

The Interaction Between Instructor Social Presence, Student-Leader-Member Exchange, Student Engagement, Learning Management System Quality, and Intent to Leave at Online Universities

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Abstract

Online education is a relatively new phenomenon in academia, and as such, there are still many gaps in understanding how to effectively transfer face-to-face components of a classroom to an online platform. One of these gaps is how to foster instructor-student relationships when the online platform inherently lacks anonymity. It can be challenging to foster relationships when professors and students are faceless names, and this lack of connection may influence students' intentions to leave a university. Therefore, it is important for universities to understand the dynamics of instructor social presence in a strictly online environment. The purpose of this correlational, non-experimental study was to examine the relationships between instructor social presence, student leader-member exchange (student-LMX), student engagement, learning management system quality, and student intent to prematurely leave their program of study. Descriptive statistics were determined using SmartPLS statistical software. SmartPLS structural equation modeling was also employed to conduct bivariate and mediation regression analyses, as well as to assess the overall model fit. The sample included 206 undergraduate students attending online primarily freshman, sophomore, and junior level courses at a 100% online university. All bivariate and specific mediation test hypotheses were significant at $p < .05$. The overall model, however, indicated that student engagement was a strong mediator, and this attenuated the mediation effect of the other mediators tested in the model, including student-leader member exchange. This study is significant because it demonstrates that student engagement serves as a strong mediator between instructor social presence and student intent to leave a university, more so than the mediating effect of student-LMX. Also, instructor social presence is strongly related to other important variables that predict student success.

Introduction/Background

Starting in the late 20th century, technological advances ensured that education would never be the same. On April 30, 1993, the World Wide Web launched in the public domain. Since then, millions of students have completed courses and earned college degrees without ever setting foot in a classroom. While there was always a niche for traditional students in brick-and-mortar institutions, non-traditional students had fewer options. As society changed and people became more transient, many individuals found it difficult to commit to a brick-and-mortar institution; thus, many chose not to pursue higher education.

The internet has opened the world of education to anyone with access to a computer and an internet connection, and educational institutions have been eager to accommodate the nontraditional student set. By 2006, 89% of public and 60% of private educational institutions were offering online courses (Gensler, 2014). From 2002 to 2016, online student enrollments increased by approximately 5% annually.

As of 2016, over 31% of students, or approximately six million individuals, were enrolled in at least one online course (Seaman et al., 2018). Educational institutions recognize the trend toward online learning, and in 2009, half of the institutions responding to a questionnaire indicated that online learning was vital to their future strategy (Allen & Seaman, 2010).

Even though college enrollments peaked in 2010 with 21 million students enrolled (National Center for Education Statistics, n.d.), the demand for higher education degrees remains high for those who want to progress in their career field and for those who wish to change careers entirely. Online education affords many non-traditional students the ability to complete college courses in non-traditional ways.

Although institutions of higher learning were eager to enter the online market, many ultimately failed. Marcus (2004) identified several contributing factors to their failure, including a lack of faculty support and a limited understanding of pedagogy regarding online learners. Bernard et al. (2004) note that online education cannot be successful using conventional instructional methods typically employed in traditional classrooms.

Whether they are for-profit or not-for-profit, universities must retain students to stay in business. The market is saturated with totally online educational institutions, and with most brick-and-mortar institutions now offering online courses, it is of the utmost importance for academic institutions to find ways to increase students' satisfaction to retain them. Heyman (2010) and Angelino et al. (2007) noted that the attrition rates of those enrolled in classes taught through distance education tend to be around 10 to 20% higher than those in classes taught in a traditional classroom setting, and several factors appear to contribute to these rates. For example, the lack of personal, face-to-face interaction with professors and other students can leave learners feeling isolated and unsupported (Willging & Johnson, 2019). Howell et al. (2003) noted that there has been a switch from a lecture-style approach to a learner-centered approach, which leaves the onus of understanding course content largely on the student. Written exchanges between students and professors can be incomplete or ambiguous, leading to misunderstandings or confusion. Additionally, students who have difficulty obtaining feedback from an instructor are more likely to drop out of a course (Park, 2007). Technological issues are often unavoidable, but they can significantly impact a student's ability to access materials and

submit assignments. In addition, the quality of a learning management system can significantly impact the entire learning experience and the student's perception of the program of study or the university. As Park (2007) notes, proper course design and technology can mitigate several external factors that lead to attrition. As more students choose to pursue an academic career, universities must address these and other issues to retain students enrolled in their courses.

Because online learning is a relatively new phenomenon, there is still much to learn about the mechanics of teaching and learning in a virtual environment. Although forms of distance education have existed since the 18th century, the internet has been used to deliver instruction only since the 1990s (Kentnor, 2015). It can be assumed that online learners have needs like those of traditional learners. Discovering how to cater to these needs in an online environment is a challenge that many universities face.

One area that universities need to consider is engagement. In a lecture-based setting, students are allowed to interact with the instructor and other students, which enables the transmission of knowledge through various means, including brainstorming and question-and-answer sessions. The online environment generally lacks this component of learning. Due to the lack of interaction with others, students must largely rely on the course materials provided. Enterprising students may venture outside the provided materials to expand their knowledge, but many students will rely on the materials available in their course. The in-person interaction component of learning is difficult to replicate in an online environment. Most courses rely on discussion boards to encourage interaction between students and instructors; however, these interactions are largely asynchronous, and not every student will receive a response to their post. It is, therefore, essential for universities offering online instruction to develop innovative ways to engage their students. This cross-sectional, non-experimental, correlational study examined the relationships between several variables using partial least squares structural equation modeling to determine the role of instructor social presence and the theory of student-LMX in student engagement and students' intent to leave their programs of study. Learning management system quality was also addressed as an independent variable to determine the effect of learning management system quality on the mediating role of student leader management exchange with respect to the student intent to stay as a dependent variable.

Literature Review

Using LMX theory to describe relationships between instructors and students is relatively new. There has been a limited amount of research conducted on the relationship between leader-member exchange theory (LMX) and student intent to leave in an online program; therefore, there is a dearth of studies related to this topic. Aside from a handful of journal articles and dissertations that focus on various aspects of student-LMX (Farr-Wharton et al., 2018; Gutierrez, 2018; Jacques et al., 2012; Juneja, n.d.; Mosley et al., 2014; Zhao et al., 2019), most LMX theory information exists in the corporate world, where it has been studied more comprehensively. Thus, the primary gap in the research is how LMX theory impacts relationships in education, and more specifically, how it affects relationships in online education. This involves understanding how it mediates the relationship between instructor social presence and student engagement, as well as a student's intent to leave a program of study. This will henceforth be referred to as student-LMX.

There is a need to expand on the research performed by the researchers mentioned above, which can be achieved by introducing variables that have not been previously studied. For example, a review of the research indicates that the quality variable of the learning management system in the proposed study has not been studied in relation to student-LMX. If the quality of the learning management system is poor, the student may blame the instructor, since most students perceive that the instructor is responsible for course content, and this may impact the perceived quality of the relationship between the student and the instructor and be a factor in a student's decision to leave the university.

Social Exchange Theory

Social exchange theory (SET) is a psychological and sociological behavioral theory that is based on the expectation of recompense in relationships. People will measure the apparent cost-benefit of entering such a partnership to determine if the risk is worth the reward (Roeckelein, 1998). The term 'exchange' implies that relationships involve a give-and-take between parties, and this reciprocity can extend beyond intrinsic emotional rewards to encompass economic rewards as well. SET's roots can be traced back 100 years, and since its inception, it has been invaluable in bridging disciplines such as sociology and social psychology. It has been used to predict and describe relationships in various circumstances, including psychological contracts (Rousseau, 1995), leadership (Liden et al., 1997), and social power (Molm et al., 1999), among others. The seminal works in SET include "The Social Psychology of Groups" (Thibaut & Kelley, 1959), "Social Behavior: Its Elementary Forms" (Homans, 1961), "Exchange and Power in Social Life" (Blau, 1964), and "Social Exchange Theory" (Emerson, 1976).

Social exchange theory served as a foundation on which the leader-member exchange theory grew. Whereas SET is concerned with relationships in general, LMX theory focuses on dyadic (two-way) relationships between leaders and followers. It evolved in the business world to quantify relationships between leaders and subordinates. Early works by Graen (1976) and Graen and Scandura (1987) placed the roots of LMX in role theory; however, the lens has widened, and LMX now relies largely on social exchange theory (Erdogan & Liden, 2002; Kadar & Van Dyne, 2007; Liao et al., 2010; Wayne & Green, 1993).

Student-LMX

As LMX theory is a subset of SET theory, student-LMX theory is a subset of LMX theory. Student-LMX theory is a relatively new addition to the realm of social theory, dating back only a couple of decades. As it is still in the early stages of study, there is a paucity of research available. The focus of student-LMX is on how the LMX relationship between the instructor and the student influences the student's intention to drop out of their studies at a given university. Retention is a particularly salient issue now that online education has experienced significant growth over the past 20 years, and competition for students is intense. The focus of student-LMX is on the relationships formed between students and their educational team through learning exchanges and activities, which include lectures, tutorials, and facilitated online forums such as discussion boards (Farr-Wharton et al., 2017). Jacques et al. (2012) argue that as leaders, university instructors use the LMX relationship to supervise student learning behavior through

the relationships formed between them and students. They went on to link student achievement to the student-LMX relationship. Likewise, Mosley et al. (2014) used student-LMX to determine overall student learning.

One point to note regarding student-LMX is that, unlike normal LMX relationships in business settings, student-LMX relationships are typically much shorter in duration. The length of sessions for many universities is anywhere from six to 16 weeks, and unless a student has an instructor for more than one session, there is a minimal amount of time for a relationship to form. For this reason, Farr-Wharton et al. (2017) consider the interactions between a given student and all their instructors throughout the degree program as the basis for the student-LMX relationship. Farr-Wharton et al. (2017) argue that the student-LMX relationship is a crucial consideration in implementing learner-centered pedagogy in universities, situated at the intersection between the student and the learning process. In this study, the principal investigator expanded on previous research to investigate how the student-LMX relationship applies in an online learning environment.

In the following section, the variables used in this study, namely, instructor social presence, student engagement, student-LMX, student retention, and learning management system quality, are addressed. A review of the current literature was conducted to determine the existing research in the field.

Instructor Social Presence

A sense of belonging can be challenging for students to achieve in an online educational environment. Barnett-Allen (2017) notes that social presence is one of the most important factors and a vital component to encourage a sense of community in online learning. That is why it is of the utmost importance for instructors to do everything possible to foster a welcoming environment in their online classrooms. One way to achieve this is through social presence. Tu (2000) notes that social presence is required to enrich and promote online interaction, which is the major means through which social learning occurs. Instructors generally set the tone in the online classroom, and an instructor who is absent cannot expect students to be active and engaged. Tu and McIsaac (2010) found that an increase in the level of online interactions was positively correlated with greater social presence; therefore, instructors need to give the impression that they are present and available. An understanding of social presence theory can help clarify the concept of social presence in an online classroom.

