Active and Independent Learning in Blended Learning

An Analysis of Student Characteristics, Trace Data,
and Academic Performance

by

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Abstract

In Higher Education, instructors provide students with opportunities to develop essential knowledge, competencies and skills. To offer students the highest quality learning experiences, effective instructors analyze their practice, intentionally seek to identify and check their teaching assumptions, and make iterative instructional decisions based on evidence. However, teaching and learning situations are complex and ill-defined and there is a lack of a parsimonious theory of student characteristics and learning conditions that elicit optimal performance in students. Moreover, learning analytics support the processing, analysis and translation of data into actionable knowledge but there is no consensus yet on which interactions are relevant for effective learning. Thus, this study sought to gain a deeper understanding on how and why students thrived and were productively engaged with insights from psychometric information and course trace data. Findings of this study contribute to the literature that seek to 1) translate trace data into actionable knowledge, 2) understand those characteristics and conditions that elicit optimal student performance, or 3) demonstrate how to use academic achievement, trace data, and psychometric characteristics to analyze an instructor's practice. This study reports on research into 4,150 unique student course interactions clustered within 46 undergraduate student trajectories during an elective blended-learning course. It sought to describe changes in students' active and independent online interaction behaviours; explore differences in interaction trajectories between students; and examine the relationship between students' interaction trajectories, psychometric characteristics and levels of achievement. Students' course interaction trace data was captured by a Learning Management System (LMS). Student characteristics were collected through self-report psychometric instruments completed as supplemental, non-graded, in-class learning activities. Finally, student achievement through total course, summative exams and formative assignment grades. Restricted Maximum Likelihood (REML) linear regressions described interindividual differences in students' growing proportion of course objects accessed across time (interaction trajectories). Maximum Likelihood (ML) multilevel longitudinal regression models, with changes in the proportion of course objects nested within individuals, significantly described students' average and individual trajectories of interaction and differences between course assessment periods and conscientiousness levels. Pearson and Spearman correlations found significant relationships between interaction trajectories and personality traits, psychosocial maturity resolutions, self-efficacy, self-regulation, reasons for studying, and major life goals, and between interaction trajectories and student achievement (knowledge/exam grades). Significant negative relationships were found between academic achievement, psychosocial intimacy-isolation resolutions, and major life aspirations to have a family life, to make meaningful contributions, and to have fun. After reflecting on these results, this instructor concluded that the courses, although beneficial, could have better promoted students' optimal performance by shifting to a more streamlined set of outcomes and a clearer learning path; and by realigning learning activities and intended learning outcomes to better match students' long-range aspirations. Findings from this study suggest that students should be treated not only as cognitive systems but that students may be productively engaged as human beings continually seeking to realize their own possibilities. Although these propositions may not be statistically generalizable, they may be analytically generalized if replicated in more education contexts.

Keywords: Active learning, independent learning, blended learning, online learning, individual differences, psychometric characteristics, individuation, learning analytics, LMS trace data, trajectories of change, interaction trajectories, multilevel longitudinal modeling, linear mixed models, correlational analysis, reflective teaching, scholarship of teaching and learning

Preface

This thesis is an original work by Luis Fernando Marin. The research project, of which this thesis is a part, received research ethics approval from the University of Alberta Research Ethics Board, Project Name “Optimal Learning and Effective Instruction”, No. Pro00075848, August 24, 2017.

Dedication

"Education is a political act because it leads you to discover and acquire the ability to seek and exercise power at the service of others; education is also an act of humility because its essence and meaning, paraphrasing Paulo Freire, is that no one teaches anyone but we all learn from everyone."

Dr. Arturo Sáenz Ferral

"Always strive to be your best. Never settle for less, because there is always something more that can be done better. For each goal achieved, always look for a new great challenge."

Luis Fernando Marin Huerta and
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Chapter 1. Introduction

Instructors in Higher Education aspire to provide each student with extensive opportunities to acquire essential knowledge and skills and help them become improved versions of themselves (Patrick et al., 2012; Roehrig et al., 2012; Reiser & Dempsey, 2018; Spector et al., 2014; Hattie, 2009; OECD, 2013). Effective teaching and learning relationships maximize the possibilities of understanding and growth (Krathwohl, 2002; L. W. Anderson et al., 2001; Krathwohl et al., 1964; Bloom et al., 1956), and inspire students to go beyond what is taught. Instructors arrange the learning situation to get the best from their students (Reiser & Dempsey, 2018; Larmer et al., 2015; Marin, 2014; Merrill, 2001, 2002, 2013; Paas et al., 2012; Baeten et al., 2010; Reigeluth & Carr-Chellman, 2009; Rychen & Salganik, 2003; Corno et al., 2002; Reigeluth, 1983, 1999; Gagné & Gagné, 1985; Gagné, 1965, 1974, 1977; Glaser, 1976; Cronbach, 1957), to ensure that students are fully learning and understanding what is being taught (Tomlinson, 2014, 2015), to facilitate an "optimal functioning of [their students'] natural propensities for growth and integration" (Ryan & Deci, 2000, p. 68; *becoming*, Allport, 1955).

Teaching and learning situations are complex and ill-defined because in learning (Snow, 1989), students differ in complex ways in response to instruction demands and opportunities. Expert teachers and students are able to handle a large portion of this complexity and adjust to different situations by making optimal decisions about teaching and learning (Meyer et al., 2014; Tomlinson, 2014, 2015; T. Hall et al., 2004; Cronbach, 1957; Corno et al., 2002; Snow, 1992, 1991, 1989; Corno & Snow, 1986; Schunk, 1984; Goldfried et al., 1978; Cronbach & Snow, 1977; Glaser, 1976). Knowing whether students are growing, learning and *actively engaged* is an essential teaching responsibility (Stronge, 2018, 2007; Cooper, 2002; Collinson et al., 1998; Wentzel, 1997; Noddings, 2005, 1992; Mayeroff, 1971). Effective teachers observe students' behaviours and continuously ask what motivates these behaviours to understand them (Prizant & Fields-Meyer, 2015; Clark, 2016, p. 472). Expert teachers probe their class and gather information to realize whether students are understanding and have the required notions, motivation or resources to move forward (Tomlinson, 2014, 2015). To be effective (Patrick et al., 2012), teachers need to make sure that students are in condition to learn *actively* and *independently*: to share the responsibility for learning, value learning, be motivated to learn and view learning and personal improvement as realistic and their primary goal (2012).

