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Learning While Working: Course Enrollment Behaviour as a Macro-Level Indicator of Learning Management Among Adult Learners

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Abstract

As the demand for lifelong learning increases, many working adults have turned to online graduate education in order to update their skillsets and pursue advanced credentials. Simultaneously, the volume of data available to educators and scholars interested in online learning continues to rise. This study seeks to extend learning analytics applications typically oriented toward understanding student interaction with course content, instructors, and peers to the program level in order to gain insight into the ways in which adult learners manage their learning progress over multiple courses and multiple semesters. Using optimal matching analysis, we identify four distinct profiles of course enrollment behaviour among 1,801 successful graduates of an online master's program that differ with respect to course load, semesters off, and graduation speed. We found that profiles differed significantly as a function of age and knowledge background, but not with respect to gender, ethnicity, or previous academic performance. Findings indicate the utility of expanding learning analytics focused on the micro-level of analysis to the macro-level of analysis and the utility of grounding learning analytics applications geared toward adult learners in a lifespan development perspective. Implications for program design and educational interventions are discussed.

Notes for Practice

- Some adult learners benefit from high levels of academic momentum, while others benefit from taking lighter course loads and more semesters off.
- Programs can be designed with enough flexibility to allow adult learners to make conscious decisions regarding the courses that they enroll in and when they enroll in them.
- Some adult learners may benefit from the removal or relaxation of requirements that mandate the frequency of course enrollment or the required time to graduation.

Keywords

Adult learning, curriculum analytics, lifespan development, course enrollment behaviour, optimal matching

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1. Introduction

1.1. Background: The Rise of Online Graduate Education and Lifelong Professional Learning

As a consequence of the fourth industrial revolution (Ghislieri et al., 2018), adults are now expected to continuously update and adapt their work-related skillsets (Rotatori et al., 2021). Recent estimations indicate that nearly 50% of the current workforce will need to upskill, reskill, or learn different job skills over the next decade as new technologies and automation reshape existing jobs and create new work roles (World Economic Forum, 2020). Calls for the development of a workforce equipped with "21st-century skills" (Neubert et al., 2015) specify a range of both technical (Deming & Kahn, 2018; Handel, 2012) and socioemotional (i.e., related to collaboration and self-managing motivation or emotion; Beier, 2021; Kanfer & Blivin, 2019) competencies that will be critical for adapting to the changing nature of work. These skills, as well as the educational experiences that lead to their acquisition, are increasingly valued by organizations. Traditionally, organizations valued workers' pursuit of educational credentials because such pursuits signal a capacity to learn, develop, and reach higher levels of achievement (Rospigliosi et al., 2014). However, employers now value such pursuits not only because they signal potential, but because they see value in the skills that adult learners acquire through advanced education. As a result, they are increasingly willing to provide support to workers pursuing degrees (e.g., reimbursement of cost, time off work, classroom space; Bills & Wacker, 2003).

Advanced skill learning related to technical fields (e.g., computer science) is increasingly provided by online, graduate-level education (Goodman et al., 2019). The rising popularity of online graduate education as an upskilling pathway may reflect the preferences of a previously untapped educational market: mid-career working adults. Evidence suggests that students enrolled in online graduate programs are often older than traditional graduate students, engaged in both their degree program and full-time work, and would not have pursued an advanced degree in a traditional delivery format (Goodman et al., 2019). Working adults may be particularly attracted to online graduate education (as opposed to traditional, co-located education or training) in part because the flexible nature of such programs allows learners to proactively manage their career and personal development (for discussion on the value of proactive career management in the context of the fourth industrial revolution; see Ghislieri et al., 2018). Additionally, online graduate programs satisfy several criteria posited by Sterns and Spokus (2020) to act as facilitators of adults' participation in lifelong learning: 1) relevance to career or personal goals, 2) ability to self-direct the learning experience, and 3) reduced financial (e.g., reduced tuition cost compared to co-located programs; Park et al., 2020) or logistical (e.g., greater scalability of asynchronous online education; Joyner, 2018; 2020) barriers to participation.

As online education has grown in popularity, the burgeoning availability of educational data has supported rapid growth of Learning Analytics (LA) and Educational Data Mining (EDM) communities that leverage non-obtrusive data to inform a more comprehensive understanding of learning processes and experiences (Baker & Siemens, 2014). In contrast, past investigations of adult learning in informal contexts (e.g., observational learning, vicarious learning, informal learning; for a review, see Tannenbaum et al., 2010), have allowed for an emphasis on self-directed learning but typically are unable to leverage behavioural data, particularly in high volume. Behavioural educational data routinely generated in online contexts (e.g., grades, enrollment patterns, interactivity with course material, participation in course forums/discussion boards) may allow for more comprehensive investigations of all stages of adults' learning processes and scale effectively to assess changes over time. To date, however, such investigations have primarily taken place in undergraduate contexts, often within a single course. As a result, learning analytics approaches may have untapped potential for understanding how successful adult learners navigate their learning experience across course options and over time. The purpose of this paper is to provide a proof-of-concept demonstration of the utility of extending analytics beyond the individual course level to better understand how adult learners proactively structure their long-term learning process process throughout program enrollment. Below, we review relevant research at multiple levels of analysis and present a study that uses a learning analytics approach to: 1) assess and interpret patterns of course enrollment behaviour among successful graduates of an online master's program, and 2) explore the demographic and educational backgrounds of students who display different enrollment patterns.

1.2. Literature Review

Below, we review literature that informed the current study in three sections. In the first two sections, we discuss how learning analytics techniques have been applied to what we refer to as the micro-level and macro-level of the learning process. While there is some inconsistency across literatures in how concepts such as "micro-learning" and "macro-learning" are defined, we define these terms according to the level at which intentional management of the learning process occurs. The micro-level of the learning process involves learners proactively planning, monitoring, and refining learning strategies within an individual learning episode or course. However, for the adult learner, managing one's progress within a single learning episode or within a single course is necessary, but not sufficient. It is also critical that the adult learner understands "what needs to be learned next and how one's learning is best accomplished" (Jossberger et al., 2010, p. 419). The macro-level of the learning process involves leveraging this understanding to manage one's learning progress over an extended period of time, including multiple courses and multiple semesters. We will argue below that the bulk of learning analytics studies that leverage behavioural data focus on the micro-level, and there are substantial opportunities to expand learning analytics approaches to the macro-level of the learning process. Finally, in the third section, we introduce a lifespan development perspective to extend learning analytics to the study of macro-level learning processes. This perspective suggests that adult learners may differ in the macro-learning process as a function of changes in demands and resources associated with different phases of life.

1.2.1. Learning Analytics and the Micro-Learning Process

As the popularity of online education continues to grow, the quantity of data available to researchers and educators interested in understanding how people learn in an online context is steadily increasing (Macfadyen et al., 2014; Taylor & Munguia, 2018). The LA and EDM communities have taken advantage of increased access to high volumes of student data to provide quantitative insights into the learning process (Baker & Siemens, 2014; Siemens, 2013; Tempelaar et al., 2017) and to inform interventions that enhance student learning (Sarıyalçınkaya et al., 2021; Wise, 2014).

To date, most studies that have leveraged learning analytics to provide insight into how people learn in an online context have focused primarily on the micro-learning process, which involves the ways in which individual learners and groups interact with course content, instructors, and peers within the context of an individual course or individual learning episode (Shum & Ferguson, 2012; Méndez et al., 2014). Prominent examples of the application of learning analytics to the micro-learning process involve leveraging what is known as "behavioural trace" data to better understand self-regulated learning (Bernacki, 2018; Panadero et al., 2016; Winne, 2010). Behavioural trace data is defined as an observable indicator of cognition that students create as they engage with a task (Winne & Perry, 2000). Examples include the vast array of behavioural data that is commonly captured by learning management systems, such as time logs of interaction with course materials (Boroujeni & Dillenbourg, 2019), online annotation of course material (Yamada et al., 2017), and information related to the frequency and nature of interaction with discussion forums (Macfadyen & Dawson, 2012). Each of these metrics has been linked to academic performance (Oi et al., 2015; Tabuenca et al., 2015; Wikle & West, 2019), and the differential choices that students make regarding their engagement with content, peers, and instructors likely reflect individual differences in motivation, perceived strengths, or perceived challenges (Roll & Winne, 2015).