Student Engagement

Engaged students tend to be more satisfied, persistent, and have better academic performance (Meyer, 2014). However, keeping students engaged in an online setting is a significant challenge. In a traditional classroom, the face-to-face aspect of engagement is often enough to keep students motivated; however, replicating this in an online environment requires a concerted effort by course creators, instructors, and students. Chickering and Gamson (1987) identified seven principles of student engagement in a face-to-face setting: contact between students and faculty, cooperation among students, active learning, timely feedback, time on task, high

expectations, and respect for diversity in leaning method which, with some planning and effort, could be utilized in an online setting as well. More recently, Kahu (2011) developed a conceptual framework that incorporates elements such as psychosocial and structural influences. The goal is to emphasize that student engagement is more than just an internal fixed state. Rather, as Kahu (2011) points out, it is an individual experience rooted in the socio-cultural context and is influenced by both the student and the institution. She notes that a significant advantage of viewing engagement in this light is that it eliminates the narrow definition of engagement related to responsibility and blame; that is, the impression that the instructor is doing a good job if the student is engaged, but the problem lies with the student if he or she is not engaged.

Student Leader-Member Exchange

In this study, student-LMX refers to the relationship between the instructor and the student in the academic setting. Most LMX studies to date have focused on the relationship between organizational leaders and their subordinates; however, a handful of studies have also examined the relationship between instructors and their students. As early as 1974, Brophy and Good identified the gap in research relating to instructor-student relationships in brick-and-mortar settings. While most studies conducted had focused on the behavior of the teacher toward the entire class, Brophy and Good recognized that instructors interacted with individual students very differently than they did with a group of students. In this context, the instructor-as-leader viewpoint aligns with the LMX model, as LMX theory posits the existence of an ingroup, a middle group, and an outgroup. Individual interactions between instructors and students reveal this occurrence.

Student Retention

One of the primary goals of colleges and universities, regardless of their profit status, is to attract and retain students. Online programs tend to excel at attracting students, but their retention rates are no better than, and often worse than, those of traditional programs. Colleges and universities need to find a way to retain the students they matriculate. There are many reasons students give for leaving their programs. Some of these include isolation, disconnectedness, and technical challenges (Bigatel & Edel-Malizia, 2017; Willging & Johnson, 2019). Some of these same reasons may also influence a student's decision not to enroll in online courses initially. Although online courses may be more convenient than attending in-person lectures, especially for students who live off-campus and have jobs and families, many students do not view the online option as a viable alternative. O'Neill and Horng Sai (2014) surveyed 48 students who had the option to take a course online but elected to take the in-person course instead, and they found that students often believed that they would not successfully complete the course in an online environment. Educational institutions need to find ways to mitigate the challenges within their control. If they have an adequate technological infrastructure in place, then technical challenges are most often found on the student's end. This, of course, is out of the institution's control. However, there are measures they can take to help combat the isolation and disconnectedness. This ties back to the concept of the professor's social presence.

Learning Management System Quality

This study differs from existing studies because learning management system quality was introduced as an independent variable to determine its effect on the mediating role played by student leader-member exchange with respect to a student's intent to leave a university. According to Revere and Kovach (2011), although online education is well established, the efficacy of learning management system design and student engagement remains unclear. They further state that when technology is used correctly, it can promote engagement and lead to increased learning and higher student satisfaction. Because of this, the quality of learning management systems needs to be a concern for both colleges and students. Jaggars (2014) reported that when students were asked about their primary concerns about online learning, 27% stated that they were concerned about the quality of their courses. There is a perception that online courses lack the quality that face-to-face instruction provides, but this is not necessarily true. Many online courses offer the same content as traditional, face-to-face courses; the primary difference lies in the method of delivery. Lecture-based course content is provided by a person standing in front of a classroom while online course content is provided via a learning management platform. However, the way the information is presented on that platform is crucial to the course's success.

In essence, online course creation involves variables that encompass not only the creation of the course itself, but also the delivery platform and method. It appears that faculty training is as important to the quality of instruction as the quality of the course itself. This adds credence to the need for instructors to be able to navigate the learning management system effectively. Additionally, it is not uncommon for an instructor to be uninvolved in the actual creation and loading of course materials into the learning management system shell. The principal investigator's experience suggests that students often attribute course errors and difficulties to the quality of the system rather than their instructor. Thus, while courses within the learning management system platform should be error-free, instructors who are familiar with their courses are more likely to identify any errors that slip through the review process and have them corrected before they affect students.

Methods

This quantitative, correlational study examines the relationships between instructor social presence, student leader-member exchange (student-LMX), student engagement, learning management system quality, and student intent to leave their program of study prematurely. The formation of dyadic relationships between instructors and students in an online environment, as well as the importance of instructor social presence in establishing a student-perceived instructor-student relationship, were examined to determine the extent to which these variables influence a student's decision to leave a program of study.

This study employs a cross-sectional questionnaire administered to a convenience sample of university students enrolled in online courses at an accredited, fully online university. The study

was nonexperimental because random assignment and random selection of participants were not feasible due to the dissemination of the survey instruments. Also, there was no treatment and control group. The G-power results yielded a minimum sample size of 129 participants; however, 206 usable surveys were obtained and used for statistical analysis.

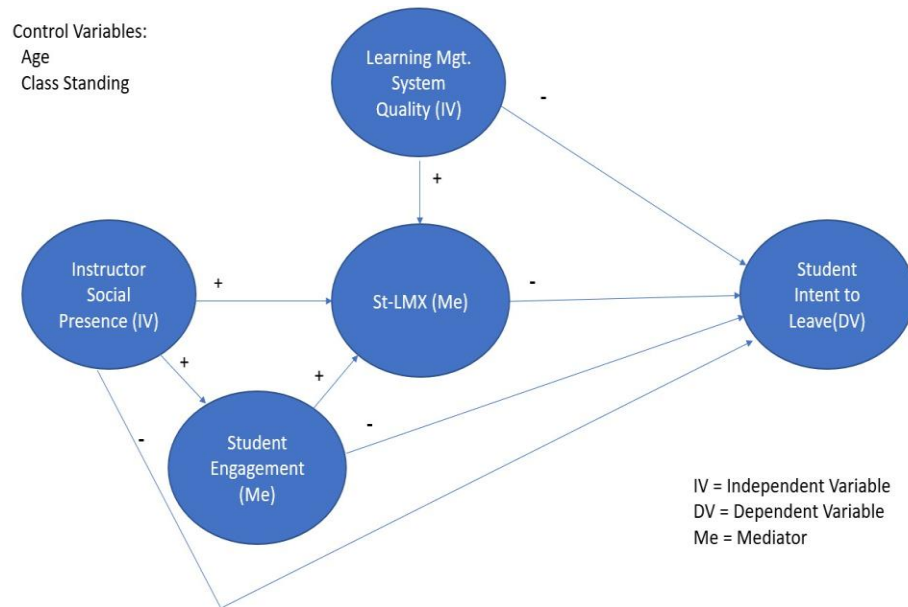
Operational Definitions

The primary variables are listed as follows to include their operational definitions:

- Instructor social presence (IV): essentially identifies the degree to which a given instructor is perceived as being socially present in the course. This is operationalized as a 10-question survey instrument developed by Pollard et al. (2014).
- Student-LMX (Mediator): The strength of relationship with the instructor in question as perceived by the student. This is operationalized as an eight-question survey instrument developed by Farr-Wharton et al. (2018).
- Student engagement (Mediator): The perceived extent to which students find themselves immersed in their coursework. This is operationalized as a seven-question survey instrument developed by Farr-Wharton et al. (2018).
- Learning management system quality 'technology' (IV): The perceived degree to which students find the course delivery system useful, useable, and appropriate. This is operationalized as a seven-question survey instrument developed by Mashaw (2012).
- Student intent to leave (DV): The degree to which students believe they will likely leave the university. This is operationalized as a four-question survey instrument developed by Farr-Wharton et al. (2018).

Figure 1 below is a visual representation of the conceptual framework that was used for this study.

Figure 1

Conceptual Framework*Research Questions*

The following research questions guided this study.

RQ1: To what extent does instructor social presence predict student engagement, student leader member exchange (student-LMX), and student intent to leave at online universities?

RQ2: To what extent does student engagement predict student-LMX and student intent to leave at online universities?

RQ3: To what extent does student-LMX predict student intent to leave at online universities?

RQ4: To what extent does learning management system quality predict student-leader member exchange (student-LMX), and student intent to leave at online universities?

RQ5: To what extent does student-LMX mediate the relationship between instructor social presence and student intent to leave at online universities?

RQ6: To what extent does student engagement mediate the relationship between instructor social presence and student-LMX and between instructor social presence and student intent to leave at online universities?

RQ7: To what extent does student-LMX partially mediate the relationship between student engagement and student intent to leave at online universities?

RQ8: To what extent does student-LMX mediate the relationship between learning management system quality and student intent to leave at online universities?

Results and Discussion

As indicated by the research questions above, several relationships between the variables operationally defined above were statistically tested using SmartPLS as an analytical tool. These variables are broken out further in Table 1 below to specify the primary roles they play in the conceptual model. Not all relationships that were tested are specified, however. For instance, student-LMX and student engagement were both tested as partial mediators and needed to play the role of both IV and DV in the process of testing for mediation. These relationships are implied in the conceptual model.

The primary bivariate analyses, conducted based on the conceptual model, are specified in Table 1 and are organized by relevant research question. The role each variable plays in the relationships to be tested is specified in the table, as is the level of measurement for each variable.

Table1

Summary of Bivariate Analysis

RQ #	IV	LOM	DV	LOM	Statistical Test
RQ 1	Instructor Social Presence	Continuous	Student Engagement	Continuous	PLS Regression Analysis
RQ 1	Instructor Social Presence	Continuous	Student-LMX	Continuous	PLS Regression Analysis
RQ 1	Instructor Social Presence	Continuous	Intent to Leave	Continuous	PLS Regression Analysis
RQ 2	Student Engagement	Continuous	Student-LMX	Continuous	PLS Regression Analysis

RQ 2	Student Engagement	Continuous	Intent to Leave	Continuous	PLS Regression Analysis
RQ 3	Student-LMX	Continuous	Intent to Leave	Continuous	PLS Regression Analysis
RQ 4	Learning Mgt. System Quality	Continuous	Student-LMX	Continuous	PLS Regression Analysis
RQ 4	Learning Mgt. System Quality	Continuous	Intent to Leave	Continuous	PLS Regression Analysis

In addition to bivariate analysis, several multivariate analyses were also necessary to fully test the hypotheses and conceptual model. These tests included covariates/controls, utilizing partial least squares regression analysis to determine if age and class status impacted the relationships examined. Age was considered as a factor because it may impact some of the variable relationships, since older individuals may be more committed to their goals and have more experiences to draw on than younger students. Class standing was also considered because the closer one is to graduating, the more likely they are to persist in the academic program they are enrolled in. A summary of the covariate analyses to be performed is provided in Table 2 below.

Table 2

Summary of Multivariate Analysis (Covariates)

RQ #	IV + CoVs 1 & 2	DVs	Statistical test
RQ 1	Instructor social presence + age + class standing	Student engagement	PLS multiple regression analysis

RQ 1	Instructor social presence + age + class standing	Student-LMX	PLS multiple regression analysis
RQ 1	Instructor social presence + age + class standing	Intent to leave	PLS multiple regression analysis
RQ 2	Student engagement + age + class standing	Student-LMX	PLS multiple regression analysis
RQ 2	Student engagement + age + class standing	Intent to leave	PLS multiple regression analysis
RQ 3	Student-LMX + age + class standing	Intent to leave	PLS multiple regression analysis
RQ 4	Learning mgt. system quality + age + class standing	Student-LMX	PLS multiple regression analysis
RQ 4	Learning mgt. system quality + age + class standing	Intent to leave	PLS multiple regression analysis

Additional multivariate analyses were also required, based on the research questions, due to the multiple mediation paths evaluated in this dissertation. The subsequent primary multivariate analyses, performed in relation to mediation, are specified in Table 3 below.

