square difference test to determine model invariance. The results indicated that there is a significant difference between traditional students and nontraditional students. Therefore, we needed to treat both groups differently.

Table 4: Chi-sqaure Difference test for Fall data set .

Statistic	Df	AIC	BIC	Chisq	Chisq diff	Df diff	Pr(Chisq)
fit	1298	31298	32309	2083.1			
weak.Invariance	1303	31294	32286	2089.1	6.086	5	0.2979
strong.invariance	1334	31261	32132	2117.8	28.644	31	0.5878
strict.Invariance	1372	31266	31990	2199.6	81.831	38	$4.755e{-}05^{***}$
Signif.codes: 0^{***}	0.001^{**}	0.01^{*}	$0.05^{\cdot}$	0.1	1		

4.3.3 SEM model 2 for Nontraditional Student (Fall Data).

The model fit test revealed that the hypothesized model was well-fitting. RMSEA =0.067 (90 percent confidence interval [CI] = [0.058, 0.075,), SRMR = 0.091, TLI =0.9 , CFI =0.9. Therefore, the model is confirmed for non-traditional students.

Table 5: Fit statistics for Nontraditional Students SEM model.

Statistic	χ^2	df	TLI	CFI	SRMR	RMSEA(90% CI)
Measurement model	1003.9	649	0.855	0.866	0.091	0.067 (0.058, 0.075)

R square:

AI = 0.709

UI = 0.359

TLI = TuckerâLewis index.

CFI = comparative fit index.

SRMR = standardized root mean squared residual

RMSEA = root-mean-square error of approximation.

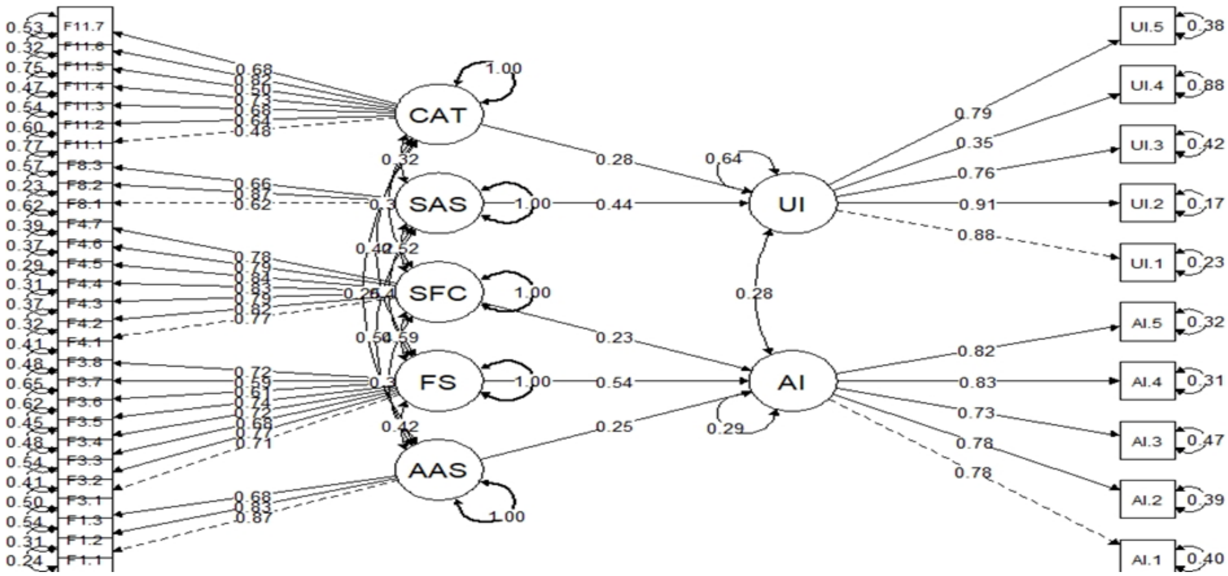

Figure 7: Path diagram for nontraditional students.