Effective online learning environments (T. D. Anderson, 2008) make extensive use of diagnostic tools and activities to become aware of the unique internal and external conditions and states that that learners bring to the learning context (Roehrig et al., 2012; Wood et al., 1990). Databases of Learning Management System interactions (LMS) systematically capture, beyond human natural perception, certain aspects of complex teaching and learning realities (e.g. Pelánek, 2017; Pardo et al., 2016; Gašević et al., 2015; Tobarra et al., 2014; Sabourin et al., 2011; del Valle & Duffy, 2009; Beal et al., 2008; Schrader et al., 2008; Ford & Chen, 2000; Lawless & Kulikowich, 1998). Computer mediated interactions between students, peers, instructors, and course content leave a trace that can be analyzed (Schildkamp et al., 2017; Shiri, 2014; Marin, 2014; Schildkamp & Lai, 2013; Ifenthaler, 2012; Jovanović et al., 2008; T. D. Anderson & Garrison, 1997; Moore, 1989, 1990). *Analytics* in Education support the processing, analysis and translation of data into actionable knowledge for teachers and researchers (Howard et al., 2018, p. 153; L. Johnson et al., 2012).

Student learning modeling (Pelánek, 2017; Pardo et al., 2018; Siemens, 2013; Siemens & Gašević, 2012), inferences about how students are learning, are derived from analyses of frequencies, patterns, and timing of what and when students are interacting with a system.

Predictive models of student learning relate students' behaviours or uses of LMS features to measures of academic success (e.g. Kelly et al., 2017; Cerezo et al., 2016; Gašević et al., 2014; Arnold & Pistilli, 2012; Reimann, 2009). Students' history of attempts (Pelánek, 2017) and their timestamps are one of many useful sources of information for learner modeling. Learning or performance curves are also used on this data to observe students' performance over time (e.g. Baker & Inventado, 2014; Baker & Siemens, 2014; Siemens & Baker, 2012; Pardo et al., 2018; B. Martin et al., 2011), link students' practice to improvements in performance (Beck, 2006, p. 21), and provide actionable insights into how different segments of the student population learn (Streeter, 2015, p. 45). In this study, this data was used to research how students' interaction behaviours change throughout a course, to describe when and how many course objects students accessed throughout their course. Empirical questions about change and event occurrence, e.g. how people mature and develop or whether and when events occur, can be addressed with longitudinal data analyses (Singer & Willet, 2003, p. v) of *how* each person changes over time (individual growth trajectories) and *what* is the association between predictors and patterns of change (heterogeneity in change across individuals, 2003, pp. 8 – 9). In this study, this type of analysis was used to research what was the shape of students' interaction trajectories and whether these trajectories of change were the same for different groups of students.

However, the ability to make claims about student learning or behaviour based solely on LMS data has strict limitations (Conijn et al., 2017; Reiman et al., 2014, p. 529; Gašević et al., 2015; Lukarov et al., 2015; Lodge & Lewis, 2012). For instance, *interactions* (Agudo-Peregrina et al., 2014) are the most basic unit of learning data in virtual learning environments, but "there is no consensus yet on which interactions are relevant for effective learning" (2014, p. 542). Furthermore, interactions alone may not presume *engagement* in a process of inquiry (Garrison

& Cleveland-Innes, 2005, p. 4; Picciano, 2002; Azevedo, 2015; S. Lee, 2014), that students are cognitively engaged in an educationally meaningful manner (2005, p. 135; *cognitive presence*, Garrison et al., 2010, 2001, 1999, p. 11; Lodge & Lewis, 2012, p. 562). The use of specific LMS features by students within a Course "does not necessarily mean that the feature would have a significant effect on the students' academic success" (Gašević et al., 2015, p. 79). Instructional conditions and individual differences in the enrolled student cohort may produce contextual differences in technology use and influence the prediction of academic success (2015). For these reasons, some researchers recommend treating patterns found within trace data "as mere hypotheses resulting from exploration" (Kelly et al., 2017, p. 65) that need to be deeply understood before using as a guide for changes (2017). Others believe that "patterns of regular event sequences are only conceptually interesting if they are sufficiently explained in theoretical terms" (Reimann et al., 2014, p. 538) and will contribute more directly to theory building when applied to data that measures theoretically relevant properties and mechanisms (2014).