Behavioural data, such as trace data, provides two important advantages over self-report measures when considering phenomena that occur over time, such as learning. First, unlike self-report measures, behavioural data is not subject to distortion due to learner memory or attitudes (Winne et al., 2002; Zhou & Winne, 2012). Second, the analysis of trace data has allowed researchers to investigate how learning unfolds over time and prevent over-reliance on snapshots that the administration of self-report measures in cross-sectional studies provides (Winne, 2010). While learning analytics has made substantial strides in applying novel analytic techniques to better understand the micro-learning process (Roll & Winne, 2015; Winne, 2017), far less progress has been made toward the application of novel analytic techniques to better understand more macro-learning processes (i.e., beyond the level of an individual course or learning episode). One of the primary purposes of this study is to extend existing LA applications commonly conducted at the micro-level of analysis to account for how students manage their learning progress and learning trajectories over a protracted period of time (i.e., multiple semesters).

1.2.2. Learning Analytics and the Macro-Learning Process

While the micro-learning process involves activities and barriers that occur during a single course or session, the macro-learning process involves managing progression through a long-term learning program (i.e., over the course of multiple semesters). As previously mentioned, LA scholars have had success utilizing quantitative analyses to identify course-level phenomena and outcomes (e.g., Macfadyen & Dawson, 2012). However, extending learning analytics to the program level of analysis has been a substantial challenge for the learning analytics community (Munguia & Brennan, 2020). One reason that scholars have found the application of learning analytics to the macro-learning process to be a challenge is that educational theories rest on the assumption that if students display adequate foundational knowledge in prerequisite courses, they have the knowledge and skills necessary to succeed in more advanced courses (Nelson et al., 2020). Yet, such a perspective does not account for factors related to student success that change over the time students are enrolled in learning programs, such as engagement, motivation, and stressors unrelated to the learning process itself (e.g., work, family; see Xu & Song, 2016). We argue that investigations of the macro-learning process that take such factors into account are of crucial importance as adults are increasingly engaged in lifelong learning in online contexts.

A common characteristic of research addressing macro-level learning processes as we have defined them is the use of course enrollment data as a metric of interest. In the same manner that trace data from learning management systems acts as a behavioural indicator of cognitive engagement with course content, we posit that course enrollment behaviour acts as an indicator of cognitive engagement with planning for program completion (i.e., behaviour that is necessary for successful program completion, but which is distinct from the content of any given course). Two areas of literature that commonly leverage course enrollment data are particularly relevant to the current study. The first of these literatures investigates the construct of academic momentum, which is defined as the speed at which students (typically undergraduate or community college students) proceed through academic programs and experiences (Wang et al., 2015). The construct of academic momentum was originally proposed by Adelman (1999, 2006), who found that students who took on heavy course loads in high school or early in college achieved higher grades and students who enrolled in summer courses were more likely to graduate. Since introduced by Adelman, the construct has been refined to focus more narrowly on indications of engaging in educational experiences likely to build momentum (e.g., enrollment in high course loads) in order to avoid conflating the construct with its outcomes, such as grade point average (Attewell et al., 2012). Other researchers have replicated and extended Adelman's initial findings by linking indicators of academic momentum to outcomes such as degree attainment, academic achievement, and successful transfer from a community or technical college to a four-year university (Attewell et al., 2012; Clovis & Chang, 2021; Doyle, 2011; Martin et al., 2013; Wang et al., 2015; Zhang, 2022). Also related to the concept of academic momentum are studies which propose that an "ideal" student career is characterized by a lack of delays in progress toward graduation (e.g., Campagni et al., 2015).

While the existing literature clearly indicates the crucial role of academic momentum in determining educational outcomes, existing studies have focused primarily on traditional undergraduate students or community college students. In fact, we are aware of no academic momentum studies that investigate the construct using a sample of adult learners, such as those often engaged in online graduate-level education. We argue that early indicators of academic momentum associated with successful outcomes for undergraduate students, such as high course loads or continuous enrollment, may not be strictly necessary for success among contemporary adult learners. Attewell and colleagues (2012) proposed two potential mechanisms through which academic momentum may influence degree persistence: 1) more comprehensive integration into the educational institution's culture, and 2) the facilitation of self-efficacy or self-concept. These mechanisms may operate quite differently among adult learners than they do among undergraduate students. Prior research indicates that undergraduate and graduate students evaluate their sense of belonging within an educational institution differently, with the primary difference being that graduate students wish to integrate education into other life demands whereas undergraduates wish to simply transition to another academic setting (Pascale, 2018). Similarly, graduate students' evaluations of their ability to succeed within their academic pursuits may very well depend on the extent to which they feel they can successfully manage learning in the context of other responsibilities at work and at home. For learners who balance substantial demands in other life domains (e.g., full-time work, childcare obligations), we suggest that greater academic momentum (i.e., maximizing course load or speed of progress) may not necessarily lead to uniformly positive outcomes. For these students, in other words, successful learning management may involve proactively managing one's learning progress by deciding to take lighter course loads or taking time away from coursework at the proper times (e.g., during a particularly demanding time at work). A failure to adjust accordingly may increase risk of program attrition.

Consistent with the approach of Campagni et al. (2015), the majority of existing studies that leverage macro-level analyses to understand the learning process have focused on the most beneficial way to progress through a long-term educational program. There is some evidence, however, that successful paths to graduation and workforce entry include room for discontinuous student enrollment. A study that followed nursing students from their undergraduate coursework through licensure examinations found that there were multiple pathways to licensure that differed with respect to the consistency of enrollment, timing of examinations, and time to graduation (Jeffreys, 2007). Studies focusing on optimal course-taking behaviour (e.g., Szafran, 2001) have made substantial contributions to researchers' ability to identify students at higher risk of program attrition, but do not necessarily contribute to understanding systematic variation in successful learners' proactive learning management over time (e.g., across semesters or years). Such an understanding is increasingly important for the context of online graduate education, where students reflect a diversity of ages and experiences. Building on the academic momentum literature, we seek to investigate course enrollment behaviour among adult learners who successfully completed an online graduate program in order to determine if there are in fact multiple pathways to successful graduation despite the level of academic momentum achieved early in enrollment.

The second area of literature particularly relevant to the current study design is curriculum analytics. Two central propositions of curriculum analytics are that courses within a learning program can be represented in terms of their semantic content, and that behavioural or administrative data can be mined to guide curriculum-related decision-making (Long & Siemens, 2011). One application of this approach is the building of more effective course recommendation systems. Raji et al. (2017), for example, used data science techniques to create a system that models and visualizes the ways in which undergraduates flow through both courses and majors during college, and suggested that their system could be used as a tool for advisors to provide recommendations regarding when students should commit to a major and which courses are critical prerequisites. Although learners are still constrained in course selection choice by various circumstances including prerequisites/program requirements, curricular structure, and course availability (Pardos & Nam, 2020), these analytics-informed tools can provide meaningful support to learners and programs.

Additional recent work in curriculum analytics considers how sequential patterns of student course-taking can improve understanding of learners' course selection decisions and at-risk status. Brown and colleagues (2018) found that students are at greater risk of experiencing sustained academic difficulty when they are concurrently enrolled in courses previously independently flagged as difficult in early warning systems, suggesting that sequence-based learning analytics studies should consider not only the order in which sequential courses are taken, but also the impact of concurrent enrollment on students. A series of studies by Pardos and colleagues (Pardos et al., 2019; Pardos & Jiang, 2020; Pardos & Nam, 2020) further showed that aggregated behavioural data (i.e., course enrollment sequences) contained embedded semantic information about course structure. As a result, inferences about course relationships and student behaviour could be made solely from assessing historical enrollment sequences.