4.3.4 SEM model 3 for Traditional Student (Fall Data).

Again, the model fit test revealed that the proposed model was well-fitting. While the model fit was satisfactory, one of the hypothesized regression pathways of the structural model (i.e., Cost-of-Attendance Support and Training to University Integration) was associated with a non-significant weight (i.e., t 1.96). In the absence of the non-significant pathway, the model was re-specified, but the model fit remained unchanged. Chi square = 720.33, RMSEA =.046 (90 percent confidence interval [0.039, 0.052]), SRMR =0.083, TLI =.934, CFI =.94. The model is therefore not supported for Traditional students.

Table 6: Fit statistics for Traditional Students without CAST SEM model .

Statistic	χ^2	df	TLI	CFI	SRMR	RMSEA(90% CI)
Measurement model	720.33	423	0.934	0.940	0.083	0.046 (0.039, 0.052)

R square:

AI = 0.654

UI = 0.214

TLI = TuckerâLewis index.

CFI = comparative fit index.

SRMR = standardized root mean squared residual

RMSEA = root-mean-square error of approximation.

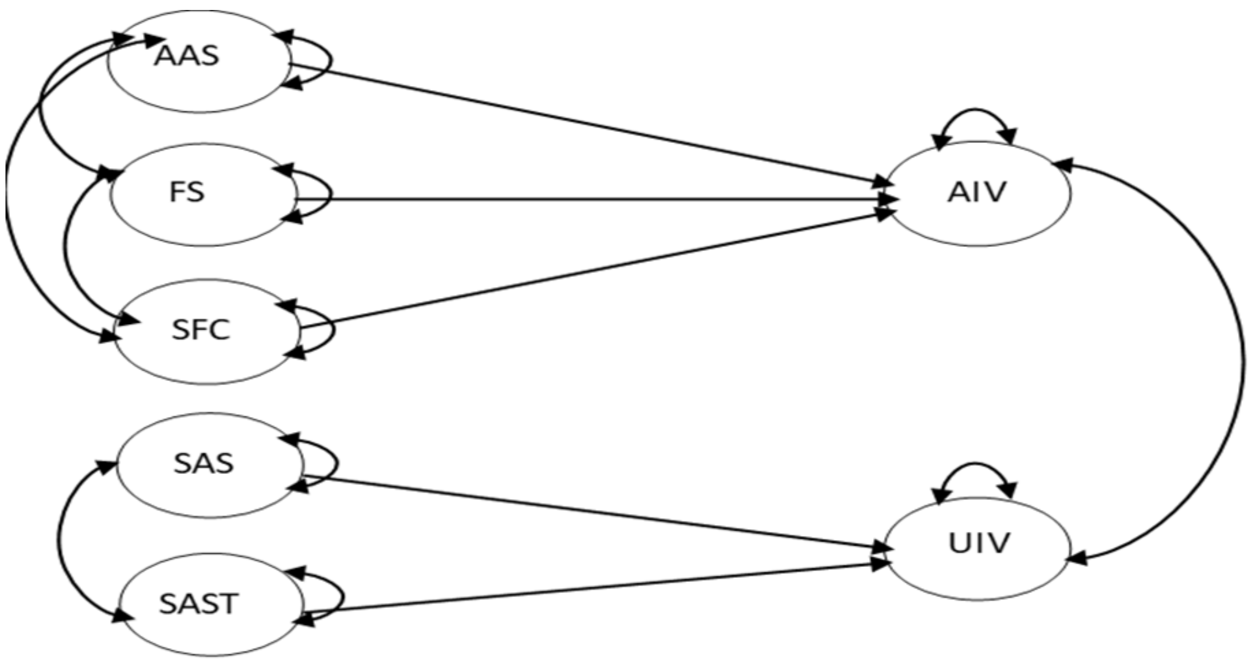

Figure 8: Hypothesized relationships

Figure 8. shows a Conceptual model, illustrating the hypothesized relationships among Academic Advisory Support (AAS), Faculty Support (FS), STEM Faculty Connection (SFC), Student Affairs support (SAS), Cost-of-Attendance support, and Training (CAST), Academic Integration (AI), University Integration (UI). It was generally predicted that AAS, FS and SFC would have some effect on AI and SAS, CAST would also affect UI.