Table 3*Summary of Multivariate Analysis (Mediation)*

RQ #	IV + Mo + Me	DVs	Statistical test
RQ 5	Instructor multiple presence LMx (Me)	Student intent regression (IV) + analysis student-	PLS social to leave with bootstrap
RQ 6	Instructor social presence (IV) + student engagement (Me)	Student-LMX	PLS multiple regression analysis with bootstrap
RQ 6	Instructor social presence (IV) + student engagement (Me)	Student intent to leave	PLS multiple regression analysis with bootstrap
RQ 7	Student engagement (IV) + student-LMX (Me)	Student intent to leave	PLS multiple regression analysis with bootstrap
RQ 8	Learning management system quality (IV) + studentLMX (Me)	Student intent to leave	PLS multiple regression analysis with bootstrap

This study utilized SmartPLS for performing regression analyses and descriptive statistics. Partial least squares do not require one to meet the assumptions of ordinary least squares regressions (Hair et al., 2016). SmartPLS structural equation modeling was employed to analyze all 10 hypotheses. This software employs partial least squares methods to analyze data and determine effect size values and R-squared values for the various regression equations generated within the model. The analytical tool also performed factor analysis for all variables utilizing an oblique rotation method, as evaluation of the factors suggests that they would be correlated to some degree (Hair et al., 2016; Osborne, 2015). This analysis provides factor loadings and model fit indices that enable the investigator to determine the best-fitting model. Convergent and discriminant validity were determined through factor loadings and analysis of average variance extracted.

Multiple mediation paths were assessed in this study. SmartPLS employs a bootstrapping analytical technique to assess mediation models, including a comparison of coefficients once bootstrapping is complete, to determine if mediation has occurred (Hair et al., 2016). The number of bootstrap iterations was set at 1000. Additionally, standard deviation and 95% confidence intervals of the mean difference were presented for all variables when appropriate.

Descriptive Statistics

Descriptive statistics were generated for all indicators utilized in the present study and are indicated in Table 4 below. Several of the items were excessively skewed and excessively kurtotic, indicating non-normal distributions. It is not required, however, to meet ordinary least squares regression assumptions when using partial least squares structural equation modeling; thus, additional assumption testing was not performed.

Table 4

Descriptive Statistics

Indicators	No. 1	Mean	Median	Min	Max	SD	Kurtosis - Skewness
Age		41.602	42	18	75	10.84	0.533 0.191
Class							
Standing	2	2.888	3	1	5	0.956	-0.459 0.226
SP1	3	4.136	4	1	5	1.005	0.385 -1.056
SP2	4	4.029	4	1	5	0.99	0.271 -0.815
SP3	5	4.194	5	1	5	1.005	1.305 -1.293
SP4	6	3.869	4	1	5	1.092	0.175 -0.865
SP5	7	3.932	4	1	5	1.064	0.019 -0.766
SP6	8	3.714	4	1	5	1.097	-0.872 -0.233
SP7	9	3.733	4	1	5	1.124	-0.637 -0.47
SP8	10	3.345	3	1	5	1.129	-0.455 -0.159
SP9	11	3.422	3	1	5	1.043	-0.335 -0.141
SP10	12	4.17	5	1	5	1.054	0.81 -1.221
LMX1	13	4.252	5	2	5	0.911	-0.037 -0.989
LMX2	14	4.121	4	2	5	0.995	-0.677 -0.753

LMX3	15	3.854	4	1	5	1.114	-0.244	-0.706
LMX4	16	3.874	4	1	5	1.09	-0.15	-0.744
LMX5	17	3.752	4	1	5	1.137	-0.558	-0.539
LMX6	18	3.859	4	1	5	0.988	0.174	-0.627
LMX7	19	4	4	1	5	1.005	0.605	-0.954
SE1	20	3.782	4	1	5	0.983	-0.041	-0.537
SE2	21	4.233	4	2	5	0.815	0.032	-0.833
SE3	22	3.961	4	1	5	0.955	-0.511	-0.563
SE4	23	4.063	4	1	5	0.871	0.605	-0.834
SE5	24	3.917	4	1	5	0.989	-0.478	-0.561
SE6	25	3.743	4	1	5	0.917	-0.042	-0.454
LMQ1	26	4.049	4	1	5	0.902	1.403	-1.016
LMQ2	27	4.272	4	1	5	0.838	1.916	-1.296
LMQ3	28	3.995	4	1	5	0.922	-0.115	-0.627
LMQ4	29	4.223	4	1	5	0.869	2.679	-1.388
LMQ5	30	4.117	4	1	5	0.998	0.39	-1.033
IL1	31	1.641	1	1	5	0.933	2.327	1.606
IL2	32	1.471	1	1	5	0.761	3.134	1.763
IL3	33	1.641	1	1	5	0.852	2.216	1.429
IL4	34	1.49	1	1	5	0.858	4.993	2.171

Collinearity

The model evaluated in the current study was a fully reflective model; therefore, a high level of collinearity is expected due to question redundancy (Hair et al., 2017). Collinearity statistics were run, and the results are presented in Table 5 below. SmartPLS flags variance inflation factors (VIFs) that exceed 5.0 in red, indicating high collinearity. There were several items indicating a VIF just over 5.0. This is not problematic since it is not a formative model.

Table 5

Collinearity Values

Item	VIF	Item	VIF
IL1	3.14	SE1	1.914
IL2	2.743	SE2	1.886
IL3	2.098	SE3	1.533
IL4	3.264	SE4	2.755
LMQ1	1.635	SE5	2.421
LMQ2	1.983	SE6	1.948

LMQ3	2.251	SP1	3.987
LMQ4	2.511	SP10	3.476
LMQ5	2.607	SP2	4.099
LMX1	1.801	SP3	3.291
LMX2	3.367	SP4	4.211
LMX3	3.359	SP5	4.544
LMX4	3.317	SP6	5.421
LMX5	2.851	SP7	5.082
LMX6	2.892	SP8	2.94
LMX7	3.146	SP9	3.245

Factor Analysis

A confirmatory factor analysis was conducted using the SmartPLS default factor analytical tool. The outer model loadings are specified in Table 6 below. There were a few lower loadings for learning management system quality and one lower loading for student engagement. Average combined factor loadings for each variable, however, resulted in values above .7, which is generally considered acceptable for SmartPLS reflective models.

Table 6

Factor Analysis Outer Loadings

Intent to LMS Social St.- St. lv. quality presence LMX engage			
IL1	0.901		
IL2	0.803		
IL3	0.721		
IL4	0.927		
LMQ1		0.611	
LMQ2		0.572	
LMQ3		0.923	
LMQ4		0.846	
LMQ5		0.759	
LMX1			0.863
LMX2			0.854
LMX3			0.751

LMX4	0.783
LMX5	0.723
LMX6	0.764
LMX7	0.87
SE1	0.931
SE2	0.814
SE3	0.514
SE4	0.703
SE5	0.73
SE6	0.684
SP1	0.877
SP10	0.87
SP2	0.879
SP3	0.854
SP4	0.851
SP5	0.905
SP6	0.873
SP7	0.819
SP8	0.646
SP9	0.702

Overall, the variables evaluated in the present study loaded rather well, with just a couple of items dropping below 0.6; however, there were some high cross-loadings, particularly between the instructor social presence and student-LMX. A table with cross-loadings is included in Appendix A. Further evaluation was subsequently necessary to establish construct reliability and validity.

Construct Reliability and Validity

Both Cronbach's alpha scores and composite reliability scores were well above 0.7 for each variable, indicating the variables tested were highly reliable (See Table 7). This essentially indicates that the responses were highly consistent for each variable. Additionally, the average variance extracted (AVE) scores were all above 0.5, indicating discriminant validity. This helps

to alleviate some concerns about the high cross-loadings between instructor social presence and student-LMX noted earlier.

Table 7

Construct Reliability and Validity

	Cronbach's alpha	Composite reliability	AVE
Intent to lv.	0.905	0.906	0.709
LMS quality	0.865	0.865	0.569
Social presence	0.956	0.957	0.691
St.-LMX	0.928	0.927	0.645
St. engage	0.88	0.876	0.548

Hypothesis Testing

This subsection presents the bivariate hypothesis testing results, a brief overview of the bivariate relationships regressed against the control variables, age and class standing, and the mediation hypothesis testing results. This subsection concludes with an analysis of the overall model proposed in this paper, along with a presentation of the best-fit model.

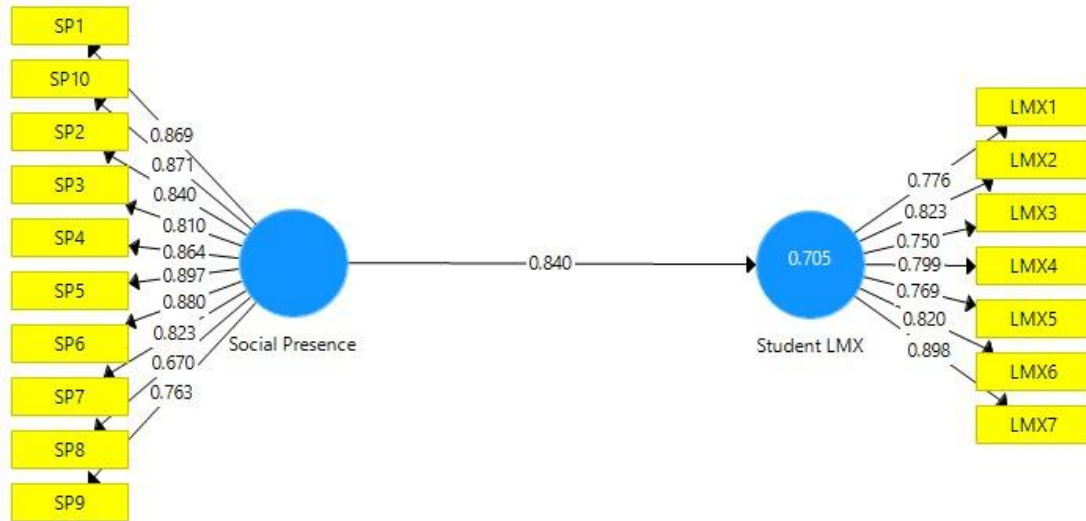
Bivariate hypothesis testing. Below are the bivariate hypothesis tests that were run utilizing SmartPLS. These results are presented in a model format to provide the reader with a visual representation of the relationships tested. Presenting data in model format is also a preferred method for structural equation modeling.

RQ1: To what extent does instructor social presence predict student engagement, student-leader member exchange (student-LMX), and student intent to leave?

H0₁: There is no relationship between instructor social presence and student-leader member exchange (student-LMX) score.

Ha₁: There is a statistically significant relationship between instructor social presence and student-leader member exchange (student-LMX) score.

A partial least squares regression analysis was conducted in SmartPLS using consistent path analysis and bootstrap methods to examine the relationship between instructor social presence and student-leader member exchange, yielding a statistically significant result of $t = 22.19$, $p < .001$, a path coefficient of 0.84, and an R^2 value of 0.705 (See Figure 2). Hence, the null hypothesis is rejected.