While our study does not investigate conceptual or semantic relationships between individual courses, we investigate questions related to those asked in curriculum analytics studies. That is, we study adult learners' behaviour (i.e., selecting into course loads of varying difficulty) and outcomes (i.e., time to graduation) by analyzing sequential patterns of learning pathways within a program. By doing so in a study with a sample of mid-career adults, we hope to build upon prior research on academic momentum and curriculum analytics that have primarily provided insight into behaviours of undergraduate and community college students. Although similar methods have been used successfully to identify and intervene for at-risk learners (e.g., Brown et al., 2018; Szafran, 2001), the current study's restriction to program graduates allowed us to most clearly determine the extent to which adult learners' success pathways may vary.

1.2.3. Lifespan Development and the Macro-Learning Process

Insights from the lifespan development literature suggest that despite the implications of most academic momentum studies, it is unlikely that there is a single pathway most conducive to success among working adults enrolled in online graduate education. The Motivational Theory of Lifespan Development (see Heckhausen et al., 2010) posits that people regulate their own development through cycles of action aimed at the pursuit of developmental goals. A key component of the theory is that individuals establish developmental goals based on the unique combination of demands and resources associated with their current circumstances, and that these goals serve as the organizing motivational units used by adults to proactively shape their own life course and development. For example, empirical evidence suggests that as learners age they are more likely to engage with material that builds on pre-existing knowledge (Ackerman & Beier, 2006; Beier & Ackerman, 2005) or allows them to compensate for resources that diminish over the lifespan (e.g., cognitive ability; Baltes & Baltes, 1990; Beier, 2021; Torres & Beier, 2018). From the perspective of the macro-learning process, the Motivational Theory of Lifespan Development suggests that student life stage will shape the developmental goals established, and in turn inform the direction and intensity of actions taken to manage long-term learning progress.

To date, most studies of self-regulated learning and self-directed learning geared toward adults have viewed academic performance (e.g., grades or grade point average) as an indication of learning success (York et al., 2015). However, from a lifespan development perspective, academic performance is unlikely to be an optimal indicator of learning success, particularly among adult learners simultaneously pursuing career advancement. For most working adults, course grades are less important to perceived and actual career goals than certified educational attainments are (Groot & De Brink, 2000). Therefore, we argue that the outcome of primary interest to most adult learners engaged in online graduate education is program completion and that a comprehensive understanding of the diverse ways that adults manage their learning progress on their path to graduation is of vital importance.

Students engaged in long-term degree programs must manage their learning activities over long periods of time, across multiple courses. In the context of traditional undergraduate education, course progression is mostly prescribed. Students are informed of the specific courses they must complete in order to graduate, and many are also informed of precisely when most students complete particular courses. Undergraduates who are unable to complete their degree programs are often unable to meet the learning demands required, either due to discrepancies in cognitive ability or prior knowledge compared to their peers (King & Cattlin, 2015; Ostrowsky, 1999).

In online graduate education, where student populations are typically characterized by a diversity of life stages, students are confronted with additional demands. Working adults pursuing advanced education must manage their learning progress in the context of their broader lives, including non-learning demands such as work and family responsibilities that are often seen as barriers to graduation (Perry et al., 2008; Willging & Johnson, 2009). A life course perspective (Elder & Shanahan, 2006) stipulates that as adults move through developmental milestones (e.g., marriage/family, career advancement), there is increased potential to experience demands outside of the classroom and increased variance in student experiences. To accommodate these extra-educational demands, online programs typically allow enrollees more flexibility in the number, type, and timing of courses taken (Gauvreau et al., 2016; Wladis et al., 2014). Consistent with a lifespan development perspective, we propose that: 1) the decisions that students in these programs make with respect to the courses that they enroll in and the timing in which they do so are reflections of agentic management of the macro-learning process, and 2) such decisions are influenced by the developmental goals of each student, which reflect their life stage. For example, learners with high levels of work and home responsibilities might choose to take only one course per semester. Alternatively, adults eager to reskill to find new employment may take more than one course each semester so that they finish the program earlier. Yet others with prior experience in the field might take fewer but more difficult courses.

1.3. The Current Study

In response to recent calls in the learning sciences for greater attention directed toward both lifelong learning (Roschelle et al., 2011; Yoon & Hmelo-Silver, 2017) and macro perspectives assessing trajectories of learning behaviour over program enrollment (Munguia & Brennan, 2020), this study examines the ways in which successful graduates of a well-known master's in computer science program managed their progress over the duration of their enrollment. Building on the notion that program or degree completion, rather than course grades, represents the key learning outcome for adult learners, we investigate the pathways through which successful online adult learners structure their learning programs. Specifically, we do so through an analysis of course enrollment behaviour that takes into account both course choice and timing. We focused only on successful program graduates, rather than students who failed to complete the program or remain enrolled, because our primary interest was identifying the diverse range of macro-learning management strategies implemented by adult learners who successfully achieved their learning goal.

Based on a lifespan development perspective (e.g., Beier, 2021; Heckhausen et al., 2010) we posit that adults' learning behaviour is influenced by a variety of both individual and contextual factors. Although the conjoint influence of person-level and contextual factors (e.g., changing capacities over the course of the lifetime; Heckhausen & Shane, 2015; changing availability of time/resources due to family and demands; Huffman et al., 2013) may be difficult to observe at a micro level (i.e., short-term duration), we expect to see their influence in the long-term, namely over a period of goal-directed learning (i.e., graduation in a master's program).

Three primary research objectives guided our study design. First, we sought to leverage analytics to quantitatively identify distinct profiles of course-taking patterns among individuals that completed the program. Second, we sought to explore the nature of each profile with respect to course load, semesters off, and time to graduation. By showing multiple distinct patterns of course enrollment that led to successful program completion, we provide quantitative evidence of different strategies used to manage learning progress over time. Finally, given our expectation that person-level attributes would influence course enrollment decisions, we sought to analyze the demographic and educational backgrounds of individuals who took different graduation paths. Accordingly, we asked the following guiding research questions:

RQ 1: Can we identify distinct profiles of course enrollment among successful online learners?
RQ 2: What is the nature of these profiles in terms of course load, semesters off, and time to graduation?
RQ 3: Are person attributes significantly related to different profiles?

The current study contributes to the lifelong learning and learning analytics literatures in at least three ways. First, we extend traditional LA applications that focus on the micro-level analysis to the macro-level of analysis. This extension provides important insights related to the ways in which learners manage their progress over the duration of their enrollment (i.e., multiple semesters and courses). Second, we contribute to the lifespan learning and development literature by providing evidence that suggests select person attributes may be important determinants of how learners manage their progress over time. Finally, our findings provide support for the value of using behaviourally based, non-obtrusive measures of student-driven structuring of a long-term learning program to inform a more complex understanding of self-directed learning over time.

2. Method

2.1. Sample

This study analyzed course enrollment data from 1,810 U.S. citizens who graduated from an online Master's of Science in computer science (OMSCS) degree program between the summer of 2015 and the fall of 2019. The OMSCS program is a nationally recognized, fully online alternative to the institution's residential program. The program was launched in the spring of 2014 and has reached an enrollment of over 10,000 students. The OMSCS program maintains the same rigour as the residential program and graduates receive the same diploma and credentials as those who graduate from the residential program. Two features differentiate the OMSCS program from the residential program: affordability and scalability. The OMSCS program charges less than one-fourth the total tuition cost of the residential program. Because online classes are limited only by grading capacity (as opposed to physical classroom space in a residential program), the program has no inherent cap on admission. In practice, this means that all qualified applications can be accepted. The program's student population, which largely consists of working adults, is older and contains more U.S. citizens in comparison to the institution's residential program (Goodman et al., 2019). By reaching a population of mid-career workers who otherwise likely would not have pursued graduate education, the OMSCS program is projected to increase the number of computer science Master's degrees awarded within the U.S. each year by approximately seven percent (Goodman et al., 2019).