Pardo and colleagues argue (2015) that "the interpretation of the meaning of learning analytics is improved when combined with qualitative data which reveals how and why students engaged with the learning tasks in qualitatively different ways" (2015, p. 305). To complement trace data, some authors have used biometric and other multiple sources of data (e.g. *Multimodal Learning Analytics*, Blikstein, 2013), qualitative analyses of students' course content such as patterns in students' participation in on-line discussion forums (Romero et al., 2013; Lockyer et al., 2013), coding behaviours (Blikstein, 2013), experiential data (Pardo et al., 2015), and other self-reported data (Pardo et al., 2016). Learning analytics studies have also explored the relation between patterns of trace data and different learners' characteristics (Dawson et al., 2014). To find out why students learn differentially these studies have explored the relation between their traced patterns of behaviour, achievement, and different concepts related to students': previous experience and motivations (Beal et al., 2008; Yeo & A. Neal, 2004; Ford & Chen, 2000; Lawless & Kulikowich, 1998), perceptions or beliefs (Lust et al., 2013; del Valle & Duffy, 2009; Beal et al., 2006), moods and affects (Sabourin et al., 2011), or self-regulated learning (Pardo et al., 2016; Gašević et al., 2017). In many cases these characteristics are considered independently and can only explain certain portions of students' behaviours in particular instructional contexts. According to Pardo (et al., 2015), finding the right framework to combine observational and experiential data sources should translate "into deeper insight and understanding of the student experience and help improve the design of effective interventions" (2015, p. 305). However, there is little agreement on which concepts to use, to focus on, or on how to measure them. There is a lack of a "parsimonious theory of performance" (Corno et al., 2002), of student characteristics and learning environment conditions that elicit optimal performance in students. For these reasons, this study examined whether there was a relationship between how students interacted with their course, their achievement levels, and a series of psychosocial characteristics that should be related to their capacity to learn actively and independently, according to theory.

Students in Blended Learning are expected to be actively involved in their courses (Dzuiban et al., 2004, p.8), to interact actively and meaningfully with class content, resources, activities and assessments (Marin, 2014, p. 8). Being actively involved in a course requires personal agency (J. Martin, 2004), "the capability of individual human beings to make choices and to act on these choices in ways that make a difference in their lives" (2004, p. 135). Voluntary independent action (Karoly, 1993; Bandura, 1991, 2012; Schunk et al., 2008) *is managed* through self-generated thoughts, feelings, and actions that are planned, performed, evaluated and cyclically adapted *to attain personal goals* over time and across changing circumstances or contexts (*self-regulation;* Zimmerman, 1986, 1989, 2008; Zimmerman & Labuhn, 2012; Davidson & Sternberg, 2003; Schunk & Ertmer, 1999; Karoly, 1993).

Classroom strategies can help improve students' ability to self-regulate (Shanker, 2010, 2012), which in turn enhances students' capacity to learn and to deal with life challenges (2012). Instructional interventions that explicitly support the development of self-regulated learning outperform other interventions (Kramarski, & Michalsky, 2009, p. 161). Learning analytics have used trace data to infer students' self-regulation capabilities and have been used to modify the design of instruction to improve these skills (Fincham et al., 2018; Gašević et al., 2017; Pardo et al., 2016; Pardo et al., 2015; Reimann et al., 2014; Azevedo et al., 2013; Azevedo et al., 2010; Hadwin et al., 2007). However, self-regulation can only explain certain portions of the variance in students' behaviours or levels of achievement. The reason for this limitation might derive from unobserved fundamental psychological development characteristics that enable students' self-regulatory processes: forethought, performance, or self-reflection (Zimmerman & Labuhn, 2012). For instance, the capacity to manage voluntary action (i.e. *self-regulation*) relies on both discrepancy production and discrepancy reduction (Bandura, 1991); it requires proactive control (goal production) as well as reactive control (regulation). Self-regulation explains how students manage their efforts in different contexts but has yet to explain why students are able to define, choose or decide on personal goals of different productive qualities.

Active and independent academic learners (Schunk, 2012; Zimmerman & Schunk, 2008) have the skill and will to learn (Woolfolk et al., 2016), a "self-reinforcing intrinsic desire to know and understand" (Seifert, 2004), a tendency towards intrinsically self-initiated and choiceful behaviours (*Self-determination Theory*, Deci & Ryan, 2008, 2000, 1985, p. 111) that tends to yield greater psychological health, more effective performance on heuristic types of activities, and greater persistence (2008, p. 183). Students that are *active* (Fromm, 1976, pp. 76-84) use their human powers *productively*, not only in terms of a visible expenditure of energy but as a manifestation of their critical reason, freedom, and independence. As such, *productive activity* (1976) is an expression of a *positive intrinsic interest*, an inner relation and satisfaction in what the person is doing, to what the person thinks the goal of living is, to what makes life meaningful, to what that person seeks from life.

Individuation (Allport, 1955, pp. 24 – 28), the capacity to form an individual style of life that is self-aware, self-critical and self-enhancing, is one of the most vital human characteristics. Throughout their life, every person develops a personal style, an idiosyncratic way of achieving definiteness and effectiveness in their self-image and in their relationships with others. "Personality is less a finished product than a transitive process" (Allport, 1955, p. 28) and "while it has some stable features, it is at the same time continually undergoing change" (p. 28). Individuality (Allport, 1955), is expressed through a creative becoming motivated by *distant and unattainable growth motives* and directed by *a value-related mature conscience*. Becoming (1955) is the course of change, of individuation, that is driven by a disposition to realize one's possibilities, to become characteristically human at all stages of development. Becoming is a matter of sorting and assessing one's own issues of life according to their relative importance, of organizing transitory impulses and societal demands and responsibilities into "a pattern of striving and interest in which self-awareness plays a large part" (1955, pp. 28-51), of planning and orienting what one does in life as the unique expression and realization of a person's propriate or distinctively unique hierarchy of interests and long-range goals. Developmentally, becoming is "the process of incorporating earlier stages (archaic and relatively isolated) into later (full psychological maturity corresponding to one's age) or when this is impossible, of handling conflict between early and late stages as well as we can" (1955, p. 28).

A person will be *free to become*, predicted Allport (1955), in direct proportion to their a) levels of self-insight or self-knowledge, b) collection or possibilities of behaviour (socialized roles, cultured facts of self), and c) the proportion to which they are directed by propriate goals (their *ordo amoris*, value system, conception or philosophy of life). A person's psychological freedom (1955) will also determine the degree to which their activity is outward directed (opportunistic) or inward directed (propriate), driven by personality, by the "forces" within the person independent of environmental stimuli. The limits to the possibilities of becoming, projected Allport (1955), to being free to become (*see a, b, & c this paragraph*) may be expanded by the capacities of reflection, self-objectification, education, and the amount of effort someone is willing to put into the process.