4.3.5 SEM Overall model 4 (Spring Data)

RStudio was used to screen and analyze initial data, and the lavaan package in R was used to conduct latent variable analyses. We calculated descriptive statistics for all the indicators that were entered into SEM, as well as internal consistency estimates for the composite scores of the constructs. The robust Maximum Likelihood estimator was used because the data exhibited some level of non-normality. With respect to Spring, Table 2 shows that the mean Social Integration (SI) index was 4.83 with a standard deviation of 0.94 (skewness = -0.53, kurtosis = -.32), while the mean Professional Integration (PI) index was 4.93 with a standard deviation of 0.73 (skewness = -0.65, kurtosis = 0.60). Similarly, the mean Academic Peer Support (F2) index was 3.87 with a standard deviation of 0.80 (skewness = -0.66, kurtosis = -0.24), while the mean Stem Peer Connection (F5) index was 3.54 with a standard deviation of 1.02 (skewness = -0.53, kurtosis = -0.27). Furthermore, the mean Out-of-Class engagement (F7) index was 3.56 with a standard deviation of 0.77 (skewness = -0.15, kurtosis = -0.13), while the mean Stem Career Development (F9) index was 3.37 with a standard deviation of 0.84 (skewness = -0.08, kurtosis = -0.22). Again, the mean General Career Development (F10) index was 3.37 with a standard deviation of 0.2.71 (skewness = 0.56, kurtosis = 0.06).

Table 7: Descriptive Statistics for Spring data set

Latent Variables	Mean	SD	SE	Skewness	Kurtosis	CA
Social Integration (SI)	4.83	0.94	0.06	-0.53	-0.32	0.92
Professional Integration (PI)	4.93	0.73	0.05	-0.65	0.60	0.86
Academic peer Support (F2)	3.87	0.80	0.05	-0.66	0.24	0.83
Stem peer Connection (F5)	3.54	1.02	0.07	-0.53	-0.27	0.86
Out-of-Class engagement (F7)	3.56	0.77	0.05	-0.15	-0.13	0.86
Stem Career Development (F9)	3.37	0.84	0.06	-0.08	-0.22	0.90
General Career Development	2.71	0.96	0.06	0.56	0.60	0.81

Note. SD = Standard Deviation, SE = Standard Error, CA = Cronbachâs alpha. Social Integration and Professional Integration were set to a six-point scale ranging from 1-6 and the rest of the latent variables were set to a five-point scale ranging from 1-5. Prior to evaluating the conceptual framework depicted in Figure 1, the data analysis process answered the research questions by combining both the measurement model and structural model in a single SEM. The results indicate the degree to which the predicted factor loadings fit the data. A loading of 0.50 is regarded as significant and provides a strong indication of the underlying construct. At the time, all factor loadings were significant. Because all loadings were greater than .50, the results indicated that the measurement model's factors possessed adequate validity. As a result, the measurement model appeared to fit the data well, necessitating no changes. The model fit test revealed that the hypothesized model was well-fitting with a Chi square = 1581.56, RMSEA = 0.06 (90 percent confidence interval [0.055, 0.065]), SRMR =0.07, TLI = 0.84, CFI = 0.85. While the model fit was satisfactory, two of the structural model's hypothesized regression pathways (i.e., Out-of-class engagement to Social Integration and General Career development to Professional Integration) were associated with a non-significant weight (i.e., p-value of 0.059 and 0.587) respectively. Therefore, the model is not confirmed.

Table 8: Fit statistics for SEM model.

Statistic	χ^2	df	TLI	CFI	SRMR	RMSEA(90% CI)
Measurement model	1581.56	886	0.84	0.85	0.07	0.06(0.055 - 0 .065)

TLI = TuckerâLewisâs index.

CFI = comparative fit index.

SRMR = standardized root mean squared residual

RMSEA = root-mean-square error of approximation.

4.3.6 Multi Group Analysis.

We compared our model for students who identified themselves as either traditional students or Nontraditional student in the survey. The model invariance tests, based on the modification indexes, revealed paths that were significantly different between traditional and nontraditional students. We conducted a chi-square difference test to determine model invariance. The results indicated that there is a significant difference between traditional students and nontraditional students. Therefore, we needed to treat both groups differently.

