Examining and Modelling Students' Selection of Course Modality

by

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Abstract

Despite online courses' growing popularity, the factors that shape undergraduates' choice of course modality are still poorly understood. This study explores the relations between a wide range of factors and students' modality selection, in a context where both modalities — face-to-face and online — were made available. Undergraduates from a Canadian University enrolled in face-to-face ($N = 335$) and online courses ($N = 315$) completed a questionnaire assessing personal factors, course attributes, goal orientation and learning strategies. Data were subject to descriptive and inferential statistical analysis, and two logistic regressions were performed to model students' enrolment and preference. Analysis revealed that the groups differed significantly in twelve variables. For example, number of previous online courses and enjoyment of online courses were significantly higher for online students. Logistic regression analysis extended these findings, indicating ten significant predictors for online enrolment, among them higher number of previous online courses and higher work-avoidance goals.

Keywords: Modality; Study mode; Higher education; Choice; Online learning; Logistic regression

Dedication

To my parents

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List of Acronymns

- CODE - Centre for Online and Distance Education
- EM - Expectation-Maximization
- FTF - Face-to-Face
- GOQ - Goal Orientation Questionnaire
- GPA - Grade Point Average
- MCAR - Missing Completely at Random
- MNAR - Missing not at Random
- MSLQ - Motivated Strategies for Learning Questionnaire
- MVA - Missing Value Analysis
- NPSAS - National Postsecondary Student Aid Study
- SFU - Simon Fraser University
- SRL - Self-regulated Learning
- VIF - Variance Inflation Factor

Glossary of Terms

Course Modality	In the context of this study, the term refers to the instructional delivery method used by a course (face-to-face, online, blended, etc.)
Mode	Used interchangeably with Modality
Face-to-Face Courses	Course modality where content is mostly delivered face-to-face, in writing or orally (Allen and Seaman, 2014). Computer-mediated instruction is sometimes used, but student and teacher interactions are mostly in person.
Online Learning	Course modality where students attend courses solely online, asynchronously or synchronously, with a faculty member delivering instruction through technological means (Clayton et al., 2010)
Distance Education	Formal, institution-based education where interactive telecommunications systems - electronic and non-electronic - are used to connect learners, resources and instructors (Simonson, 2003).
Hybrid or Blended Courses	Instruction that combines face-to-face with computer-mediated instruction (Graham, 2006). Some sources define specific ranges, for instance, Allen and Seaman (2014) says 30 to 79 percent of the content should be delivered online to classify a course as hybrid (Allen and Seaman, 2014).

Chapter 1

Introduction

Undergraduate students today are faced with unprecedented economic challenges: more overall student debt (Houle and Warner, 2017), government funding cuts that lead to increases in net tuition (Chakrabarti et al., 2012; Cain, 2016; Shaker and Macdonald, 2015), delayed degree completion times (Houle and Warner, 2017) and a rise in students' hours of paid work (Behr and Theune, 2016). Educational institutions, equally challenged by budget cuts, attempt to manage the situation by pursuing strategies like increasing non-resident enrolments (Contact North, 2012) and creating online education programs that might help close the financial gap.

Although the costs of creating and offering online courses vary quite a bit and are heavily dependent on institutional design and implementation decisions, some advocates argue that online courses create important economies of scale (Bowen, 2012) and savings that can be passed on to students, resulting in lower overall educational costs over time (Deming et al., 2015). Schedule flexibility (Powell and Keen, 2006; Bates, 2017) and the expanded geographical reach afforded by online learning (Brown, 2012a) can be seen as powerful incentives to adopt this mode of delivery. While there once was criticism that online learning could not provide the same level of learning outcomes as "regular" classes, there is now a considerable body of research comparing examination results from online and face-to-face courses, and overall, learning outcomes are not significantly different (Allen and Seaman, 2014; Johnson et al., 2000; Arbaugh and Stelzer, 2003; Daymont and Blau, 2008; Driscoll et al., 2012; Cavanaugh and Jacquemin, 2015), though student dropout rates are generally higher in fully online courses.

Not surprisingly, the percentage of students taking at least one distance education course has been growing steadily in the last few years in the United States, and reached 31.6% of all higher education enrolments recently (Seaman et al., 2018). In Canada, during 2015, online course enrolment represented around 16% of all course enrolments in universities (Bates, 2017). Even though these numbers have been increasing consistently, it is perhaps puzzling that they are not even larger, given all the aforementioned constraints and challenges that universities face today, and all the benefits and incentives for online education. If more than two-thirds of undergraduate students in the United States are not taking even one online course, why is that so?

The present study tries to address this fundamental question by exploring students' choice of modality (online or face-to-face) and the factors or circumstances that may predict course modality preference and enrolment. Specifically, the study explores undergraduates' modality choice in situations where both modalities (online and face-to-face) are simultaneously available to them. What leads some students to actively pursue the online modality? What drives others to choose the face-to-face modality? Using surveys, descriptive and inferential statistics, and logistic regression modelling, the study aims to better understand these choices and to identify predictors of students' choice.

1.1 State of Research and Problem Context

Previous research on modality choice has examined a variety of variables that can influence students' decisions regarding the modality in which they take a course. Convenience and flexibility are by far the most common reasons given by students for choosing online courses (Thomerson and Smith, 1996; Kleisus et al., 1997; Braun, 2008; Noel-Levitz, 2010; Nguyen, 2011; Harris and Martin, 2012; Kowalski et al., 2014). Experience with online courses is a predictor of student's behavioural intent to take online courses in the future (Cullum, 2016). However, the effect may be mediated by the quality of their previous experiences, with students more likely to declare an intention of taking online courses in the future if they were satisfied with their recent online learning outcomes (Nguyen, 2011). Socialization factors may also play a role. In one study, the most important negative predictor of students' decision to take online courses was the belief they would miss face-to-face communication with the instructor and classmates (Nguyen, 2011); and this finding has been echoed in more recent research.

Kuzma (2015) investigated whether students perceived certain types of classes to be more difficult to take online, and the majority of students believed that courses involving a great amount of description or terminology could more easily be taken online. That finding suggests the possibility that modality choice is influenced by course subject or class type. Also in terms of perceptions, students' ideas about quality of learning in each modality seems to be a decision factor: O'Neill and Sai (2014) surveyed face-to-face students who had actively avoided an online version of the same course and the most commonly cited reason for this was the belief that they would learn more in the face-to-face mode.

Finally, demographic factors of various types are frequently considered in the literature, and mixed results were obtained in terms of how much these factors influence modality choice. Commonly studied variables are sex, income, age, marital status, level of work commitment, and whether the students were veterans or parents. Few studies cover more complex or nuanced demographic factors like race/ethnicity, disability and non-traditional student characteristics (like delayed enrollment, no high school diploma or single-parent status) (Wladis et al., 2015; Terras et al., 2015).

For some time, post-secondary institutions have developed their online course offerings with the assumption that face-to-face students can essentially be converted into online students at the institution's convenience (Chen, 2009; Hixon et al., 2012). However, a much more complex empirical picture emerges from recent research. A more thorough understanding of how students make enrolment choices can be beneficial to both educational institutions and students. When institutions don't understand or can't properly predict students' choices, they may end up offering modalities that fail to meet the needs of students. Financial concerns can dictate the replacement of face-to-face courses with online alternatives, regardless of student demographics or course subject matter, and this may lead to high drop-out rates, student dissatisfaction, or classes that fail to enrol the target number of students. A better understanding of student choice may prevent these types of institutional losses. Students themselves may also benefit from improved research, since it may make it possible for them to be better supported and advised in their decisions, reducing frustration, attrition and underachievement.

1.2 Purpose and Significance of the Study

Although recent studies in this area have had impressive sample sizes, most only include perspectives from either online or face-to-face students, but not both (Braun, 2008; Paechter and Maier, 2010; O'Neill and Sai, 2014). Many studies also cover only one discipline or area of study (Kuzma et al., 2015; Artino, 2010) or have focused on limited subsets of characteristics as explanations for student's choice of modality (Willging and Johnson, 2009; Ortagus, 2017). Yet others have small sample sizes (Braun, 2008; Willging and Johnson, 2009), and no study has addressed studentsâĂŹ competence in the language of instruction as a possible factor in their choice of course modality. These methodological limitations are sharpened by the complexity of the choice landscape: for example, even a student who is keen on peer-learning and face-to-face socialization may face a challenging commute and opt for the online modality when the course is a low-priority elective.

While each of the factors studied previously may play a role in modality choice, a more fruitful approach is to attempt to put these factors into relation with one another and to assess their relative importance and contingency. Therefore, the present study aims to include a much wider range of factors than previous research. To this end, the research team created a very comprehensive survey that addressed a subset of studentsâĂŹ personal characteristics, beliefs and circumstances, while also addressing previously ignored factors such as self-perceived language competence and disability. The survey also included two independently-developed instruments for measuring self-regulatory learning strategies and affective aspects of motivation.

The online learning context at SFU also provides a unique research opportunity since, for many courses, undergraduate students are offered both modalities (face-to-face and fully online) at the same time and in all other aspects, these are equivalent classes. This context is advantageous for studying modality choice since we can not only compare two groups, but we can also better isolate the choice variable and compare students who have not only decided for a modality but also, against the other.

The two objectives of the study are, first, to examine the relations between choice and a number of factors that may be influencing it; and second, to create a preliminary binary logistic regression model for predicting student's actual enrolment or preference for a particular modality. Given the large number of variables under study, a large sample was deemed necessary.

Although the logistic models presented in the study are preliminary, there is great potential in this sort of analysis as a first step towards more mature explanatory statistical models of students' modality choice. An approach such as the one demonstrated in the present study could eventually support institutions in their strategic and administrative decisions - decisions such as which courses to offer in which modes, or which students should be advised to enrol in which modes to minimize attrition and maximize student satisfaction.

1.3 Research Questions

The principal research questions that frame the current study are:

1. What are practically measurable potential influences on students' modality of course enrolment that can be operationalized on the basis of previous research?

2. Which factors contribute the most significantly, and which contribute the least to modality choice?

3. Can a logistic regression model significantly predict modality of enrolment?

4. Can a logistic regression model significantly predict modality of preference?

1.4 Methodology

To address these questions, the study utilized an online survey which was voluntary and anonymous. Participants were recruited from three Faculties at Simon Fraser University: Arts and Social Sciences, Sciences and Education. Importantly, only students enrolled in courses that were offered simultaneously in both modalities were targeted for recruitment. Data collection occurred in two waves: the first group in the Fall of 2017, and the second in the Spring of 2018. Responses were obtained from 650 participants in total: 335 enrolled in face-to-face courses, and 315 enrolled in online courses. Participants were mostly undergraduate students. There were no exclusion criteria for participation in this study. Missing data analysis, response rate analysis, descriptive and inferential statistics, and logistic regressions were performed with R-Studio and IBM SPSS Statistics v24.

1.5 Structure of the Thesis

The present chapter provides an overview of the problem and objectives of this thesis. Chapter 2 will review the literature on student modality choice and the many factors that may be influencing student's selection process. Chapter 3 will explain the context of the present study, its objectives and rationale, its hypotheses and research questions. Additionally, this chapter will review and detail all methods and instruments used in the study. Chapter 4 will present the data analysis, descriptive and inferential statistics grouped by type of variable, and results. Finally, Chapter 5 will summarize and discuss the findings, draw conclusions, outline the limitations of the study, and suggest directions for future research.

Chapter 2

Review of Literature

University students today are confronted with many new challenges. Recent data suggests that students are taking longer on average to complete their degrees than in the recent past, and are accumulating more debt along the way (Houle and Warner, 2017). In the United States, state and local public funds for colleges and universities have fallen every year between 2001 and 2011 while college enrolment numbers swelled from 8.6 million to 11.8 million in the same period. Government funding cuts are associated with increases in net tuition at public schools, particularly since the recession (Chakrabarti et al., 2012).

In Canada, university tuition fess have risen 40% in the decade between 2006 and 2016 (Cain, 2016). Between 1992 and 2012, the percentage of government funding for university operating revenue declined from 77% to 55% and tuition fees also as a share of university operating revenue) increased from 20% to over 37%. The outcome for students is that, on average, tuition and compulsory fees have tripled in this same period (although the increases vary quite a bit between provinces) (Shaker and Macdonald, 2015). As of 2015, when Statistics Canada interviewed college students about their debt, average debt remaining for those who still owed was $13,500 (Statistics Canada, 2015). This number is still lower than the debt of American college seniors from public and private non-profits, who borrowed on average USD$28,650 as of 2017 (TICAS, 2018).

With rising tuition fees, many students must spend more hours pursuing paid work than in the past, and cannot manage as many courses per semester, or cannot manage them as well as they otherwise would (Behr and Theune, 2016). From the perspective of the educational institutions, challenges are also mounting up. Faced with increased economic pressures, institutions pursue a myriad of strategies. Many are increasing non-resident enrolment, given provincial fee regulations that allow institutions to charge higher fees to international students (Contact North, 2012).

2.1 Online Learning as a solution for current challenges

In discussing these pressing concerns, many argue that online education could play a major role in helping the "land-based campus" to adapt (Mazoué, 2012). As the number of "non-traditional newer students" (Falk and Blaylock, 2010) continues to increase as a proportion of overall undergraduate student population, so does the need for institutions to cope with their different needs - like flexible schedules, more affordable pricing and decreased used of traditional on-campus facilities and resources. Some argue that online learning should be part of a strategic response by higher education administrators to remain competitive (Falk and Blaylock, 2010).

In the context of this study, the term "online learning" will refer to courses that students attend solely online, asynchronously or synchronously, with a faculty member delivering instruction through technological means (Clayton et al., 2010). The term distance education will refer to formal, institution-based education where interactive telecommunications systems are used to connect learners, resources and instructors (Simonson, 2003). The term telecommunications encompasses both electronic and non-electronic means, like television, internet, telephone and the postal system. Finally, the term blended learning will refer to instruction that combines traditional face-to-face with computer-mediated instruction (Graham, 2006).

It is argued that online learning technologies could potentially help cut costs of post-secondary education, by supporting larger-sized classes and less face-to-face interaction, a result of which would be reduced labour costs (Bowen, 2012). Online courses are also seen as a solution for students' financial woes, because online enrolment is commonly charged at lower tuition prices, and this suggests that increases in online learning might 'bend the cost curve', i.e., result in lower overall educational costs over time (Deming et al., 2015). Online education is also potentially advantageous because it can cater to students with no easy access to face-to-face courses or those who need more flexibility in their schedules (Powell and Keen, 2006; Bates, 2017). Institutions in rural and remote locations may see online learning as a solution to offer a richer selection of courses and to make sure students graduate on time (Brown, 2012a). Finally, a large number of studies comparing examination results between fully online and face-to-face courses have suggested that overall, learning outcomes in the two modalities are not significantly different - though there is wide variation in each (Johnson et al., 2000; Arbaugh and Stelzer, 2003; Daymont and Blau, 2008; Driscoll et al., 2012; Cavanaugh and Jacquemin, 2015).

Due to all these factors, online education is increasingly seen as an important strategic direction for traditional Universities. A survey on Canadian Universities and Colleges shows that almost three-quarters of responding institutions saw online learning as a means to increase student enrolments and two thirds considered it extremely or very important for the institution's long term plans (Bates, 2017). The Sloan Consortium yearly survey on online education in the United States (Allen and Seaman, 2013) shows that the proportion of chief academic officers that see online education as critical to their institution's long-term strategy has grown consistently in the last few years. In 2012, the proportion of respondents that agreed with this proposition reached an all-time high of 69%. Fully online courses have been widely adopted by many brick and mortar post secondary institutions to provide increase flexibility for students and to maintain of expand enrolment (Seaman et al., 2018).

Schiffman et al. (2007) found other nuances in the responses of administrators of both for profit and non-profit institutions, when asked about reasons for engaging with online learning. The two most common reasons were to get students from new geographic regions or markets (57% agree) and to contribute to extension efforts (46% agree). Students taking at least one distance education course comprise 31.6% of all higher education enrolments in the United states, a percentage that has been growing steadily in the last few years (Seaman et al., 2018). In Canada during 2015, online course enrolment represented around 16% of all course enrolments in Universities (Bates, 2017). The same survey shows that approximately three quarters of all Canadian post-secondary educational institutions (76%) offer distance education courses or programs for credit, with that percentage increasing to 90% if only Universities are considered.

These lines of argumentation seem to assume that face-to-face students can be seamlessly converted into online students at the convenience of the institutions themselves (Chen, 2009; Hixon et al., 2012). However, in some previous research, while past exposure to online classes was positively associated with perceptions of general equivalence, comparative flexibility, comparative knowledge gained, and comparative level of interaction in online versus face-to-face classes, students that had never attended online classes before seemed to perceive them not to be equivalent to face-to-face classes (Platt et al., 2014). Students may see fully online courses as requiring more self-discipline and greater willingness to teach oneself (Konrady, 2015). In some research, students expressed the belief that online courses provided learning of lesser quality (O'Neill and Sai, 2014). Lack of community and connection to instructors and peers also appear as concerns for students (Konrady, 2015), and lack of interaction and collaboration with peers or the instructor is cited as the most critical barrier to online learning (Muilenburg and Berge, 2005). When asked about what advice they would give to potential online students, unsuccessful online students consistently refer to the demand for soft-skills like time management, communication and simply advise "don't get behind" (Fetzner, 2013).

Interestingly, these perceptions may also differ between students and faculty. Otter et al. (2013) in their study of faculty members and students at a large public university in the southeastern United States found that, compared to faculty perceptions, students see online courses as more self-directed and believe that online students must be more willing to teach themselves. Additionally, they found that students in online courses reported they feel more disconnected from professors and fellow students than professors believe them to be and faculty tend to see the role of the professor as more critical to the success of online courses than students do (Otter et al., 2013). Matters are complicated further because Faculty for traditional face-to-face courses may find difficult to transition to online education. In many situations where instructors are expected to prepare their own online courses, proper training, support or incentives are commonly lacking and the workload can be very challenging to manage (Kebritchi et al., 2017). Faculty list increased workload, time commitment, lack of personal relationship with students, frequent technology failures and inadequate compensation for instruction as some of the main obstacles for participating in online education (Lloyd et al., 2012).

Institution administrators hold a yet different perspective on potential barriers to online learning. For academic leaders, the most relevant barrier to the widespread adoption of online learning seems to be lack of student discipline, with 88.8% saying that it is either important or very important that students become more disciplined in online courses (Allen and Seaman, 2013). A Survey of Canadian educational institutions showed that around two-thirds of the institutions identified lack of training or pedagogical knowledge, and resistance from instructors, as a main barrier or challenge to developing online learning alternatives. Different provinces seemed to emphasize different barriers, with Faculty resistance being highest in Quebec (75%), while perceived lack of training or pedagogical knowledge was highest in British Columbia (88%) and Manitoba (83%) (Bates, 2017). The same survey indicated that over half the responding institutions identified perceived quality of online learning as a challenge, with an even greater percentage (62%) if only Universities were considered (Bates, 2017).

Finally, one of the most common criticisms directed at online learning is higher rates of attrition. A fairly long history of research reports higher dropout rates for distance or online education students, in comparison to face-to-face students (Phipps and Merisotis, 1999; Diaz, 2002; Simpson, 2003; Levy, 2007; Lee and Choi, 2011). However, there is very little research on the actual social and financial costs of high online dropout rates (Simpson, 2010).

2.2 Student Modality Selection

If students' course selections are "among the most defining in the success of their learning" (Zocco, 2009, p.2) then today's undergraduate students must feel exacerbated pressure, since they must choose not only their courses but also the modality in which to experience them. For example, consider the hypothetical case of a biology major who is taking a first-year English course as an elective to meet a breadth requirement for graduation. The student has a part-time job and a 40-minute commute to campus. The courses required for her major will necessitate travel to campus for a minimum of two days per week for lectures. One of her biology courses also requires a lab, which is offered multiple times per week. One of the lab sections occurs on the same day as its associated lecture (potentially saving travel time), but conflicts with the face-to-face offering of the English course that is of greatest interest to her. If the instructor for the English course has been strongly recommended to the student by friends, and/or she feels that face-to-face presence will help her to maintain her enthusiasm for the course and keep up with the assignments, she may opt to commute to campus one additional day per week for the biology lab so that she can attend the face-to-face offering of the English course. In this case she may work fewer hours at her part-time job as a result. However, if she does not expect much learning benefit from the English instructor's lecture performance and/or feels that she is self-disciplined enough to keep up with the assignments in the English course on her own, she may instead opt to take the English course online in order to avoid travelling to campus one additional day per week. In this case she may be able to work more hours at her job. This example illustrates the complexity of the choices that today's undergraduates must make multiple times per year.

A better understanding of how students make these choices can lead to improved institutional practices for defining what courses to offer online and when to offer them. When students' choices are poorly understood, institutions may mandate modalities that fail to meet the needs of students, simply because they are viewed as more cost-effective. However, these are likely false efficiencies if a lower proportion of students successfully completes these courses, or if they fail to enrol the target number of students. These could lead to waste of time and resources, both from the instructor and institution perspectives. A deeper understanding of what influences modality choice may also lead to helping students in their pathway of decision, engaging them early on so they don't register in modalities that don't suit them, reducing frustration, dropped courses and underachievement.

2.2.1 Previous online learning experience

As discussed above, the last decade has seen an increasing number of research publications about students' perceptions of and attitudes toward online learning, their experiences of online learning, and how these may affect students' choice of modality and student learning outcomes. Previous experience with online learning seems to play an important role. Students who have attended more online courses in the past seem more likely to intend to enrol in that same mode in the future. In the logistic regression model of behavioural intent to take online courses by Cullum (2016), only three of the many independent variables investigated were statistically significant predictors. A higher number of current online courses being attended increased the probability of student behavioural intent to take online courses in the future. On the other hand, higher motivation to take face-to-face courses implied lower probability of student behavioural intent to take online courses. Higher social influence scores (ie., whether the student felt influenced by peers to take online courses) also increased intent for online enrolment. Further statistical analysis of demographic data revealed that the college of chosen major also significantly influenced behavioural intent to take online courses, while age, sex, and year in school were found not to be significant influences on behavioural intent to take online courses.

A different result was found by Braun (2008), in a survey of a small sample (N=90) of Master's students pursuing Degrees in Education. Students were almost equally divided between those belonging to a hybrid cohort - a model where the course is delivered partly via face-to-face interaction and partly through online content - and those in a solely online degree cohort. When asked about what type of course they would prefer next time (hybrid or fully online), 98% of the hybrid students said they would take hybrid courses again. However, only 44% of solely online students would choose that mode again, with 55% of them actually preferring hybrid courses in the future. More nuance is observed when studies look at the quality of previous experiences, since students appear to be influenced by this when deciding whether to pursue further online studies. Online students that answer negatively when asked if they would take similar online courses in the future are those that had more negative perceptions of the effects of the distance learning environment on their learning process, and less satisfaction with their recent learning outcomes. Contrarily, students who answer positively are those who have had less negative perceptions of the learning process, and more satisfaction with their recent learning outcome (Nguyen, 2011).