Learning how to teach, and working to become an excellent teacher, is a long-term process (Villegas-Reimers, 2003, p. 8) that involves the development of complex practical skills, acquisition of specific knowledge, and the promotion of certain ethical values and attitudes. This work is an instructor's effort, as instructional designer and educational psychologist, to gain a deeper understanding on how and why students are able to thrive, to be actively and independently engaged and make the most out of a course. This work seeks to use trace data to help students and teachers improve their understanding of their learning situations: to inform their own sets of goals and expectations in the context of their teaching-learning relationships. This effort is worthwhile because instruction can be improved when teachers are engaged in active conversations around analyses based on student data (Schildkamp et al., 2017; Schifter et al., 2014; Schildkamp & Lai, 2013; Mandinach, 2012), because clear evidence of improvement in student learning outcomes results in significant change in teachers' attitudes and beliefs (Guskey, 2002), because dialogue focused on student data (assessments, work and behavioural information) and instruction is associated with positive changes in instructional delivery (Marsh et al., 2015), and because across hundreds of meta analysis (Hattie, 2009), "the creation of situations in classrooms for the teachers to receive more feedback about their teaching" (p. 12) is the most powerful influence enhancing student achievement. This work contributes to three bodies of knowledge by addressing the following gaps: 1) knowledge that allows instructors and practitioners to better translate data into actionable knowledge by improving LMS data analysis claims about LMS higher education students' behaviour through longitudinal interaction trends and students' qualitative data (course content and psychological characteristics); 2) insights related to those student characteristics and learning environment conditions that elicit optimal active and independent performance in students, a framework for observing students' differences by finding evidence of an association between the degree to which students have developed an individual self-aware pattern of striving and interest, differences in their interaction behaviours and achievement; and 3) a demonstration of a practical way in which this information, interactions, characteristics, and achievement may be used by instructors, by teaching and learning scholars, to be analytical about their own practice and make iterative improvements based on evidence. As such, this inquiry was guided by the following research questions:

Research Questions

1. How student interactions changed throughout the course?
2. Is there a relationship between student characteristics?
3. Is there a relationship between students' interaction trajectories and their characteristics?
4. What is the shape of students' longitudinal interaction behavior (change trajectories) and is this change the same for students of varying characteristics?
5. Is there a relationship between students' characteristics, interactions and achievement?

Chapter 2. Literature Review

Trajectories of Change

Data is in school data-driven decision-making (Schildkamp et al., 2017), “information that is systematically collected and organized to represent some aspect of schools” (2017, p. 242; Schildkamp & Lai, 2013, p. 177). In data-based decision making in schools, qualitative or quantitative methods are used to obtain: input data (e.g. student background data), process data (e.g. classroom observations and teacher interviews), context data (e.g. type of classroom), and output data (e.g. student achievement, student satisfaction). *Interactions* (Agudo-Peregrina et al., 2014) are the most basic unit of learning data in virtual learning environments “but there is no consensus yet on which interactions are relevant for effective learning” (2014, p. 542). *Analytics* in Education support the processing, analysis and translation of data into actionable knowledge for teachers and researchers (Howard et al., 2018, p. 153).

In educational situations, instructors plan series of lectures, resources to be studied, activities to be performed, and assessments to be taken. For many years now, *actions or behaviours*, easily observed bits of behaviour in controlled settings, have been used to observe and predict changes in organisms’ rates of response (e.g. Skinner, 1957, pp. 343 – 344). *Student learning modeling* (e.g. Reimann, 2009; Arnold & Pistilli, 2012; Kelly et al., 2017) are derived from analyses of frequencies, patterns, and timing of what and when students are interacting with a system. Students’ actions help gain insights into how and which students learn in real-life contexts (e.g. Cerezo et al., 2016; Agudo-Peregrina et al., 2014, 2012; Baker et al., 2011; Chi et al., 2011; or L. V. Morris et al., 2005), how different groups of students learn (i.e. interact with a system) and how those patterns are related to academic performance (e.g. Azevedo, 2015; Gašević et al., 2016; Cerezo et al., 2016; Siemens et al., 2014).

Features

What students <u>*do*</u> to bring about change is the primary source of change (Aristotle et al., 1960; Ross, 2005; Falcon, 2015). Students' actions may vary in terms of selection (*what*, choice of activity or behaviour, and *how much*, frequency of occurrence), time (*when*, timing, and for *how long*, duration), and quality of interaction (*how*) which results in varying levels of achieved performance (*achievement*, *marks* or *grades). LMS* data afford a wide range of analysis of students' task times, task selection, and quality of interactions.

Selection. In most classroom situations, increased interaction improves student achievement (Beaudoin, 2002, p. 48). Students that are not learning may be significantly disconnected from the course, they may show significantly lower number of essential activities opened or the quality of their interactions with these resources or activities might be significantly lower than the rest of the class. L. V. Morris and colleagues (2005) classified students as "withdrawers" and "successful completers" based on number of activities opened and time spent on LMS activities and concluded that "time spent on task and frequency of participation are important for successful online learning" (2005, p. 228). Boechler and colleagues (2017) found that under certain instructional conditions, students that engaged more intensely with non-essential or supplemental online learning activities obtained significantly higher grades. Pardo and colleagues (2018) interpreted sequences of trace data as study tactics, groups of study tactics as learning strategies, and groups of weekly learning strategies as learning paths to conclude that students' trajectories of strategy change had a significant effect on academic performance (p. 1).