4.3.7 SEM models 5 and 6 for both Traditional and Nontraditional Students (Spring Data).

Following the completion of an individual model analysis for both traditional and nontraditional students, it was determined that the fit of the model was not very satisfactory. Chi-square = 3382.56, RMSEA = 0.09 (90 percent confidence interval [0.089, 0.098]), SRMR =0.09, TLI = 0.70, CFI = 0.72. Out-of-class engagement to social integration is becoming an increasingly important pathway for traditional students. The General Career development to Professional Integration pathway, on the other hand, is still associated with a weight that is not statistically significant for traditional students (i.e., a p-value of 0.804). This result is not consistent with the finding by Legum and Hoare (2004) as well as Kalchik and Oertle (2010) that career development had a significant positive effect on professional integration of students. Literature revealed that students benefit from career development because it integrates theory and practice (Iyioke Iyioke, 2020).

The effectiveness of career development has been demonstrated in the training of teachers and medical students (Kori, Pedaste Must, 2018). Students who had career development support find it easier to be integrated professionally than those who graduated at a young age without any career development support. The insignificance of career development to professional integration by traditional students may be explained by the fact that professional integration is portrayed by combining professional work and professional personality during the time spent at school, while traditional students are more often not engaged in work (Kamel, 2020). The career development supports did incorporate both the widespread and the socially unambiguous parts of being a professional and embedding professional personality with more extensive social standards and belief systems of the students (Ramdhony, Mooneeapen, Dooshila Kokil, 2021). In order to ensure that career development plays significant roles in the professional development of the students, the social standards and belief systems of the students should be considered.

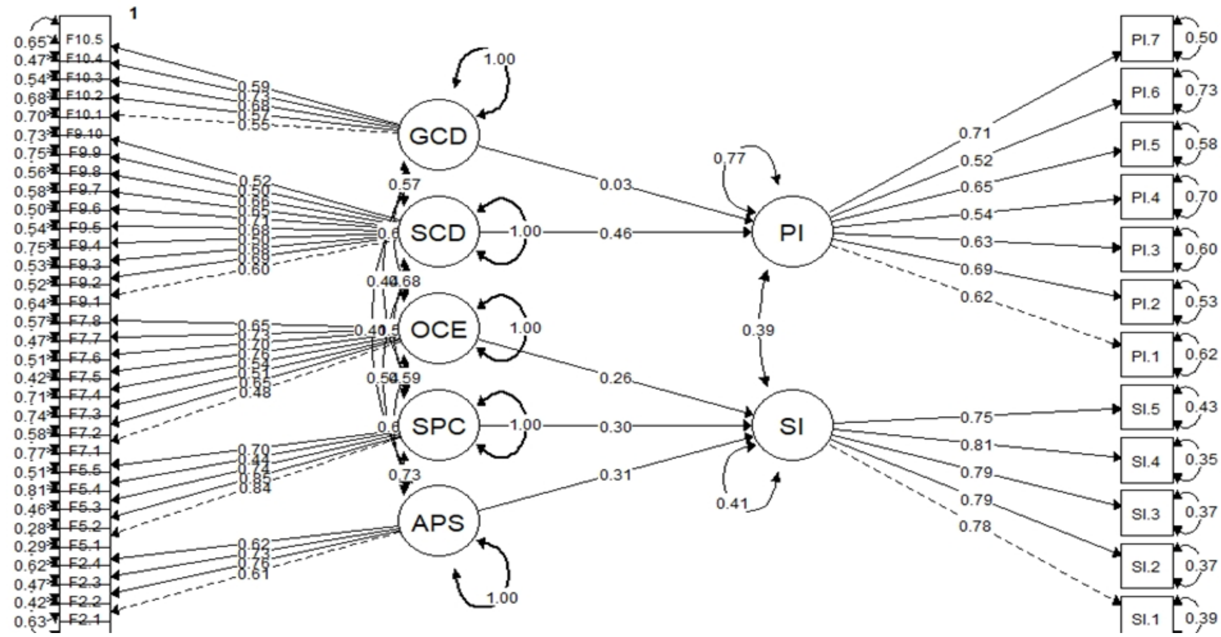

Figure 9: Path Diagram for Traditional Students.