An even more extreme result was found by Ladyshewsky and Taplin (2013) in their survey of Business Administration Masters students attending a course that was offered in three modes: face-to-face, online and hybrid. When students (N = 113) were asked what mode would they choose if they were given the opportunity to do the course again, no online student expressed the desire to choose online learning again. This can be contrasted with face-to-face students, 90% of whom reported that they would choose to do the course face-to-face again, and hybrid students, 15% of whom reported that they would have chosen the same mode again. A statistically significant relationship was found between mode of study and self-reported amount of learning. Surprisingly, online students reported the highest amount of learning, even though none of them would repeat this mode of study. Also, significant differences were found in terms of reported reasons for selecting the mode of study, with importance given to flexibility of study time, type of assessment, and speed of completion being significantly higher for online students. Student and teacher contact were significantly more important for face-to-face students.

2.2.2 Socialization Factors

Socialization factors recurrently appear as reasons for opting out of online learning. In a survey by Harris and Martin (2012), one third of face-to-face students declared that they chose this mode because they believed online courses would prevent them from connecting with or working with others, which points to a view of online courses as isolating. A logistic regression analysis by Nguyen (2011) found that the most important variable negatively affecting the student's decision to take online courses is the perception of missing face-to-face communication with the instructor and classmates. In terms of impact, this was followed closely by the perceptions of having additional volume of materials to learn and extra time required to do assignments in an online course compared to traditional courses, both of which also negatively affected the student's decision to take online courses. The perceived benefit of flexible class scheduling was the only variable found to positively influence the choice of online modality.

2.2.3 Flexibility

Actually, convenience and flexibility are the most common or most important reasons given by students for choosing online courses (Thomerson and Smith, 1996; Kleisus et al., 1997; Braun, 2008; Noel-Levitz, 2010; Nguyen, 2011; Harris and Martin, 2012; Kowalski et al., 2014). In a study (Braun, 2008) to discover why students participate in online courses, they were asked about reasons for enrolling: 80% indicated flexibility of schedule as a motive and 74.4% indicated the ability to do coursework at home as another motive. Curiously, only 11% of students marked enjoyment of online work as a motive. Further, 77% of students said online courses were either much more or slightly more demanding than traditional courses. Harris and Martin (2012) survey's results indicated that the three primary motivations for students choosing online programs were convenience, flexibility, and the ability to fit courses into a current work schedule. Only 17% of the online students in their sample actually stated a preference for online learning (versus face-to-face).

2.2.4 Subject Matter

Another factor to consider is that the subject matter itself could potentially be viewed by students as more or less apt for online instruction - for example, when conceptual knowledge in the subject matter or skills in the application of one's knowledge are to be acquired, students may prefer face-to-face learning. However, when skills in self-regulated learning are to be acquired, students may advocate online learning (Paechter and Maier, 2010). In an attempt to understand student perceptions and experiences of traditional face-to-face courses versus online courses, Kuzma et al. (2015) surveyed 290 students enrolled in upper-level business courses at a North American university. Students came from different Business Majors (Marketing, Management, Accounting, etc.) and had varied level of previous experience with online courses. They were asked about the type of class they perceived to be more difficult to take online ("heavily descriptive" like biology or history, "theoretical" like economics, or "analytical" like statistics) and overall, 66% of the students found that courses involving a great amount of description or terminology could more easily be taken online. However, students found that courses involving a high level of theory or analysis would be the most difficult to take online. When asked if they learned more from online than traditional (face-to-face) courses, 66% of students disagreed with the statement, while only 16% agreed.

2.2.5 Personal factors and Perceptions

Artino (2010) investigated personal factors and their relation to students' choice of instructional format for 564 undergraduates from a U.S. Service Academy. These students had just completed a mandatory, short-duration (160 minutes) online training program for aviation physiology and survival training, and they were presented with a survey that covered demographics, self-efficacy beliefs, task-value (how interesting or important the course was), achievement emotions (like enjoyment, boredom and frustration), and satisfaction with the course. Students were also asked which mode (face-to-face or online) they would prefer if they had to learn about these particular concepts in the future. A binary logistic regression model was created to predict group membership based on this preference. Artino found moderate effect sizes for higher levels of self-efficacy for learning online and greater satisfaction with the recent online learning experience for students that preferred taking future courses online. The logistic regression indicated three significant predictors of group membership: task-value, self-efficacy and satisfaction. Membership in the online preference group was more likely for every one unit increase (as self-reported) in the self-efficacy and satisfaction sub-scales. In contrast, membership in the online preference group was less likely for every one unit increase in the task-value sub-scale.

It is important to consider that perceptions and attitudes towards online learning may change over time and with students' lived experiences. That is to say that the importance that students ascribe to the particular factors that influence their modality choice may change substantially over time. For example, Bailey et al. (2015) surveyed 744 Faculty of Arts BA students in three modalities (roughly equivalent to face-to-face, hybrid and online modes) in 2 waves of questionnaires. The same questionnaire was administered to each student twice: once at point of enrolment, and again after completing one or more units of study. The variables gauged included demographics, motivational questions (why they were pursuing University-level studies), technology skills and the importance of each factor that influenced their choice of modality (e.g. personal factors, logistics, marketing, environment and access to services, among many others). Between the 3 different modalities, the only factors that showed significant difference (and strong effect size) were the environmental factors, with face-to-face students giving higher importance to access to personal support services, campus facilities, and meeting and socializing with other students. Small effect sizes were found for differences in the within-subjects analysis, with the personal, logistics, teaching/learning and support factors presenting significant differences. For example, logistics and support factors seemed to have decreased in importance in time for online students, while personal factors have increased in importance.

While the great majority of studies reviewed focused in understanding why and how students are selecting to study online, an equally relevant question is often neglected: why student may be *avoiding* the online modality. To understand what may motivate students to avoid online courses, O'Neill and Sai (2014) surveyed 48 students enrolled in a face-to-face class which had an equivalent online course offered in the same semester, with a comparable tuition rate and identical credit value. The most commonly cited reason (58%) was the belief that they would learn more in the face-to-face mode, closely followed by a reported distaste for online courses (52%) and the expectation that they would earn a better grade in the face-to-face mode (25%). In contrast, students may also harbour the sometimes false expectation that an online course will be easier than its face-to-face equivalent. When asked why they chose to take web-based courses, the most frequent response by student in a College of Education was that they thought it would be less difficult (chosen by 33% to 44.3% of students, depending on the semester) (Brown, 2012b). The next most frequent response (22.4-26.4%) was that they lacked time to attend regular classes.

2.2.6 Demographic Factors

The review of the literature shows that many demographic factors have been speculated to influence perceptions of and satisfaction with online learning. Gender seems to affect how students perceive their online learning environment and experiences (Rovai and Baker, 2005; Johnson and D., 2011; González-Gómez et al., 2012; Ashong and Commander, 2012) and it could be argued that these perceptions may influence modality choice. Many of the studies reviewed included demographic characteristics and attempted to establish relationships between demographic factors and the likelihood of students enrolling and being successful in online courses. Willging and Johnson (2009), for example, surveyed students who had dropped out of an Online Master's degree program in Human Resource Education from a North American University. The researchers obtained demographics and outcome measures for both dropout students (28) and persisters (83). Variables were limited to Gender, Age, GPA, Ethnicity and Occupation. A logistic regression analysis was applied to determine if any of the variables could predict dropout and interestingly, none of the variables was found to do so.

Ortagus (2017) reported on a study with a large sample (tens of thousands of students) that used data from the National Post-secondary Student Aid Study (NPSAS). They used multinomial logistic regression to examine the changing profile of online students in American higher education between 2000 and 2012. The outcome variable differentiated 3 categories: students enrolled in no distance education, some distance education, and all distance education courses (courses included both distance education and online education). Variables examined included a wide variety of demographic aspects (work commitment, marital status, sex, income, age and whether the students were veterans or parents) and course or institution characteristics (major, class year, type and size of institution). Ortagus found that being a full-time employee, being a parent, and being married were positively related to enrolling partially or entirely in online courses. Ortagus also found that being a female, older, or veteran was positively related to enrolling in either some online courses or in fully online degree programs. Finally, although the proportion of minority students doing online classes has increased over time, the estimated odds of minority students enrolling in some online courses were lower when compared to their white peers (between 21.0% and 13.9% lower, depending on the year). This finding would support previous research showing that minority students are less likely to engage with online education (Jaggars, 2015), but contradicts other sources that suggest minority students were more likely to enrol in online courses (Chen et al., 2010). Although their study was restricted to first-year and senior college students at 45 American higher education institutions, Chen et al. (2010) had found that minority and part-time students were more likely to enrol in online courses.

Although recent studies cover more nuanced aspects of demographic factors like race/ethnicity, disability and non-traditional student characteristics (Wladis et al., 2015; Terras et al., 2015), the literature is still sparse in these areas.

2.3 Limitations of Earlier Studies

Despite the scale at which students are now taking online courses, research does not yet paint a complete or cohesive picture of what shapes students' choice of modality or whether they make these choices to their greatest advantage. Even though the last decade has seen an increase in studies focusing on the conditions and characteristics that may influence modality selection, the literature is still growing and many questions persist. Limitations of previous studies include small sample sizes (Braun, 2008; Willging and Johnson, 2009), perspectives from either online students or face-to-face students, but not both (Braun, 2008; Paechter and Maier, 2010; O'Neill and Sai, 2014) and inclusion of only one discipline or area of study (Kuzma et al., 2015; Artino, 2010). Previous studies have also focused on limited subsets of characteristics as explanations for student's choice (Willging and Johnson, 2009; Ortagus, 2017).

Additionally, for reasons discussed above, post-secondary institutions in North America and elsewhere host many international students, and since the benefits of a face-to-face class are potentially limited by one's ability to follow a lecture of discussion in real time (Fitze, 2006) it would be reasonable to investigate if self-perceived competence in the language of instruction could relate to student choice of course modality. Fully online courses, which often place a lesser demand on students for real time aural comprehension and verbal participation, might be preferred by students with lesser aural and or verbal competence in the language of instruction. Although some studies do include this perspective (Hood, 2013; Muilenburg and Berge, 2005), the vast majority of the studies reviewed neglected this aspect.

Chapter 3

Research Methods

A review of the literature indicates that most studies in the modality choice area tend to focus on students' general perceptions of and preferences for online learning, and when choice is measured, they are mostly limited to measuring stated intentions of registration or asking students to speculate if they would have chosen a different modality next time. These hypothetical choices are limited and a more adequate survey would investigate students who have actually made the choice to enrol in an online course when they could realistically have chosen the face-to-face class (and vice-versa). Since very few studies have examined the particular situation where a student is offered the very same course in both modalities, and exercises a choice in these circumstances, we identified the need for a study that would address this specific scenario.

3.1 Context of Study

Face-to-face courses at Simon Fraser University, like such courses elsewhere, range from large lecture courses with hundreds of students per section, to seminar courses (generally at 3rd and 4th year) of 30 students or less (sometimes much less). At the time this study was being conducted, most instructors at Simon Fraser University made use of the campus Learning Management System, though many instructors were using it only for posting the syllabus and reading materials. A central unit (the Centre for Online and Distance Education, or CODE) was supporting faculty in designing and delivering fully online courses, mostly at the undergraduate level. These online courses (henceforth also refered as OL) used the same learning management system that face-to-face courses did, and were designed to meet the same academic requirements. However, assignments and supporting materials could be different, and staffing differed. Each OL course was supervised by a faculty member (often the designer of the course), but grading of assignments and student support were primarily carried out by Tutor-Markers, who were typically graduate students hired on a semesterly basis.

The University would commonly offer many undergraduate courses in both modes of delivery — online and face to face — at the same time. The context at SFU was therefore especially well suited to the study of modality choice, because for many undergraduate courses students could select between two modalities (face-to-face and fully online) while other course characteristics were held constant. Both modalities were charged similar tuition fees (OL courses had a small additional materials fee), and identical policies were applied regarding dropping courses or issuing refunds. Finally, student transcripts did not explicitly mention the modality in which a course was completed.

3.2 Study Rationale

To better understand the conditions and characteristics that may influence modality choice, the present study expands on previous research and includes a wider range of variables for analysis. Personal characteristics and circumstances assessed were derived from the literature review and expanded to include often ignored aspects such as self-perceived language competence and disability.

As the literature review indicated, it is important for research on modality choice to include students from courses in a wide range of areas and disciplines. This permits a more representative picture of how the choice of modality is made, since students may believe that some subjects are better suited to online study than others. For example, in some disciplines early courses require substantial memorization (e.g. biology) while others require practice (e.g. foreign languages), and this may be material to student's choice of modality. In the present study, courses were included from a wide range of disciplines including Archaeology, Bio-medical Studies, Computing Science, Criminology, Economics, Education and English literature.

By surveying only participants enrolled in courses that were being offered in both modes, the study aimed to specifically target students who would have had the realistic opportunity to exercise choice. This should give the findings greater validity.

It has been argued that in online learning environments, students must have high self-regulatory skill to accomplish their learning (Dabbagh and Kitsantas, 2004) and previous research identified that self-regulated learning strategies (SRL) may indeed enable learners to be more successful in online environments (Winters et al., 2008) and to better attain their goals (Azevedo and Cromley, 2004). To explore whether differences in self-regulatory skill could also explain modality choice, this study included extensive instruments that measure self-regulatory learning strategies and affective facets of student's motivation.

3.2.1 Binary Logistic Regression

Researchers, policy advisers and administration leaders in educational institutions are constantly faced with issues like enrolment levels, retention targets, courses to offer or modalities in which to offer them. These outcomes are the product of many factors that interact with each other in complex ways, but frequently, they express themselves dichotomously. For example, either the student drops out of a course or not, engages in research or not, obtains a bachelor degree, or not. A series of statistic techniques are available to quantify these effects, but few of these conform to the dichotomous nature of the outcomes so frequently studied (Cabrera, 1994).

Given that the chosen dependent variable in the present study (student enrolled online or not) was binary, a linear regression analysis would not be appropriate, since this method requires a continuous dependent variable. Another technique considered was the Mantel-Haenszel Odds Ratio (Mantel and Haenszel, 1959), especially popular in the medical sciences. This method uses a dichotomous outcome variable and multiple independent variables, which are stratified into two or more levels of the confounding factor, so as to create a series of two-by-two tables that represent the association between the variables and outcome at two or more levels of the confounding variable. Finally, a weighted average of the odds ratios across the strata is computed. Unfortunately, the number of variables in our survey was so large that the computation of the two-by-two tables would have been too taxing. Additionally, the Mantel-Haenszel Odds Ratio method admits only categorical explanatory variables, or demands that continuous variables are categorized with arbitrary breaking points, which would again be very time consuming.

Another popular technique for a dichotomous dependent variable is binary logistic regression. It has a long history of been applied to model educational choices and outcomes (Bishop, 1977; Manski and Wise, 1983; Stampen and Cabrera, 1988; Dey and Astin, 1993; Artino, 2010; Cullum, 2016). The logistic regression model presumes that a logistic function can represent the association between the binary outcome (in the case of this study, FTF or OL) and given independent variables. This function expresses the expected probability of Y (dependent variable) across different values of x (independent, predictor variables), each x with a regression coefficient β. For models with more than one predictor variable, the null hypothesis underlying the model states that all β equal zero, or, that there is no linear relationship in the population. A rejection of this null hypothesis would mean that at least one beta is not zero in this population. In practical terms, this can be interpreted to mean that the logistic regression equation can predict the probability of the outcome better than the mean of the dependent variable Y (Peng et al., 2002).

In this study, a binary logistic regression was chosen for modelling purposes because it elucidates two important points: a) can we accurately predict category membership given this set of predictor variables? and b) what is the relative importance of each predictor? Additionally, the technique is quite flexible, since predictors don't have to be normally distributed, linearly related or of equal variance within each group, and the predictors can be a mix of continuous, discrete and dichotomous variables (Tabachnick and Fidell, 2007).

3.2.2 Study Objective

The objectives of this study were to a) better examine the relation between the aforementioned factors and students' choice of modality (online of face-to-face), b) create a preliminary binary logistic regression model for predicting student's enrolment in either online courses or face-to-face courses and c) create a second binary logistic regression model that represents students' "choice" of online modality (since many student may enrol in online courses, but that was not their first preference).

Research Questions

The research questions that framed the study were: 1) What (if any) variables influence student's modality enrolment given very similar online and face-to-face course options? 2) Which factors contribute the most significantly, and which contribute the least 3) Can a logistic regression model significantly predict modality of enrolment, and modality of choice? If so, which predictors are more significant and influence the model the most?

Study Hypotheses

The hypotheses proposed are that the multiple factors described in details below (such as students' personal characteristics, circumstances and expectations, course characteristics, motivational beliefs and learning strategies) may influence whether students enrol in online or face-to-face courses. For example, students' propensity for peer-learning, social interaction or help-seeking, or even their perception of their ability to self-regulate, could be related to choice of modality. Given the large number of variables included (54 questions in the survey) and also considering that many of the variables were being used for the first time in this research context, the hypotheses were kept non-directional (or it was hypothesized that the independent variables would have an effect on the mode of enrolment, but the direction of the effect was not specified).

3.3 Ethics Review and Approval

The Simon Fraser University Office of Research Ethics has reviewed the proposal for the present research project and provided their approval before data were collected. A few of the ethical considerations addressed were confidentiality, consent and reimbursement. In terms of confidentiality, none of the questions on the research survey were designed to gather personally identifiable information. However, it was possible to enter personally identifiable information in responses to the open-ended question. Participants were assured that their responses would be anonymized. Any statements they made on the survey or in the interview were edited carefully so as to conceal their identity. This was important specially because the study was done in collaboration with the Centre for Online and Distance Education, where many of the respondents were actively enrolled.

To ensure data were obtained with informed consent, the online survey was implemented to first show the electronic consent form. Only after indicating consent students had access to the survey's questions. Participation (or lack of participation) in the study would not influence student's course standing or grades in any way, and that was clearly stated in the consent form to make students aware that participation was voluntary. The consent form text also highlighted the expected benefits of the project and explained the technical and operational steps taken by SFU to ensure data security and confidentiality. Students were told that participation could be withdraw at any time, and were given the contact for the Office of Research Ethics, in case of concerns or complains.

Reimbursement for participation can also be an ethically contentious issue, in the sense that too large a payment may constitute pressure to participate, but low or no reimbursement can be a failure in recognizing the value of students' time and contribution. In this research, each participant was paid $5 CAD in either cash (Fall 2017) or as a Starbucks coffee gift-card of the same value (Spring 2018) for completing the survey. To contact participants to schedule payment (or to send them the gift-card), email addresses had to be collected. To ensure that responses would remain confidential, after completing the survey students were directed to a second anonymous survey, that asked them only for their SFU e-mail address. This procedure ensured that their emails would not be associated with their responses to the research survey.

3.4 Computational Tools for Data Analysis

3.4.1 R-Studio

R-Studio is a popular, free and open source tool that provides a user-friendly interface for R. R is both a programming language and an environment for statistical computing and graphics. Even though statistical analysis in R requires some knowledge of computer coding, the recent availability of good and free statistical packages for this platform actually allows for very little need of manual coding. A major advantage of an open source, multi-platform tool like R is that it allows for easier collaboration between different research groups: the same analysis code or data set could potentially be shared among researchers in one group or among different groups in different locations, which improves reproducibility of the analysis. Additionally, R-Studio has reporting capabilities which allow both LATEX code and math code to be written continuously in a single document. This document can be later compiled and presented in the form of a text report. This not only streamlines the work of reporting results, but also guarantees that any changes to the data set or analysis will be immediately and effortlessly reflected in the text report. Given all these advantages, R-Studio was chosen to produce all descriptive and inferential statistics in this study, and all the plots included in this Thesis document.

3.4.2 IBM SPSS Statistics

Due to its all-in-one solution for Missing Value Analysis (MVA), Data Imputation and Logistic Regression Modeling, IBM SPSS Statistics v24 was used to prepare the dataset for modeling, to validate all model pre-conditions and to run both models.

3.5 Procedures

Data collection occurred between Fall of 2017 and Spring of 2018 at Simon Fraser University. Participants were recruited from three Faculties: Arts and Social Sciences, Sciences and Education. Preference was given to courses with large enrolment numbers, but the critical criterion for selection was that the course be offered in both modalities: (a) fully online (no required campus attendance) and (b) face-to-face (with little or no online components). Since fully online courses are centrally organized at the institution and the online education unit was collaborating closely on the study, the investigators were able to create a list of all courses being offered in both modalities in each semester of data collection. Every instructor of a course being offered simultaneously in both modalities was invited to participate in the study, but a course was only included in the study if participation was secured from the instructor of both modalities.

The survey template (for a list of all questions, see Appendix B) was changed slightly between Fall 2017 and Spring 2018 , with two new questions added. Once course selection had been made, instructors were contacted and data collection proceeded in those courses in which the instructor agreed to cooperate. The research team visited the face-to-face classes to invite students to participate in an online survey. Students in the online courses were contacted via email by their respective course teachers or via an announcement on the course management system. In this manner, all students from the selected courses were invited to complete the survey, though participation was completely voluntary on students' part. To maximize participation and rate of student response, participants were informed that they would be given $5 CAD gift card for completion of the 50 items survey.

Both groups were provided with directions for accessing the online survey system and how to complete the survey. Each group (OL for online students and FTF for face-to-face students) was provided their own unique URL, so that each should, in theory, only have access to the survey corresponding to their mode of enrolment. The online survey system was also configured to ensure that each student could only respond to the survey once.

3.6 Targeted Courses

Courses were also selected from a wide range of disciplines, since perceived demands vary across disciplines, and existing studies suggest that these perceived demands could shape student's choice of course modality (Paechter and Maier, 2010; Kuzma et al., 2015).

All references to course codes below (and throughout this document) were partly masked so as not to identify specific courses. Course names were also suppressed. It is important to note that, given the trimester structure of study at SFU, student progression is expressed in levels. The first digit of each course code gives an idea of student level: 100 series courses are for first and second level students (roughly equivalent to first and second trimester students) and 300 and 400 series courses are for students beyond level 4.

Five courses were surveyed in Fall 2017: Health Sciences 14X, Criminology 13X and 31X, Education 10X and 47X. During Spring 2018, eleven courses were surveyed: Archaeology 11X and 12X, Computing 1XX, Criminology 11X, 12X, 31X and 32X, Economics 1XX, Education 1XX and 4XX and English 1XX.

3.7 Participants

The study participants were mostly undergraduate students, primarily from first-year courses, with a smaller percentage of third and forth year students. There were no exclusion criteria for participation in this study. Further response rate analyses are presented in the next chapter.