However, sometimes minimal online participation may not compromise grades (Wise at al., 2011; Beaudoin, 2002). Sometimes low-visibility students dedicate more time to reflection and processing of course material beyond the context of the visible online environment and do better than visible average students (Beaudoin, 2002, pp. 152 – 153). Students who do not post messages in online discussions may learn adequately by observing and actively processing other students' interactions (Sutton, 2001; Rourke & Anderson, 2004; Garrison & Cleveland-Innes, 2005; Wise et al., 2011). Conversely, larger amounts of interaction do not guarantee that students are cognitively engaged, that there is cognitive development, meaningful learning and understanding (Garrison & Cleveland-Ines, 2005, p. 135). Sometimes students may post online messages just for the sake of being present (Beaudoin, 2002), or because they are obliged to, because they "have to" (Rourke, 2005, p. 261).

Time. Instructional activities have different timings or planned sequences: some may follow certain timelines, some might be important milestones (e.g. exams or assignments) and some others might be planned to occur during certain periods of time (e.g. read a text, study a video, answer a quiz, participate in a discussion, collaborate in a group, etc.). Students' activities may have varying patterns of engagement or tempos (*timing)*, for example, in any certain course some students may choose to work ahead of schedule, some others to follow the schedule to the letter, and some others might have trouble keeping up (Cerezo et al., 2016). In a recent study, Boechler and colleagues (2017) found two distinguishable patterns of first-time access to online course materials (*tempo*) and also found that students that predominantly access these materials when presented in the course (*distributed practice tempo*) perform significantly better than those who access these materials predominantly right before exams (*cramming tempo*).

Studies of learning as a function of amount of time (Fredrick & Walberg, 1980) have usually predicted learning outcomes at a modest level, but indicators of time-on-task and content-specific outcome measures strengthen correlational evidence (1980, p. 183). Carroll's *Model of School Learning* (1963, 1989, 2005; Haertel et al., 1983, p. 78) states that students will master instructional objectives to the extent that they are allowed and are willing to invest the time needed to learn the content (1983, p. 78). An *enrichment view* of the relation between amounts of time and learning (Walberg, 1971, 1975, 1980) assumes that for a given constant time student achievement will be normally distributed as a function of aptitude (cognitive and affective) and quality of instruction. An *acceleration view* of the relation between amounts of time and learning (e.g. *Mastery Learning*, Bloom, 1971, 1976; Carroll, 1963, 1989, 2005) assumes that for any fixed criterion level of achievement, the amount of time will be normally distributed as a function of aptitude (cognitive and affective) and quality of instruction.

Quality. A deeper understanding of students' behaviour also requires an observation of qualitative properties (*how something is done*) of students' interactions. Being able to construct meaning and understand constructs and concepts is an essential part of learning. In this sense, quality may entail or be reflected in students' performance, levels of attainment or achievement, or instructors' summative and formative judgements. Quality may refer to particular characteristics of students' activities or work, e.g. participation in class discussions, quality of content (depth, understanding), or quality of presentation (mechanics, spelling, grammar, citation style). Quality may also refer to the combined composition of all these elements, the overall quality. Quality may refer to the lack of defects or to conformance to certain standards or requirements, but quality may also refer to evidence of growth beyond the expectations of the course, to divergent, creative, innovative, or critical work and modes of thinking.

Methodology

Applied research (Ary et al., 2019, p. 15) aims to solve an immediate practical problem, as opposed to basic research, which aims to obtain empirical data that can be used to formulate, expand, or evaluate a theory (2019, p. 15). Action research is done by educators for themselves

(Ary et al., 2019, p. 16; Mertler, 2016), it is research that is situated in a local context and focused on a local issue, and results in an action or a change implemented by the practitioner. Classroom action research (Hendricks, 2009) aims to improve classroom practice and it involves teachers in their classrooms. Learning Analytic tools generate results in particular contexts (Lukarov et al., 2015; Lockyer et al., 2013; Siemens, 2013), and analytics researchers usually demonstrate their data analysis techniques through case studies. Multilevel analysis (Snijders & Bosker, 2012; Heck et al., 2013, 2010) allows the analysis of data with complex nested patterns of variability. Social phenomena usually have a multilevel structure, and on each level, there is variability that has a distinct interpretation. For example, students of different characteristics (Level 1 unit) that learn in classes of varying compositions and teachers (Level 2 units) within schools of certain characteristics (Level 3 units).

Change. Research design for the measurement of change can be (Singer & Willet, 2003, p. 4): experimental or observational, data can be collected prospectively and retrospectively (ex post facto), time can be measured in a variety of units, and the data collection schedule can be fixed (same periodicity for everyone) or flexible (each person has a unique schedule). Longitudinal data can help describe how each person in a sample changes over time, can help model *change* (2003, p. 9). Analysis of change require (2003, p. 9): three or more waves of data, an outcome whose values change systematically over time, and a sensible metric for clocking time. According to Singer and Willet, two kinds of question form the core of every study about change (2003, p. 8): 1) what is each person's pattern of change over time (within-individual change)?, and 2) what is the association between predictors and the patterns of change (interindividual differences in change)? The goal of the first question is to "describe the shape of each person's individual growth trajectory" (2003, p. 8). The goal of the second question is to "detect heterogeneity in change across individuals and to determine the relationship between predictors and the shape of each person's individual growth trajectory" (2003, p. 8).

To answer the first question, "the simplest way of visualizing how a person changes over time is to examine an empirical growth plot" (2003, p. 24). A nonparametric trajectory summarizes each person's empirical growth record and requires no assumptions. Then, a parametric approach requires assumptions but yields a fitted trajectory based on a separate regression model to each person's data and provides numeric summaries of the trajectories (estimated intercepts, slopes, and goodness of fit) (2003, p. 26). Adopting a parametric model for individual change "allows to learn about the observed average pattern of change by examining the sample averages of fitted intercepts (initial status) and slopes (rates of change)" (2003, pp. 35 – 36). The observed variability in initial status and rates of change in the sample, the observed individual differences in change, can be observed by examining the sample variances and standard deviations of the intercepts and slopes (2003, p. 36).