Nine students were excluded from analysis because records indicated that they graduated in fewer than five semesters, which is not possible due to administrative limits on hours enrolled per semester. These students likely transferred into the OMSCS program and were permitted to transfer course credits from another program. They were excluded from analysis because their experience does not reflect the course enrollment pattern of typical OMSCS students. Excluding these participants brought the usable sample to a total of 1,801 students. Descriptive statistics for the sample's demographic characteristics and educational background are provided in Table 1.[1] The average age of the graduates included in this sample at the time of their enrollment was approximately 32 years old (*M* = 31.75, *SD* = 8.19). The sample was primarily male (89.89%) and white (67.19%). Only 9.67% of the sample were underrepresented minorities (i.e., Black or Hispanic). Over half of the sample (54.97%) entered the program with undergraduate degrees from a computer science or information technology-related field (CS/IT), while 44.42% entered with undergraduate degrees from fields other than CS/IT. A small number of graduates (0.61%) reported undergraduate degrees that were uninterpretable on their application (e.g., abbreviations) and were placed in a separate category of "Unknown." The average undergraduate GPA of the sample was 3.37 (*SD* = 0.40).

Table 1. Sample Demographic Characteristics and Educational Background

Demographic Characteristics					
Age		Gender		Ethnicity	
Mean	31.75	Male	1,619, 89.89%	White	1,208, 67.19%
SD	8.19	Female	182, 10.11%	Asian	323, 17.96%
Range	18–67			Black/Hispanic	174, 9.67%
				Other	3, 0.17%
				Mixed	90, 5.01%
Educational Background					
Undergraduate GPA		Undergraduate Major			
Mean	3.37		CS/IT		990, 54.97%
SD	0.40		Non-CS/IT		800, 44.42%
Range	1.77–4.00		Unknown		11, 0.61%

2.2. Data

Data for the study was integrated from three sources. Demographic information (i.e., age, gender, ethnicity) and educational variables (i.e., college GPA and major) were obtained from students' applications to the OMSCS program. OMSCS course enrollment data from the spring semester of 2014 through the fall semester of 2019 were obtained from the institute Registrar's Office. Finally, ratings of course difficulty and workload were obtained from a student-run website in which OMSCS students provide evaluative information, advice, course descriptions, and feedback (Duncan & Joyner, 2019). Students leave course reviews in which they indicate each course's difficulty on a Likert-type scale ranging from 1 = "Very easy" to 5 = "Very hard" and the average hourly workload per week for the course. Course difficulty and workload ratings were moderately to strongly correlated with the number of withdrawals per total enrollment from each course per semester, suggesting that the ratings do meaningfully reflect OMSCS student perceptions of course difficulty and workload ($r_{\text{difficulty, withdrawal}} = 0.54$, $r_{\text{workload, withdrawal}} = 0.43$). Difficulty and workload ratings within a single course were strongly correlated ($r = 0.81$) and were therefore combined into a single composite variable representing course load. Students' per-semester course load was calculated using unit-weighted z-scores, which allowed for both variables to be placed on the same scale and aggregated into a single composite score.

3. Results

3.1. Learner Profiles

The results presented in this section address RQs 1 and 2, which prompted a consideration of whether distinct course enrollment behaviour profiles could be identified among successful graduates and whether the nature of those profiles differed with respect to course load, semesters off, and speed to graduation. Optimal matching (OM) analysis was used to investigate course enrollment and to identify distinct profiles of learner enrollment. OM is a form of sequence analysis commonly used to analyze patterns within longitudinal trends of categorical data (Cornwell, 2015). Accordingly, a longitudinal, categorical variable

[1] Based on the nature of our Institutional Review Board approval and data privacy restrictions in other countries, the students included in our analyses are U.S. citizens. Citizens of other countries and permanent residents of the U.S. who did not hold citizenship were excluded. Therefore, the demographic and educational backgrounds of the students included in this sample do not necessarily represent those of the entire student population.

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(course load per semester) was created prior to conducting analyses. Specific steps taken to calculate this variable are described below. Per-semester course load composite values were converted into one of three categorical states. Participants with a course load composite score lower than one standard deviation less than the mean composite score associated with that particular semester were characterized by a "low" course load, participants with a composite score that fell within one standard deviation of the mean were characterized by a "moderate" course load, and participants with a composite score higher than one standard deviation greater than the mean were characterized by a "high" course load. Participants were sorted into course load states based on data from all students enrolled each semester, including students who did not graduate and are therefore not included in this study's sample. Participants not enrolled in courses in a given semester were sorted into one of two categories: either "Missing," indicating they were not enrolled in courses, or "Graduate" indicating they completed the program at the end of the preceding semester.

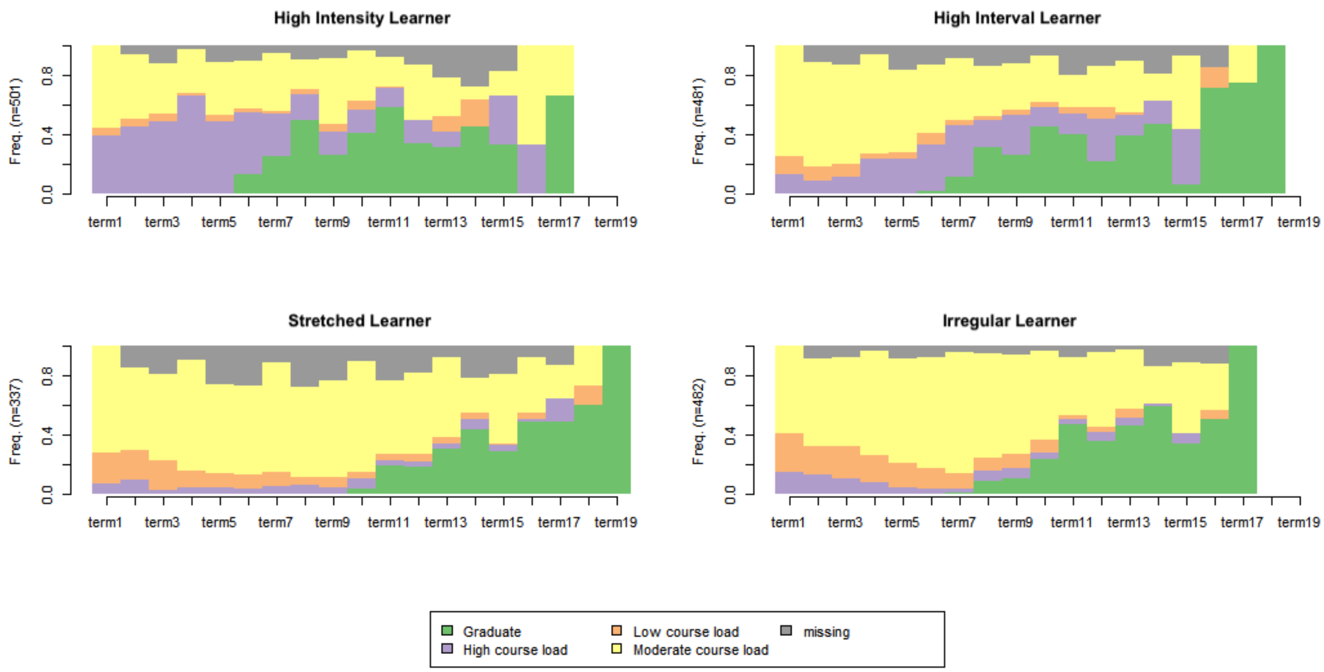

Figure 1. State distributions of learner profiles
Note. Each plot provides a distribution of how many participants from the profile were in each state during each semester. Participants are characterized as "Graduate" in the semester after they complete their final course and are not included in the distribution in later semesters. OM analyses were computed and visualizations were created using the TraMineR package (Gabadinho et al., 2009; Gabadinho et al., 2011).