3.8 Instrumentation

The study instrument was an online survey composed of 54 items, with question formats that included simple yes/no, numeric answers and Likert-type items. All Likert-type items had response scales ranging from 1 to 7, labelled from "Disagree Strongly" to "Agree Strongly". Two survey templates were implemented: one for OL students, the other for FTF students. Both templates had the exact same 54 items, but questions were slightly re-phrased to account for modality context (for example, the commute time question would ask how many minutes does it take to get to class from home, or alternatively, how long would the commute be if they were not taking this class online).

Survey items can be grouped in the following areas:

3.8.1 Personal Characteristics

Personal characteristics items included participant's age, sex (Female/Male/Transgender/Other or Prefer not to say), presence of physical disability that could impair commute. Additionally, standard scales were used to assess motivation and goal-orientation. These will be discussed in sections below.

3.8.2 Personal Circumstances

Personal circumstances items inquired about hours of paid work per week and commute time in minutes. A Likert-type scale was used to assess whether participants had primary responsibility at home for taking care of others (such as children or elderly parents). Two Likert-type items measured whether participants were satisfied with their grades overall, and if they felt the need to raise their GPA. English is the language of instruction in most courses at SFU, and of all courses in which students were recruited for participation. Yet international students represent 20.4% of the total undergraduate population at SFU (SFU, 2018a), and a majority of those do not speak English as their first language. Likert-type items assessed student self-perception on two fronts: listening English comprehension and ability to write well in English.

3.8.3 Course Characteristics and Expectations

Besides confirming participant's course and mode of enrolment (the dependent variable, dichotomously coded to either FTF or OL) the questions in this section tried to capture how the specific course fit into the student's degree requirements. Namely, whether the course was elective, required, pre-requisite, etc. Other questions assessed whether they were aware that the course was also offered in the other mode, and if they had attempted to enrol in the other modality. Other items captured how many college or university level courses the student had previously taken completely online. two other Likert-type questions measured the student's self-efficacy for fully online learning and if they liked online courses. Finally, a series of Likert-type questions assessed participant's perceptions and expectations of the course, with such items as "I am interested in the subject of this course", "I expect to earn a good grade in this course", "I expect the Face-to-Face version of the course to be harder" and "I expect to earn higher grades [in the modality of enrolment]".

3.8.4 Scales

GOQ Sub-scales

To capture the facets of student's motivation, the Goal Orientation Questionnaire (GOQ) was used. The GOQ (Nesbit et al., 2009) examines achievement goal orientations, social goal and work avoidance goals in students. Similar to the Achievement Goal Questionnaire (Elliot and McGregor, 2001), it tries to capture the relationship between achievement goals and other motivational variables. However, the GOQ also includes affective aspects of achievement motivation, with items extended to measure emotional constructs like work avoidance and social goals (Nesbit et al., 2009). For the present survey, only these two affective sub-scales were used: The Social Goal subscale (three items) and the Work Avoidance subscale (four items). Both scales consisted of likert-like answers ranging from 1 to 7, or "Disagree Strongly" to "Agree Strongly". A sample item for the Social Goal scale would be "In this course I prefer working with others", and a sample item for the Work Avoidance scale is "In this course I feel unhappy when a task takes too much time". One of the Social Goal questions was found to refer too specifically of group work ("In this course, I feel responsible for my group's performance"). Since online courses may include less group work than face-to-face courses, the question was remove from the subscale. Instead, the question "In this course I am happy to be at the same level as my friends" was added.

Scores were calculated by taking the mean of the items that compose each scale. For instance, an individual's score for a subscale with 3 questions is obtained by adding those 3 items and dividing by 3. Since the amount of missing data within items of the subscale was very low (less than 1.7%), scores with missing data were simply calculated for all answered questions (for example, if the student only answered 3 items of a 4 item scale, the 3 answers were added and divided by 3).

MSLQ Sub-scales

Many standardized questionnaires have been used to assess students' self-regulatory behaviour. The MSLQ (Motivated Strategies for Learning Questionnaire) is a widely used self-report instrument designed to assess students' motivational orientations and their use of different learning strategies (Pintrich et al., 1991). By targeting the roles of both motivation and cognition during learning, the MSLQ is reflective of a line of research on self-regulated learning which emphasizes the interface between motivation and cognition (Schunk and Zimmerman, 1994; Zimmerman and Schunk, 1989). Prior research using the MSLQ has found relationships between its motivational sub-scales — such as intrinsic/extrinsic goals, task value, self-efficacy — and use of learning strategies — rehearsal, elaboration, organization, critical thinking, meta-cognition, time management, study environment and effort regulation (Dahl et al., 2005; Muis et al., 2007). While some previous research found strong relationships between academic achievement and scores on the MSLQ (Bell, 2006; Langley and Bart, 2008) other authors found weaker relationships (Barker, 1997; Lewis, 2006). Recent meta-analysis of that body of research suggests that the MSLQ is a reasonably reliable measure of constructs, and that some constructs do exhibit relationships with College academic performance (namely self-efficacy, effort regulation, and time and study environment sub-scales) (Credé and Phillips, 2011)

The MSLQ instrument includes a motivational section and a learning strategies section. The learning strategies section consists of nine sub-scales, and is based on a general cognitive model of learning and information processing (Weinstein and Mayer, 1986). Given that the entire MSLQ survey was judged too lengthy for the present research context, four specific sub-scales were chosen for inclusion in the study's survey:

1. an eight-item subscale assessed students' management of Time and Study Environment

2. a four-item subscale assessed students' regulation of their own effort in learning

3. a four-item subscale assessed students' inclination to seek help

4. a three-item subscale assessed students' propensity for peer learning

The MSLQ instrument was designed to measure college undergraduatesâĂŹ motivation and self-regulated learning as they relate to a specific course (Artino, Anthony, 2005), and it is also assumed that motivational variables and learning strategies can change across tasks. For example, Rotgans and Schmidt (2009) found within-person variation in MSLQ scores across three subjects (English, Math, Science). Therefore it could be seen as a limitation to use some of the MSLQ subscales in the present study, since it aims to describe and model student choice and preference in general. However, as pointed out by Credé and Phillips (2011), some authors do use the MSLQ to measure general tendencies (Wolters, 2003) and the measured constructs may also exhibit stability across classes for the same individual (Bong, 2001; Warr and Downing, 2000; Credé and Phillips, 2011).

The subscales chosen for this survey form what (Pintrich et al., 1991) call "Resource Management" strategy. Sample subscale items included "I make good use of my time for this course" (Time and Study Environment), "When I can't understand the material in this course, I ask another student in this class for help" (Help Seeking), and "When course work is difficult, I give up or only study the easy parts" (Effort Regulation). All questions in these sub-scales were Likert items, with response scales ranging from 1 to 7, labelled from "Disagree Strongly" to "Agree Strongly". Some of the questions in each subscale were reversed (negatively worded). Items from all 4 sub-scales were presented scrambled and reordered in the surveys. To score each subscale, negatively worded items were reversed (so if the participant selected "Disagree Strongly" (1), the value was reversed to "Agree Strongly" (7)). Similarly to the GOQ scales, scores were calculated by taking the mean of the items that compose each scale. Missing data within items of the subscale was also low (less than 2.2%), so scores with missing data were calculated in the same way described for GOQ scales.

3.8.5 Reason for Modality Enrolment

A final open-ended question prompted the participants to explain their choice of modality in their own words. The question asked "Would you like to say anything else about why you chose to take this course [on campus/online]?" Of the 650 overall respondents to the survey, 383 students chose to respond to the open-ended question (178 online registrants and 205 face-to-face registrants). Although analysis of these data is out of scope for this Thesis, findings from the qualitative analysis revealed complexities in students' choices that it may be possible to capture quantitatively in future surveys. For example, while authors have often described online students as seeking convenience, respondents often detailed circumstances in which they chose an online course to avoid time conflicts with face to face courses already on their load, to avoid traveling to campus for only one course on a particular day, or even to avoid writing more than one final exam on the same day (O'Neill et al., 2020).

Chapter 4

Data Analysis and Results

4.1 Missing Data

Prior to conducting data analysis, it was necessary to address the issue of missing data. All survey questions had at least a small percentage of missing responses. This is due to the technical settings of the survey software that was used, which prevented likert-like questions from being mandatory. Therefore, there was opportunity for participants to leave some of these questions unanswered. Of note, all categorical variables (except Disability) had a 100% response rate. In addition to respondents choosing not to respond all questions on our survey, some questions were only added to the survey between the first and second administrations. For example, the question regarding disabilities that might impair commuting was added to both the online and face-to-face versions of the survey in Spring 2018, and the commute time question was added for online students in this administration as well (previously only face-to-face students were asked about commute time). As a result, responses to these questions are either partly or entirely missing for the Fall 2017 responses

Table 4.1 below provides a summary of all items with percentage of missing values above 1%, with the first six items having percentages of missing values above 5%.

Table 4.1: Missing Data Summary

	Missing	% of Total	Valid
Disability	280	43.1%	370
Commute_time	164	25.2%	486
Good_at_online	148	22.8%	502
Enjoy_online	145	22.3%	505
Expected_FTF_harder	43	6.6%	607
Expected_higher	42	6.5%	608
Satisfaction	18	2.8%	632
GPA	12	1.8%	638
Receptive_English	7	1.1%	643

Disability and Commute Time had the highest percentage of missing data (43% and 25% respectively). Descriptive statistics will be provided below for all variables and further concerns about missing data handling will be addressed in the context of the Logistic Regression (Section 4.5.6).

4.2 Response Rate Analysis

The undergraduates surveyed were enrolled in courses across several disciplines. Tables 4.2 and 4.3 below present details of survey response rate, comparing total number of enrolled students (E) in each course/modality with actual survey submissions (n) for each course and modality. Since for the 2017's version of the survey the course name was not captured, the rate of response for Fall 2017 is only presented as a total.

Of the 650 students that answered the online survey, 335 were Face-to-Face (FTF) students, and 315 were online students (OL). For data collection during Fall 2017, 280 surveys were answered, and average response rate for Fall 2017 Face to Face students was 18%, while average response rate for OL students was 36%. During Spring 2018, 370 participants answered the survey. Average response rate of Face to Face students was 10%, while average response rate for OL students was 26%.

Table 4.2: Response Rate for both terms and modalities

	FTF			OL			Totals		
	E	n	%	E	n	%	E	n	%
Fall 2017	684	122	18%	434	158	36%	1118	280	25%
Spring 2018	2030	213	10%	615	157	26%	2645	370	14%
Totals	2714	335	12%	1049	315	30%	3763	650	17%

Table 4.3 presents details for courses and response rates for Spring 2018. Similarly, E represents total number of students enrolled per modality and course, n is the number of respondents per modality and course, and % presents the percentage of enrolled students responding.

Table 4.3: Spring 2018 - Response Rate for classes participating in Spring 2018

	FTF			OL			FTF + OL		
	E	n	%	E	n	%	E	n	%
Archaeology 11X	363	0	0%	55	11	20%	418	11	3%
Archaeology 12X	280	4	1%	56	33	59%	336	37	11%
Computing 1XX	167	17	10%	72	16	22%	239	33	14%
Criminology 11X	281	2	1%	48	9	19%	329	11	3%
Criminology 12X	144	25	17%	0	0	0%	144	25	17%
Criminology 31X	120	35	29%	45	9	20%	165	44	27%
Criminology 32X	29	6	21%	53	16	30%	82	22	27%
Economics 1XX	385	79	21%	65	10	15%	450	89	20%
Education 1XX	50	18	36%	89	20	22%	139	38	27%
Education 4XX	68	19	28%	90	22	24%	158	41	26%
English 1XX	143	8	6%	42	11	26%	185	19	10%
NA	2030	213	10%	615	157	26%	2645	370	14%

Finally, Table 4.4 summarizes the representativeness of each course in the total number of participants in each modality, for Spring 2018.

Table 4.4: Spring 2018 - Representativeness of each course in the sample

	% of n_{FTF}	% of n_{OL}
Archaeology 11X	0%	7%
Archaeology 12X	1.9%	21%
Computing 1XX	8%	10.2%
Criminology 11X	0.9%	5.7%
Criminology 12X	11.7%	0%
Criminology 31X	16.4%	5.7%
Criminology 32X	2.8%	10.2%
Economics 1XX	37.1%	6.4%
Education 1XX	8.5%	12.7%
Education 4XX	8.9%	14%
English 1XX	3.8%	7%

As can be seen, some courses are much more represented in one modality than the other, despite the fact that all courses were offered in both modalities during the semesters in which data collection took place. For example, students from Archaeology (11X and 12X) represent 28% of the OL sample, while representing only around 2% of the FTF sample. Economics students represent 37.1% of the FTF sample, but only 6.4% of the OL sample. This sampling bias is acknowledged as placing limits on how the forgoing data analyses can be interpreted.

4.3 Scale Validity and Reliability

4.3.1 Validity

Scales are commonly evaluated in terms of their construct validity and reliability. Validity relates to the degree to which a score can be interpreted as representing the intended underlying construct. The GOQ instrument is quite new as compared to the MSLQ, so there are few studies that corroborate its validity. Adesope et al. (2015) presents an exploratory and confirmatory factor analysis of a five-factor model for the GOQ, that has yielded an acceptable fit for seventeen items of the scale. The MSLQ instrument has a longer history and it is widely used in educational research (Duncan and McKeachie, 2005). Although previous research supports the MSLQ's predictive validity (Pintrich et al., 1993), there are also recent contributions that point to limitations and suggest enhancements that aim to improve MSLQ's scale structure (Dunn et al., 2012; Hilpert et al., 2013).

4.3.2 Reliability

When evaluating scale reliability, it is important to differentiate concepts like unidimensionality and internal consistency. A scale is taken to be undimensional if the items are measuring a single construct. Recent research points to certain redundancies on pairs of sub-scales from MSLQ (Credé and Phillips, 2011) and lack of evidence for unidimensionality of other sub-scales (Tock and Moxley, 2017), but we can say that, broadly, there is support for the theoretical structure of the MSLQ (Credé and Phillips, 2011) and reliability generalization studies demonstrate that it can be used with reasonable confidence for obtaining generally reliable scores (Taylor, 2012).

Internal consistency is a measure of the inter-relatedness of respondent scores on a sample of test items (Tavakol and Dennick, 2011). Cronbach's α is the statistic most widely used today for estimating internal consistency (Gardner, 1995). The α value will range from 0 to 1, and will be higher if the items in a scale are correlated with each other. In a very succinct way, α expresses the extent to which different subsets (of items of the scale) would produce similar measurements (Taber, 2017). Importantly, a high alpha value does not imply that the scale is uni-dimensional. Actually, high α values can be obtained in either uni-dimensional or multidimensional scales (Sijtsma, 2009), since a multidimensional scale may have sets of sub-items that correlate with each other. Additionally, higher α values may be obtained by increasing the number of items in the scale (ie. the length of the test), however, this may also suggest a high level of redundancy within the scale, which should also be avoided (Taber, 2017).

In order to further explore internal consistency of the instruments used, Cronbach's α was calculated for all GOQ and MSLQ sub-scales using the data from the present study. Items with higher values of Cronbach's alpha were inspected for redundancy (for a full list of survey question and scale groupings, see Appendix) and found to be sufficiently non-redundant. Additionally, scales with lower Cronbach's α values were re-inspected to check if items within a particular scale could be creating any confusion. In doing so, it was noticed that a sub-item of the "Time and Study" scale stated "I attend class regularly". This could clearly have been misconstrued by online students, so the item was dropped from the scale. Similarly, for the "Peer Learning" scale, the item "I ask the instructor to clarify concepts I don't understand well" was seen as a possible source of confusion for students, since the specific conditions of online courses at SFU provide little opportunity for students to directly access the course instructor of record for the course.

Table 4.5 presents Cronbach's α values for all scales, after removal of the aforementioned items. Cronbach's α for the sub-scale ranged from 0.62 to 0.83, or between acceptable and good.

Table 4.5: Cronbach's α for GOQ and MSLQ Subscales

Sub-scale	Cronbach's α	Number of Variables
GOQ		
Social Goal	0.72	3
Work Avoidance	0.83	4
MSLQ		
Help Seeking	0.62	3
Effort Regulation	0.71	4
Peer Learning	0.71	3
Time and Study Environment	0.77	7

4.4 Results

To simplify reporting of results, descriptive and inferential statistics are presented in two separate groups: a) Categorical Questions, followed by b) Numeric and Likert-like Variables.

4.4.1 Categorical Questions - Descriptive Statistics

Disability

The question concerning whether students had any disability ("Do you have a physical disability that makes it difficult for you to travel to or around campus?") was only posed in the Fall 2018 semester survey, but the data are included here for completeness. Among OL students, 2 indicated that they had a physical disability, out of a sample of 157 (or 1.27%). For Face to Face students, only 1 reported having a disability, out of a total of 213 students (or 0.47%).

Sex

As indicated in Table 4.6, the sample included 193 men (29.69%) and 451 women (69.38%). When comparing the breakdown of self-reported sex for the FTF and OL participants, we see similar percentages: 71.11% of OL participants were female, while 67.76% of FTF participants were female. The high percentage of women in these samples is inconsistent with the makeup of the overall student population at SFU, where females currently represent 54% of total students (SFU, 2018b). Therefore, it appears that across both modalities, females were more likely to volunteer to participate in this research. While this could perhaps be explained if courses with higher proportion of females — like Archeology, Education, English — were contributing the most participants, it is hard to ascertain since the course of enrolment was only registered for Spring 2018 participants. It is worth mentioning that this pattern of more female repondants is consistent with previous research on survey non-response bias (Smith, 2008; Porter and Whitcomb, 2004; Sax et al., 2003).

Table 4.6: Sex (*n* and % of Group)

	FTF		OL		Totals	
Female	227	67.76%	224	71.11%	451	69.38%
Male	106	31.64%	87	27.62%	193	29.69%
Other	1	0.3%	1	0.32%	2	0.31%
Prefer not to say	0	0%	3	0.95%	3	0.46%
Transgender	1	0.3%	0	0%	1	0.15%
Totals	335	100%	315	100%	650	NA%

Modality Awareness and Choice

On all versions of the survey, students were asked the question "Did you know that this course was also offered online this semester?" or "Did you know that this course was also offered Face to Face this semester?", depending on their modality of enrolment. Students were also asked the question "Did you attempt to register in the online version of this course?" or "Did you attempt to register in the face to face version of this course?", depending on their modality of enrolment, to get a sense of the extent to which students wound up in their preferred mode. A larger percentage of OL students (87.3%) were aware of the availability of the other modality alternative, versus face-to-face students (57.91%). Likewise, more OL students seem to have attempted enrolment in the face-to-face modality (29.21%), if compared to face-to-face students having attempted OL enrolment (11.04%).

Table 4.7: Modality Awareness and Choice

	FTF			OL		
	n_{yes} (%)		n	n_{yes} (%)		n
Knew other mode offered	194	(57.91%)	335	275	(87.3%)	315
Attempted other mode	37	(11.04%)	335	92	(29.21%)	315

Course Attributes

Students were asked a series of questions related to course attributes such as whether the course was Required, Elective or a Pre-requisite for another course in their program. Questions were phrased as "This course is required for your major/minor/certificate?" or "This course is an elective". All course attribute questions were to be answered with Yes or No. The survey also asked about "W/Q/B" requirements, which is a concept specific to SFU. "W" indicates a writing-intensive course, "Q" indicates a quantitative course, and "B" indicates a breadth course. All students admitted to an undergraduate degree at Simon Fraser University must complete a minimum of 36 units of courses designated as "Writing, Quantitative, or Breadth" to receive the W/Q/B credits. The stated aim of this requirement is to ensure that students graduate as improved writers, with better quantitative reasoning skills and a greater breadth of knowledge. At a minimum, the student must complete two courses with the "W" designation (Writing), and two with the "Q" designation (Quantitative). They must also complete eight "B" courses — two from each of the main categories (Breadth-Humanities, Breadth-Science, Breadth-Social Sciences) and two additional courses outside the student's major subject. In the survey, students were asked whether "This course is meeting a W/Q/B requirement".

Table 4.8: Course Attributes Questions

	FTF			OL		
	n_{yes} (%)		n	n_{yes} (%)		n
This course is required for your major/minor/certificate	205	(61.19%)	335	149	(47.3%)	315
This course is an elective	109	(32.54%)	335	138	(43.81%)	315
This course is a pre-requisite for another course you need	51	(15.22%)	335	32	(10.16%)	315
This course is meeting a W/Q/B requirement	121	(36.12%)	335	124	(39.37%)	315

As table 4.8 shows, the proportion of students that answered affirmatively on whether the course was a pre-requisite is fairly similar between modalities (15.22% for FTF and 10.16% for OL). The same can be said for W/Q/B requirement (36.12% for FTF and 39.37% for OL). However, for the questions Required and Elective, the proportions seem more dissimilar. To further examine this difference, tests of proportions are presented in the next section.

4.4.2 Categorical Variables - Inferential Statistics

The analysis presented in table 4.9 is a comparison between the two modalities for all variables related to modality selection, course attributes and sex. Z tests of two proportions were used to examine whether the two groups differed significantly in each characteristic. The null hypothesis was that there were no differences between the two group's proportions, or more specifically, that the difference was zero (H_0: p_1 - p_2 = 0, $\alpha = 0.05$)

Table 4.9: Sample Proportions - Modality Selection, Course Atributes, Sex

	Prop. FTF	Prop. OL	p	95 % C.I.	
				LL	*UL*
Knew about other mode	0.58	0.87	0.0000	-0.36	-0.23
Attempted the other modality	0.11	0.29	0.0000	-0.24	-0.12
Required Course	0.61	0.47	0.0004	0.06	0.21
Elective Course	0.33	0.44	0.0031	-0.19	-0.04
Pre-Requisite Course	0.15	0.10	0.0531	0.00	0.10
WQB Course	0.36	0.39	0.3935	-0.11	0.04
Sex - Female Students	0.68	0.71	0.3544	-0.10	0.04

Note:

Prop. of 'Yes' in sample. For Sex, proportion of Females

Face-to-face students were less likely to be aware that they had a choice of modality than online students were ($Z = 8.35$, $p = 0.0000$). For face-to-face students, 58% were aware that the same course was being offered online in the same semester, while for online students, that proportion was 87%. This difference is perhaps to be expected given that SFU, despite the large number of courses it offers online, remains primarily a "land-based" institution. It is thus not surprising that students perceive face-to-face as the default modality.

Face-to-face students were also less likely to have attempted to enrol in the online modality, than vice-versa ($Z = 5.8$, $p = 0.0000$). Around 29% of online students attempted to enrol in the face-to-face offering first, while only 11% of face-to-face students attempted the online enrolment first.

Significant differences were also found in terms of the course being Required ($Z = 3.55$, $p = 0.0004$) or Elective (Z = 2.96, $p = 0.0031$). There was a significantly higher proportion of Face-to-face students enrolled in Required courses, and a higher proportion of Online students enrolled in Elective Courses. We found no significant differences between the online and face-to-face groups in terms of the course being a prerequisite for the student's program or meeting a W/Q/B graduation requirement.