Similarly, the general Career development to Professional Integration pathway was associated with a weight that was not statistically significant for nontraditional students (0.803). As explained by Kori, Pedaste and Must (2018), most of the nontraditional students were already working and thus extra career development stupor may not be necessary for their professional integration, unless the support system is related to their promotion or diversion from their current profession. The authors believed that professional integration is just an arbitrary classification because it incorporates elements of social and academic integration. Nontraditional students are socially and academically integrated at work when they interact with other professionals and address problems that are connected to their line of work (RozvadskÃ¡ NovotnÃ½, 2019). In this respect, an extra career development support may not play a significant role in the professional integration of such nontraditional students.

Another point that needs discussion, is the finding that out-of-class engagement to Social Integration pathways was associated with a weight that was not statistically significant for nontraditional students (p-value of 0.854). Therefore, the model is still not confirmed for any group. Polmear, Chau and Simmons (2021) explained in their study that out of

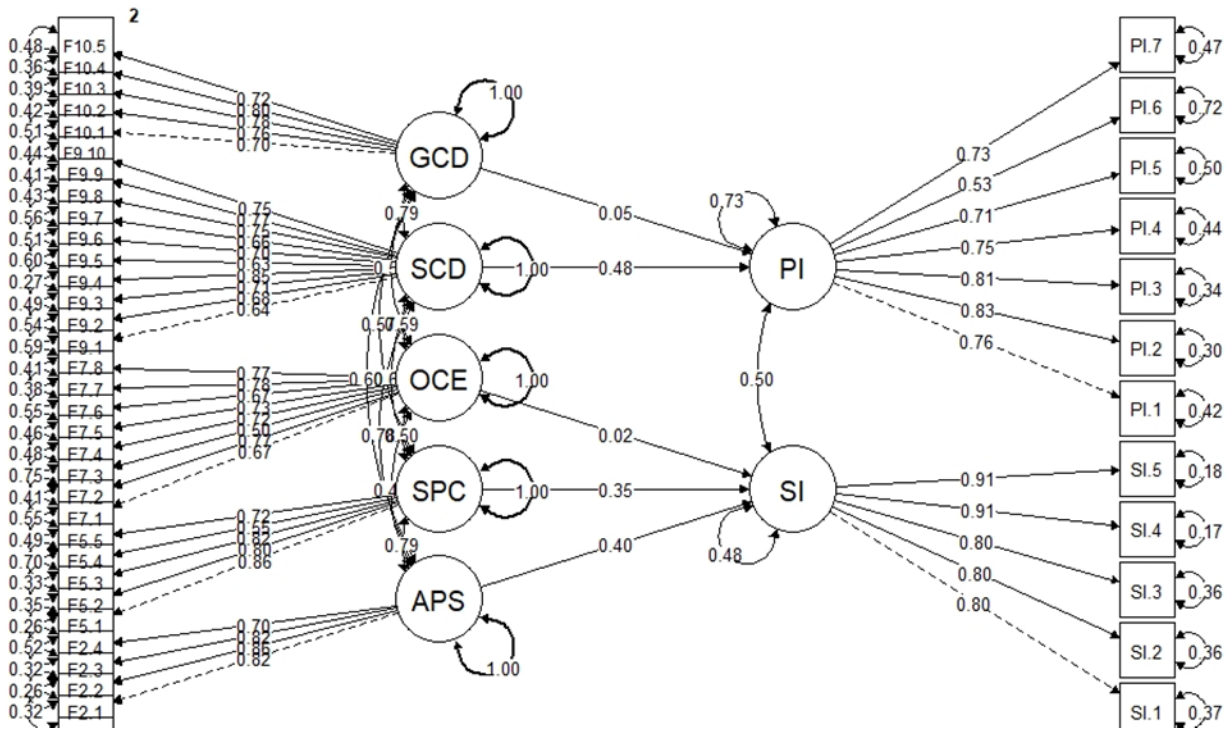

Figure 10: Path Diagram for Nontraditional Students.

class activities may not result into social integration because out-of-class engagements vary by setting, gender, race, and ethnicity of the students. As noted by Gunuc (2021), these issues highlight ways to use extracurricular activities to promote Social Integration by taking into account the contextual nuances of interaction that may reflect the background of the students. Therefore, in order to ensure that the supportive system of the school help in the integration of the students, the general career development, and the out-of-class engagement need to be revised to embrace the specific needs of each student.