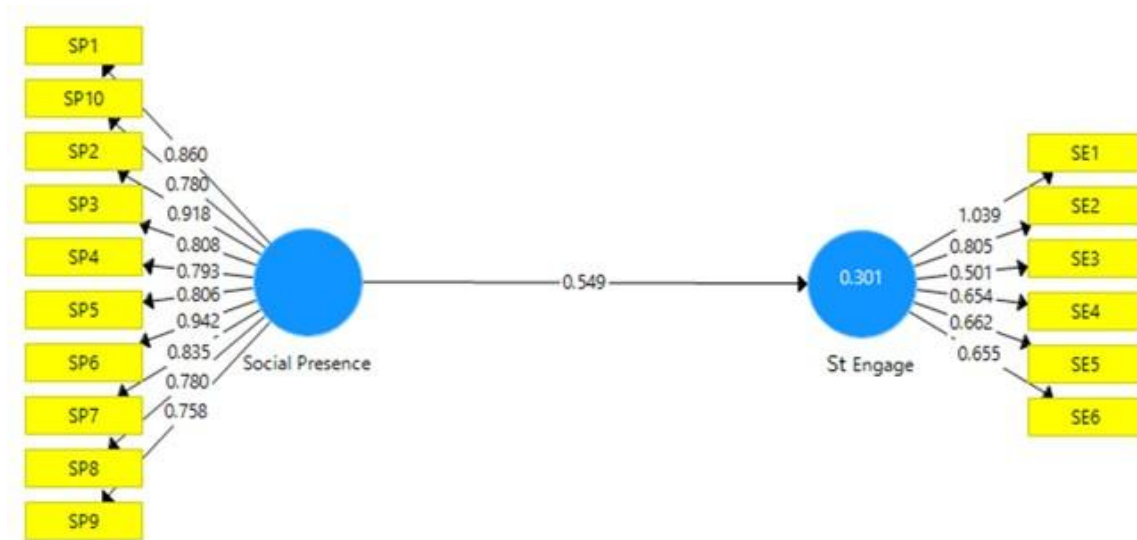
Figure 2*Hypothesis 1 Bivariate Analysis*

RQ1: To what extent does instructor social presence predict student engagement, student-leader member exchange (student-LMX), and student intent to leave?

H0₂: There is no relationship between instructor social presence and student engagement.

Ha₂: There is a statistically significant relationship between instructor social presence

A partial least squares regression analysis was conducted in SmartPLS using consistent path analysis and bootstrap methods to examine the relationship between instructor social presence and student engagement, yielding a statistically significant result of $t = 10.18$, $p < 0.001$, a path coefficient of 0.549, and an R^2 value of 0.301 (See Figure 3). Hence, the null hypothesis is rejected.

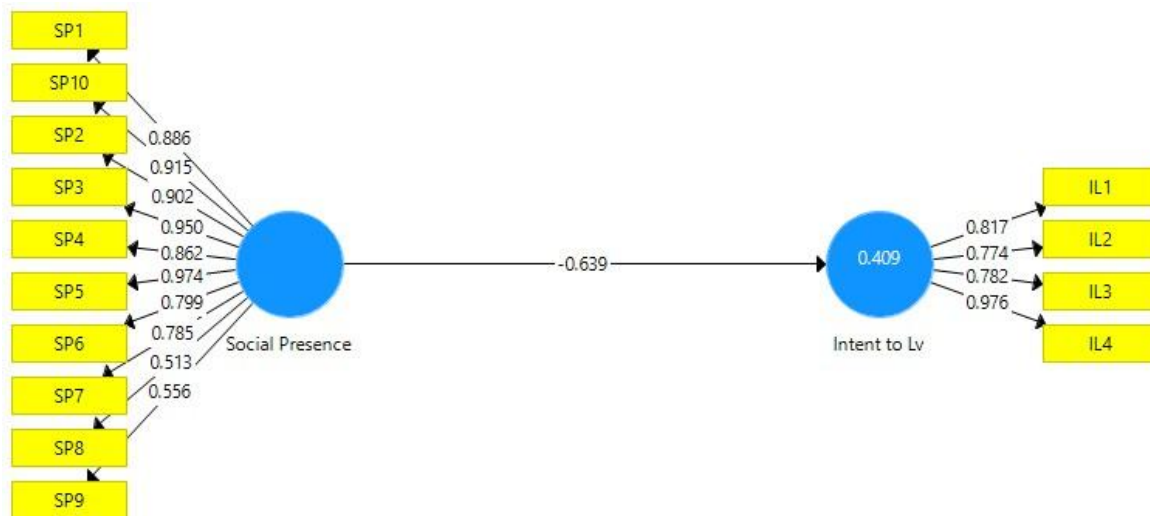
Figure 3*Hypothesis 2 Bivariate Analysis*

RQ1: To what extent does instructor social presence predict student engagement, student leader member exchange (student-LMX), and student intent to leave?

H0₃: There is no relationship between instructor social presence and student intent to leave.

Ha₃: There is a statistically significant relationship between instructor social presence and student intent to leave.

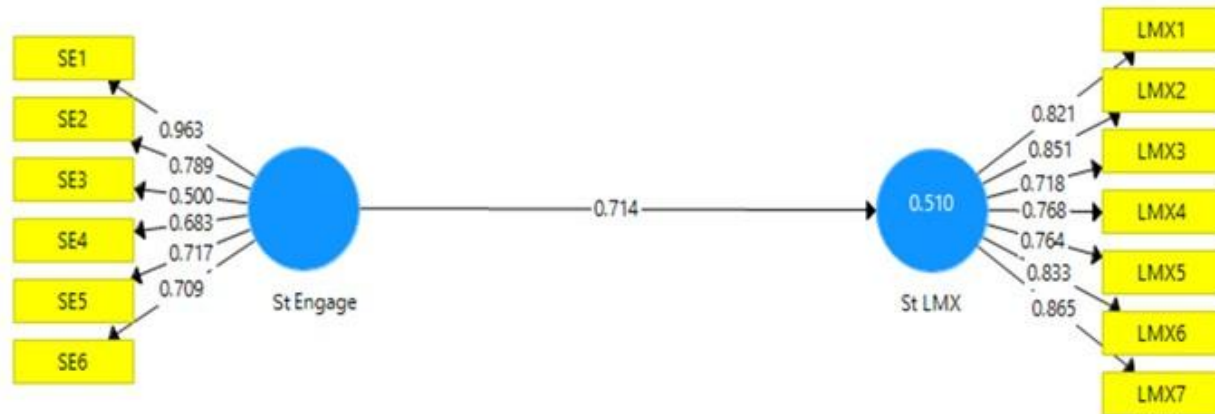
A partial least squares regression analysis was conducted in SmartPLS using consistent path analysis and bootstrap methods to examine the relationship between instructor social presence and student intent to leave, yielding a statistically significant result ($t = 10.841$, $p < .001$), a path coefficient of 0.639, and an R^2 value of 0.409 (See Figure 4). Hence, the null hypothesis is rejected.

Figure 4*Hypothesis 3 Bivariate Analysis***RQ 2: To what extent does student engagement predict student-LMX and student intent to leave at online universities?**

H0₄: There is no relationship between student engagement and student-LMX.

Ha₄: There is a statistically significant relationship between student engagement and student-LMX.

A partial least squares regression analysis was conducted in SmartPLS using consistent path analysis and bootstrap methods to examine the relationship between student engagement and student-LMX, yielding a statistically significant result ($t = 19.018$, $p < .001$), a path coefficient of 0.714, and an R^2 value of 0.510 (See Figure 5). Hence, the null hypothesis is rejected.

Figure 5*Hypothesis 4 Bivariate Analysis***RQ 2: To what extent does student engagement predict student-LMX and student intent to leave at online universities?**

H0₅: There is no relationship between student engagement and student intent to leave. Ha₅: There is a statistically significant relationship between student engagement and student intent to leave.

A partial least squares regression analysis was conducted in SmartPLS using consistent path analysis and bootstrap methods to examine the relationship between student engagement and student intent to leave, yielding a statistically significant result ($t = 12.418$, $p < .001$), a path coefficient of -0.578 , and an R^2 value of $.334$ (See Figure 6). Hence, the null hypothesis is rejected.

Figure 6*Hypothesis 5 Bivariate Analysis*

RQ 3: To what extent does student-LMX predict student intent to leave at online universities?

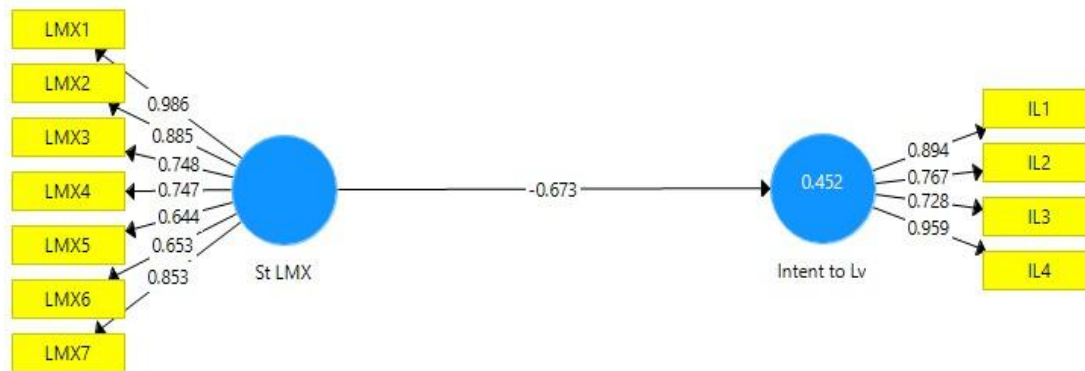
H0₆: There is no relationship between student-LMX and student intent to leave.

Ha₆: There is a statistically significant relationship between student-LMX and student intent to leave.

A partial least squares regression analysis was conducted in SmartPLS using consistent path analysis and bootstrap methods to examine the relationship between student-LMX and student intent to leave, yielding a statistically significant result ($t = 11.745$, $p < .001$), a path coefficient of $-.673$, and an R^2 value of $.452$ (See Figure 7). Hence, the null hypothesis is rejected.

Figure 7

Hypothesis 6 Bivariate Analysis

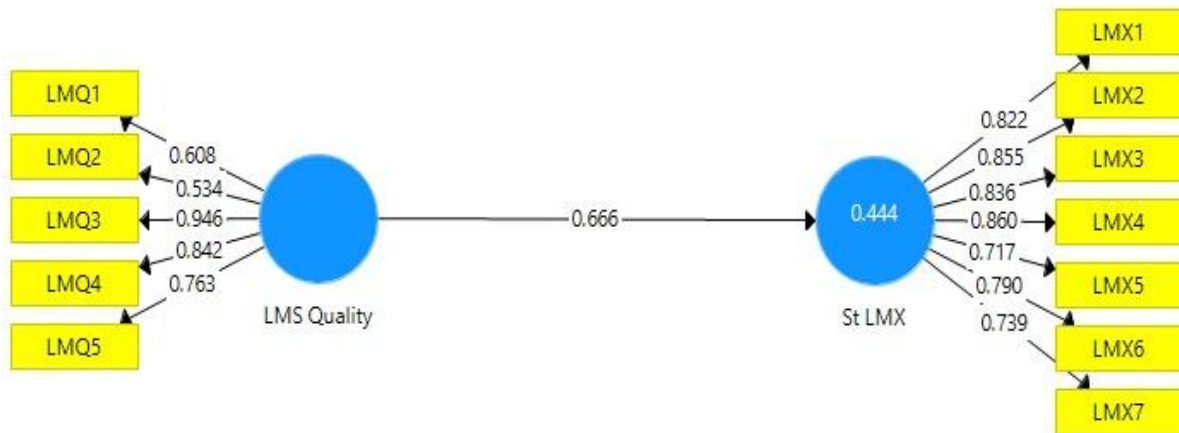


RQ4: To what extent does learning management system quality predict student-leader member exchange (student-LMX), and student intent to leave?