The longitudinal, categorical data were analyzed using an approach that combined OM with agglomerative cluster analysis to identify a sequence typology. This approach to sequence analysis has been used in both sociology and biology. For example, it has been used to identify trends in career histories and career mobility (Abbott & Hrycak, 1990; Biemann et al., 2020; Blair-Loy, 1999; Chan, 1995; Dlouhy & Biemann, 2018; Halpin & Cban, 1998), life course trajectories (Gabadinho & Ritschard, 2013; Martin et al., 2008; Pailhé et al., 2013), and DNA and protein sequences (Durbin et al., 1998; Kruskal, 1983). Within the learning analytics community, OM has been used to identify study pattern sequences among MOOC learners (Boroujeni & Dillenbourg, 2019). We chose to use optimal matching analysis rather than latent class analysis, another form of analysis for longitudinal sequences, because latent class analysis is superior to optimal matching only in cases where variation in sequence trajectory is random (e.g., DNA mutation; Barban & Billari, 2012). The use of optimal matching analysis is justified given that course enrollment behaviour from one semester to the next is likely not random — a course enrollment decision in one semester may very well influence a decision the next semester.

The 1,801 graduates displayed 1,527 distinct sequences, ranging in length from five to 18 semesters. OM was used to calculate the dissimilarity between each individual sequence in a pairwise manner. Distance was defined as the minimal cost in terms of insertions, deletions, and substitutions needed to create two identical sequences (Abbott & Forrest, 1986). A matrix containing the OM distance between each sequence was used as the input for agglomerative cluster analysis to identify typical trends that underlie the sequences. The clusters were aggregated using Ward's linkage method, which minimizes within-cluster sums of squares (Ward, 1963).

Three internal cluster validation measures (Connectivity, Dunn Index, and Silhouette Width; Brock et al., 2011) were consulted to determine the most appropriate typology to describe the 1,801 total course enrollment sequences. Indices suggested a variety of cluster solutions ranging from two to five clusters. Each solution was considered, and a four cluster-solution was selected because it provided the most appropriate combination of parsimony and theoretical justification. While the two-cluster and three-cluster solutions were relatively parsimonious, they did not reflect differences in key course enrollment variables of interest to this study. For example, clusters in these solutions collapsed observable differences in the likelihood of not enrolling in any course at a given point in time (i.e., of taking semesters off). Meanwhile, the five-cluster solution did not show additional, meaningful differences between clusters that justified its selection over the more parsimonious four-cluster solution. In sum, the four-cluster solution provided relevant information about all enrollment pattern characteristics of interest and permitted a relatively parsimonious interpretation.

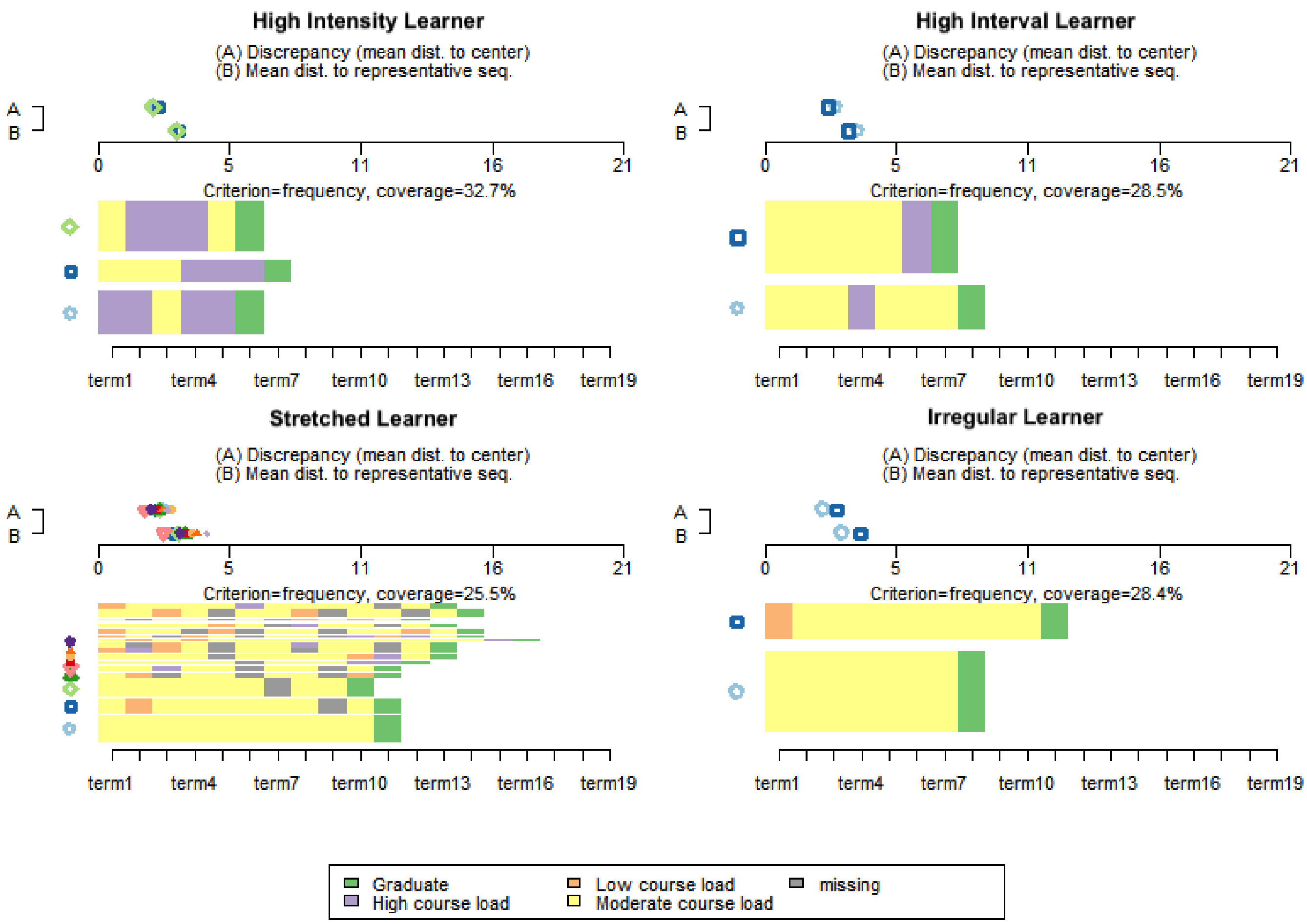

Figure 2. Representative sequences of learner profiles

Note. This visualization depicts course enrollment sequences typical of each profile (i.e., most frequently observed). A minimum of 25% of each cluster is characterized by the sets of sequences included in these plots. Sequences observed more often are printed larger. Coverage indicates the percentage of each cluster characterized by the sequence set. Discrepancy and mean distance to representative sequence describe the similarity of each representative sequence. OM analyses were computed and visualizations were created using the TraMineR package (Gabadinho et al., 2009; Gabadinho & Ritschard, 2013).

The four-cluster solution indicates four distinct profiles that describe how successful OMSCS students (i.e., graduates) manage their online learning through course selection and enrollment behaviours. The *R* package "TraMineR" (Gabadinho et al., 2009) was used to create two visual representations of the typical enrollment behaviour for each profile. Figure 1 provides a state distribution for each profile that clearly displays the proportion of participants in each independent "state" (i.e., low course load, moderate course load, high course load, missing, graduate) during each semester or "term" (Gabadinho et al., 2011). In other words, Figure 1 shows how student preferences for course load varies by each of the four learner profiles. These different preferences are discussed below. Figure 2 outlines representative sequences, defined as a set of individual sequences that, when combined, are present in at least 25% of the cluster (Gabadinho & Ritschard, 2013). In other words, Figure 2 presents prototypical (i.e., "representative") course enrollment patterns from entry to graduation for each of the four learner profiles. The differences between representative sequences for each profile are interpreted below.