Finally, the proportion of men and women in the two groups did not differ significantly.

4.4.3 Numeric, Likert-type Variables and Likert Scales - Descriptive Statistics

This section will present descriptive statistics for all numeric variable, scales and likert-like questions, followed by analysis of differences between means.

Table 4.10: Age in Years

	Min.	Max	Mode	$\bar{x}$	SD
FTF	18	63	19	21.19	4.5
OL	18	72	22	21.68	4.86

Numeric Variables

1. Age

   The participants ranged in age from 18 to 72, but most were between the ages of 19 and 22, and so of traditional age for post-secondary studies. Outliers (e.g. reported age below 10 years old) were removed from this analysis. Mean age was very similar for the two groups: 21.19 years for Face-to-Face and 21.68 for OL students. These means are very similar to the average age of all students at SFU at that period (21 years for full-time students, 22.1 years for part-time students, or 21.6 years for all undergraduates). (SFU, 2018b)

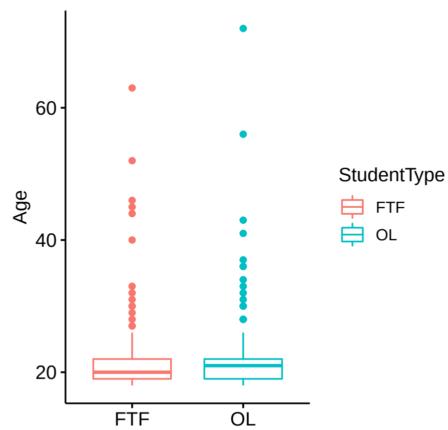

Figure 4.1: Boxplot - Age (in years) for FTF and OL samples

2. Commute Time

   The commute time question was asked only of face-to-face students during Fall 2017 data collection. For Spring 2018, the survey was changed and the question rephrased to ask of online students "If you had taken this course on campus, how many minutes would it take (approximately) for you to get to this class from home, or wherever you normally leave from?". The box plot below and the means-difference analysis for commute time includes both OL and FTF students for Spring 2018, but only FTF students for Fall 2017.

Table 4.11: Commute Time in Minutes

	n	Min.	Max	Mode	$\bar{x}$	SD
FTF	329	0	120	60	43.73	24.39
OL	157	0	300	60	54.54	39.59

Table 4.12: Workhours per week

	n	Min.	Max	Mode	$\bar{x}$	SD
FTF	335	0	50	0	10.88	10.44
OL	313	0	55	0	12.42	12.05

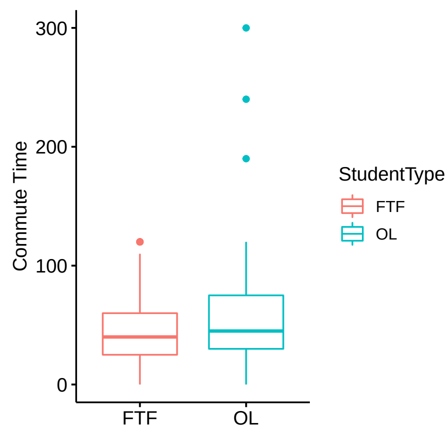

Figure 4.2: Boxplot - Commute Time (in minutes) for FTF and OL samples

3. Work-hours

   Students were asked "Approximately how many hours per week do you work a paid job?".

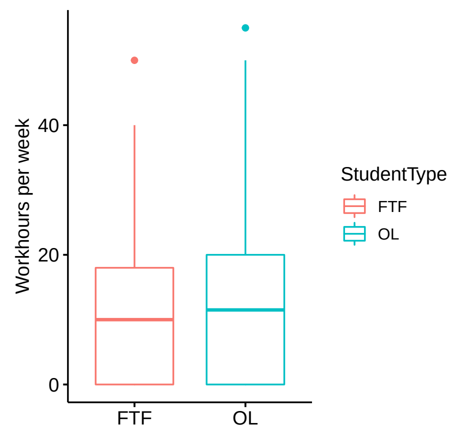

Figure 4.3: Boxplot - Work-hours for FTF and OL samples

Further inspection of the frequencies of each response shows large proportion of students reporting close to zero weekly work-hours in both groups (close to 100 students for both FTF and OL).

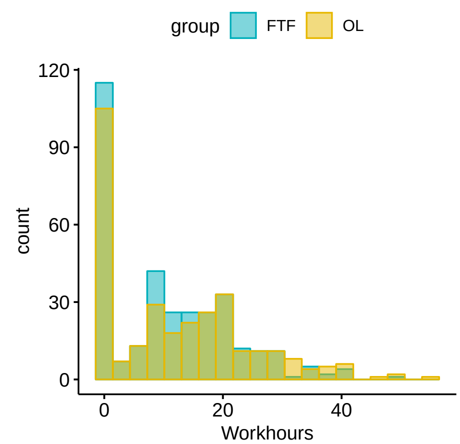

Figure 4.4: Histogram - Work-hours for FTF and OL samples

4. Courses taken online

   Students were asked "How many fully online courses have you taken in the past, at the college or university level?"

Table 4.13: Prior courses taken online

	n	Min.	Max	Mode	$\bar{x}$	SD
FTF	335	0	10	0	1.01	1.73
OL	314	0	42	0	2.44	3.76

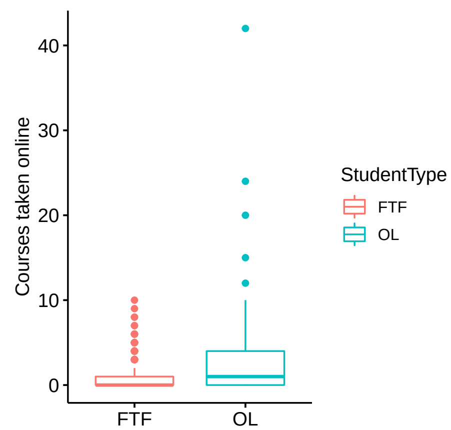

Figure 4.5: Boxplot - Prior online courses taken, for FTF and OL samples

Likert-type Items

The survey included 13 Likert-type questions. Frequency plots are presented below for all 13 items, and include only valid answers (missing data was removed). The x-axis represents the seven possible answers marked from 1 to 7, or from "Disagree Strongly" to "Agree Strongly". The y-axis shows the proportion (%) of students that chose each of these answers, in relation to the total number of valid responses for each question.

1. Question "I have responsibility at home to care for others"

   The most common answer for FTF students was "Agree Slightly" and the most frequent response for OL students was "Disagree Strongly" . Only 2 out of 335 FTF students didn't answer this question. For OL students, all 315 answered this question.

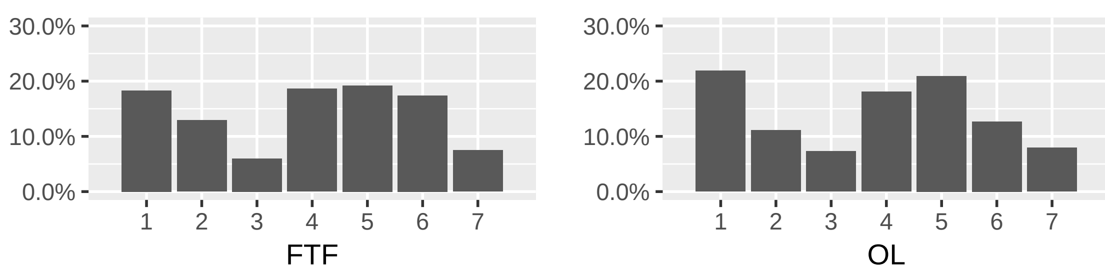

Figure 4.6: Frequency plots for question "Caregiver"

2. Question "I feel satisfied with my grades overall "

   The most common answer for FTF and OL students was "Agree Slightly". A total of 10 FTF students didn't answer this question, while 325 did. For OL students, 8 didn't answer while 307 did.

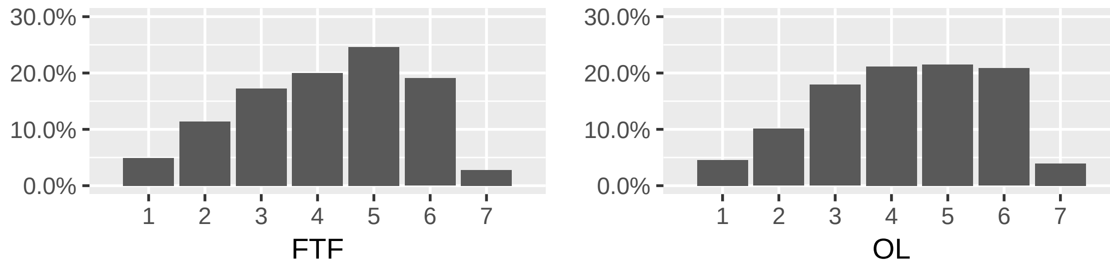

Figure 4.7: Frequency plots for question "Satisfaction"

3. Question "I feel the need to raise my GPA"

   The most common answer for FTF students was "Agree Strongly". The most frequent response for OL students was "Agree" . A total of 8 FTF students didn't answer this question, while 327 did. For OL students, 4 didn't answer while 311 did.

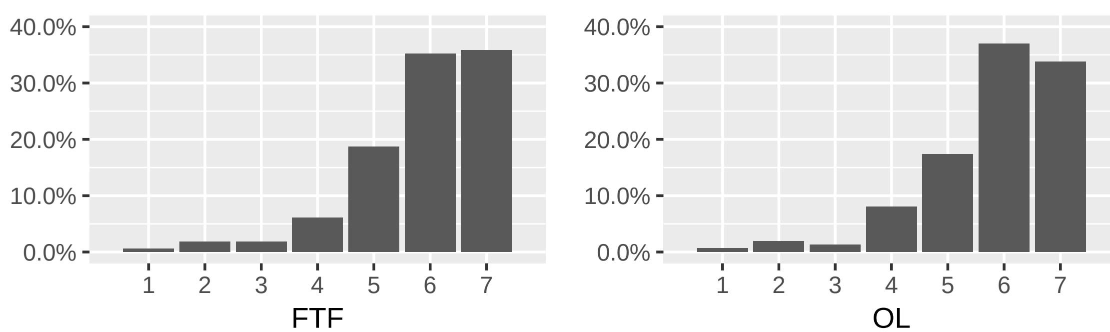

Figure 4.8: Frequency plots for question "GPA"

4. Question "I am interested in the subject of this course"

   The most common answer for both FTF and OL students was "Agree". There was no missing data for FTF students, while for OL students, 4 out of 315 didn't answer.

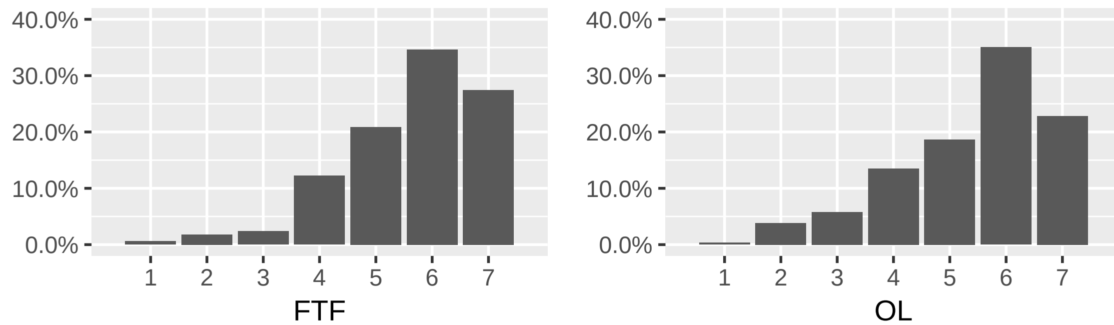

Figure 4.9: Frequency plots for question "Interest"

5. Question "The language this course is taught in is one that I can understand well orally (spoken)"

   The most common answer for both FTF and OL students was "Agree Strongly". Only 2 FTF students didn’t answer this question, while 333 did. For OL students, 5 didn’t answer while 310 did.

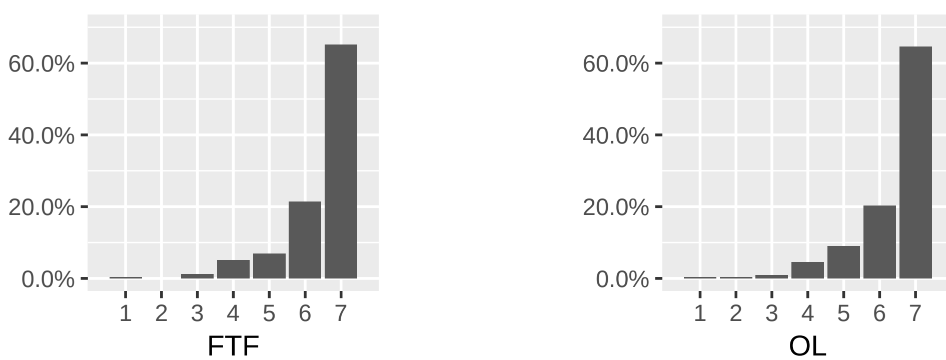

Figure 4.10: Frequency plots for question "Receptive English"

6. Question "I can read and write well in the language that this course is taught in"

   The most common answer for both groups was "Agree Strongly". Only 1 out of 335 FTF students didn’t answer this question. For OL students, 2 didn’t answer while 313 did.

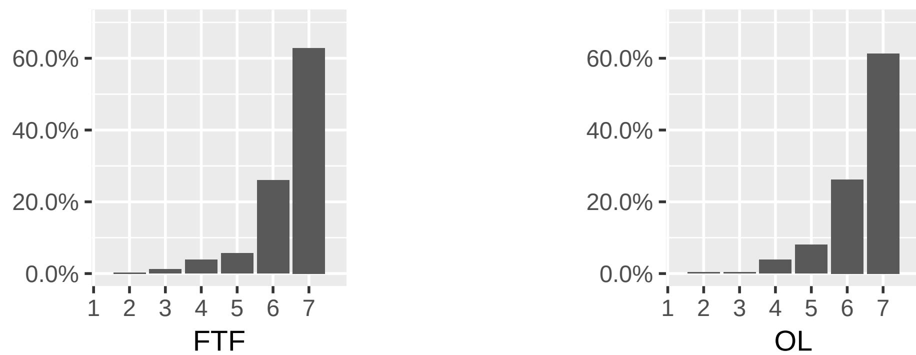

Figure 4.11: Frequency plots for question "Written English"

7. Question "The material in this course is important for me to learn "

   The most common answer for FTF and OL students was "Agree". Only 1 FTF students didn’t answer this question, while 334 did. For OL students, 4 didn’t answer while 311 did.

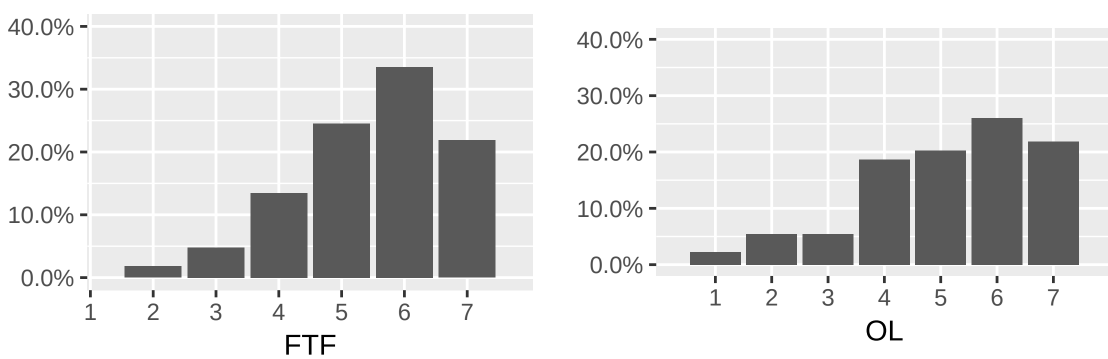

Figure 4.12: Frequency plots for question "Course Importance"

8. Higher Grade in modality of enrolment

   The two groups received slightly different versions of this question. FTF students were asked "Compared to the fully online version of this course, I expected to earn a higher grade in the face to face version" while OL students were asked "Compared to the fully face to face version of this course, I expected to earn a higher grade in the online version". The most common answer for both groups was "Neutral". A total of 39 FTF students didn’t answer this question, while 296 did. For OL students, 3 didn’t answer while 312 did.

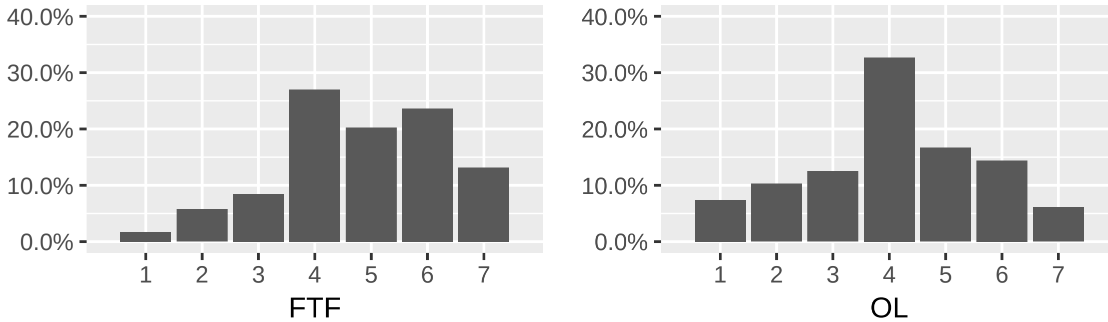

Figure 4.13: Frequency plots for question "Higher Grade"

9. Expected Face to Face to be harder

   FTF students were asked "Compared to the fully online version of this course, I expected the Face to Face version of this course to be harder" and OL students were asked "Compared to the fully online version of this course, I expected the Face to Face version of this course to be harder". The 2 most common answers for FTF students were "Disagree" and "Neutral". The most frequent response for OL students was "Neutral" . A total of 39 FTF students didn't answer this question, while 296 did. For OL students, only 4 didn't answer while 311 did.

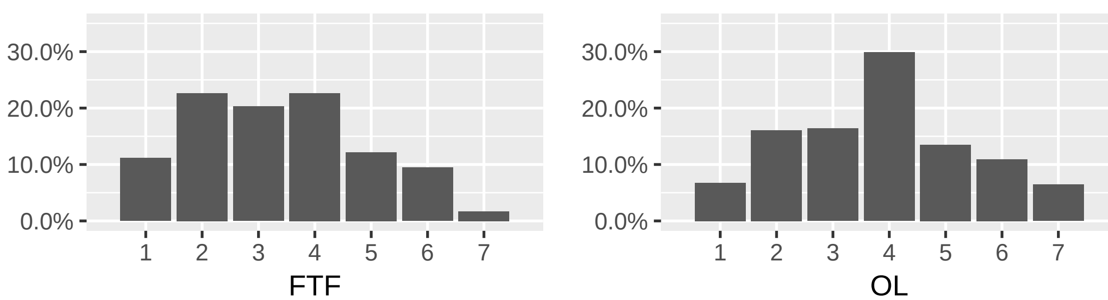

Figure 4.14: Frequency plots for question "FTF more difficult"

10. Question "I expect to earn a good grade in this course"

    The most common answer for both FTF and OL students was "Agree".All 335 FTF students answered this question and 4 OL students didn't.

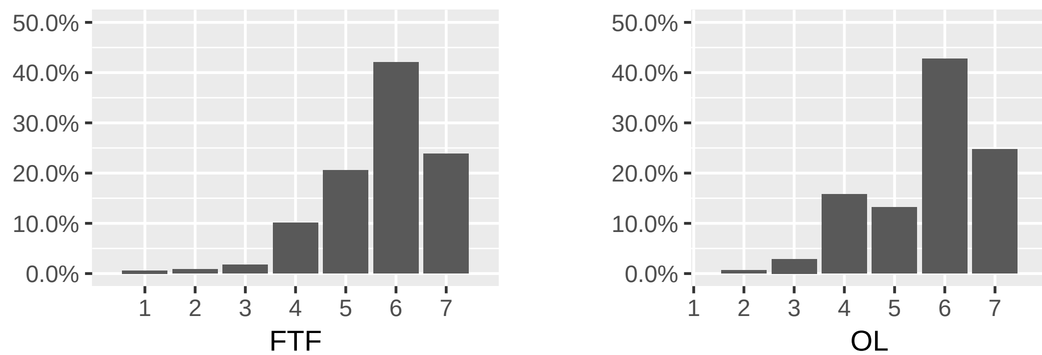

Figure 4.15: Frequency plots for question "Expects Good Grade"

11. Question "I expect to be able to access the help I need to succeed in this course from the professor, Tas and fellow students "

    The most common answer for both groups was "Agree". All 335 FTF students answered this question. Out of 315 OL students, only 2 didn't answer.

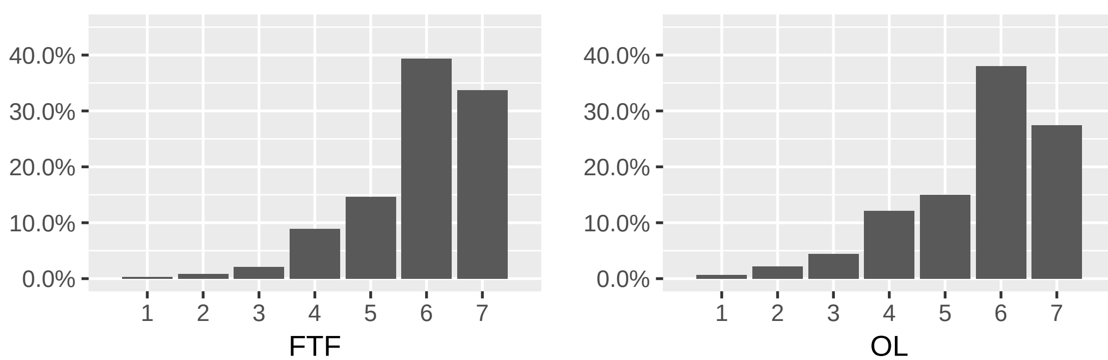

Figure 4.16: Frequency plots for question "Expects Help"

12. Question "I seem to be good at online courses

    The most common answer for FTF students was "Neutral" while the most frequent response for OL students was "Agree". A high number of FTF students didn't answer this question: 141 out of 335. For OL students, 7 didn't answer while 308 did.