H0₇: There is no relationship between learning management system quality and student-leader member exchange (student-LMX) score.

Ha₇: There is a statistically significant relationship between learning management system quality and student-leader member exchange (student-LMX) score.

A partial least squares regression analysis was conducted in SmartPLS using consistent path analysis and bootstrap methods to examine the relationship between learning management system quality and student-leader member exchange, yielding a statistically significant result of $t = 12.418$, $p < .001$, a path coefficient of 0.666 , and an R^2 value of 0.444 (See Figure 8). Hence, the null hypothesis is rejected.

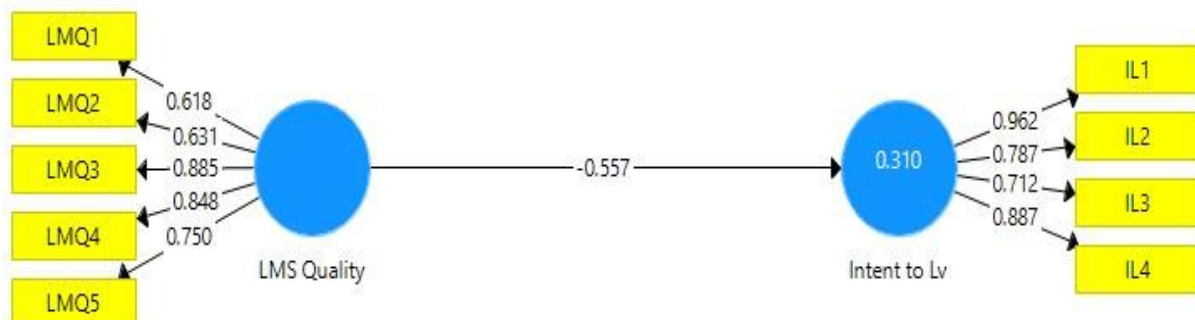
Figure 8*Hypothesis 7 Bivariate Analysis*

RQ4: To what extent does learning management system quality predict student-leader member exchange (student-LMX), and student intent to leave?

H0₈: There is no significant relationship between the quality of the learning management system and students' intent to leave.

Ha₈: There is a statistically significant relationship between learning management system quality and student intent to leave.

A partial least squares regression analysis was conducted in SmartPLS using consistent path analysis and bootstrap methods to examine the relationship between learning management system quality and student intent to leave, yielding a statistically significant result ($t = 7.944$, $p < .0001$), a path coefficient of $-.557$, and an R^2 value of $.310$ (See Figure 9). Hence, the null hypothesis is rejected.

Figure 9*Hypothesis 8 Bivariate Analysis*

Multivariate analysis – mediation. Below are the mediation hypothesis tests that were run utilizing SmartPLS. These results are presented in a model format to provide the reader with a visual representation of the tested relationships.

RQ5: To what extent does student-LMX mediate the relationship between instructor social presence and student intent to leave at online universities?

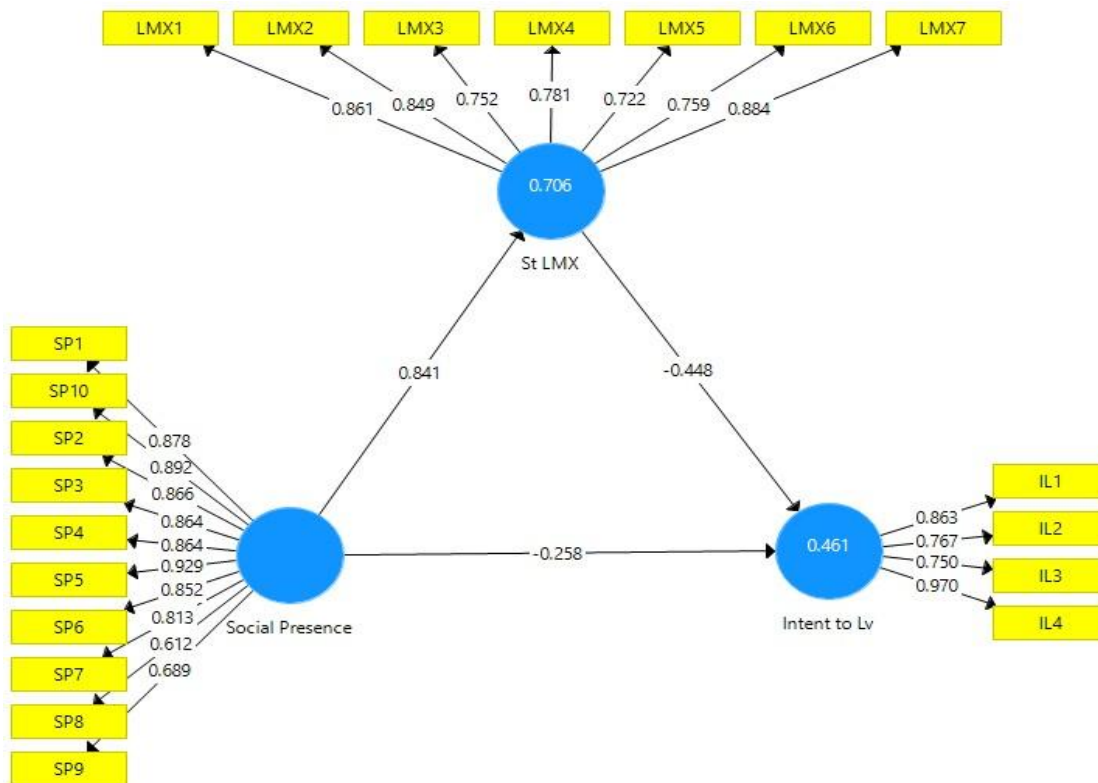
H0₉: Student-LMX will not partially mediate the relationship between instructor social presence and student intent to leave.

Ha₉: Student-LMX will partially mediate the relationship between instructor social presence and student intent to leave.

A mediation analysis was conducted to determine the extent to which student-LMX mediates the relationship between instructor social presence and student intent to leave utilizing PLS continuous bootstrapping algorithm. The isolated mediation model is depicted in Figure 10 below.

Figure 10

Hypothesis 9 Mediation Analysis



P values corresponding to the specific paths are specified in Table 8 below.

Table 8*Path Coefficients and p Values for Ha9 Mediation Analysis*

Path	Path coefficient	P values
Social presence -> Intent to lv.	-0.258	0.013
Social presence -> St.-LMX	0.841	.000
St.-LMX -> Intent to lv.	-0.448	.000

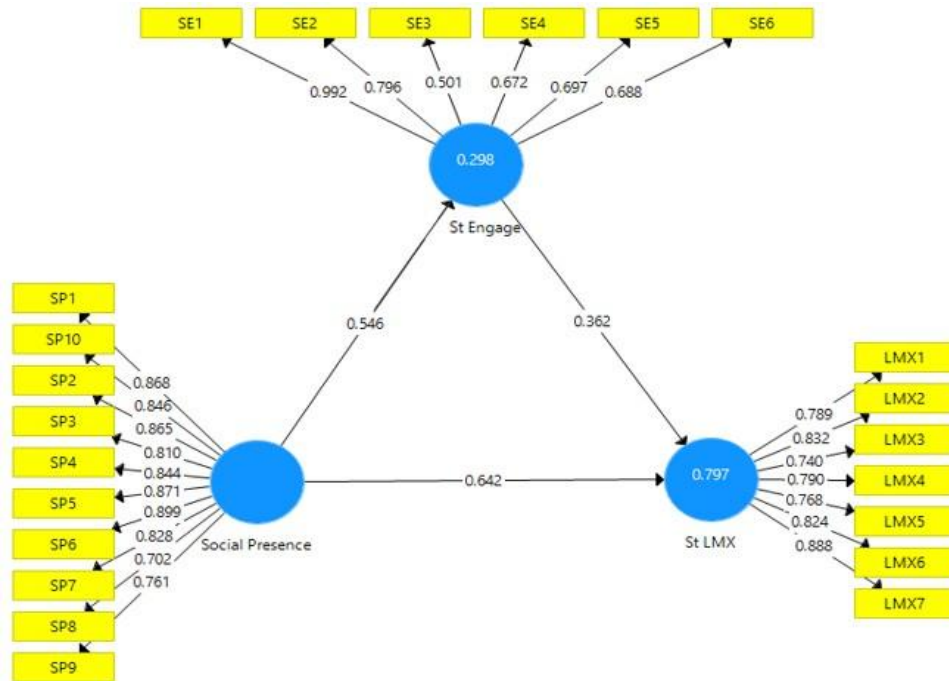
Based on Table 8, all three pathways in the mediation model are significant. The indirect effect for this mediation model for the Social presence -> St.-LMX -> Intent to lv. The pathway resulting from the PLS continuous bootstrap algorithm also indicated a p-value of <.000. Thus, mediation is taking place along this pathway, and the significant value for the direct pathway indicates partial mediation. Full mediation would have resulted in no significant result for the Social presence -> Intent to lv. pathway. Hence, the null hypothesis is rejected.

RQ6: To what extent does student engagement mediate the relationship between instructor social presence and student-LMX and between instructor social presence and student intent to leave at online universities?

H₀₁₀: Student engagement will not partially mediate the relationship between instructor social presence and student-LMX.

Ha₁₀: Student engagement will partially mediate the relationship between instructor social presence and student-LMX.

A mediation analysis was conducted to determine the extent to which student engagement mediates the relationship between instructor social presence and student-LMX utilizing PLS continuous bootstrapping algorithm. The isolated mediation model is depicted in Figure 11 below.

Figure 11*Hypothesis 10 Mediation Analysis*

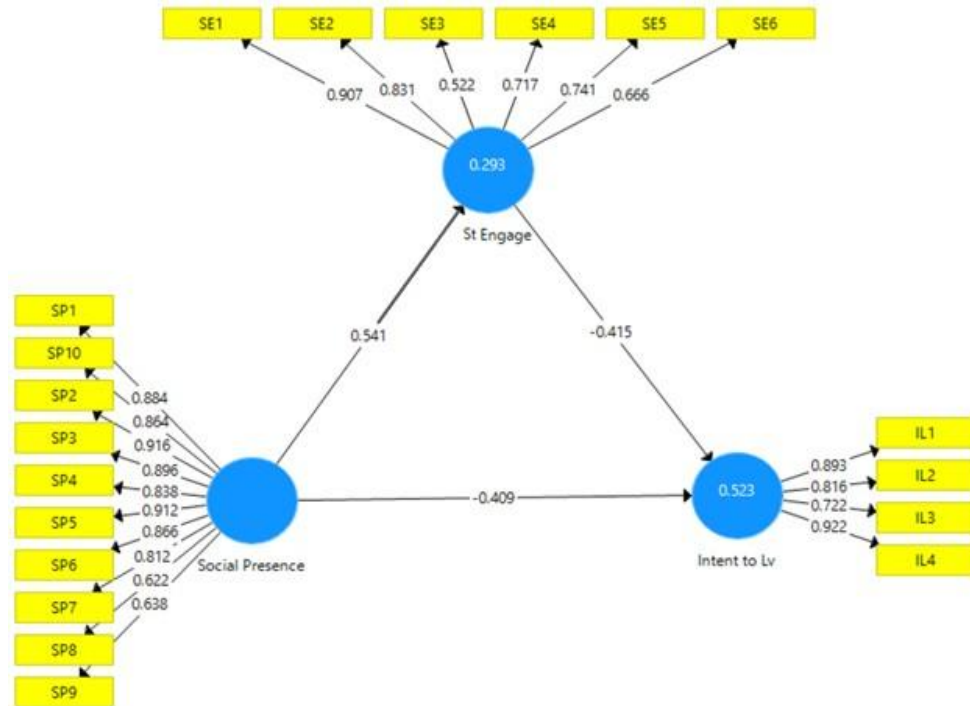
All three pathways in the mediation model were significant ($p < .001$). The indirect effect for this mediation model, involving the social presence $\rightarrow$ St. engage $\rightarrow$ St.-LMX pathway, was also indicated by the PLS continuous bootstrap algorithm to have a value of $p < .000$. Thus, mediation is occurring along this pathway, and partial mediation is indicated by the significant value for the direct pathway. Hence, the null hypothesis is rejected.