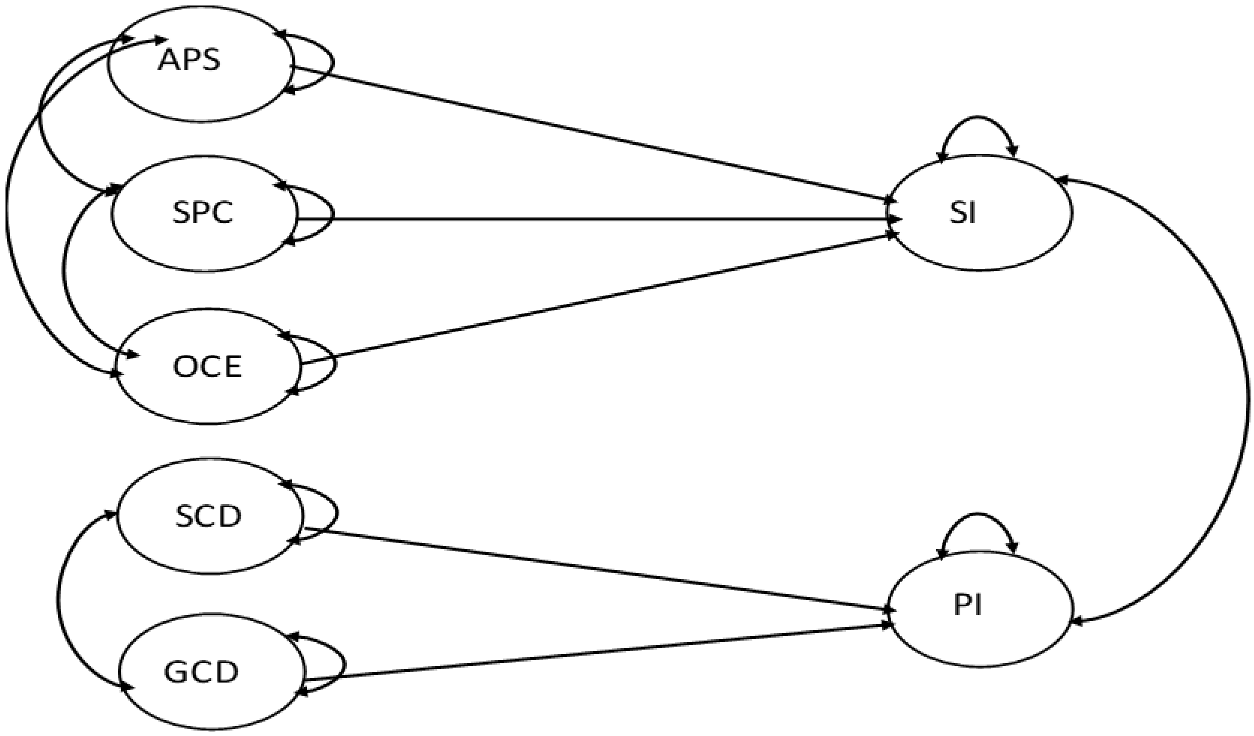

Figure 11: Conceptual model illustrating the hypothesized relationships

Figure 11. shows Conceptual model illustrating the hypothesized relationships among Academic Peer Support (APS), STEM Peer Connections (SPC), Out-of-Class Engagement (OCE), STEM Career Development (SPC), and General Career Development (GCD). It was generally predicted that APS, SPC, and OCE would have some effect on Social Integration (SI) and also, SCD, and GCD would also affect Professional Integration (PI).

4.4 Design of Shiny web application to create an interactive dashboard to better visualize the survey data.

Figure 12: Shiny Dashboard interface

The provided Shiny web application is designed to create an interactive dashboard that facilitates the exploration and visualization of data from two datasets, shinyDataSpring.csv and shinyDataFall.csv. This dashboard enables users to display data based on demographic variables, datasets (Spring or Fall), integration summary variables, and support summaries, offering a comprehensive understanding of the information at hand. To achieve this, the application employs multiple R packages for dashboard creation, data processing, and the generation of plots and tables.

The primary components of the code include loading the required libraries, reading the datasets, defining the User Interface (UI), establishing the server logic, and running the app. The necessary R packages are loaded, and the two CSV files, shinyDataSpring.csv and shinyDataFall.csv, are read and stored as data frames. The dashboardPage function is utilized to create the overall structure of the dashboard, which comprises a header, sidebar, and body. The sidebar houses input elements for users to select demographic variables, datasets, integration summary variables, and the option to show support summaries. The body features three primary sections: Graphs, Tables, and Supports Summary.