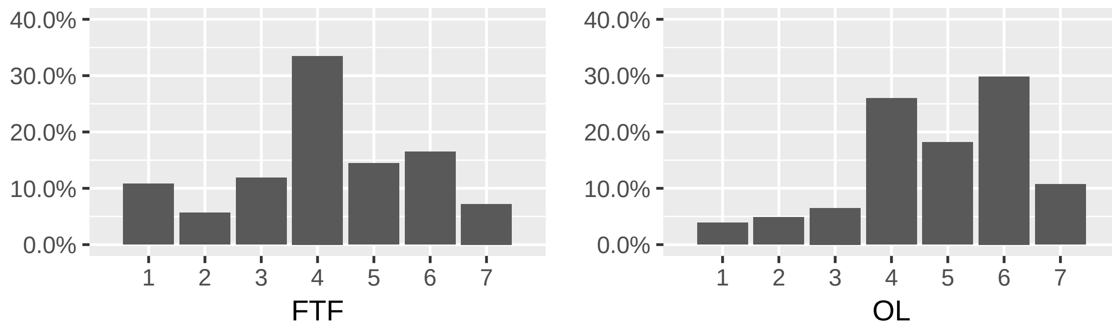

Figure 4.17: Frequency plots for question "Good at Online"

13. Question "I enjoy online courses"

    The most common answer for FTF students was "Neutral" and the most frequent response for OL students was "Agree". Similarly to the previous question, a total of 141 FTF students didn't answer this question, while 194 did. Further inspection of the data set shows high missing data overlap for these two question in the FTF group. In other words, the vast majority of students that didn't answer "Good at Online" also chose not to answer "Enjoy Online". For OL students, only 4 didn't answer while 311 did.

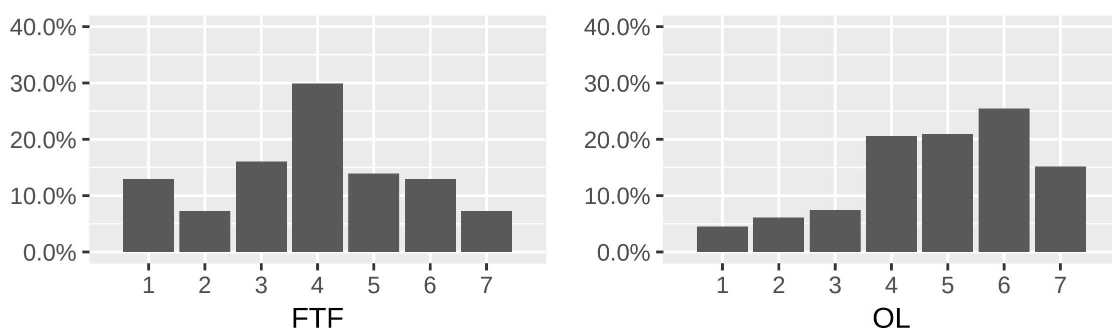

Figure 4.18: Frequency plots for question "Enjoy Online"

Likert Sub-scales

The survey included 6 sub-scales: two affective sub-scales from the Goal Orientation Questionnaire (GOQ), and four sub-scales from the learning strategies section of the MSLQ (Motivated Strategies for Learning Questionnaire). All items were Likert-type, with response scales ranging from 1 to 7 ("Disagree Strongly" to "Agree Strongly"). The score for each subscale was calculated by taking the mean of the items (as described in section 3.7.4

of the Methods chapter). Table 4.14 below summarizes sample sizes (valid answers), means, Standard Deviations, minimum and maximum scores for each Sub-scale.

Table 4.14: n, $\bar{x}$, SD, Min and Max values for Likert Subscales, Cronbach's α

	FTF					OL					
	n	$\bar{x}$	SD	Min.	Max	n	$\bar{x}$	SD	Min.	Max	α
SocialGoal	335	4.51	1.18	1.00	7.00	309	3.96	1.14	1.00	7.00	0.72
WorkAvoidance	335	3.39	1.30	1.00	7.00	309	3.59	1.27	1.00	7.00	0.83
HelpSeeking	335	3.91	1.26	1.00	6.67	312	3.17	1.28	1.00	6.67	0.62
EffortReg	335	5.14	1.01	1.50	7.00	312	5.23	0.99	2.25	7.00	0.71
TimeStudy	335	4.69	0.94	1.57	7.00	312	4.87	0.97	1.86	7.00	0.77
PeerLearning	335	3.69	1.34	1.00	7.00	312	3.04	1.31	1.00	7.00	0.71

The six histograms below show the distribution of the scores for each subscale, for both groups (FTF and OL).

1. GOQ - Social Goal The Social Goal subscale was formed by three items, with questions like "In this course I prefer working with others" and "In this course I am happy to be at the same level as my friends" (for a complete list of all survey questions, refer to Appendix B).

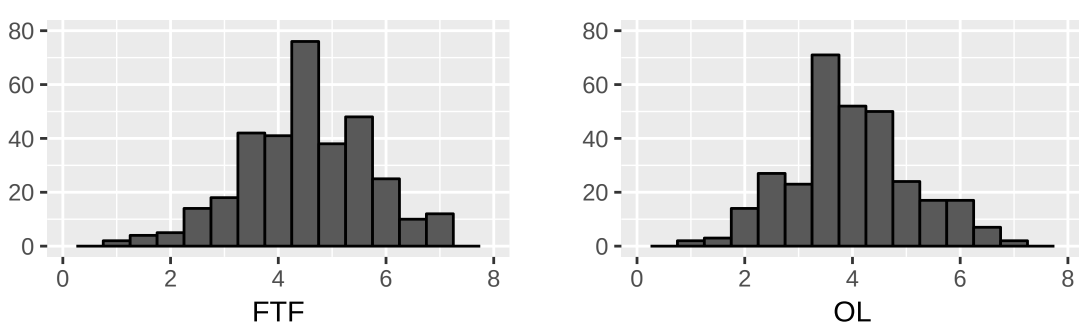

Figure 4.19: Histogram for GOQ scale "Social Goal"

2. GOQ - Work Avoidance The Work Avoidance subscale was formed by four items, and included questions like "In this course I avoid doing more work than is necessary" and "In this course I feel annoyed when I am required to make an effort".

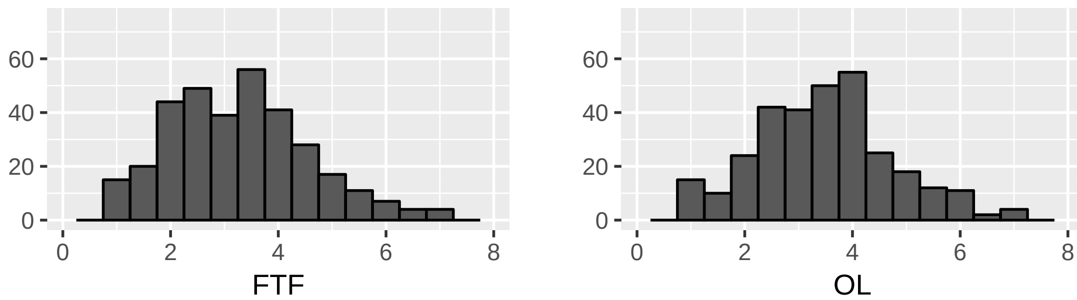

Figure 4.20: Histogram for GOQ scale "Work Avoidance"

3. MSLQ - Help Seeking The Help Seeking subscale was composed of three items, with questions like "When I can't understand the material in this course, I ask another student in this class for help " and "I try to identify students in this class whom I can ask for help if necessary". One of the items was reversed.

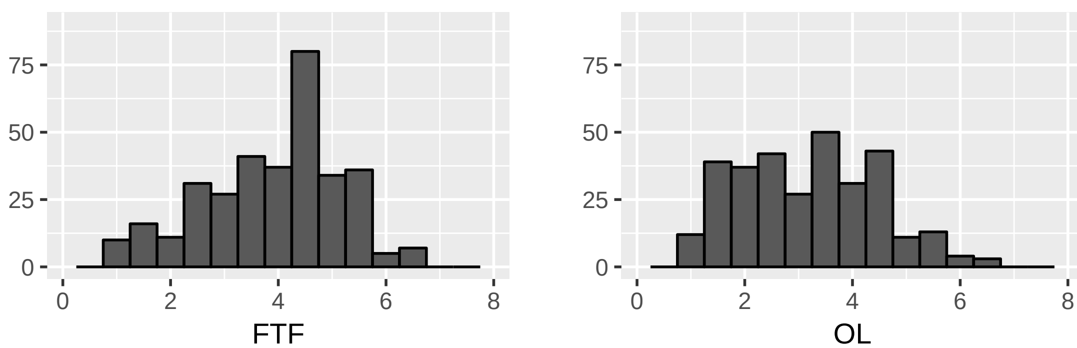

Figure 4.21: Histogram for MSLQ scale "Help Seeking"

4. MSLQ - Effort Regulation The Effort Regulation subscale was also formed by four items, questions included "I work hard to do well in this class even if I don't like what we are doing" and "Even when course materials are dull and uninteresting, I manage to keep working until I finish". The two other items on this scale were reversed.

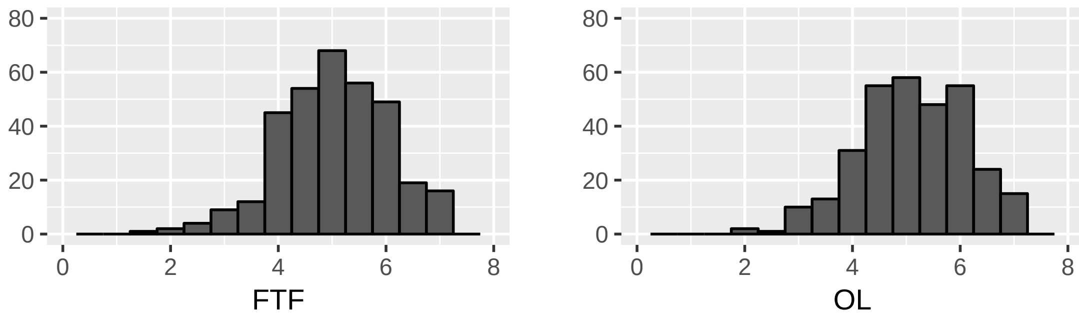

Figure 4.22: Histogram for MSLQ scale "Effort Regulation"

5. MSLQ - Time and Study Environment While the Time and Study Environment subscale has eight items, due to one of the question having potentially led to misunderstandings (see section 4.3.2), the subscale was only calculated with seven items. Of these, 3 were reversed. Questions included "I make sure I keep up with the weekly readings and assignments for this course " and "I usually study in a place where I can concentrate on my course work. ".

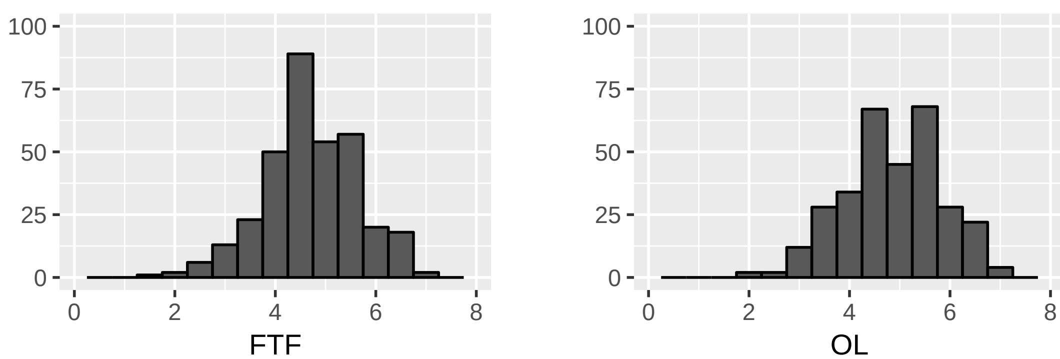

Figure 4.23: Histogram for MSLQ scale "Time and Study Environment"

6. MSLQ - Peer Learning While the Peer Learning subscale has four items, since one item was also removed (see section 4.3.2), the subscale was calculated with only three items. Questions included "When studying for this course, I often try to explain the material to a classmate or a friend." and "When studying for this course, I often set aside time to discuss the course material with a group of students from the class".

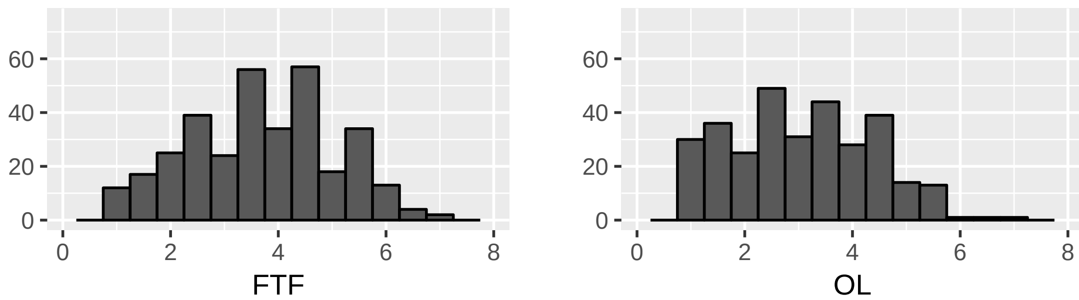

Figure 4.24: Histogram for MSLQ scale "Peer Learning"

4.4.4 Inferential Statistics - Numeric and Likert-type Variables

QQplots for all variables in both groups were inspected (see Appendix A), and for those variables that passed a visual check for normality, an independent-samples t-test was run to determine whether there was a statistically significant difference between the means of the two groups. The null hypothesis was that the means for the two groups were equal (H_0: $\mu_1 = \mu_2$, $\alpha = 0.05$). In addition, a Mann-Whitney test was run for all variables. To control inflation of type I error associated with multiple comparisons, a Holm-Bonferroni adjustment was used (target $\alpha = 0.05, n = 23$). After the adjustment, results revealed statistically significant group differences on eight of the variables. Table 4.15 below presents results from both independent-samples t-test and Mann-Whitney U tests, sorted by effect size (largest to smallest). The eight top rows present the statistically significant results after the Holm-Bonferroni adjustment.

Table 4.15: Means, SD, Means Difference (D), p-values, Cohen's d

	FTF		OL			t-test	M.W.	
	$\bar{x}$	SD	$\bar{x}$	SD	D	p	p	d
MSLQ - Help Seeking	3.91	1.26	3.17	1.28	0.74	0.00	0.00	0.58
Enjoy online courses	3.92	1.71	4.84	1.62	-0.92		0.00	0.55
MSLQ - Peer Learning	3.69	1.34	3.04	1.31	0.65	0.00	0.00	0.49
Previous online courses	1.01	1.73	2.44	3.76	-1.43		0.00	0.48
Expect higher grade	4.82	1.46	4.09	1.58	0.73		0.00	0.48
GOQ - Social Goal	4.51	1.18	3.96	1.14	0.54	0.00	0.00	0.47
Good at online courses	4.13	1.66	4.82	1.51	-0.69		0.00	0.43
Expect FTF harder	3.37	1.54	3.86	1.60	-0.49		0.00	0.31
Commute time (min.)	43.73	24.39	54.54	39.59	-10.81		0.01	0.31
Course importance	5.49	1.21	5.15	1.54	0.34		0.02	0.24
Expects help	5.90	1.11	5.63	1.30	0.27		0.01	0.22
MSLQ - Time/Study	4.69	0.94	4.87	0.97	-0.17	0.02	0.02	0.18
Interest in course	5.65	1.23	5.43	1.36	0.22		0.06	0.17
GOQ - Work Avoidance	3.39	1.30	3.59	1.27	-0.20	0.05	0.02	0.16
Workhours	10.88	10.44	12.42	12.05	-1.53		0.20	0.14
Age	21.08	4.76	21.56	5.08	-0.48		0.01	0.10
MSLQ - Effort Reg.	5.14	1.01	5.23	0.99	-0.09	0.26	0.26	0.09
Care for others	3.90	1.95	3.75	1.97	0.15		0.30	0.08
Grade Satisfaction	4.16	1.52	4.23	1.53	-0.07		0.61	0.04
Need raise GPA	5.89	1.18	5.86	1.18	0.03		0.66	0.03
Spoken language	6.43	0.96	6.41	0.99	0.02		0.80	0.02
Expects good grade	5.71	1.11	5.69	1.13	0.02		0.95	0.02
Written language	6.45	0.89	6.43	0.86	0.01		0.67	0.01

A number of variables did not show significant differences between the modality groups. Average age distribution was not found to be significantly different. Neither were significant differences observed between online and face-to-face registrants with regard to their satisfaction with their current grades, or self-reported need to increase their grade point average. Though it was speculated that students with more limited ability to benefit from an oral lecture or discussion might register more often in the online modality, this idea did not find support in our data. The two modality groups did not differ significantly with regard to their self-reported receptive and written English. With regard to their self-reported commute time to campus, there was a small difference: online registrants reported commute times that were roughly 11 minutes longer on average than those of face-to-face registrants, but the difference could not be classified as significant.

The popular image of online education is that it caters to students who do not have convenient access to face-to-face courses, or who require greater flexibility in their schedules for paid work or other reasons (Powell and Keen, 2006). However in our sample, we found no significant differences overall between face-to-face and online students with regard to the mean number of hours of paid work they reported doing each week, or their reported degree of care-giving responsibilities at home, which tended towards neutral or slightly lower (FTF Mean = 3.90 and OL Mean = 3.75).

The analysis identified several other significant differences between students enrolled in the face-to-face and online modalities, with medium effect sizes (Cohen's d ranging around 0.31 and 0.58). Experience with online courses was an important difference between the two groups. Online registrants reported having taken approximately 2.5 times as many online courses on average previously than face-to-face registrants had, which amounted to a significant difference. Relatedly, on average, online registrants reported a stronger belief that they were good at online courses versus face-to-face students. In relation to enjoyment of online courses, online students also expressed greater enjoyment than face-to-face registrants.

Online registrants generally expected the face-to-face offering to be harder, with face-to-face students believing this to a lesser degree, but the effect size was the lowest among the significantly different means. On the other hand, face-to-face students ($M = 4.82, SD = 1.46$) expressed stronger expectations of a higher grade in their modality of registration, with online students reporting lower expectations of a higher grade ($M = 4.09, SD = 1.58$).

With regard to psychological and motivational variables, a few differences were significant. On average, face-to-face registrants ($M = 3.91, SD = 1.26$) reported a greater inclination to seek help (MSLQ Help-Seeking) when they knew they were struggling while online students reported being less likely to do so ($M = 3.17, SD = 1.28$).

Face-to-face registrants also expressed a stronger orientation toward goals such as working with others, helping others, engaging with peers to learn, and working in groups. This was corroborated by two distinct scales: the GOQ - Social Goal subscale and the MSLQ - Peer Learning subscale. For the Social Goal item, face-to-face students expressed a significantly stronger preference, which they also did in the Peer Learning subscale.

4.5 Modelling Modality Enrolment

While overall comparisons between students who enrolled in each modality are informative, another important objective of this research was to understand the relative importance of different variables in determining students' modality of registration. Specifically, to assess the predictive power of the survey items in identifying modality of enrolment for students.

For this purpose, a logistic regression analysis was conducted, and a first exploratory model was created, including all variables. The underlying research question was whether the surveyed variables had an influence on the probability of enrolling in online courses (yes or no) and if so, how much.

4.5.1 Missing Data Analysis for the Regression Model

Before proceeding with the modelling, it was necessary to handle the missing data, since this sort of predictive model can be sensitive to it. For all variables, the percentage of missing values was calculated. As mentioned in section 4.1, the majority of the variables had some amount of missing data (percentages missing varying between 0.2% and 43%) and six of them had percentage of missing values higher than 5%. These were:

1. Disability
2. Commute time
3. Good at Online
4. Enjoy Online
5. Expected FTF harder
6. Expected higher grade

Importantly, there was no missing data for categorical predictors, only for numerical of likert-type items.

To further explore patterns of missingness, an SPSS MVA was run with a t-test to see if missingness was related to any of the other variables, with $\alpha = 0.5$ and tests done only for variables with at least 5% of data missing. The t-tests showed a systematic relationship between all 6 predictors cited and the dependent variable (FTF or OL), and therefore the missingness could be classified as MNAR (Missing Not at Random) (Rubin, 1976) . These 6 predictors therefore were dropped from the model (Tabachnick and Fidell, 2007).

4.5.2 Data Imputation

Data imputation is a technique or procedure to replace missing data with estimated values. Because the sample was quite large, an alternative way to handle the MCAR missing data would have been to drop it list-wise from the analysis, without biasing the estimates. However, so as not to reduce sample size and given the high number of predictors to be analysed, imputation was preferred.

In general terms, to input data, the available information in the data set is used to estimate a probable value for the missing items and once all missing values are replaced, data analysis can proceed as if the data is complete. However, imputation should be used only when missing data is similar enough to a random sample of the complete data, i.e., when the data is MCAR (Missing Completely at Random) (Rubin, 1976). This means that the "missingness" in a given variable does not depend on any other variable (observed or unobserved). The Little's MCAR test (Little, 1988) is a common test for confirming the data are MCAR. Little's MCAR test was run with the remaining predictors, to see if they were missing completely at random. A statistically non-significant result ($p = 0.623, \alpha = 0.05$) indicates no statistically significant deviation from randomness, which supports imputation of missing values.

Many algorithms can be used to impute missing data. An easy alternative is to calculate the mean of each variable and replace that for each of the missing values. This approach has serious disadvantages because it reduces the variance of the data set and ignores that some variables can be correlated with others. Two other approaches — Expectation-Maximization (EM) and Multiple Imputation (MI) — are more robust and preferred (Dong and Peng, 2013). Given that the literature consistently documents the superior power of EM (Collins et al., 2001; Graham et al., 2007; Schafer and Graham, 2002), this method was chosen for this study. Fifty-two cases with missing values on continuous predictors were imputed using the EM algorithm through IBM SPSS MVA.

4.5.3 General Assumptions for Logistic Regression

Three basic assumptions need to be confirmed before a binomial logistic regression can be performed (Laerd Statistics, 2015). These are heavily dependent on survey design. First, the dependent variable needs to be dichotomous. This is clearly the case since the outcome variable is enrolment in either Face-to-Face class or Online class. Second, a minimum of two independent variables must be included, which can be either continuous variables or nominal variables. The study included more than 20 independent variables, which were either nominal, continuous or ordinal. For the purposes of the regression model, ordinal variables were treated as continuous. Third, there must be no known dependence between cases (Tabachnick and Fidell, 2007). Each student participated in the survey only once, excluding the possibility of intra-participant dependence. Some participants did enrol in the same courses, opening the possibility of inter-participant dependence. We chose to ignore this possible source of dependence and thus our results should be accepted with caution. Additionally, the categories of the dichotomous dependent variable and all the nominal independent variables should be mutually exclusive and exhaustive. This was observed for all nominal variables in the study.