RQ6: To what extent does student engagement mediate the relationship between instructor social presence and student-LMX and between instructor social presence and student intent to leave at online universities?

H0₁₁: Student engagement will not partially mediate the relationship between instructor social presence and student intent to leave.

Ha₁₁: Student engagement will partially mediate the relationship between instructor social presence and student intent to leave.

A mediation analysis was conducted to determine the extent to which student engagement mediates the relationship between instructor social presence and student intent to leave utilizing PLS continuous bootstrapping algorithm. The isolated mediation model is depicted in Figure 12 below.

Figure 12*Hypothesis 11 Mediation Analysis*

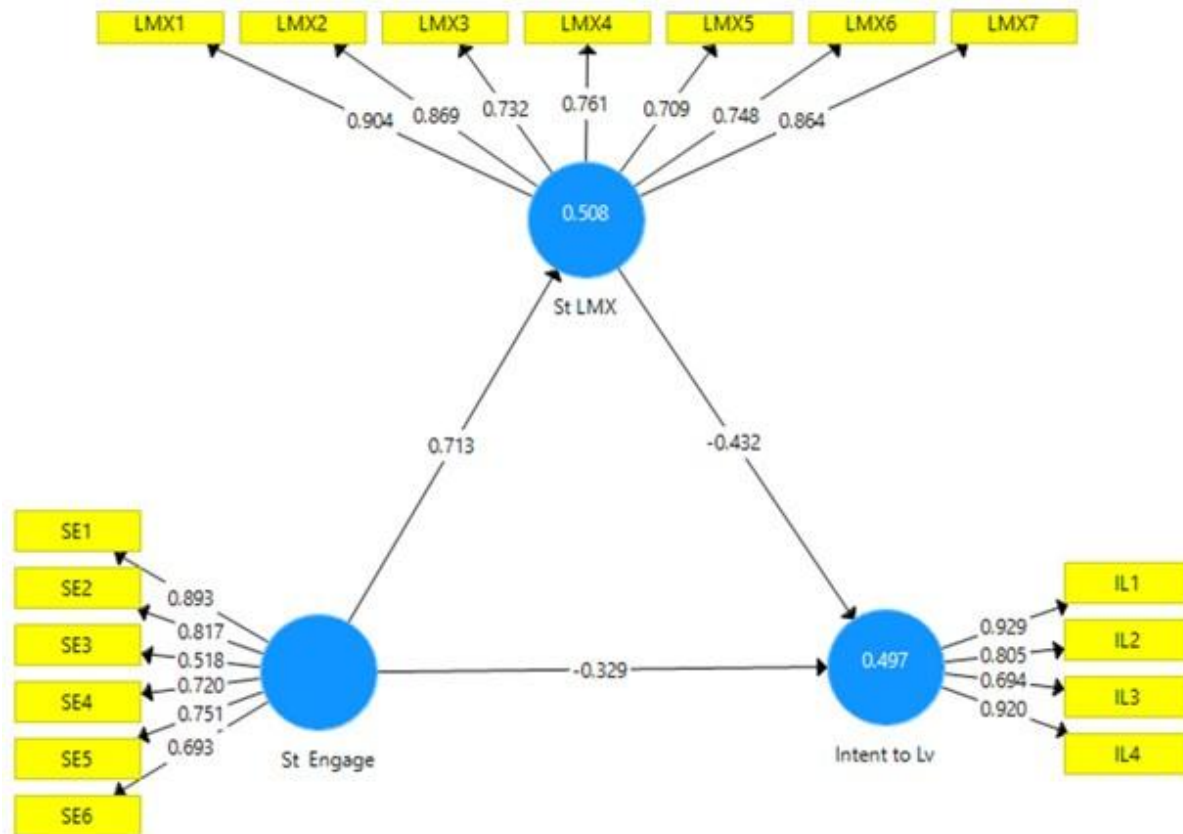
All three pathways in the mediation model were significant ($p < .001$). The indirect effect for this mediation model is for Social presence $\rightarrow$ St. engage $\rightarrow$ Intent to leave. pathway resulting from the PLS continuous bootstrap algorithm also indicated a value of $p < .000$. Thus, mediation is taking place along this pathway and partial mediation is indicated by the significant values for the direct pathway. Hence, the null hypothesis is rejected.

RQ7: To what extent does student-LMX partially mediate the relationship between student engagement and student intent to leave?

H0₁₂: Student-LMX will not partially mediate the relationship between student engagement and student intent to leave.

Ha₁₂: Student-LMX will partially mediate the relationship between student engagement and student intent to leave.

A mediation analysis was conducted to determine the extent to which student-LMX mediates the relationship between student engagement and student intent to leave utilizing PLS continuous bootstrapping algorithm. The isolated mediation model is depicted in Figure 13 below.

Figure 13*Hypothesis 12 Mediation Analysis*

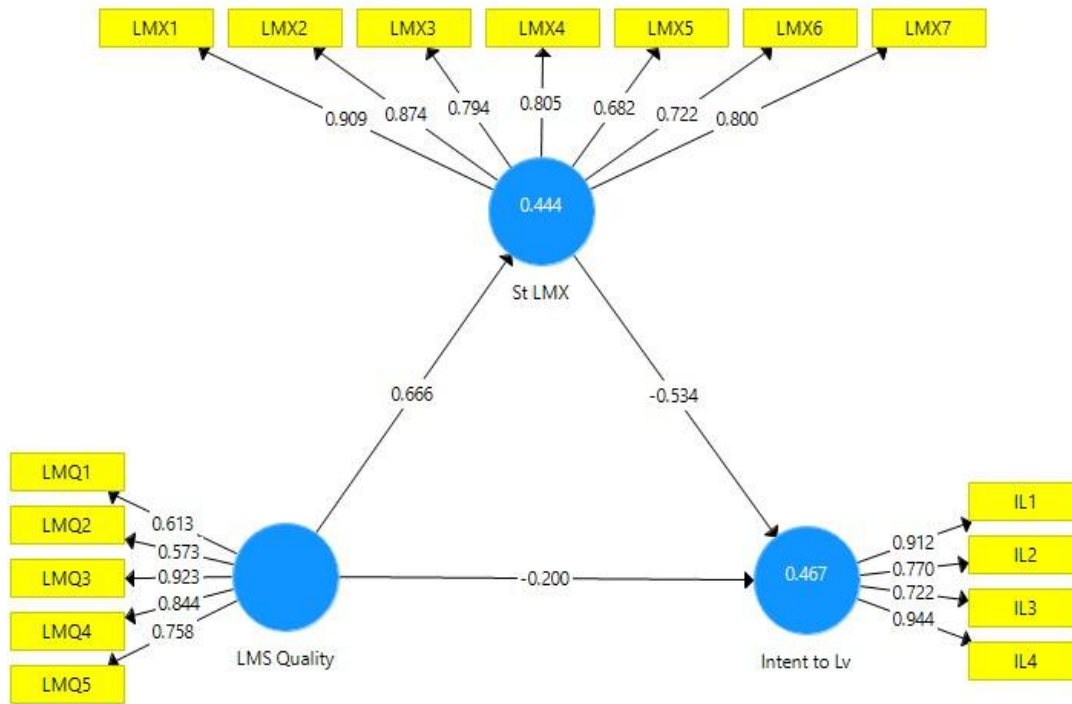
All three pathways in the mediation model were significant ($p < .001$). The indirect effect for this mediation model for the St. engage $\rightarrow$ St.-LMX $\rightarrow$ Intent to lv. pathway resulting from the PLS continuous bootstrap algorithm also indicated a value of $p < .000$. Thus, mediation is taking place along this pathway, and the significant values for the direct pathway indicate partial mediation. Hence, the null hypothesis is rejected.

RQ8: To what extent does student-LMX mediate the relationship between learning management system quality and student intent to leave at online universities?

H0₁₃: Student-LMX will not partially mediate the relationship between learning management system quality and student intent to leave.

Ha₁₃: Student-LMX will partially mediate the relationship between learning management system quality and student intent to leave.

A mediation analysis was conducted to determine the extent to which student-LMX mediates the relationship between LMS quality and student intent to leave, utilizing PLS continuous bootstrapping algorithm. The isolated mediation model is depicted in Figure 14 below.

Figure 14*Hypothesis 13 Mediation Analysis*

P values corresponding to the specific paths are specified in Table 9 below.

Table 9*Path Coefficients and p Values for Ha13 Mediation Analysis*

Path	Path Coefficient	P Values
LMS quality -> Intent to lv.	-0.200	0.125
LMS quality -> St.-LMX	0.666	.000
St.-LMX -> Intent to lv.	-0.534	.000

Based on Table 9, only the mediation pathways in the model are significant; the main effect is not. The indirect effect for this mediation model for the LMS quality -> St.-LMX -> Intent to lv. pathway resulting from the PLS continuous bootstrap algorithm, however, is significant ($p < .000$). Thus, mediation is taking place along this pathway. However, hypothesis testing for Ha8 indicated a strongly significant relationship between LMS quality and intent to leave. This indicates full mediation through the student-LMX pathway. Hence, the null hypothesis is rejected only if mediation did not take place. The mediation effect, however, was full mediation rather than partial mediation.

Model Mediation Effects

Although all the isolated mediation models presented above indicated either partial or full mediation, evaluation of the complete causal model indicates that the relationships identified in the isolated mediation models do not translate to the causal model. Some of the mediation effects are masked when all variables are considered together in the full model. This is due to the influence of multiple variables on the overall model outcomes. The analysis of mediation pathways for the causal model is presented in Table 10 below and illustrated in Table 13. Note that only two of the mediation pathways are identified as producing a statistically significant indirect effect. These two pathways are 1) Social presence -> St. engage -> Intent to lv. and 2) Social presence -> St. engage -> St.-LMX. In both cases, student engagement is the mediating variable, indicating a stronger efficacy as a conduit in the model for explaining variation between variables.

None of the other proposed mediation pathways that demonstrated mediation when tested as isolated models were significant in the overall model. Again, this demonstrates the central importance of the student engagement variable for explaining relationships in the model.