Overall, the four profiles can be distinguished by three aspects: 1) time to graduation, 2) semesters not enrolled in courses, and 3) semester course load — that is, semesters enrolled in low, moderate, and high course loads. The first profile contains 27.82% of the sample (n = 501) and may be referred to as the "High Intensity" learner profile. Learners in this profile generally graduated faster than learners in any other profile, with an average graduation time of just over 7 semesters (*M* = 7.31, *SD* = 1.85). Participants in this profile also enrolled in more high course load semesters (*M* = 3.41, *SD* = 1.22), fewer low course load semesters (*M* = 0.32, *SD* = 0.61), and took fewer semesters off (*M* = 0.57, *SD* = 0.82) than learners in any other profile. The second profile contains 26.71% of the sample (n = 481). Learners in this profile — the "High Interval" learner profile — also enrolled in more high course load semesters (*M* = 1.95, *SD* = 1.14), fewer low course load semesters (*M* = 0.58, *SD* = 0.79), and took fewer semesters off than participants in all profiles aside from the High Intensity learner profile (*M* = 0.98, *SD* = 1.38). However, in contrast to the High Intensity profile, learners in the High Interval profile took on average one semester longer to graduate (*M* = 8.48, *SD* = 2.17) and were more likely to take a semester off.

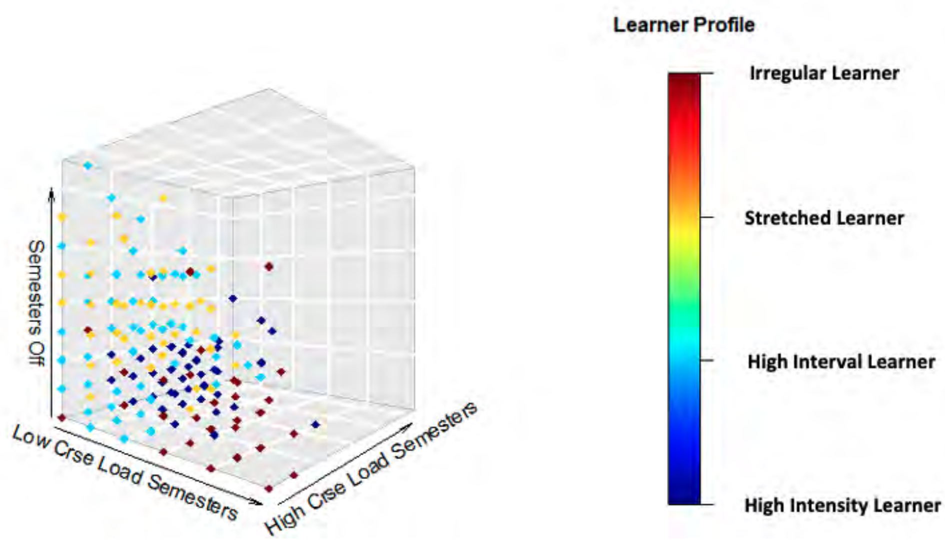

Figure 3. Three-dimensional display of learner profiles
Note. This visualization displays the four learner profiles regarding course load and semesters off.

The third profile contains 18.71% of the sample (n = 337). Compared to the other three profiles, learners in this profile took the longest time to graduate (*M* = 12.42, *SD* = 2.07), were most likely to take semester(s) off (*M* = 2.31, *SD* = 1.36), and enrolled in the fewest high course load semesters (*M* = 0.66, *SD* = 0.86). We refer to learners in this profile as "Stretched" learners, reflecting this group's choice to take lower course loads and longer to graduate. The fourth profile consisted of the remaining 26.77% of the sample (n = 482). While this profile and the Stretched profile showed overall longer graduation times, more semesters off, and lower course loads than the High Intensity and High Interval profiles, the fourth profile can be further distinguished from Stretched learners by course load preferences. In contrast to the Stretched profile, participants in the fourth profile graduated slightly faster (*M* = 10.10, *SD* = 1.88), were less likely to take a semester off (*M* = 0.66, *SD* = 0.94), and enrolled in more high course load semesters (*M* = 0.77, *SD* = 0.95). However, participants in this profile also enrolled in more low course load semesters than participants in the Stretched profile (*M* = 1.56, *SD* = 1.22). We refer to learners in this profile as "Irregular" based on their propensity to take both high course load semesters and low course load semesters.

A visualization of profile differences in the four main criteria (i.e., time to graduation, low course load semesters, high course load semesters, semesters off) is provided in Figure 3, and a summary of these differences is provided in Figure 4.

High Intensity Learners
- More high course load semesters than all other profiles.
- Fewest low course load semesters of all profiles.
- Fewest semesters off of all profiles.
- Fastest graduation of all profiles.

High Interval Learners
- Second most high course load semesters of all profiles.
- More low course load semesters than High Intensity Learners, but fewer than Stretched and Irregular learners.
- Fewer semesters off than Stretched learners, but more than High Intensity and Irregular Learners.
- Second fastest graduation time of all profiles.

Irregular Learners
- Fewer high course load semesters than High Intensity and High Interval learners, but more than Stretched learners.
- More low course load semesters than all other profiles.
- More semesters off than High Intensity learners, but fewer than High Interval and Stretched learners.
- Faster graduation time than Stretched Learners, but slower than High Intensity or High Interval learners.

Stretched Learners
- Fewest high course load semesters of all profiles.
- More low course load semesters than High Intensity and High Interval learners, but fewer than Irregular learners.
- More semesters off than all other profiles.
- Slowest graduation time of all profiles.

Figure 4. Comparative summary of learner profiles on time to graduation, low course load semesters, high course load semesters, and semesters off

3.2. Person Attributes

RQ 3 pertains to whether person attributes significantly predict learner profile membership. To investigate this question, three demographic variables (age, gender, and ethnicity) and two educational variables (college GPA and major) were entered into a multinomial logistic regression equation predicting learner profile membership. Both numeric variables (i.e., age, college GPA) were centred prior to conducting analyses. A reference group was chosen for each categorical variable, which provided a baseline by which to compare levels within the variable. The High Intensity profile was chosen as the reference group for learner profile, male was chosen as the reference group for gender, white was chosen as the reference group for ethnicity, and CS/IT was chosen as the reference group for college major. These reference groups were chosen to allow for comparison against the most frequently represented groups in the dataset. Table 2 presents descriptive statistics of the five person attributes for each of the four learner profiles. Results of multinomial logistic regression analyses, summarized in Table 3 and described below, identified person attributes that significantly predicted learner profile membership while holding other variables in the equation constant.

Participants represented by the Stretched profile were the oldest (M = 34.88, SD = 9.04), followed by the Irregular profile (M = 32.45, SD = 7.94), the High Interval profile (M = 30.71, SD = 7.91), and the High Intensity profile (M = 29.96, SD = 7.38). Using the High Intensity profile as the reference group, age was a significant predictor of membership in the High Interval profile (b = 0.02, z = 2.06, $p < 0.05$) the Stretched profile (b = 0.08, z = 8.49, $p < 0.01$), and the Irregular profile (b = 0.05, z = 5.39, $p < 0.01$). Interpretation of odds ratios indicates that a one-year increase in age increases the chances of being characterized by the High Interval profile rather than the High Intensity profile by a factor of 1.02, the chances of being characterized by the Stretched profile rather than the High Intensity profile by a factor of 1.08, and the chances of being characterized by the Irregular profile rather the High Intensity profile by a factor of 1.05. Taken together, these results indicate that older working adults tended to enroll in lower course loads, to take more semesters off, and to take longer to graduate. However, gender and ethnicity were not significant predictors of learner profile.