4.5.4 Number of Variables

The decision about the number of variables to include in the model is critical, since the maximum likelihood estimation algorithm in logistic regression requires that there be more outcomes than independent variables to cycle the different solutions (Stoltzfus, 2011). Too few cases in each independent variable could lead to model over-fit: when a model has coefficients that are much higher than they should be, and higher than expected standard error (Hosmer and Lemeshow, 2000). Unfortunately, there is no universally accepted standard for deciding on the number of variables to include. Some sources recommend that, for each independent variable, there should be no fewer than 10 outcomes for each binary category (Agresti, 2007), while others recommend 20 outcomes per independent variable (Feinstein, 1996). It is also recommended that the least common outcome determines the maximum number of independent variables to include in the model. So considering the Online students (with a total of 315 cases to be included, versus cases 335 for Face-to-Face Students), the logistic regression model could theoretically accommodate a maximum of 31 variables to avoid over-fit (Stoltzfus, 2011). This would allow for the inclusion of all 25 remaining variables to the model.

Tabachnick and Fidell recommend that an analysis of expected frequencies be performed if the model is to be subject to a goodness-of-fit test, since the test would have little power if the expected frequencies were too small (Tabachnick and Fidell, 2007). For all pairs of discrete variables (including outcome variable), (a) expected frequencies should be greater than 1, and (b) no more than 20% of the cells in a two-way table should have frequencies less then 5. After cross-tabulating all discrete variables with SPSS CROSSTABS, it was observed that expected frequencies for Sex in categories "Other", "Prefer not to say" and "Transgender" were quite low, with many cells lower than 1. So those 3 categories plus "Male" were collapsed. Sex was therefore re-coded to "Female" or "Not Female". After this adjustments, both assumptions above (a and b) were met.

4.5.5 Data Fit Assumptions for Logistic Regression

Three more assumptions must be met so that the binomial logistic regression can provide a valid result:

1. It is assumed that there is a linear relationship between the continuous independent variables and the logit transformation of the dependent variable. The Box-Tidwell procedure can be used to assess linearity (Box and Tidwell, 1962). Using this technique, new terms are added to the logistic regression model formed by the interaction between each (continuous) predictor and its natural logarithm. If one or more of the added terms is statistically significant, then the assumption of linearity is violated. The Box-Tidell procedure was applied in SPSS. For predictors that had values of zero (Work-hours and Courses Taken Online), a constant was first added to each score, so that the natural logarithm could be applied. Finally a Bonferroni correction was applied using all 44 terms in the model, resulting in statistical significance being accepted when $p < .0011$ (Tabachnick and Fidell, 2007). Based on this assessment, all continuous independent variables were found to be linearly related to the logit of the dependent variable.

2. Logistic regression algorithms are sensitive to extremely high correlations between predictor variables (Tabachnick and Fidell, 2007). Multicollinearity is the situation where two or more independent variables highly correlate with each other and may occlude which independent variable actually contributes to the variance explained in the dependent variable. In a logistic regression, absence of multicollinearity is assumed. The Variance Inflation Factor analysis (VIF) can shows us how much the variance of the coefficient estimate is being inflated by multicollinearity. There is no agreed, definitive cutoff value to use with VIF (some sources say that VIF above 10 is an indicator of multicolinearity (Hair et al., 1995) while other sources say the same about VIF higher then 5 (Ringle et al., 2015). The SPSS collinearity statistics function was used to calculate VIFs for all predictors, with none of them presenting VIF above 2.607, which is taken as a good indication of absence of multicollinearity.

3. Lastly, logistic regressions assume the absence of outliers (Tabachnick and Fidell, 2007). If there are enough outliers (cases that are in one category, but for which the model attributes high likelihood of being in other category), the model will have poor fit. An initial analysis showed that there were 7 cases for which standardized residual were greater than 3 standard deviations. These seven cases were excluded from the model.

4.5.6 Logistic Regression Results

After validating these assumptions, a direct logistic regression was performed to discern the effects of all 25 predictor variables on the likelihood that participants were enrolled in Online courses. This analysis was performed using IBM SPSS Statistics v24, which for direct regression is capable of entering all predictors in the equation simultaneously on the first step of the analysis. Data from 643 students were available for the regression: 330 Face-to-Face Students and 313 Online Students. A test of the full model with all predictors against a constant-only model was statistically significant, $X^2(25, N = 643) = 264.855$, $p = 0.000$, indicating this set of predictors reliably distinguished between Online and Face-to-Face students. The model correctly classified 76.4% of cases (cut off point set to 0.50).

Type I errors (rejection of a true null hypothesis or "false positive"), in the context of logistic regressions, can best be expressed by "Specificity", or the percentage of cases that did not have the observed characteristic (i.e. were not online students) that were also correctly predicted as not having the observed characteristic (i.e., true negatives, or correctly identified as face to face). Model specificity was 76.7%. Type II errors (failure to reject a false null hypothesis, or false negative), can be expressed as "Sensitivity", or the percentage of cases that had the observed characteristic (were online students) which were correctly predicted by the model (i.e., true positives). Model Sensitivity was 76%.

Two other measures of model quality are Positive and Negative predictive values. Positive predictive value is the percentage of correctly predicted cases that were indeed online students, compared to the total number of cases predicted as being online students. The Model's Positive Predictive value was 75.5%. Negative predictive value is the percentage of correctly predicted cases that were really not online students, compared to the total number of cases predicted as not being online (so in this particular case, the predicted as face-to-face that truly were face-to-face, compared with all predicted to be face-to-face student). The Model's Negative predictive value was 77.1%.

The c-statistic for the model was 0.842 (or, for 84% of all possible pair of students — Online and Face-to-Face — the model correctly assigned a higher probability to Online students). An inferential goodness-of-fit test was run (Hosmer-Lemeshow), which yielded a $X^2(8, N = 643)$ of 10.943 and was insignificant ($p = 0.205$), suggesting that the model was fit to the data well.

The table below shows regression coefficients (B) in log-odds, Standard Error, Wald chi-square statistics, degrees of freedom, significance ($\alpha = 0.05$), Odds Ratios ($Exp(B)$) and Confidence Intervals for each of the 25 predictors. Categorical variables were coded as Yes = 1, No = 0, and Sex was coded as Female = 1, Not Female = 0.

Table 4.16: Logistic Regression Model - Enrollment

	B	SEB	W. χ^2	df	p	e^B	95% C.I for e^B LL	95% C.I for e^B UL
Age	-0.032	0.021	2.443	1	0.118	0.968	0.930	1.008
Sex - Female Students	0.145	0.227	0.411	1	0.522	1.157	0.741	1.804
Workhours	0.008	0.009	0.651	1	0.420	1.008	0.989	1.026
Care for others	0.022	0.053	0.172	1	0.679	1.022	0.922	1.133
Grade Satisfaction	-0.044	0.082	0.288	1	0.592	0.957	0.814	1.124
Need raise GPA	0.050	0.092	0.288	1	0.592	1.051	0.877	1.259
Required Course	-0.167	0.285	0.343	1	0.558	0.846	0.484	1.479
WQB Course	0.165	0.223	0.547	1	0.460	1.179	0.762	1.826
Elective Course	0.622	0.274	5.170	1	0.023	1.863	1.090	3.186
Pre-Requisite Course	-0.324	0.341	0.904	1	0.342	0.723	0.370	1.411
Knew course offered other mode	1.418	0.252	31.685	1	0.000	4.129	2.520	6.764
Attempted other mode	1.585	0.278	32.513	1	0.000	4.881	2.830	8.417
Written language	-0.233	0.158	2.185	1	0.139	0.792	0.582	1.079
Interest in Course	0.093	0.124	0.566	1	0.452	1.098	0.861	1.399
Course importance	-0.135	0.113	1.430	1	0.232	0.874	0.701	1.090
Expects good grade	-0.030	0.111	0.072	1	0.789	0.971	0.780	1.208
Spoken language	0.304	0.150	4.121	1	0.042	1.355	1.011	1.816
Expects help	-0.250	0.105	5.731	1	0.017	0.779	0.634	0.956
Previous online courses	0.411	0.059	48.696	1	0.000	1.509	1.344	1.694
GOQ - Work Avoidance	0.305	0.101	9.175	1	0.002	1.357	1.114	1.654
GOQ - Social Goal	-0.257	0.097	6.988	1	0.008	0.773	0.639	0.936
MSLQ - Help Seeking	-0.286	0.101	8.010	1	0.005	0.751	0.616	0.916
MSLQ - Effort Reg.	-0.062	0.150	0.169	1	0.681	0.940	0.700	1.262
MSLQ - Time/Study	0.660	0.162	16.664	1	0.000	1.934	1.409	2.655
MSLQ - Peer Learning	-0.069	0.098	0.492	1	0.483	0.934	0.771	1.131
Constant	-5.014	1.559	10.348	1	0.001	0.007		

Note:
Coeficients in log-odds, Standard Error, Wald chi-square, degrees of freedom, Significance, Odds Ratios for the predictors and Confidence Intervals

Ten predictor variables could be classified as statistically significant ($\alpha = 0.05$): Elective Course, ($p = 0.023$), Knew about other mode ($p = 0.000$), Attempted the other mode ($p = 0.000$), Spoken Language ($p = 0.042$), Expects help ($p = 0.017$), Previous Online Courses

(p = 0.000), GOQ - Work Avoidance (p = 0.002), GOQ - Social Goal (p = 0.008), MSLQ - Help Seeking (p = 0.005) and MSLQ Time/Study (p = 0.000). Odds ratios ($Exp(B)$) greater then 1 reflect an increase in odds of the student being enrolled in an online class, for every one-unit increase in that predictor. Odds ratio less then one reflect a decrease in the odds of being an online student with a one-unit change of the predictor (Tabachnick and Fidell, 2007).

For continuous variables, four of them had significant *positive* predictive values. For each additional course previously taken online by the student, the odds of being an online (versus face-to-face) student increased by 50% ($exp(B) = 1.509$). For each additional unit in the GOQ - Work Avoidance scale, the odds of being an online student increased by 35% ($exp(B) = 1.357$). For each additional unit in the Spoken Language question, the odds of being an online student increased by 35% ($exp(B) = 1.355$). Finally for each additional unit in the MSLQ - Time/Study scale, the odds of being an online student increased by 93.4% ($exp(B) = 1.934$).

Three continuous variables had *negative* predictive values. For every one unit increase in the Expects Help response, the odds of being an online student decreased by 22% ($exp(B) = 0.779$). For each additional unit in the GOQ - Social Goal scale, the odds of being an online student also decreased by 22% ($exp(B) = 0.773$). Lastly for each additional unit in the MSLQ - Help Seeking scale, the odds of being an online student decreased by almost 25% ($exp(B) = 0.751$).

Three categorical variables had positive predictive value. The odds of being an online student (versus face-to-face) were 4 times higher ($exp(B) = 4.129$) for students that were aware of the availability of the course in another mode and almost 5 times higher ($exp(B) = 4.881$) for students that had attempted to enrol in the other modality. Finally, the odds of being an online student increased 1.8 times ($exp(B) = 1.863$) for students who were enrolled in Elective courses.

4.6 Modelling Modality Choice

The previous model attempted to predict student registration in online course. In inspecting two of the variables — knew modality choice and attempted other modality — it can be seen that many students from the sample were actually not aware that they could have chosen a different modality, and also that many students ended up enrolled in a modality that was not their first choice. So to gain a better sense of how the actual choice of modality could be predicted, a second model was created. For this model, all respondents who said they attempted to register in the other modality were removed from the sample. Similarly, all respondents that were not aware that the other modality was offered were removed as well. The underlying research question was whether the surveyed variables had an influence on the probability of actively choosing online courses, and if so, how much influence.

The original data set, when subjected to the restrictions mentioned above, was reduced to a sample of 344 entries, or 158 face-to-face participants and 186 OL participants. Missing data analysis was performed and again the same six variables had missing data percentages above 5% (Disability, Commute Time, Good at Online, Enjoy Online, Expected FTF Harder, Expected Higher Grade). An SPSS MVA was run again and showed a systematic relation between these 6 predictors and the dependent variables, so these 6 predictors were dropped from the model. Little's MCAR test was run with the remaining predictors and a statistically non-significant result ($p = 0.973, \alpha = 0.05$) supported data imputation. SPSS MVA was used to input missing data.

The number of predictors to be included in the model had to be adjusted, since the sample sized was reduced significantly. So considering Stoltzfus (2011) recommendation that the least common outcome defines the maximum number of predictors, and since the smaller respondent group (face-to-face) had 158 entries, a maximum of 15 variables could be included in the model. Eight predictors were therefore removed. The variables chosen for removal were the 8 variables with less significant means differences in the previous t-tests or Mann-Whitney tests. These were: Age, Expects good grade, Written Language, Spoken Language, GPA, Grade Satisfaction, Care for others and MSLQ Effort Regulation. SPSS CROSSTABS showed that all remaining predictors had expected frequencies greater than one and none was less than 5. Three outliers were found where the standardized residual was greater than 3 standard deviations, and these were removed from the sample. A Box-Tidel; procedure was applied in SPSS with a Bonferroni correction, and all continuous independent variables were found to be linearly related to the logit of the dependent variable. Finally, SPSS Collinearity statistics function shows that none presented VIF superior to 2.554, which is an indicator of the absence of multicolinearity.

A logistic regression using IBM SPSS Statistics v24 was performed to identify the effects of 15 predictor variables on the likelihood that participants had chosen Online courses. A test of the model with all 15 predictors against a constant-only model was statistically significant, $X^2(15, N = 341) = 114.067$, $p = 0.000$, indicating this set of predictors reliably distinguished between Online and Face-to-Face students. The model correctly classified 74.5% of cases (cut off point set to 0.50). Model specificity was 71.6% and model sensitivity was 76.9%. Positive Predictive value was 76.4%. Negative predictive value was 72%. The c-statistic for the model was 0.812 (or, for 81% of all possible pair of students — Online and Face-to-Face — the model correctly assigned a higher probability to Online students). An inferential goodness-of-fit test was run (Hosmer-Lemeshow), which yielded a $X^2(8, N = 341)$ of 9.414 and was insignificant ($p = 0.309$), suggesting that the model was fit to the data well.

The table below shows regression coefficients (B) in log-odds, Standard Error, Wald chi-square statistics, degrees of freedom, significance ($\alpha = 0.05$), Odds Ratios ($Exp(B)$) and Confidence Intervals for each of the 15 predictors. Categorical variables were coded as Yes = 1, No = 0, and Sex was coded as Female = 1, Not Female = 0.

Table 4.17: Logistic Regression Model - Choice

							95% C.I for e^B	
	B	SEB	W. χ^2	df	p	e^B	LL	LU
Sex - Female Students	-0.261	0.302	0.746	1	0.388	0.770	0.426	1.393
Workhours	0.003	0.012	0.056	1	0.813	1.003	0.980	1.026
Required Course	-0.749	0.385	3.794	1	0.051	0.473	0.222	1.005
WQB Course	0.104	0.298	0.122	1	0.726	1.110	0.619	1.990
Elective Course	0.511	0.351	2.120	1	0.145	1.666	0.838	3.313
Pre-Requisite Course	0.120	0.509	0.056	1	0.813	1.128	0.416	3.056
Interest in course	0.175	0.155	1.283	1	0.257	1.191	0.880	1.613
Course importance	-0.415	0.153	7.346	1	0.007	0.660	0.489	0.891
Expects help	-0.146	0.131	1.246	1	0.264	0.864	0.669	1.117
Previous online courses	0.399	0.076	27.766	1	0.000	1.491	1.285	1.729
GOQ - Work Avoidance	0.348	0.139	6.268	1	0.012	1.416	1.078	1.859
GOQ - Social Goal	-0.153	0.132	1.334	1	0.248	0.858	0.662	1.112
MSLQ - Help Seeking	-0.434	0.132	10.895	1	0.001	0.648	0.501	0.838
MSLQ - Time/Study	0.433	0.179	5.854	1	0.016	1.543	1.086	2.192
MSLQ - Peer Learning	0.127	0.130	0.958	1	0.328	1.135	0.881	1.463
Constant	0.161	1.351	0.014	1	0.905	1.175		

Note:

Coeficients in log-odds, Standard Error, Wald chi-square, degrees of freedom, Significance, Odds Ratios for the predictors and Confidence Intervals

Five predictor variables were statistically significant ($\alpha = 0.05$): Course importance ($p = 0.007$), Previous Online Courses ($p = 0.000$), GOQ - Work Avoidance ($p = 0.012$), MSLQ - Help Seeking ($p = 0.001$) and MSLQ Time/Study ($p = 0.016$).

For continuous variables, three of them had significant *positive* predictive values. For each additional course previously taken online by the student, the odds of being an online student increased by 50% ($exp(B) = 1.491$). For each additional unit in the GOQ - Work Avoidance scale, the odds of being an online student increased by 41% ($exp(B) = 1.416$). Finally for each additional unit in the MSLQ - Time/Study scale, the odds of being an online student increased by 54.4% ($exp(B) = 1.543$).

Two continuous variables had *negative* predictive values. For every one unit increase in the Course importance response, the odds of being an online student decreased by 34% ($exp(B) = 0.66$). For each additional unit in the MSLQ - Help Seeking scale, the odds of being an online student decreased by almost 35% ($exp(B) = 0.648$).

Chapter 5

Conclusion

Academic institutions, in an attempt to cope with financial constraints and to provide a more flexible and effective academic environment for undergraduates, have increasingly incorporated online educational offerings to curricula and in the present day context, there seems to be a presumption that this should be so. Online learning is seen as an strategic direction for traditional Universities, as a way to increase enrolments and a very important part of the institution's long-term plans. However, despite the growing popularity of online courses in the context of undergraduate education, the factors that shape students' choice of modality remain incompletely understood, and have not been a focus of careful research for very long.

Limited scholarly understanding of modality choice is problematic. Undergraduates may be more willing to enrol in online courses due to living complex lives and having to attend to a large number of non-academic activities at the same time as their studies, including paid work, family care and commuting. Online courses may be seen to offer some additional flexibility to balance these priorities successfully. Yet students seem to perceive online courses as not equivalent to face-to-face classes, declaring that online learning requires a very different set of skills, or even that it provides learning of lesser quality. It is important to understand what sort of complex trade-offs and compromises students are making in choosing enrolment modality, so as to better advise and support them in these critical decisions.

From the institutional perspective, understanding modality choice is crucial. In the future, "land-based campuses" will have to continuously adapt to technological innovation and a rapidly changing academic environment. As "nontraditional newer students" (Falk and Blaylock, 2010) numbers continue to grow, their different needs will increasingly pressure administrators towards more flexible schedules, more affordable tuition and more cost-effective methods of course delivery. Yet, drop-out rates for online courses are higher when compared to face-to-face equivalents. Also, as mentioned above, students may not welcome online offerings, so enrolment targets may not be met if these are relied upon too greatly. Both situations lead to waste of resources and time. A more thorough understanding of modality choice could help institutions with their strategic planning regarding online offerings, so that the right types of courses are offered to the right students at the right moment, while also ensuring that institutions can make the best use of their limited infrastructure and human resources.

The last decade has seen increased research into students' perceptions of and experiences with online learning, and how these may affect their choice of modality. Many factors seem to influence the decision: previous experience with online courses, student characteristics, social goals, needs for flexibility of schedule and location, views regarding the suitability of specific subject matter for study online, and a variety of subjective psychological factors.

Previous studies had important limitations, such as small sample sizes, inclusion of a limited array of disciplines, or focus on a restricted subset of characteristics as possible explanations for student' choice of modality. An especially critical limitation of all studies reviewed is that students were not afforded the option to actively chose between both modalities (face-to-face and online) under equal conditions. So the "choice" being assessed relates more to perceptions of and preferences for online learning, or, when measured, choice was framed as a stated intention for future registration.

The present study is motivated by the challenges faced by both students and institutions of higher education with respect to modality choice, and tries to address the gap in knowledge in this still incipient research field. The study tries to advance understanding of whether and how much the choice of modality is influenced by demographic factors, perceptions, motivational aspects or learning strategies. the research methods used afforded several advances over prior research, like the inclusion of a large number of respondents, a broader range of disciplines, and increased number of potentially explanatory variables. Most critically, the study focuses on students who had made the choice to enrol in the online mode when they could realistically have selected an equivalent face-to-face class (or vice-versa), providing a unique opportunity for the study of this particular research problem.

5.1 Summary of Findings

Of the seven categorical variables included on the survey, four showed significant differences in proportions between the registration modality groups: Required course, Elective Course, Knew other mode and Attempted other mode. Face-to-face students were less likely to be aware that they had a choice of modality and also less likely to have attempted to enrol in the online modality. A higher proportion of face-to-face participants' courses were required, and a higher proportion of online participants' courses were electives.

Inferential statistics showed that 15 out of the 23 numeric or Likert-type variables did not differ significantly between modality groups. Among the numeric variables, neither Age, Commute time or Work hours showed significant differences. Both self-perceived language ability questions (written and spoken) showed no difference. The motivational scale and the learning strategies scale divided evenly, with half their sub-scales showing no significant difference (namely GOP - Work Avoidance, MSLQ Time/Study Environment, and MSLQ Effort Regulation).

Course importance and Interest in Course were not significantly related to course modality. How much responsibility the students had at home to care for others, how satisfied they were with their grades overall, and whether they felt the need to raise their GPA were not significantly related to course modality. Finally, expectations for help or for a good grade (in this course) were also not significantly related.

Inferential statistics also found that 8 out of the 23 numeric or Likert-type variables were significantly related to course modality. For 4 of these 8 variables, the means for the OL group were significantly higher. By order of effect size, these were: Enjoyment of online courses, Number of previous online courses taken, self-reported ability for online courses, and Expectation of face-to-face mode being harder. For the other 4 variables, the means for the face-to-face group were significantly higher. By order of effect size, these were: MSLQ Help Seeking, MSLQ Peer Learning, Expectation of a higher grade in the modality of registration, and GOQ Social Goal Orientation.

A logistic regression model constructed to predict online enrolment showed that as many as nine predictor variables could be classified as statistically significant. Positive predictors were: Number of previous online courses, GOQ Work Avoidance score, MSLQ Time/Study Environment score, Knowledge that the other mode was available, having attempted to register in the face-to-face mode and whether the course was an elective for the student. Negative predictors were: Expectation of help, GOQ Social Goal orientation score, and MSLQ Help Seeking score.

A second logistic regression aimed to model online preference for the online modality. This model showed that five predictor variables were significant. Positive predictors were: Number or previous online courses completed, GOQ Work Avoidance score and MSLQ Time/Study environment score. Negative predictors were Course Importance and MSLQ Help Seeking score.

5.2 Discussion

In an ideal world, students' choice of course modality should be completely free, and should be informed by their best knowledge of the conditions for learning that suit them best personally. However, from the analysis above, it was apparent that logistics (e.g., ability to register in their preferred modality) have a strong effect on students' ultimate modality of registration. As seen in table 4.9, while 87% of OL students were aware of the other modality option, only 58% of the face-to-face students were aware of the option of online enrolment. Conversely, only 11% of the face-to-face students had first attempted to enrol in the online modality, before finally ending up in the face-to-face course. Among online students, almost 30% had attempted first to enrol in a face-to-face version of the same course. Both these conditions have a limiting effect on the analysis, and prompted the development of the second logistic regression model presented above, which included only participants who were actually aware of the modality choice, and registered in their preferred mode.