The server function contains the logic necessary to process user input and generate appropriate output based on user selections. This involves selecting the relevant dataset, generating summary statistics, creating bar plots, and rendering data tables. Finally, the shinyApp function is called to run the Shiny web application with the defined UI and server logic. In conclusion, the Shiny dashboard provides users with an interactive platform to explore and visualize data from the Spring and Fall datasets based on various demographic and summary variables. Bar plots and data tables are displayed, allowing users to gain a deeper understanding of the data and derive meaningful insights.

5 Conclusions

This study was about understanding support for nontraditional students using structural equation modeling. Thus, the support for nontraditional students was modeled for the Fall semester and the Spring semester using structural equation modeling. The study established that differences exist among the traditional and nontraditional students and thus their support system were exclusively modelled. The omnibus support model as well as the support model for traditional were not confirmed in both the Fall and the Spring semesters. In Fall, all the factors such as academic integration, university integration, academic advisory support, faculty support, stem faculty support, student affairs support, and cost-of-attendance support training contributed to support for nontraditional students contributed significantly to support for nontraditional students. Therefore, the Fall model for nontraditional students was confirmed. The implication is that in order to support traditional students in the Fall semesters, the authorities of the University needs to pay attention to academic integration, university integration, academic advisory support, faculty support, stem faculty support, student affairs support, and cost-of-attendance support training. In spring, though social integration, professional integration, academic peer support, stem peer connection, stem career development, and general career development contributed to support for nontraditional students, out-of-class engagement to social integration pathways was associated with a weight that was not significant. Therefore, the spring support model for nontraditional students was not confirmed. This implies that in order to support traditional students in the Spring semesters, the authorities of the University need to maintain existing social integration, professional integration, academic peer support, stem peer connection, stem career development, and general career development structures, while out-of-class engagement to social integration pathways is reviewed to reorient the nontraditional students to use their out-of-class engagement for social integration. The uniqueness of this study is that unlike the previous studies that did omnibus analysis on students, irrespective of being traditional or nontraditional student, this study disaggregated the data and modeled support for nontraditional students exclusively. The relevance of this study is that it provides important insights for understanding support for nontraditional students using structural equation modeling. Co-curricular support has been practice bias, which makes it difficult for emerging institutions to provide need based support for their nontraditional students, but this study could serve as a baseline for those institutions. The institutions in need of co-curricular support, could focus on the integrated factors that significantly contribute to support for the nontraditional students, while work on viable means of integrating the factors that did not contribute significantly.

6 APENDIX

Youngstown STATE UNIVERSITY

One University Plaza, Youngstown, Ohio 44555
www.ysu.edu

February 23, 2023

Dr. Cory Brozina, Principal Investigator
Ms. Alanis Chew, Co-investigator
Mr. Kingdom Aglonu, Co-investigator
Rayen School of Engineering
UNIVERSITY

RE: HSRC PROTOCOL NUMBER: 067-2021
TITLE: Nontraditional Students in Engineering: Studying Student Support and Success Experiences to Improve Persistence

Dear Dr. Brozina and Ms. Chew and Mr. Aglonu:

The Human Subjects Research Committee has reviewed the modifications you have requested to the above-mentioned protocol. The addition of qualified student personnel does not change the risk associated with your project. Therefore, your project continues to meet the condition of minimal risk and is fully approved.

Any other changes in your research activity should be promptly reported to the Institutional Review Board and may not be initiated without IRB approval except where necessary to eliminate hazard to human subjects. Any unanticipated problems involving risks to subjects should also be promptly reported to the IRB.

The IRB would like to extend its best wishes to you in the conduct of this study.

Sincerely,

Severine Van slambrouck, Director of Research Services
Digitally signed by Severine Van slambrouck, Director of Research Services
Date: 2023.04.21 15:52:48 -04'00'

Dr. Severine Van Slambrouck
Director of Research Services, Compliance and Initiatives
Authorized Institutional Official

SVS:cc

c: Dr. Frank Li,
Director Rayen School of Engineering

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