To answer the second question, evaluating the impact of predictors "can help uncover systematic patterns in the individual change trajectories corresponding to interindividual variation in personal characteristics" (2003, p. 37). Fixed effects (relevant population averages) capture systematic interindividual differences in change trajectory and represent the effects of the predictors (2003, p. 60). Residuals are stochastic components and represent the portions of the outcomes that remain unexplained and help explain how much heterogeneity in true change remains after accounting for the effects of the predictors (2003, pp. 61 -62).

Case Study. A case study (Yin, 2009, 2012) is "an empirical inquiry that investigates a contemporary phenomenon within its real-life context, especially when the boundaries between phenomenon and context are not clearly evident" (2009, p. 13). Case studies may lack generalizability but can be useful and help advance knowledge through modelling when their descriptions are rich in detail. A case study inquiry technically requires the researcher to cope with a large number of variables of interest and very few data points, relies on multiple sources of evidence, and benefits from theoretical propositions that guide data collection and analysis (2009, p. 13). Case studies are the preferred research strategy when “the investigator has little control over events, and when the focus is on a contemporary phenomenon within some real-life context” (2009, p. 1). In contrast, in experiments an investigator can manipulate behaviour directly, precisely, and systematically.

Case studies are generalizable to theoretical propositions (analytic generalization) and not to populations or universes (statistical generalization). In order to be accepted, a theory must be tested through replications of the findings in a second or a third case where the theory specifies that the same results should occur. *Reliability* in case studies refers to the notion that “if a later investigator followed exactly the same procedures as described by an earlier investigator and conducted the same case study all over again, the later investigator should arrive at the same findings and conclusions” (2009, p. 36). Reliability of case studies may be increased by documenting the procedures followed by using a case study protocol (by making as many steps as operational as possible) and by developing a case study database.

Ex-Post Facto. In Ex Post Facto studies the investigation starts “after the fact has occurred without interference from the researcher” (Nunes-Silva, 2010, p. 465). An independent variable that a researcher can directly manipulate is an *active independent variable* and attribute independent variables are characteristics such as motivation, intelligence, age, ethnicity, gender, self-concept, and many others that subjects have before a study begins (Ary et al., 2006, pp. 355 – 356). The research is conducted after variation in the variable of interest has already been determined in the natural course of events (2006). This type of study normally starts with groups that are already different and try to determine the consequences of or the antecedents of these differences (2006). Ex post facto research is used in contexts in which it is not possible or acceptable to manipulate the characteristics of human participants, when there is no direct control of the independent variable and when random selection of the participants is not possible (Nunes-Silva, 2010). Ex post facto research studies may present important internal validity and external validity issues (2010): internally, being sure that all independent variables that caused the facts were included in the analysis, if these facts would have resulted from other causes in different circumstances, or if the situation is a case of reverse causation, and externally, that the lack of random selection limits the possibility of statistical inference, of generalization.

Internal validity in ex post facto research studies may be strengthened when numerous empirical evidences point to the existence of a statistically tested causal relationship between the independent and dependent variables selected by the researcher (2010). In order to make strong inferences about causal relationships (Ary et al., 2006) it is important to gather evidence that: a) there is a statistical relationship between two factors, b) that the causing factor preceded the resulting factor in time, and c) that other factors did not determine the resulting factor. These other factors or alternative explanations could be: that both the independent and dependent variables have a common cause, that the reverse of the suggested hypothesis could also account for the finding (reverse causality), or that other independent variables may also be antecedent factors for the variation in the dependent variable (2006, pp. 358 – 369).

Course Design

Education and the processes of teaching and learning are the organized means by which we acquire valuable knowledge and develop our capacities to the fullest of their potential

(OECD, 2007, 2017, 2018; Rychen & Salganik, 2003). Effective Teaching entails those factors in the teaching and learning environment that contribute to meet a given learning activity's stated objectives. Effective teaching and learning relationships maximize the possibilities of understanding and growth. Teachers design, curate and prepare sets of instructional activities and educational resources assuming a set of characteristics of their students (Corno et al., 2002, p. 1). The collection of data on learning activities should be focused on confirming the accuracy of these suppositions in an agreed pedagogic practice (Griffiths et al., 2012, p. 103), on the formative evaluation of learning activities and course designs (Richards & DeVries, 2011).

A *situation* (Magnusson, 1981) is that part of the environment that is immediately available to the person on every occasion. Individuals are involved in these continuously ongoing, reciprocal interaction processes with their environments. Psychological analyses of a situation (1981, pp. 4-5) focus on the *actual environment*, its formal and abstract (e.g. physical and biological) characteristics or on the *perceived environment*, the subjective psychological situation. Behaviour takes place in situations; behaviours are carried out by an individual in a situation. Understanding the individual in the situation requires: a) knowledge of the person, b) knowledge of the situation, and c) their dynamic interaction. Teaching and learning relationships (Pianta et al., 2002, 2003) are systems of dynamic reciprocal interactions between: 1) selected individual features and attributes, 2) individual understandings of the relationship, 3) information exchange processes, behavioural interactions, language, and communication that feedback in the relationship, and 4) external influences such as class, classroom, school, or community.

A situation may have *general effects*, comparable changes in intensity of behaviour for all individuals, and *differential effects*, non-comparable changes in level of intensity of behaviours per individual or idiosyncratic pattern profiles. Properties or characteristics that may help describe situations (Magnusson, 1981) are: a) actual or *structural characteristics* such as complexity, clarity, strength, behaviour promotive or restrictive, and type of tasks, rules, roles, physical settings, and other persons; and b) person-bound properties or *content characteristics* such as goals, perceived control, expectancies, needs and motivations, and affective tones or emotions. Block and Block (1981) also proposed a larger set of structural parameters to help characterize different situations, their goals, pathways, and constraints, in formal, abstract, terms (pp. 91 – 101).