Given that SFU is primarily a land-based institution, it is not surprising that students perceive face-to-face as the default modality. Therefore when variables relating to awareness of and previous experience with online courses are included in the logistic model of enrolment, they end up as the more significant "predictors" of online mode (with the odds of being an online student 4 times higher ($exp(\beta) = 4.129$) for those that were aware of the availability of the course in another mode and almost 5 times higher ($exp(\beta) = 4.881$) for students that had attempted to enrol in the other modality).

Previous experience with online courses was an important difference between the two groups. Online registrants reported having taken approximately 2.5 times as many online courses on average previously than face-to-face registrants had. This is similar to results found in previous research (Cullum, 2016), where students with more experience in online courses were more likely to enrol in the online modality. The number of previous online courses was a strong predictor of online enrolment and choice in the logistic models, with each additional course previously taken increasing the odds of being an online student by close to 50%.

The present study also found that enjoyment of online courses was a significant difference between face-to-face and OL students, with online students reporting an average enjoyment of online courses 23% higher than face-to-face students. Unfortunately, due to high levels of missing data, the "Enjoy Online" item was not added to the logistic models and therefore we cannot assess whether it would be a predictor for online enrolment.

In this study, measures designed to capture socialization were significantly different between OL and face-to-face students. The GOQ Social Goal subscale (with questions like "In this course I prefer working with others") and the MSQL Peer Learning subscale (where one of the questions was "I try to identify students in this class whom I can ask for help if necessary") had significantly different means ($p < 0.001$), with medium effect sizes. This finding is in alignment with previous studies, where face-to-face (versus online) students gave higher importance to meeting and socializing in their choice of study mode (Bailey et al., 2015). It also agrees with previous findings that the factor most negatively affecting students' decision to take future online classes is their perception that they would miss face-to-face communication with the instructor and classmates (Nguyen, 2011), or that students justify their preference for face-to-face classes due to feeling that online courses would preclude them from connecting or working with other students (Harris and Martin, 2012). This is further corroborated by the present finding that the GOQ Social Goal subscale was a negative predictor for online enrolment (for each additional unit in the subscale, the odds of being an online student decreased by 22% ($exp(\beta) = 0.773$). Furthermore, in our second logistic regression model (which aimed to predict preference for online registration), Social Goal was not a significant predictor.

The MSLQ - Help Seeking subscale was shown to be significantly different between registration groups, with the largest effect size of all variables considered ($d = 0.58$). This subscale considers how likely students are to ask for help of either their instructor or peers in class. In our sample, face-to-face students were more likely to ask for help, and this variable proved to be a negative predictor of online enrolment for both models created (with each additional unit in the scale decreasing the odds of enrolling online by 25%, and decreasing the odds of choosing online by almost 35%).

In agreement with Cullum (2016), whose regression model of students' behavioural intent to take online classes showed that age and sex were not significant predictors, in the current study, age and sex were not significantly different between the two groups. On the other hand, this finding disagrees with some previous results by Ortagus (2017), who found that being a female, older, and veteran was positively related to enrolling in either some online courses or in fully online degree programs. However, their models were not statistically significant for every 4-year range examined.

Flexibility was the factor most cited in the literature review as a reason to chose online courses (Thomerson and Smith, 1996; Kleisus et al., 1997; Braun, 2008; Noel-Levitz, 2010; Harris and Martin, 2012; Kowalski et al., 2014). A majority of students enrolled in online courses indicated personal preference of flexible schedule for studying as the reason why the chose the online mode (Nguyen, 2011) and Ortagus (2017) found that working full time, being a parent or being married were positively related to enrolling in online modalities. A few of the variables included in the present study were chosen as proxies for the need for greater flexibility, such as a longer commute time, more weekly work hours or more need to care for others at home. However, none of these variables showed significant differences between the registration modality groups, and none figured as significant predictors in either of the logistic regression models.

A possible explanation for the similarity between the two registration groups (in terms of age, care giving and work hours) is that the undergraduate student population at SFU tends towards young overall. SFU is a traditional, "land-based" university, and the vast majority of programs are face-to-face (with a few optional online courses) and a very small number of programs are offered fully online. This can create a self-selection process for students, who can only attend SFU if their life circumstances permit this level of commitment. For example, for years 2017/18, SFU's full-time students had on average 21 years of age, and part-time student had on average 22.1 years of age (SFU, 2018b). (SFU Research and Planning statistics did not include standard deviations for these numbers). These age groups are quite young and therefore we can argue less likely to be married or employed full-time. Unfortunately, the present survey did not capture whether respondents were in a full-time of part-time program, so it can't really be assessed if their low rates of care-giving and work-hours are due to being full-time students or not.

Among respondents, there was no significant difference for pre-requisite courses or courses designed to meet general University graduation requirements. However, there was a significantly higher proportion of face-to-face students enrolled in required courses, and a higher proportion of online students enrolled in elective courses. This finding contrasts with results found by Clayton et al. (2018), who asked undergraduate students to chose between three learning environments (face-to-face, hybrid, online) for a hypothetical courses identified as core (required) or elective, finding that students significantly preferred the face-to-face environment for either type of course.

It was found that being enrolled in an elective course was predictive of online enrolment, with the odds of the respondent being an online student increasing 1.8 times for students who were enrolled in elective courses. Whether a course was an elective for the respondent was, however, not a predictor for the modality preference model. Given the variability introduced by the representativeness of each course in the sample, results should be taken with caution.

Online registrants tended to expect the face-to-face offering of the course to be harder. This finding is aligned with previous research by Brown (2012b), who found that the reason online students reported choosing this mode is because they believed it would be less difficult.

However, in inspecting the response frequency distributions in the present study, we see that the three most common replies for this question in the face-to-face group were disagree, disagree slightly or neutral (with around 20% each), while the most common answer for the OL group was neutral, followed by disagree and disagree slightly (around 30%, 15% and 15% respectively). So in a way both groups were either neutral or in disagreement with that statement, but the face-to-face group was in slightly greater disagreement overall. This is corroborated by additional previous research, which approached this question in different ways. For example, Braun (2008) asked online, hybrid and face-to-face students how academically challenging online courses were when compared to traditional classroom courses (so the question was in the opposite direction from the one use in the current study), and found that 77% of respondents said online courses were much more demanding or slightly more demanding than traditional courses. And Nguyen (2011) found significant differences between students that would take online courses in the future, and those who would not, in three questions related to effort, with students that would not take online courses again being more in agreement that they demand more effort.

In the present study, face-to-face registrants expressed stronger expectations of a high grade. This finding is also corroborated by previous research by O'Neill and Sai (2014), which found that face-to-face students believed they would not only learn more in the face-to-face mode, but also earn a better grade. Previous research by Artino (2010) found that self-efficacy for online learning (students' confidence in their ability to learn the material presented in a self-paced, online format) was a significant positive predictor of online registration. In a similar fashion, the current study's findings showed that students' perception of how good they are in online courses was significantly higher for online students.

Regrettably, due to high levels of missing data, the items as expectation of the face-to-face modality being harder, expectation of a higher grade in the modality of registration and self-efficacy for learning online could not be added to the logistic models.

Artino (2010) also found that task-value (students' judgments of how interesting, important, and useful the online course was to them) was negatively predictive of students registering online. Our study corroborates this finding only partially. The present study separated these factors into two variables: Course Importance and Course Interest. Course importance was slightly higher for face-to-face students; however the effect size was small and after Holm-Bonferroni adjustment, not significant. When considered in the logistic regression model, however, Course Importance was found to be a negative predictor of online registration. For every one unit increase in the Course Importance score, the odds of being an online student decreased 34%. Course Interest was found not to be significantly different between both registration groups, and neither model indicated Course Interest as a significant predictor.

In a previous survey of students in a face-to-face course, it was not uncommon for respondents to report that they deliberately avoided the online modality out of concern that they would not keep up with readings and assignments if they did not attend class weekly (O'Neill and Sai, 2014). In a similar way, both the GOQ Work Avoidance and the MSLQ Time/Study Environment subscale were positive predictors of both enrolment and choice of online mode. For each additional unit in these sub-scales, the odds of being enrolled in the online mode increased by 35% and 93.4% respectively. For each additional unit, the odds of having chosen the online mode increased by 41% and 54.5% respectively.

5.3 Study Strengths

Previous studies have established that modality choice is a complicated process that may involve many factors: previous experience, socialization goals, demographics, subject matter, need for flexibility, and personal characteristics or perceptions. For example, while students' perception of a course's importance and the course being a degree requirement may generally be predictors of face-to-face registration, a student who self-regulates well in online courses and has a long commute may still chose the face-to-face modality for a required course that they deem interesting or important. The present study improved on previous research by including a wider range of characteristics, beliefs and circumstances, so that these factors could be seen in relation to one another and to assess their relative importance and contingency.

Additionally, previous research on the area of student modality choice had significant limitations in terms of sample sizes. The present study improved on that by using a considerably large sample size (650 participants) and including responses from both perspectives (online and face-to-face students). Since different disciplines can place (or be perceived to place) different demands on students, and since these perceived demands shape students' choice of course modality (Paechter and Maier, 2010; Kuzma et al., 2015), a wide range of courses were included in this study, with participants from disciplines like Archaeology, Bio-medical Studies, Computing Science, Criminology, Economics, Education and English literature.

Finally, the online learning context at SFU provided an exceptional situation for the present research, since instead of assessing students self-declared preferences or hypothetical future choices for online learning — as most previous research in this area did — it was possible to analyse students' actual enrolment choices. By focusing onlyt on online and face-to-face students who could have realistically chosen the other modality for enrolment, results were not confined to preferences or future intentions, but instead could model actual modality enrolment or modality choice.

5.4 Study Limitations

Data collection and analysis involved a number of limitations that should be borne in mind. First, there appears to be bias in our sample with regard to representation of the sexes. Around 70% of OL participants were female, while 67% of FTF participants were female. Unfortunately information regarding sex breakdown for participating courses is unavailable, but it is known that the overall female student population at SFU for 2017/18 was 54% of total students (SFU, 2018b). Assuming that these courses had male/female distribution similar to overall SFU population, across both modalities it seems that females were more likely to volunteer to participate in the research. Although this is a source of bias in the sample, it may also be consistent with previous research on survey non-response bias (Smith, 2008; Porter and Whitcomb, 2004; Sax et al., 2003).

Since participation on the survey was completely voluntary, no inferences can be made about non-responders and data may not be representative of the whole student group. For example, some disciplines are more represented in the face-to-face sample (e.g., Economics), and some disciplines are more represented in the online sample (e.g., Archaeology). Also, response rates within the same course varied between online and face-to-face modalities. For example, Archaeology 12X had 280 face-to-face students enrolled in Spring 2018, but only 4 answered the survey; while the online version had 56 enrolled students, and 33 answered the survey. This uneven representation is an acknowledged source of variance in the data, and a limitation since within-group heterogeneity may limit the generalization of findings.

Some potentially important predictors (Commute time, Good at Online, Enjoy Online, Expected FTF harder and Expected higher grade) had to be excluded from our regression model due to a high volume of missing data. The technical limitations of the survey system were such that certain types of questions could not be made mandatory, which led to a high percentage of students choosing not to answer them. Relatedly, as many questions didn't offer the option to indicate "don't know", some students may simply have chosen not to respond, which could explain the high rate of missing data in questions such as "I seem to be good at online courses".

An additional technical limitation of the survey was that duplicate responses could not be completely ruled out. Manual controls were implemented to try to ensure that each student was participating only once, but it is possible that the data contain some duplication — findings of the logistic regression should be accepted with caution. In a similar manner, since a great number of variables had to be omitted when running the second logistic regression model (due to smaller sample size), there are limited gains from comparing the models or predictors from both models.

A crucial limitation of the study is that all findings relied on the accuracy of self-reported perceptions. In questions like "I seem to be good at online courses" and "I expect to earn a good grade in this course", subjective interpretation may vary between participants, which would lead to reference bias: when survey responses are influenced by differing standards of comparison. Self-reported questions also suffer from social desirability bias, like when students are inclined to select certain ratings in order to appear more attractive to researchers or to themselves.

The fact that student status (full-time or part-time) or current course load were not part of the survey limits interpretation since some of the differences found could have been explained by one of the groups having more (or less) percentage of part-time students. However, it is interesting to note that for the period of the study at SFU (2017/2018) average age across both status was quite similar (21 years old for full-time students, 22.1 years old for part time students) and percentage of females in both status was also comparable (54.7% for full time, 53.1% for part time).

Further generalization of the findings is restricted as well due to other limitations. Data from this study derived from only a single institution and was restricted to undergraduate students, so the results are to some degree limited to that context. SFU can be considered a "traditional" university: it has mostly face-to-face programs and its undergraduate programs focus on "traditional students" (Falk and Blaylock, 2010): 18 to 22 years old, recent high school graduates. It can be said that traditional students are more heavily represented in the sample than non-traditional ones.

5.5 Implications for Future Research and Practice

The findings in this study shed some light on the process by which undergraduate students at a traditional land-bases public University in Canada chose their modality of registration in courses across several different disciplines. To generalize these results, further studies could be conducted at other universities that serve different student clientele, could be designed to include other student groups (e.g. graduate students or undergraduates from third or fourth years) and other online education contexts (e.g. private rather than public institutions). The study also demonstrated a process by which student data might be gathered and analysed to inform institutional decision-making. A better understanding of what motivates students to take particular courses online could guide administrators in developing strategic growth plans for their institutions.

With caution, the current findings related to modality choice and its predictors could be used to inform enrolment management. Given that the most significant predictor of choosing online modality was number of online courses previously taken, it would be reasonable for administrators to consider this variable in their planning (specially since this information is more easily obtainable than the other significant predictors, which would demand extensive psychometric surveys). Also of relevance for administrators are the variables that were found not to be significant predictors of modality choice, yet that are commonly thought to be influential on students' decision-making: age, number of weekly work-hours and commute time. These findings may point to the need to review common assumptions that inform administrative practices for modality offerings.

Future research on this topic could include exploring models that may predict modality preference using only data already available through the student information system, instead of data that must be gathered through a self-report survey (given the high cost of obtaining this type of data). Another interesting avenue for future research is to include longitudinal data that would help understand if and how modality choice changes over time. For example, some factors may be more predictive initially but become less predictive over time as students progress in their degree programs and/or gain familiarity with online courses.

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Appendix A

QQ Norm Plots

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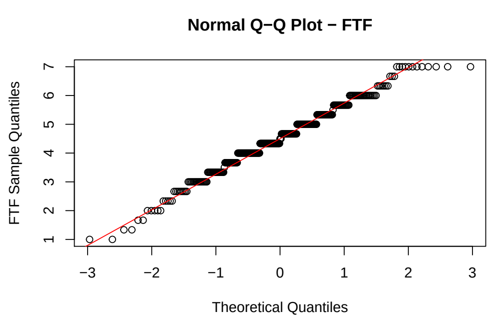
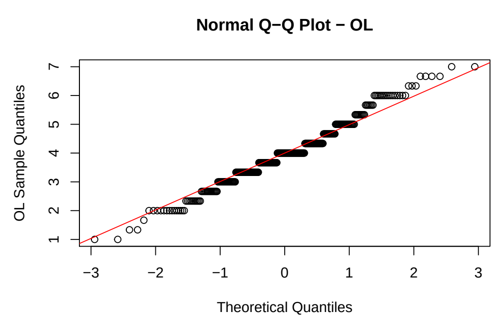
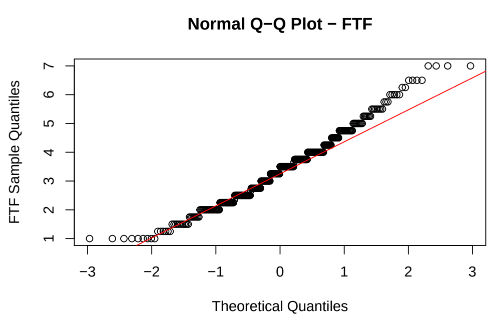
A.1 Scales