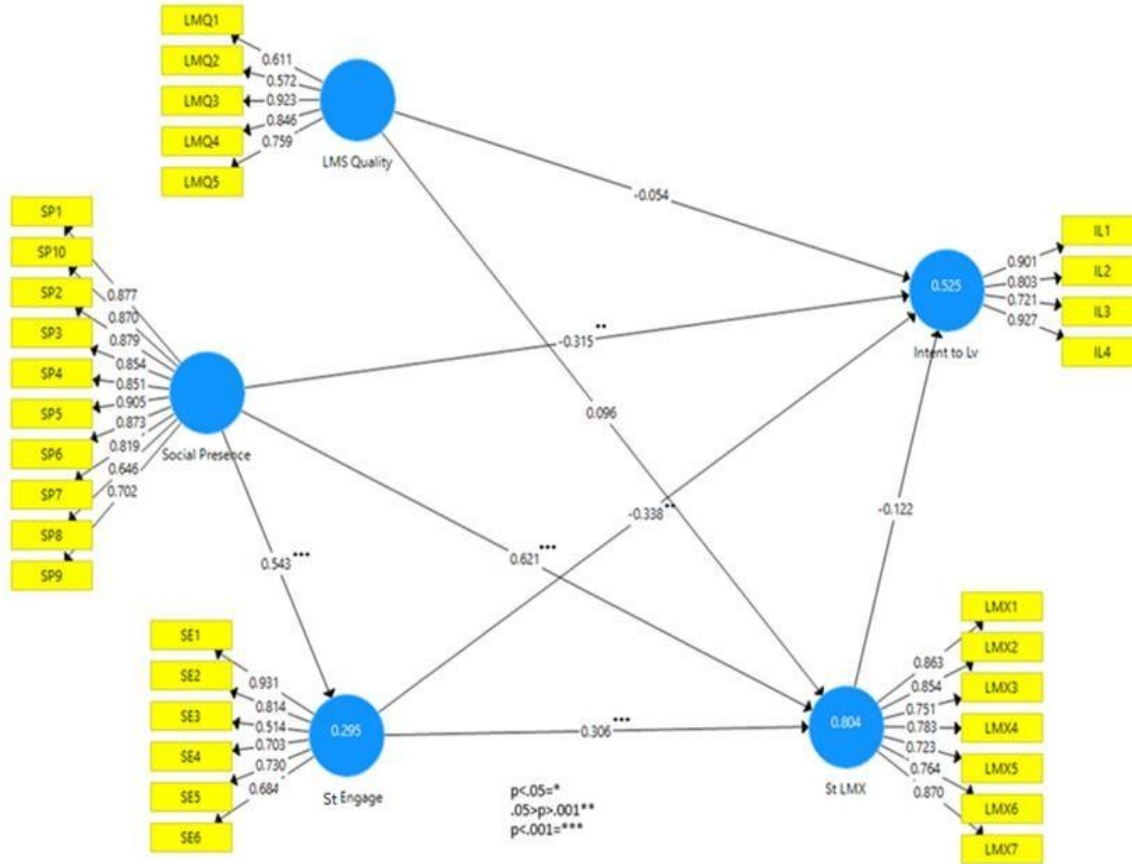
Table 10

Specific Indirect Effects - Model

	T Statistics	P Values
Social presence -> St.-LMX -> Intent to lv.	0.796	0.426
St. engage -> St.-LMX -> Intent to lv.	0.802	0.423
Social presence -> St. engage -> Intent to lv.	2.342	0.019
Social presence -> St. engage -> St.-LMX	4.671	0.000
Social presence -> St. engage -> St.LMX -> Intent to lv.	0.79	0.43
LMS quality -> St.-LMX -> Intent to lv.	0.574	0.566

Causal Model and Model Fit

The causal/structural model is indicated in Figure 16 below. In evaluating model fit, an attempt was made to eliminate lower loading variables LMQ2 and SE3 with only minor differences noted in the overall model path coefficients and levels of significance. Thus, the original model outcomes are indicated in Figure 15 below.

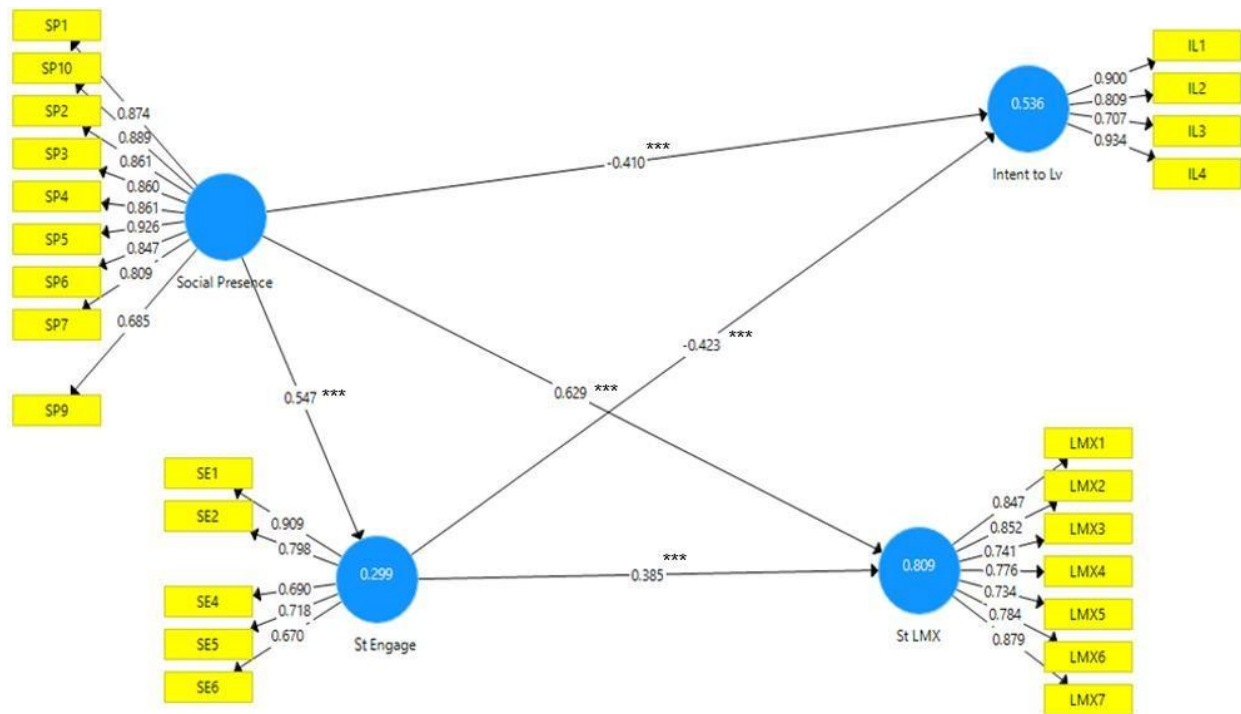
Figure 15*Causal Model***Table 11***Causal Model Path Coefficients and T-test Outcomes*

	Path Coeff.	T Statistics	P Values
LMS quality -> Intent to lv.	-0.054	0.337	0.736
LMS quality -> St.-LMX	0.096	1.427	0.154
Social presence -> Intent to lv.	-0.315	2.86	0.004
Social presence -> St.-LMX	0.621	9.953	0.000
Social presence -> St. engage	0.543	9.846	0.000
St.-LMX -> Intent to lv.	-0.122	0.766	0.444
St. engage -> Intent to lv.	-0.338	2.502	0.012
St. engage -> St.-LMX	0.306	4.787	0.000

Proponents of PLS argue that although model fit indices are appropriate for covariance-based structural equation modeling, they are not appropriate for PLS PLS-based models. Fit indices are included in the SmartPLS analytical tool suite; however, interpreting these fit indices should be done with caution (Gaskin, 2018). The standardized root mean square residual (SRMR) is considered the most reliable of the fit indices in the SmartPLS analytical suite, and a value of less than 0.08 is considered appropriate for demonstrating model fit. The model above had an SRMR of 0.09. The other value identified as a more reliable indicator is the normed fit index (NFI) with a value of at least 0.9. The NFI value for the model identified above was .71.

Although the intent of this study was to focus on hypothesis testing rather than identifying model fit, an attempt was made to improve the model fit by implementing several intuitive changes to the model. First, two variables that did not load strongly were removed. This resulted in a very minor decrease in SRMR. Further exploratory steps yielded a model with an SRMR below 0.08.

Since LMS quality did not yield any significant paths to either St.-LMX or Intent to lv., the variable was removed. Additionally, the path between student-LMX and intent to leave was insignificant in the causal model and was therefore removed. This yielded an SRMR of .059 and an NFI of 0.793. Note that this model is consistent with the discussion of overall model mediation effects discussed in the previous section in that the student engagement variable serves as the primary mediator in both the causal model diagramed above and the adjusted model depicted in Figure 16 below.

Figure 16*Adjusted Model***Table 12***Amended Model Path Coefficients and T-test Outcomes*

	Path Coefficients	T Statistics	P Values
Social presence -> Intent to lv.	-0.41	4.888	.000
Social presence -> St.-LMX	0.629	11.274	.000
Social presence -> St. engage	0.547	9.571	.000
St. engage -> Intent to lv.	-0.423	5.688	.000
St. engage -> St.-LMX	0.385	6.585	.000

Summary

In this section, descriptive statistics, factor analysis and related tests, bivariate analyses, multivariate analyses, and the overall causal model were discussed. Considerable attention was paid to discussing the factor analysis due to high cross-loadings between the instructor's intent to stay and student-LMX variables, which raised concerns about discriminant validity. Overall, the variables utilized in this study provided indicators of good reliability and validity.

Hypothesis testing was also presented. All bivariate statistical tests utilizing SmartPLS partial least squares regression analysis resulted in rejection of the respective null hypotheses. Likewise, each mediation hypothesis was studied in isolation from the overall model for hypothesis testing. All mediation analyses resulted in rejection of the respective null hypotheses except for the LMS quality -> St.-LMX -> Intent to lv. pathway, which resulted in full mediation.

Analysis of the overall causal model revealed that several pathways were no longer significant compared to the bivariate analysis results. Also, several of the mediation analyses depicted in the causal model were no longer significant as compared to the mediation analyses conducted for each mediation hypothesis. These discrepancies were due to interacting effects of the variables in the model. Also, instructor social presence served as a strong independent variable overall, resulting in significant pathways with student intent to leave, student-LMX, and student engagement variables. Student engagement served as the primary mediator in the model.

Recommendations and Conclusions

When considering the effort and resources required to recruit students and get them to enroll in a particular university program, it is more cost-effective to retain a given student than to try to solicit more prospective students through marketing and outreach efforts (Willging & Johnson, 2019). The purpose of this study was thus to identify potential strategies to help retain students in an online program by highlighting the importance of the instructor as a relationship builder with students and the influence that stronger instructor-student relationships might have on preventing students from leaving the university. This study, therefore, focused on understanding how factors such as instructor social presence, the exchange relationship between the instructor and the student, a student's engagement in his or her coursework, and the quality of the learning management system all interplay to influence a given student's intent to leave his or her program of study.

To determine the interplay of these variables in influencing a student's intent to stay or leave a university's program, this study employed a correlational, cross-sectional, non-experimental design using a survey instrument administered to students attending an online university. The survey was provided online, and student were notified that they could voluntarily take the survey via an announcement posted in their courses. Respondents were required to view an informed consent statement and agree to the terms prior to taking the survey.