Cronbach (1957) proposed "if for each environment there is a best organism, for every organism there is a best environment" (p. 679). Differences appear because of sampling mismatch between persons and tasks, when the person cannot adapt completely to the demands and opportunities of the outer environment or vice versa (Snow, 1980, 1987). Persons differ in the way they adapt to demands and opportunities of the environment; in learning, students differ in complex ways in response to treatment demands. The complexity or difficulty of a task can only be observed and understood in the interaction between individual differences and task differences (Snow, 1989). Teaching and learning situations are unique, and we can suspect that there will always be a certain amount of favorable effective teaching conditions that match certain sets of favorable optimal learning dispositions.

Effective teaching occurs (Tomlinson, 2014, 2015) when teachers ensure that students are fully learning and understanding what is being taught. In an effective classroom (Patrick et al., 2012) students and teachers share responsibility for learning, value learning, are motivated to learn or to promote learning, and view learning and personal improvement as realistic and their primary goal. Effective teachers (Stronge, 2018, 2007, pp. 100 – 102) care deeply, recognize complexity, communicate clearly, and serve conscientiously. Effective or excellent teachers at the University of Alberta (Forgie, Nocente, Vargas, Best-Bertwistle, 2017, p. 20): appropriately convey the knowledge and skills that students need to obtain, manage to engage students despite the difficulty of course material, get high students' rating of instruction scores and teaching awards, are innovative in their teaching practices, know how to challenge students, regularly update their course material and information, research the effects of their teaching practices, are supportive of students, seek to improve their pedagogical practices, and also learn from students.

Instruction

Universal Student Ratings of Instruction (USRI) are questionnaires administered electronically to students "to initiate constructive change in curriculum and instruction" (GFC, 2014, 111.3C) as part of multifaceted efforts to evaluate teaching. Free expression of views is encouraged through student confidentiality and anonymity. When responding to USRI's, students use a Likert-like scale to express their perceptions related to clearness of course goals and objectives, effective use of in-class time, their motivation to continue learning more, relative achievement, overall quality of the course, and whether the instructor spoke clearly, was well prepared, treated students with respect, provided constructive feedback, and overall was excellent. USRI also allow students' open-ended comments. Statistical summaries of students' responses present descriptive statistics from Tukey's box-and-whisker plot analysis: median, 25 and 75 percentiles, and the lower Tukey Fence outlier reference score (25^{th} percentile – 1.5 the range between the 25^{th} and the 75^{th} percentiles). Students' ratings of instruction have been contested and criticized for different compelling reasons, e.g. biased designs and implementations (Cheeseman et al., 2013, pp. 68 – 69), some of which are reflected in the following cautionary preface presented together with all USRI reports:

> "… Factors other than an instructor's teaching ability may influence ratings. These factors include class size, class level, Faculty, time in class, required versus optional course, grade expectations, student GPA, gender, race, ethnicity, age of both students and instructors." (GFC, 2014)

Learning

Achievement or performance indicators, summative assessments and evaluations are the most widely accepted and commonly used information on the outcomes of teaching and learning. Course evaluations help measure, for summative and formative purposes, how much learning has occurred. Scores or grades usually provide valuable information about the amount of knowledge that was acquired or the degree to which skills were developed during the process of learning. Students' industry may prove to be optimal or effective in terms of attained course expected outcomes and of accomplishment of their own goals. Instructional activities are designed to help students achieve certain learning objectives, develop certain competencies, or attain certain outcomes. Students attain varying degrees of factual, conceptual, procedural, or metacognitive types of knowledge (Krathwohl, 2002; Anderson, et al., 2001) and cognitive, affective, or psychomotor educational goals (*Bloom's Taxonomy*, Harrow, 1972; Simpson, 1972, 1966; Dave, 1970; Krathwohl et al., 1964; Bloom et al., 1956).

Assessments collect information about how much knowledge and skills students have learned and help make judgements about the adequacy or acceptability of students' levels of learning (Snowman, & McCown, 2011). To *measure* is to assign numbers or to rate certain attributes of students' activities or attributes according to rule-governed systems. To *evaluate* is to use a rule-governed system to make judgements about the value or worth of measures. Assessments may be summative or formative in their purpose (Bloom et al., 1971). Summative assessments sum up how well the student has performed over time and at a variety of tasks;

summative judgements are assessments *of* learning. Formative assessments monitor progress and help plan instruction and learning accordingly, to make sure students are keeping up with the pace of instruction and better facilitate students' development; formative judgments are assessments *for* learning.

Grades are judgements of student achievement made by instructors (UofA, 2020). Educational institutions normally establish evaluation procedures, assessment and grading policies (e.g. GFC, 2012) to promote consistency in assessment and grading practices and adherence to appropriate academic standards (p. 1). Assessment at the University of Alberta (2012) is guided by the following seven principles: 1) should be integrated into and aligned with the learning experiences and stated objectives or outcomes of a course and program, 2) design and delivery may take innovative forms but must meet minimum expectations, 3) methods and grading standards must be communicated clearly to students, 4) criteria must be clear and transparent, 5) should provide reliable and valid information, 6) should be varied, summative and formative, and timely, and 7) summative assessments' design, delivery and reporting processes should be open, accountable and equitable.