Findings obtained for educational variables show that knowledge background, as defined by undergraduate major, was a significant predictor of learner profile membership. Interestingly, in comparison to students with CS/IT knowledge backgrounds, students with non-CS/IT knowledge backgrounds were more likely to fall into the High Intensity profile and less likely to fall into the High Interval profile (b = –0.51, z = –3.864, $p < 0.01$), the Stretched profile (b = –0.64, z = –4.24, $p < 0.01$), or the Irregular profile (b = –0.57, z = –4.27, $p < 0.01$). Odds-ratios indicated that having a non-CS/IT knowledge background lowered the probability of being characterized by the High Interval profile rather than the High Intensity profile by a factor of 0.60, the probability of being characterized by the Stretched profile rather than the High Intensity profile by a factor of 0.52, and the probability of being characterized by the Irregular profile rather than the High Intensity profile by a factor of 0.57. In other words, working adults with a CS/IT knowledge background were less likely to take high course loads and progress quickly through the program compared to working adults with non-CS/IT knowledge backgrounds. The findings related to knowledge background were unexpected and are explored in the discussion section. College GPA was not a significant predictor of learner profile membership across any of the four profiles.

Table 2. Person Attributes by Learner Profile

		High Intensity	High Interval	Stretched	Irregular
Demographic Variables					
Age	Mean	29.96	30.71	34.88	32.45
	SD	7.38	7.91	9.04	7.94
	Range	18–67	21–62	20–65	22–59
Gender	Male	450 89.82%	439 91.27%	301 89.32%	429 89.00%
	Female	51 10.18%	42 8.73%	36 10.68%	53 11.00%
Ethnicity	Not Black or Hispanic	460 91.82%	433 90.02%	306 90.80%	428 88.80%
	Black or Hispanic	41 8.18%	48 9.98%	31 9.20%	54 11.20%
Educational Variables					
College GPA	Mean	3.37	3.37	3.37	3.38
	SD	0.39	0.41	0.40	0.41
	Range	2.10–4.00	1.77–4.00	2.09–4.00	2.10–4.00
College Major	CS/IT	230 45.91%	280 58.21%	199 59.05%	281 58.30%
	Non CS/IT	268 53.49%	200 41.58%	134 39.76%	198 41.08%
	Unknown	3 0.60%	1 0.21%	4 1.19%	3 0.62%

Note. Portions of some participants' data is not reflected in these statistics because it is missing in the data provided by the college of computing. Specifically, three participants did not have ethnicity data and five participants did not have college GPA data. Percentages indicate members within a specific profile that occur at each level of categorical variables. For example, 89.82% of the graduates in Profile 1 are male.

4. Discussion

Our findings provide empirical support for the existence of multiple distinct learner-driven patterns of success among working adults enrolled in an online advanced education program. Using course enrollment data as an index of self-driven management of learning progress over time to graduation, we identified four distinct profiles that varied in terms of time to graduation, course load, and semesters taken off. We also found that these profiles differed in terms of learner age and knowledge background, though not in terms of gender, ethnicity, or previous academic performance. Our findings have implications for understanding how working adults manage their progress over a period of advanced skill training that is typical in the process of upskilling. Our findings also provide meaningful suggestions as to how program progress might be better managed by adult learners and supported by program administrators. Given the popularity of advanced online degrees among working adults and the financial and personal costs of enrollment, we also identify new research directions for researchers interested in working adults' participation in online learning and development.

Table 3. Multinomial Logistic Regression

	High Interval				Stretched				Irregular			
	b	SE	Wald	Odds Ratio	b	SE	Wald	Odds Ratio	b	SE	Wald	Odds Ratio
Demographics												
Age	0.02	0.01	2.07*	1.02	0.08	0.01	8.52**	1.08	0.05	0.01	5.36**	1.05
Female	–0.10	0.22	–0.47	0.90	0.09	0.24	0.39	1.10	0.15	0.21	0.72	1.16
Black/Hispanic	0.21	0.23	0.92	1.23	0.20	0.26	0.76	1.22	0.39	0.22	1.76	1.48
Education												
College GPA	0.08	0.17	0.46	1.08	0.24	0.18	1.33	1.28	0.23	0.17	1.40	1.26
Non-CS/IT	–0.51	0.13	–3.92**	0.60	–0.66	0.15	–4.46**	0.52	–0.55	0.13	–4.23**	0.57
College Major: Unknown	–1.36	1.16	–1.17	0.26	0.08	0.79	0.11	1.09	0.08	0.83	–0.46	0.68

Note. $^{*}p < 0.05$, $^{**}p < 0.01$. The High Intensity learner profile was used as the reference group for learner profiles. Male was used as the reference group for gender. White was used as the reference group for ethnicity. CS/IT was used as the reference group for college major.

4.1. Theoretical Contributions

From a theoretical perspective, our findings provide proof-of-concept for extending applications of LA at the micro-level of analysis to account for the ways in which learners manage their progress over extended periods of time and in the context of substantial non-learning demands (i.e., the macro-level of analysis). LA has provided important insights into the ways in which learners self-regulate to maximize the likelihood of obtaining learning goals and desired academic performance (Winne, 2017). However, prior investigations have tended to focus on data from a single course or learning episode. Our findings suggest that adult learners not only manage their learning progress through micro-level strategies such as effort regulation and attention control, but also through macro-level strategies such as course choice and timing. Additionally, it appears that data related to course choice and timing may be used as a proxy for proactive learning management over extended periods of time. While previous investigations of the macro-learning process have focused on "ideal" pathways to goal attainment (Campagni et al., 2015), our findings suggest that there are likely multiple pathways to success in online education, particularly among adult learners. As access to non-obtrusive educational data continues to increase, the LA and EDM communities are likely well positioned to leverage analytics to inform a more comprehensive understand of the macro-learning process.

Moreover, our findings have implications for existing literatures commonly acknowledged by LA scholars that leverage non-obtrusive data to better understand course enrollment behaviour as well as relationships between courses. In our review of literature pertaining to management of the macro-level of the learning process, we discussed two primary areas: curriculum analytics and academic momentum. Our findings have important implications for better understanding the extent to which findings from these literatures extend to adult learners. With respect to curriculum analytics, our study builds upon existing research that has leveraged semantic information and analyses of course sequences to characterize similarities and differences among courses (e.g., Pardos & Nam, 2020) by applying sequence analyses to a context in which learners likely have higher levels of competing demands and curriculums are less structured in comparison to traditional undergraduate or community college contexts (although these learners still face constraints, e.g., availability of preferred courses). Our findings suggest that course characteristics such as difficulty and workload may be just as if not more important than course content in determining behaviour among adult learners. Next, our findings suggest that the construct of academic momentum, as it is currently defined and operationalized, may not be as precise a determinant of success for adult learners as it is for traditional college students. While the academic momentum literature indicates that successful students typically enroll in high course loads early in their degree program and remain continuously enrolled throughout the duration of their program, our study suggests that some successful adult learners do the same while others proceed at a slower or more intermittent rate. Importantly, the latter group (i.e., those who moved through the program more slowly or with intervals and were not characterized in the High Intensity profile) constitutes a large majority of successful graduates in our study at just under 75% of the total sample. These results imply a potentially fruitful opportunity for learning analytics scholars interested in academic momentum to evaluate the circumstances under which adults' more diverse early course enrollment behaviours contribute to relevant academic outcomes.