One of the more interesting results from analyzing the collected data indicated that instructor social presence is crucial in ensuring students remain engaged in their courses, and this interaction is inversely related to student intent to leave the university. There are, of course, some key limitations to the study. Having a cross-sectional design, for instance, limits one's ability to infer cause and effect. Additionally, only one university was included in the sample, which may have limited the generalizability of the findings. These issues will be explored in more detail in this chapter, which presents many of the findings identified in the previous

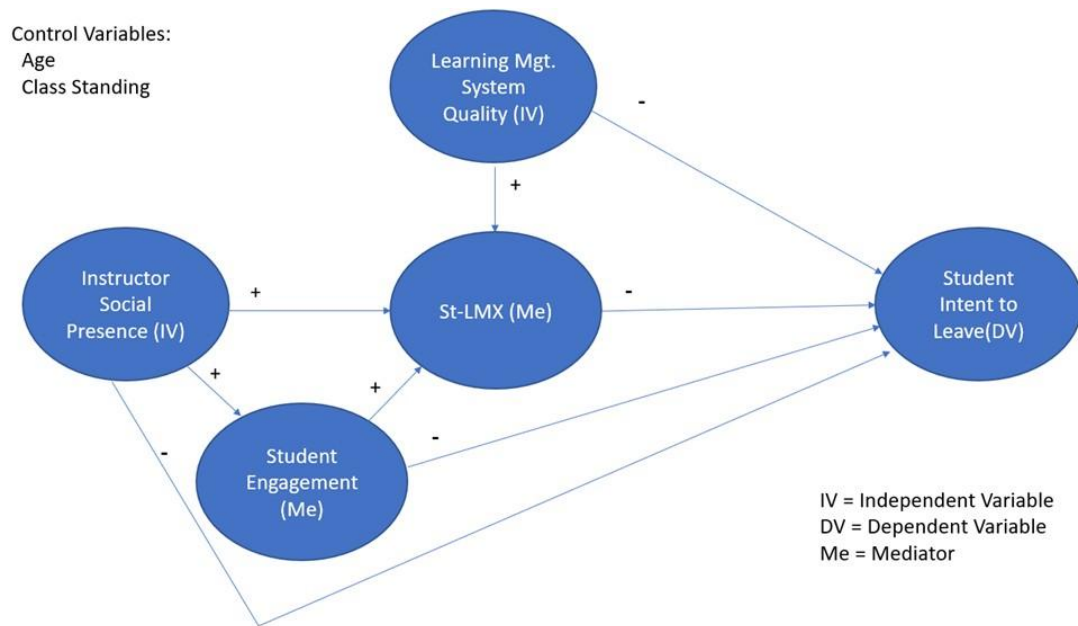
chapter, including insights into some of the interaction effects related to the set of research questions initially presented in Chapter I. Some theoretical and practical implications will also be considered, and recommendations will be presented.

General Findings and Implications

The best way to conceptualize the gist of the research questions and hypotheses examined in this study is to revisit the theoretical model. See Figure 17 below.

Figure 17

Theoretical Model



Each path in the model represents a hypothesis, and each hypothesis reflects one of the research questions presented. Examining the bivariate relationships depicted, each was identified as statistically significant through partial least squares regression analysis. Likewise, each of the mediation pathways was also determined to be statistically significant. The only exception noted in the mediation analyses was the pathway between learning management system quality, student-LMX, and student intent to leave. This mediation analysis indicated a full mediation effect of student-LMX.

Based on these findings, all the research questions were answered affirmatively. The partial least squares bivariate and mediation analyses provided strong evidence to support the following statements in response to RQs 1-8, respectively:

1. Instructor social presence is positively related to student engagement and student-LMX and negatively related to student intent to leave at online universities.

2. Student engagement is positively related to student-LMX and negatively related to student intent to leave at online universities.
3. Student-LMX is negatively related to student intent to leave at online universities.
4. Learning management system quality is positively related to student-leader member exchange (student-LMX) and negatively related to student intent to leave at online universities.
5. Student-LMX partially mediates the relationship between instructor social presence and student intent to leave at online universities.
6. Student engagement partially mediates the relationship between instructor social presence and student-LMX and between instructor social presence and student intent to leave at online universities.
7. Student-LMX partially mediates the relationship between student engagement and student intent to leave at online universities.
8. Student-LMX fully mediates the relationship between learning management system quality and student intent to leave at online universities.

Much of the research conducted on student attrition to date has focused on various aspects and attributes of the students themselves, rather than on actions that universities and their instructors can take to help with student retention. A significant portion of the research on student attrition, for instance, has linked students who exit universities prematurely to student attributes such as minority status, gender, and economic hardship (Edwards & McMillan, 2015; Farr-Wharton et al., 2018). And although it is good to maintain a focus on student demographics as they relate to successful educational outcomes for the purposes of establishing useful policies in an effort at achieving social equity, it is also important to consider strategies that might be enacted at the university level to help decrease attrition regardless of minority or economic standing.

Unfortunately, many universities do not invest in helping their instructors ensure student success through efforts aimed at building instructor-student relationships. According to Paquette (2016), Instructors are hearing words like motivation, persistence, and retention, yet they do not know how to develop or instruct online courses that encourage their students to engage and interact with their classmates. They are unaware that assuring that they interject social presence into their online courses could change the entire atmosphere of a course. This is regardless of the ongoing research that clearly indicates the important role instructors play in getting students engaged in their courses or how such engagement impacts successful outcomes.

Based on the results of the present study, instructor social presence is crucial for fostering a positive relationship with students, and it is also essential to ensure that students remain engaged in their coursework. What is particularly noteworthy, given the study's results, is that the pathway from social presence through engagement was the strongest predictor of intent to leave in the overall model. In fact, this pathway attenuated both the LMX mediator pathways as compared to when each mediation effect was considered separately. Note in Table 13 below that only the independent variable, instructor social presence, and the mediator, student engagement, remained significantly related to the student intent to leave variable when the entire model was considered. This suggests that social presence and student engagement have superior explanatory power compared to other considered pathways.

Table 13*Causal Model Path Coefficients*

	Path coeff.	T statistics	P values
LMS quality -> Intent to lv.	-0.054	0.337	0.736
LMS quality -> St.-LMX	0.096	1.427	0.154
Social presence -> Intent to lv.	-0.315	2.86	0.004
Social presence -> St.-LMX	0.621	9.953	0.000
Social presence -> St. Engage	0.543	9.846	0.000
St.-LMX -> Intent to lv.	-0.122	0.766	0.444
St. Engage -> Intent to lv.	-0.338	2.502	0.012
St. Engage -> St.-LMX	0.306	4.787	0.000

This, of course, does not mean that the relationship between the student and instructor is unimportant. As noted in the bivariate and mediation analyses, LMX is strongly indirectly related to intent to leave, except when instructor social presence and student engagement are considered. Thus, relationship building is important, but the instructor's social presence appears to have the strongest impact on student engagement, which in turn decreases the likelihood that students will drop out of the program.

Implications

From a theoretical perspective, the primary implications of this research are twofold. First, all the proposed hypotheses were supported when simple bivariate and mediation models were examined, which were based on existing student-leader management exchange theory and social presence theory. Second, the observation is that the path between instructor social presence and intent to leave, as well as the interaction between instructor social presence, student-LMX, and intent to leave, played a significant role in describing variance-based relationships in the proposed model.

Thus, research on the impact of student-LMX on student attrition appears to be sound and supported by this research. However, the instructor social presence -> student engagement pathway seems to be worthy of additional consideration and research. This finding is consistent with the work of Oyarzun et al. (2018), who demonstrated that the degree of instructor social presence significantly influences instructor perceptions of student achievement, and that a well-designed, collaborative learning activity can be an effective strategy for building instructor social presence.

From a practical perspective, it is essential for universities to take the role of instructors seriously as individuals who have a direct impact on driving student engagement and how this can affect student attrition. Identifying strategies to ensure instructors are creating an environment that encourages students to be engaged can be an important strategy for enhancing student retention. One such strategy would be to develop training programs for instructors to

inform them of the theory and practices that are useful for conveying social presence (Paquette, 2016). Kim and Thayne (2015) demonstrated that video lectures incorporating relationship-building strategies yielded more positive student attitudes toward their online learning experiences compared to those that did not employ such strategies. Other strategies have also been identified based on social presence theory.

We noted that online universities have historically had a harder time retaining students as compared to brick-and-mortar universities. One of the goals of this study was to inform the understanding of this problem and identify potential strategies to support the retention of online students at online universities. Overall, this study suggests that instructors should be educated on how to establish a stronger social presence in their courses. This helps build relationships through the student-LMX pathway, but more importantly, it motivates students to become engaged in their coursework, which in turn helps them achieve success.

Recommendations

The primary recommendation for future research would be to expand the sample population to include other online universities. This would be important to determine if the quality of learning management systems plays a larger role than indicated in the current study, given the sophisticated quality systems used by the focal university to ensure consistency between course formatting and delivery. This would also help to expand the degree to which the findings of this study might be generalized to a larger population of online universities. Additionally, it is reasonable to assume that the findings of this study may also be applicable to traditional brick-and-mortar universities, which tend to have a younger demographic.

Ultimately, it may be beneficial to consider creating measurement scales for social presence and learning management systems that are more distinct from one another. Delving deeper into LMX and social presence theory and research to develop measurement scales that are more distinct from each other could be useful in future research.

Conclusion

The primary takeaway from this study is that online universities should consider investing in their faculty by providing professional development to help course faculty and instructors understand the value of having a strong social presence in their courses and teach them how to achieve it. The importance of relationship building with students should also be addressed. The results of this study clearly indicate that instructor social presence is strongly related to student engagement, and student engagement is negatively related to student attrition. Studies have shown that engagement is also related to student success (Farr-Wharton et al., 2017). Additionally, the return on investment in developing a faculty culture that fosters high levels of course engagement, with the goal of building stronger relationships with students, appears worthwhile compared to the efforts currently employed to attract new students. Retaining students through decreased university attrition should help to ensure overall growth for online institutions.

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Appendix A

Cross Loadings

		LMS quality	Social presence	St. LMX	St. engage
IL1	Intent to lv 0.901	-0.535	-0.518	-0.596	-0.62

IL2	0.803	-0.437	-0.489	-0.507	-0.549
IL3	0.721	-0.396	-0.497	-0.481	-0.413
IL4	0.927	-0.495	-0.619	-0.64	-0.545
LMQ1	-0.344	0.611	0.34	0.403	0.531
LMQ2	-0.35	0.572	0.255	0.354	0.489
LMQ3	-0.494	0.923	0.573	0.629	0.601
LMQ4	-0.473	0.846	0.461	0.56	0.573
LMQ5	-0.416	0.759	0.406	0.509	0.56
LMX1	-0.664	0.547	0.653	0.863	0.587
LMX2	-0.596	0.57	0.691	0.854	0.606
LMX3	-0.502	0.557	0.628	0.751	0.51
LMX4	-0.503	0.572	0.67	0.783	0.548
LMX5	-0.433	0.477	0.643	0.723	0.544
LMX6	-0.439	0.525	0.687	0.764	0.593
LMX7	-0.574	0.491	0.754	0.87	0.618
SE1	-0.512	0.653	0.565	0.687	0.931
SE2	-0.54	0.628	0.439	0.563	0.814
SE3	-0.339	0.338	0.275	0.359	0.514
SE4	-0.484	0.538	0.357	0.488	0.703
SE5	-0.504	0.486	0.364	0.511	0.73
SE6	-0.427	0.535	0.356	0.506	0.684
SP1	-0.566	0.404	0.877	0.731	0.472
SP10	-0.581	0.447	0.87	0.736	0.427
SP2	-0.575	0.497	0.879	0.709	0.503
SP3	-0.605	0.43	0.854	0.683	0.441
SP4	-0.549	0.438	0.851	0.725	0.433
SP5	-0.622	0.476	0.905	0.756	0.441
SP6	-0.511	0.541	0.873	0.738	0.515
SP7	-0.501	0.499	0.819	0.694	0.455
SP8	-0.324	0.443	0.646	0.56	0.422
SP9	-0.353	0.465	0.702	0.64	0.409