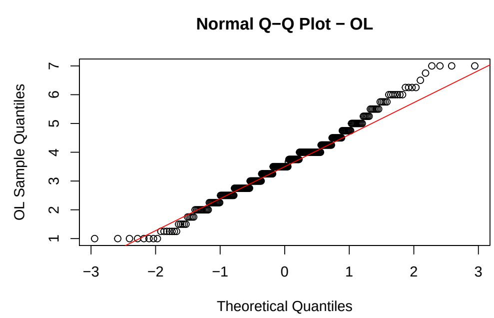
1. Social Goal



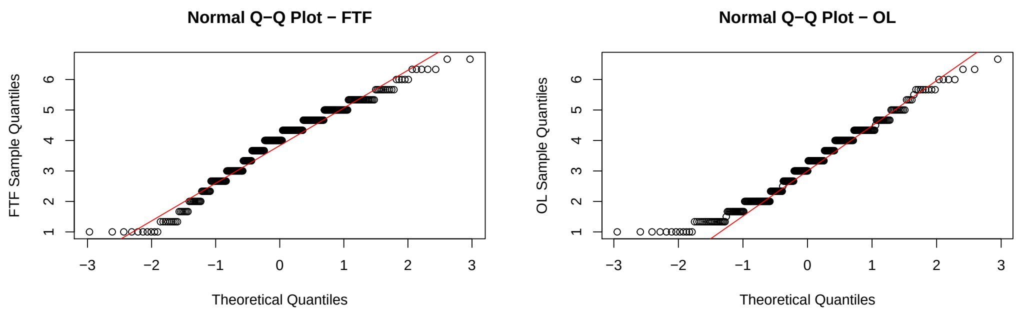


2. GOQ Work Avoidance

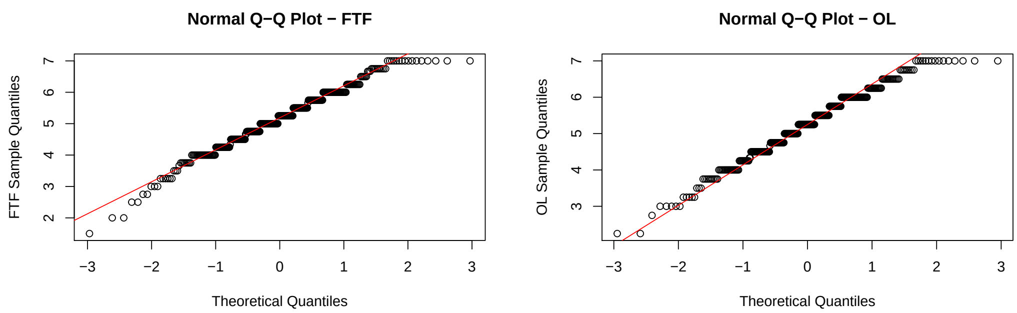




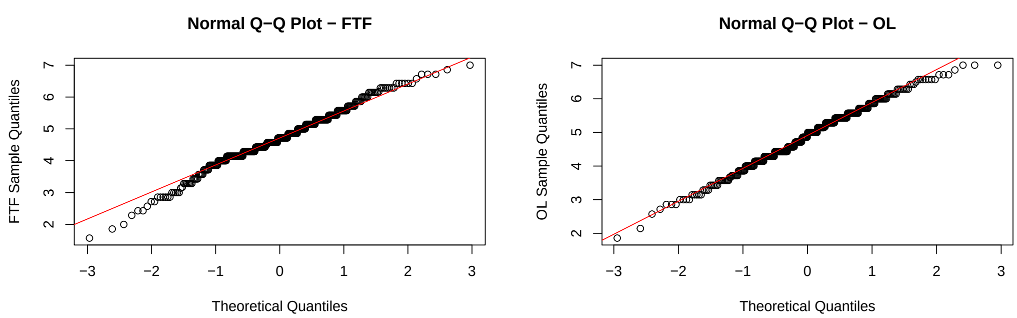
3. MSLQ Help Seeking



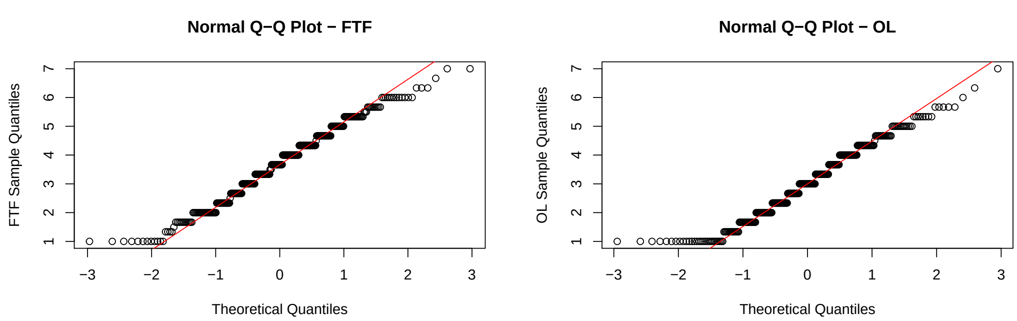
4. MSLQ Effort Regulation



5. MSLQ Time and Study Environment

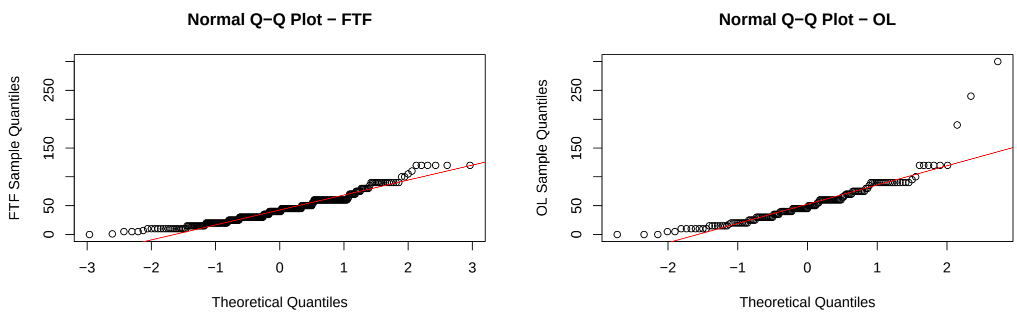


6. MSLQ Peer Learning

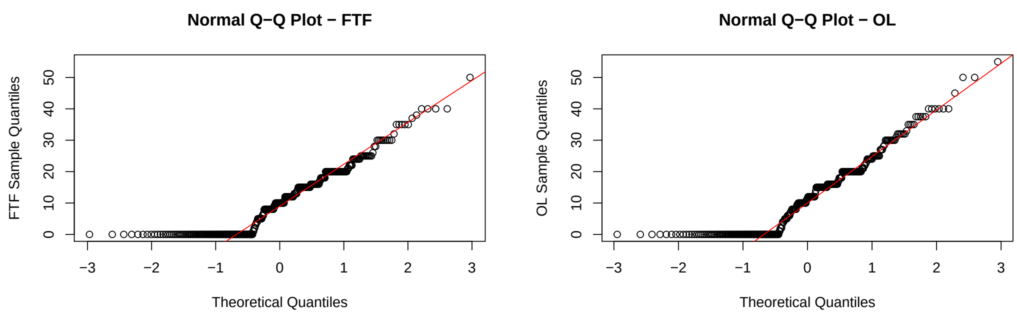


A.2 Numeric Variables

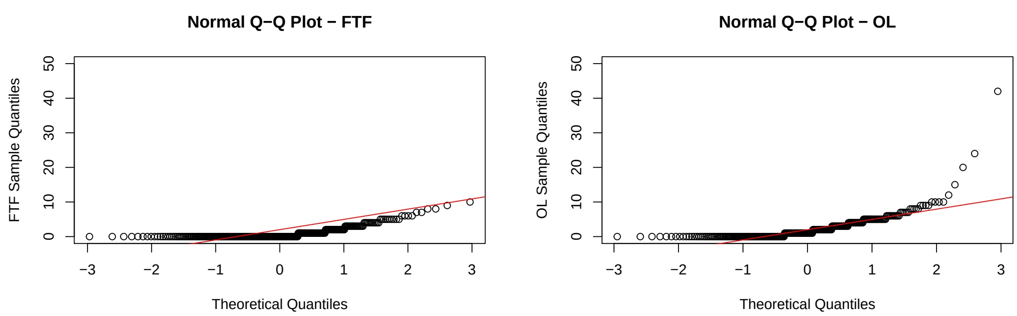
1. Commute Time



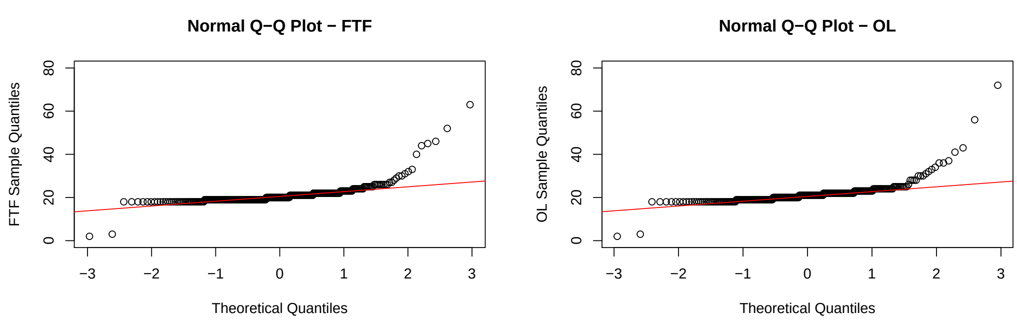
2. Workhours



3. Courses taken online

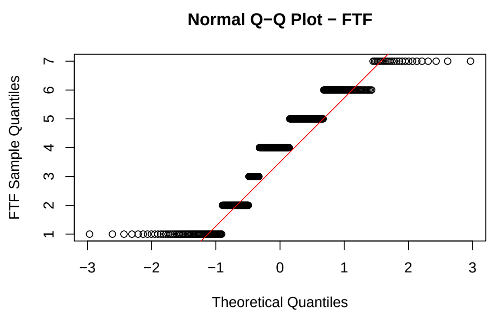


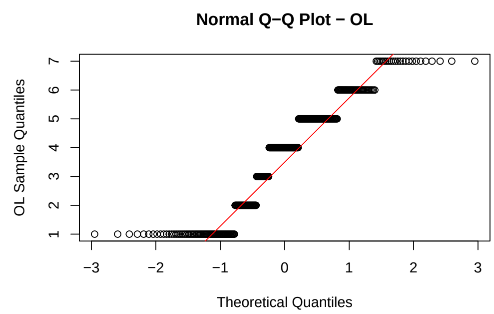
4. Age



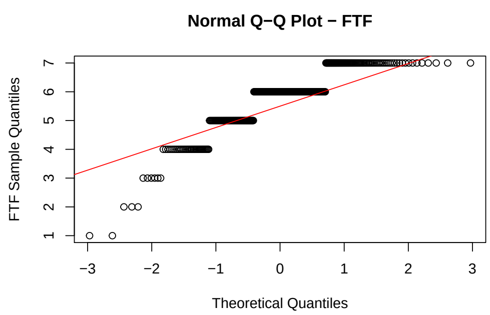
A.3 Likert-Type Variables

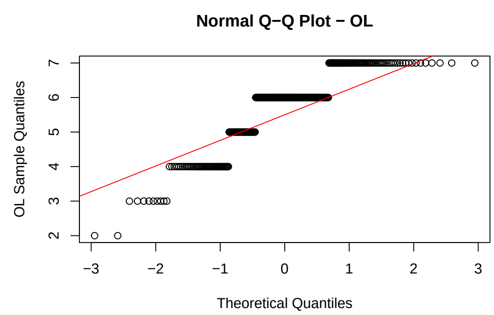
1. Caregiver



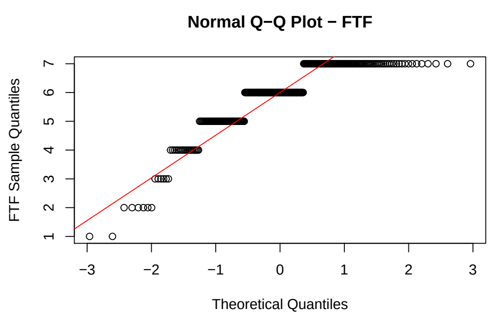


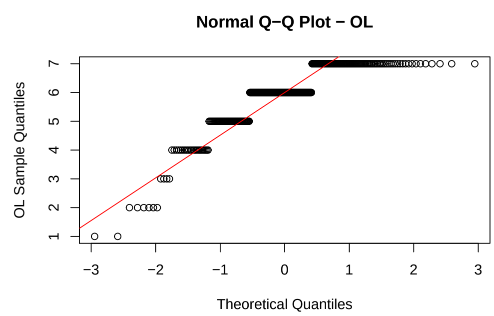
2. Expects Good Grade



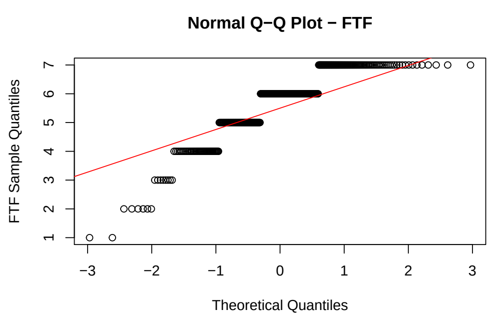


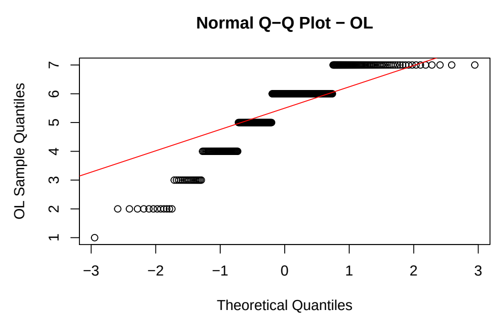
3. Need GPA



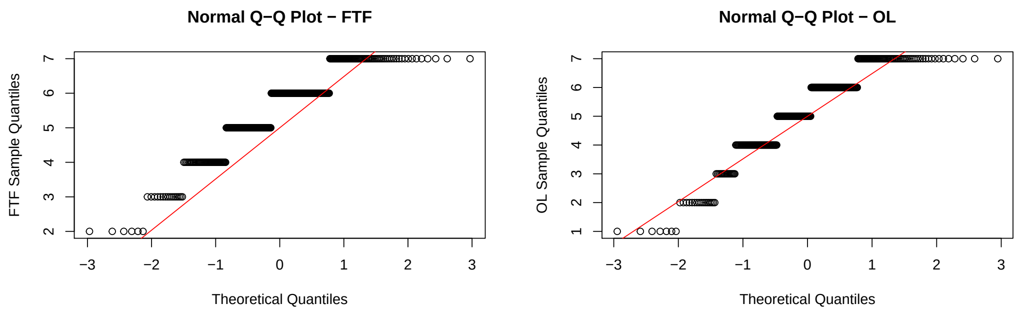


4. course Interest

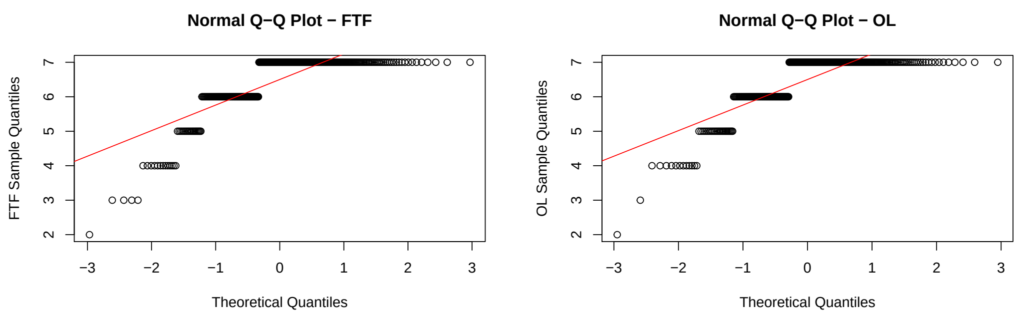




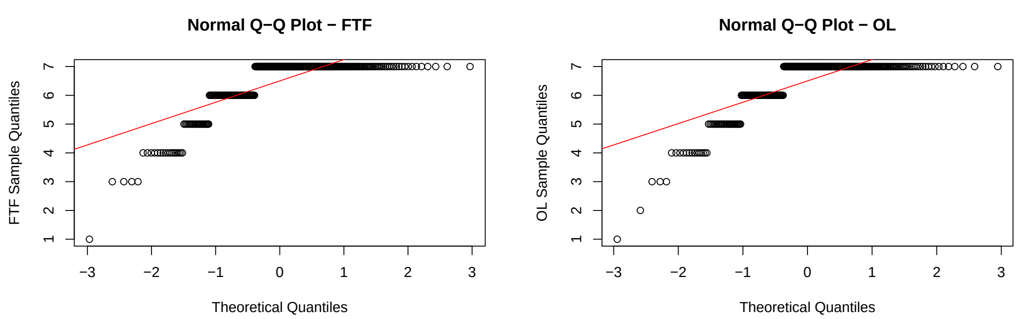
5. Course Importance



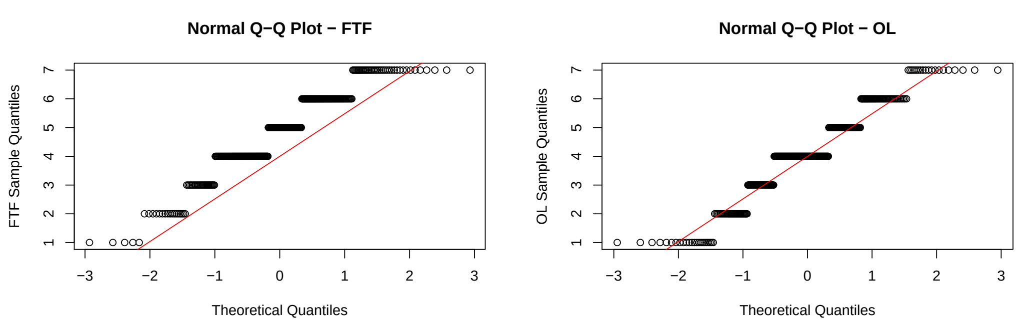
6. Written English Competency



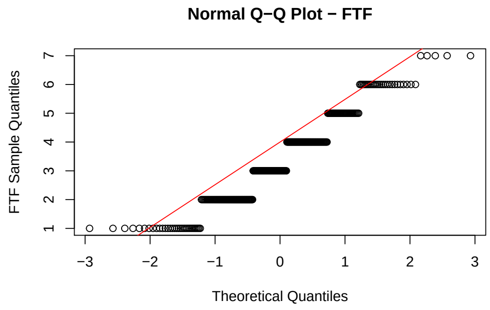
7. Receptive English Competency

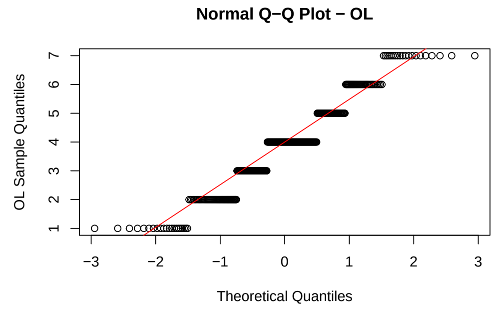


8. Expects Higher Grade in modality of enrolment

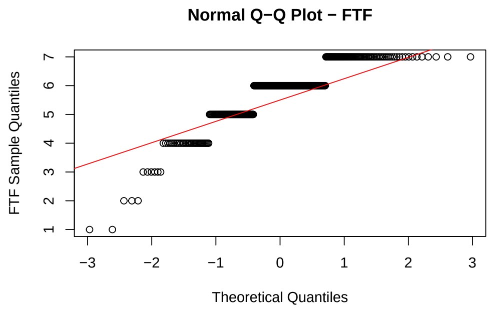


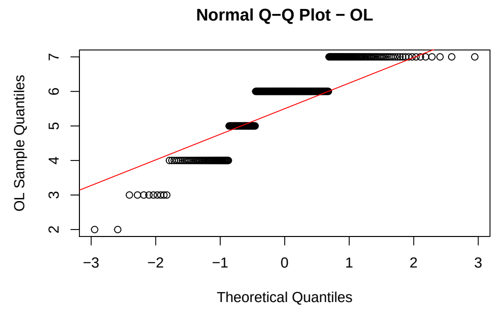
9. Expects Face to Face version to be harder



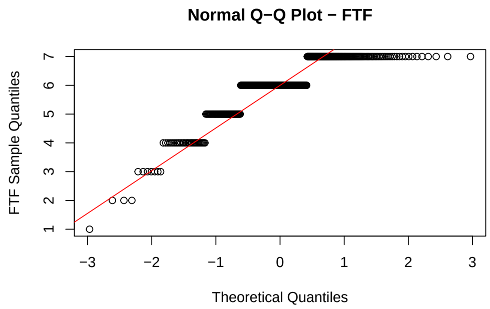


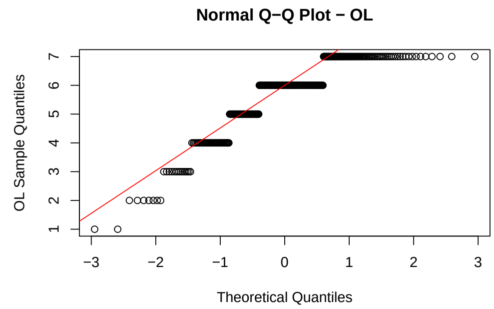
10. Expects Good Grade



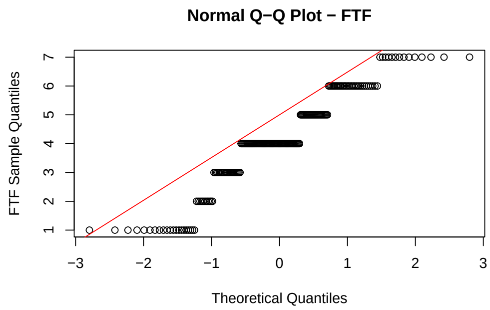


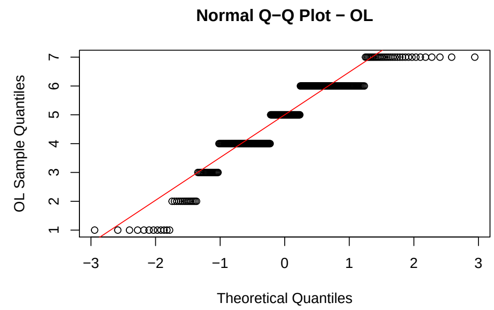
11. Expects Help



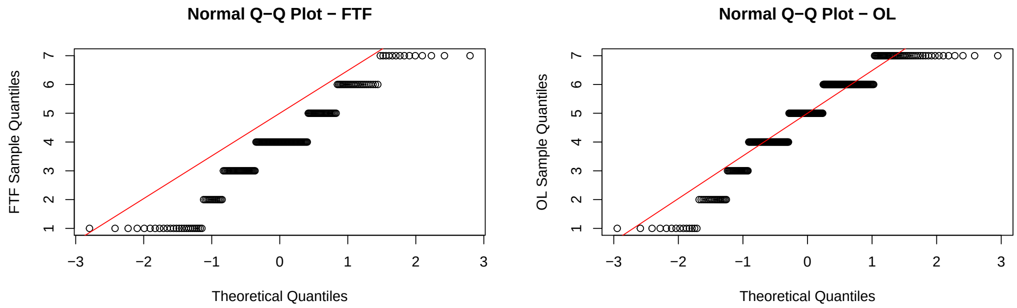


12. Good at Online





13. Enjoy online Courses



Appendix B

Survey Template - Spring 2018

This survey is designed to explore the reasons why students choose to take a particular course online or on campus. It should take about 15 minutes to complete, and you will be paid $5 for your time.

- In which course did you receive the survey invitation? (Please DO NOT answer the survey if you are not enrolled in one of these courses.) - drop down selection.
- How many years old will you be on December 31 of this year? (numeric answer)
- What is your sex? (check one)
  - Female
  - Male
  - Transgender
  - Other
  - Prefer not to say
- Approximately how many hours per week do you work a paid job? (numeric answer)

B.1 Your responsibility to care for others at home

Answers range from 1 (Disagree Strongly) to 7 (Agree Strongly)

- I have responsibility at home to care for others (e.g. children, siblings, parents and/or grandparents)

B.2 Your satisfaction with your grades

Answers range from 1 (Disagree Strongly) to 7 (Agree Strongly)

- I feel satisfied with my grades overall
- I feel the need to raise my GPA

B.3 Course Attributes and Personal Characteristics

- For you, is this course (check all that apply)
  - Required for your major/minor/certificate
  - Meeting a W/Q/B requirement
  - An elective
  - A pre-requisite for another course you need
- If you had taken this course on campus, how many minutes would it take (approximately) for you to get to class from home, or wherever you normally leave from? (time in minutes).

  For Face-to-Face students, the question would instead ask "How many minutes does it take (approximately) for you to get to this class from home, or wherever you normally leave from? (time in minutes)"
- Do you have a physical disability that makes it difficult for you to travel to or around campus? (Y/N)
- Did you know that this course was also offered face-to-face this semester? (Y/N)
- Did you attempt to register in the face-to-face version of this course? (Y/N)

B.4 Interest, importance and language

Answers range from 1 (Disagree Strongly) to 7 (Agree Strongly)

- I can read and write well in the language that this course is taught in
- I am interested in the subject of this course
- The material in this course is important for me to learn
- I expect to earn a good grade in this course
- The language this course is taught in is one that I can understand well orally (spoken)
- I expect to be able to access the help I need to succeed in this course from the professor, Tutor-Markers and fellow students

B.5 Time and effort committed to this course

[Questions from this section represent the Social-approach Goals (SAG) and the Work-avoidance Goals (WAV) subscales from the Goal Orientation Questionnaire (GOQ) instrument (Nesbit et al., 2009). GOQ question numbers are presented in brackets below for reference. The questions are presented grouped by subscale, however in the original survey, questions were de-identified and scrambled.]

Answers range from 1 (Disagree Strongly) to 7 (Agree Strongly)

- Social-approach Goals
  - In this course I enjoy helping others. *[GOQ-SAG-05]*
  - In this course I prefer working with others. *[GOQ-SAG-10]*
  - In this course I am happy to be at the same level as my friends. *[GOQ-SAG-07]*
- Work-avoidance Goals
  - In this course I feel annoyed when I am required to make an effort. *[GOQ-WAV-01]*
  - In this course I avoid doing more work than is necessary. *[GOQ-WAV-16]*
  - In this course I feel unhappy when a task takes too much time. *[GOQ-WAV-17]*
  - In this course my goal is to get by with the least amount of work. *[GOQ-WAV-22]*

B.6 How you study in this course

[Questions from this section represent subscales from the Motivated Strategies for Learning Questionnaire (Pintrich et al., 1991). MSLQ question numbers are presented in brackets. The letter "R" indicates reversed questions. The questions are presented grouped by subscale, however in the original survey, questions were de-identified and scrambled.]

Answers range from 1 (Disagree Strongly) to 7 (Agree Strongly)

- Time and Study Environment
  - I usually study in a place where I can concentrate on my course work. *[MSLQ5-35]*
  - I make good use of my study time for this course. *[MSLQ5-43]*
  - I find it hard to stick to a study schedule. *[MSLQ5-52R]*
  - I have a regular place set aside for studying. *[MSLQ5-65]*
  - I make sure I keep up with the weekly readings and assignments for this course. *[MSLQ5-70]*
  - I attend class regularly. *[MSLQ5-73]*

  - I often find that I don't spend very much time on this course because of other activities. *[MSLQ5-77R]*
  - I rarely find time to review my notes or readings before an exam. *[MSLQ5-80R]*

- Effort Regulation
  - I often feel so lazy or bored when I study for this class that I quit before I finish what I planned to do. *[MSLQ5-37R]*
  - I work hard to do well in this class even if I don't like what we are doing *[MSLQ5-48]*
  - When course work is difficult, I give up or only study the easy parts. *[MSLQ5-60R]*
  - Even when course materials are dull and uninteresting, I manage to keep working until I finish. *[MSLQ5-74]*

- Peer Learning
  - When studying for this course, I often try to explain the material to a classmate or a friend. *[MSLQ5-34]*
  - I try to work with other students from this class to complete the course assignments. *[MSLQ5-45]*
  - When studying for this course, I often set aside time to discuss the course material with a group of students from the class. *[MSLQ5-50]*

- Help Seeking
  - Even if I have trouble learning the material in this class, I try to do the work on my own, without help from anyone *[MSLQ5-40R]*
  - I ask the instructor to clarify concepts I don't understand well. *[MSLQ5-58]*
  - When I can't understand the material in this course, I ask another student in this class for help *[MSLQ5-68]*
  - I try to identify students in this class whom I can ask for help if necessary. *[MSLQ5-75]*

B.7 Please rate the following statements

Answers range from 1 (Disagree Strongly) to 7 (Agree Strongly)

- I seem to be good at online courses
- I enjoy online courses
- Compared to the fully online version of this course, I expected the face-to-face version of this course to be harder
- Compared to the face-to-face version of this course, I expected to earn a higher grade in the online version.

  For face-to-face students, this question was phrased "Compared to the fully online version of this course, I expected to earn a higher grade in the face-to-face version".

B.8 Other Questions

- How many fully online courses have you taken in the past, at the college or university level? (numeric answer)
- Would you like to say anything else about why you chose to take this course on campus? (open ended question)