Additionally, as the demand for lifelong learning continues to increase (Dachner et al., 2021), our findings suggest that the LA and EDM communities should consider fundamental differences between learners of different ages and life stages and the ways in which such differences influence learning (Sterns & Harrington, 2019). For example, where K–12 education is compulsory and its end marks a transition into young adulthood (Elder & Shanahan, 2006), adult learning is typically volitional and may occur at any time during the lifespan, meaning that individuals have greater agency over the timing and content of learning. Consistent with a lifespan development approach (Beier et al., 2020; Heckhausen & Shane, 2015; Sterns & Harrington, 2019), our findings suggest that the choices students make with respect to course choice and timing may reflect efforts to manage learning and non-learning demands that fluctuate over the lifespan.

From our perspective, there are at least three theoretically plausible explanations for the finding that older graduates generally enrolled in more low course load semesters and took more semesters off compared to their younger peers. However, we offer these explanations as conjectures given that the current study does not contain sufficient data to evaluate the accuracy of each explanation. First, it may be that older learners had greater difficulty meeting the learning demands of their coursework as a result of the gradual decline in specific cognitive abilities experienced over the lifespan (Kanfer et al., 2012). Alternatively, it is also possible, and in our opinion more likely, that older learners experienced greater non-learning demands on their time (e.g., work and family responsibilities) and were unable to devote substantial, continuous time to online learning. Their decision to take fewer high course load semesters and more semesters off may reflect an attempt to manage their learning trajectory in the context of their broader lives. Finally, it is also possible that older learners' more gradual progression to graduation reflects differences in motivation. Perhaps, as complementary research suggests, adult learners pursue online graduate education for more intrinsic reasons (Duncan et al., 2020) and the speed with which they graduate may not be the most important indicator of success for these students. As adult learners continue to pursue advanced education via online delivery, the LA and EDM communities would be well served by using lifespan approaches to learning and development to inform efforts to leverage analytics in pursuit of a more comprehensive understanding of adult learning online.

Finally, our findings reiterate the need to broaden criterion variable choices beyond single course grades and GPA to include learning outcomes that are likely to be more salient and relevant to working adults. Whereas course grades and GPA typically represent important predictors of success in educational pursuits (e.g., college admission), working adults and employers tend to focus on skill-set competencies indexed by multi-course programs that provide certificates or other educational credentials (Mardis et al., 2018). From a person-centric perspective, longitudinal study of personal resource allocations across roles and over protracted periods of time may yield important differences in effects on lifelong learning attitudes and career success.

4.2. Limitations and Future Recommendations

In addition to meaningful findings that suggest the utility of extending LA applications to the program-level of analysis and grounding LA applications targeted toward adult learners in a lifespan development approach, there are several limitations associated with this study that should be highlighted and may inform fruitful directions for future research. The first set of limitations is associated with findings that were either unexpected or null. We found that knowledge background was significantly related to learner profile membership, though not in the way we expected. Given their foundational knowledge and skills, we anticipated that learners with a CS/IT background would be capable of handling higher course loads and would therefore progress through the program at a more rapid pace. However, our findings reflect the opposite pattern. Students with a non-CS/IT knowledge background were *more likely* to fall into the High Intensity profile than students with a CS/IT knowledge background. While we cannot provide a definitive explanation for this finding based on our current data, we suggest that future research focus on the learner's learning motives and their relationship to learning behaviours. It may be that students with a non-CS/IT background are engaged in a more intense learning pattern because they are using the program to enter the CS/IT sector and obtain an entry-level position. In contrast, among learners with a CS/IT knowledge background who are more likely to already hold employment in the CS/IT sector, the primary motive for enrollment may be less transformative and more related to updating their skillset (i.e., upskilling rather than reskilling). Future research should explore motives and other factors that might contribute to differences in how and to what extent individuals prolonged learning opportunities.

Next, we did not detect significant differences among learner profiles in terms of gender and ethnicity. The null findings associated with gender and ethnicity were likely a reflection of the homogenous nature of our sample (i.e., mostly male and white). While these demographic characteristics do reflect the larger population of working adult learners who are U.S. citizens enrolled in the OMSCS program (see Goodman et al., 2019), the modest number of individuals within underrepresented groups such as women and racial/ethnic minorities made it difficult to detect differences in learner profiles related to these characteristics. Because there is a need to close gender and ethnicity gaps in both education and employment within Science, Technology, Engineering, and Math (STEM) fields (Estrada et al., 2017; John & Carnoy, 2019) and advanced education is one potential avenue to accomplishing this goal, there is substantial need for future research to investigate self-regulated learning behaviours in samples that afford greater demographic diversity.

A final limitation of this study relates to the absence of insights from enrollment behaviour data for students who did not successfully complete the program. Although we found multiple pathways for program success, our design did not provide insight into the enrollment patterns of working adults who did not complete the program. Given that the OMSCS program allows for up to a six-year program of study and began enrolling students in 2014, there were very few students that could be definitively characterized as having withdrawn or been unsuccessful by fall of 2019. As these types of programs continue to mature and such classifications become more possible, we anticipate that important insights related to intervention development may be gleaned from studies that compare the enrollment behaviours and post-training outcomes of graduates and non-graduates.

4.3. Practical Implications

The findings from this study have important implications for both curriculum design and educational interventions. Our analyses revealed that there is no single pathway to learning success among working adults engaged in online graduate education. Adult learners made markedly different decisions with respect to course choice and timing. While these decisions influenced the speed with which they graduated, they did not hinder these students from attaining an important learning goal: obtaining an advanced degree. We recommend that educators and administrators take these findings into account when designing the curriculum for online advanced education programs geared toward adult learners. Specifically, programs should be designed with enough flexibility to allow for adults to make conscious decisions regarding the courses that they enroll in and when they choose to enroll in them. Such flexibility may involve allowing students substantially more time to graduate than is necessary for some students, as others may benefit from taking lighter course loads in order to balance their work and family responsibilities with their learning demands. Additionally, programs may remove requirements that mandate the frequency with which students must enroll in courses (i.e., requirements for continuous enrollment) to allow learners the flexibility to take semesters off to balance non-learning demands. Designing programs to allow for maximum flexibility may allow adult learners to proactively manage their learning progress in the context of their broader lives, or to accommodate unforeseen changes in personal circumstances (e.g., job loss, child's or spouse's illness).

Additionally, the age-related differences in course enrollment behaviour revealed by our analyses suggest that person characteristics are important determinants of the pathways that successful learners take to graduation. These characteristics may inform targeted interventions to help adult learners manage their progression through the program. For example, our findings suggest that older students benefit from taking lighter course loads and more semesters off. Based on these findings, educators and administrators could leverage early course enrollment data to identify older students taking consecutive, heavy course load semesters and implement targeted interventions that help them manage their learning progress and balance the demands of their degree program with demands from other areas of their lives. Such interventions may have promise for increasing graduate rates and decreasing attrition rates in online graduate education.

4.4. Conclusion

Our findings provide empirical support for extending LA applications to the macro level of analysis to account for the ways in which students manage their progression over multiple courses and semesters. Using non-obtrusive, longitudinal course enrollment data and OM analysis, we identified four distinct profiles of successful learning management. The findings support the notion of multiple avenues to successful achievement of adult learning goals and the benefits of using enrollment data to gain valuable insight into the self-driven management of adult learning activities. Further, the existence of multiple pathways to successful graduation among adult learners in an online master's program, some of which were characterized by slower graduation speed and intermittent breaks in which students were not enrolled in courses (e.g., Stretched and High Interval learners), is an important contribution to the academic momentum literature that clarifies assumptions to be made about adult learners.

Adult online graduate education has grown rapidly in recent years, particularly as technology and automation change the nature of work and require employees to learn new technical skills to remain employable. Identifying key determinants of adult learner choices to support learning and development is quickly becoming a topic of critical importance to educational researchers. Our findings document the potential of a dynamic, integrative perspective that takes account of person attributes, resources, constraints, using trace and non-obtrusive data. We hope our findings stimulate work in this important direction.

Declaration of Conflicting Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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