Student learning may be measured (Snowman, & McCown, 2011) by *what is known about something* (written tests such as selected response, short-answer, and essay tests) or by the degree to which students know *how to do something* (performance assessments such as direct writing, portfolios, exhibitions, and demonstrations). Useful tests of knowledge measure skills and knowledge that are worthwhile and important (significant), that can be acquired through effective instruction (teachable), that can be measured and described (describable), that can help identify inadequate areas of instruction (reportable) and should not take an excessive amount of time (non-intrusive). Useful assessments of performance focus on process and products (emphasis on active responding), have higher degrees of realism, emphasize complex, open-ended and ill structured problems, are a variation or extension of a task initiated during instruction, use rubrics or scoring guides to specify the capabilities students should exhibit, describe the qualitative levels or categories into which the responses will be sorted, and specify how the response will be scored. Evaluations of student learning (2011) may compare a student's level of performance with the normal level of other groups of students (e.g. vs average performing students or vs all class members) to reflect differences in amount of learned material (norm-referenced grading). Evaluations of student learning may also compare a student's performance with clearly defined objectives about what students need to know and what they need to do to meet their teacher's expectations (criterion-referenced grading).

In certain situations, an average score might imply that a learning situation produced the highest relative achievement (ZPD; Vygotsky, 1978, 2011), ignited a passion for knowing, or maximized the possibilities of growth. The Zone of Proximal Development (ZPD; Vygotsky, 1978, 2011) observes individual-instruction interaction in terms of mental development readiness and optimal difficulty of instruction. The ZPD is an estimation of the potential range of learning, of what the student is capable of learning, an observation of the "functions that are not mature yet but are currently in the process of maturation" (2011, p. 204). Students' actual levels of development can be observed in those tasks that they can solve independently. Students' ZPD measures what the student can do with the guidance of an educator. With such guidance, students will be able to solve problems of different difficulty. The difference between a student's actual development and such level of complexity determines the student's zone of proximal development.

Relative achievement is the degree to which the student learns something new, the gains in knowledge that result from instruction, the difference between what the student knew before and after instruction. *Absolute achievement* refers to the fulfilment of course or school requirements, of demonstrating that one possesses certain knowledge or skill regardless of quality or appropriateness of instruction. In theory (2011), the strongest gains in relative achievement, that is, optimal conditions for development will be obtained when the difficulty of classroom learning, and the student's zone of proximal development coincide, when studies are neither too easy nor too difficult.

Student Characteristics

There is "a great deal of knowledge about how people learn best" (Tomlinson, 2015, p. 8), for example, that each learner must make meaning of what teachers seek to teach and that this meaning-making process is influenced by the student's prior understandings, interests, beliefs, by how the student learns best, and the student's attitudes about self and school (p.8). The psychological and socio-cultural reality of the student provides a complex set of personal resources and motivations that afford and drive the student´s active involvement in the course (Marin, 2014, p. 10).

Understanding anyone's actions require an understanding of their causes because, "we do not think we know a thing until we have grasped its cause" (Aristotle et al., 1960; Heidegger, 1975; Ross, 2005; Falcon, 2015). The psychological description of a person, of their intellectual, affective, and behavioural functioning, comprises the following dimensions: *the material*, who the student is (e.g. in terms of skills or experience in comparison to others); *the formal*, who the student thinks is (a set of self-perceptions and beliefs) including who students value themselves to be (e.g. self-worth or self-esteem) and expect to be (expectations and perceptions of their own potential); *final*, the reasons for which students do something (as in motivations, aspirations, or intentions), e.g. who students aspire or would like to be; and *efficient*, what students actually do and how they do it (e.g. activity, behaviour).

Ideas or Beliefs

Motivations and ideas that persons have about themselves and the situation are an important part of the learning equation (Bruner, 1960, 1966; Carroll, 1963, 1989; Gagné, 1974, 1977; Bloom, 1976; Preece, 1985; Parkerson et al., 1984; D. R. Johnson et al., 2005). Students' social, behavioural, motivational, affective, cognitive, and metacognitive characteristics have been found to be the set of proximal variables that most impact learning outcomes (DiPerna et al., 2002; Wang et al., 1997, 1990; Parkerson et al., 1984), and noncognitive factors (Stankov, 2013; De Raad & Schouwenburg, 1996) such as measures of confidence and self-beliefs, predict achievement and measures of crystallized intelligence (2013, p. 727).

The mind is as "an instrument for producing worlds" (Bruner, 1986; Goodman, 1984). Language creates or constitutes knowledge or reality, not just transmits it. Thus, there is no unique real world independent of human mental activity and symbolic language. Humans create worlds of appearance through their symbolic procedures; create worlds with their minds, with their languages and other symbol systems. The human world is a complex of meanings. Persons give meaning to and construct critical elements of situations, including goals, means, and criteria for success (Corno et al., 2002, p. 232), of perceived needs and opportunities in every situation. Therefore, understanding individuals' conceptions of the world (Magnusson, 1981, p. 5) and an interpretation of their perception and interpretation of the specific situation in which they find themselves makes it possible to understand their actual behaviour in that situation.

The interface between person and situation (Corno et al., 2002, p. 219; Snow & Mandinach, 1999, p. 32; Glaser, 1976) can be explained by a) the subjective perception of the situation, the match between what is offered and what is needed or sought for, and b) the ability to construct and adapt one's performance to each situation, to continually changing demands and opportunities in tasks, and one's declarative knowledge, expectancies, beliefs, affects, goals, values, and competencies. These result in subjective perceptions of the situation, such as the subjective experience of exertion (*effortfulness*; Helm et al., 2015).

Individuals' perceptions of themselves and their capabilities in relation to the perceived situation are also "vital forces in their success or failure in achievement settings" (Schunk & Pajares, 2005, p. 85; Schunk et al., 2008; Torre-Gibney et al., 2017). Perception is (Rogers, 1959) "a hypothesis or prognosis for action which comes into being in awareness when stimuli impinge on the organism" (1959, p. 199). Students' perceptions or evaluations of themselves influence their functioning (*self-perceptions*, e.g. Nyatanga, 1989; Akeret, 1956, 1959); people "tolerate a much wider range and variety of feelings" (Rogers, 1963, p. 28) and these feelings are "usefully integrated into their more flexibly organized personalities" (1963, p. 28) when they grow to be more satisfied "at being and becoming" (1963, p. 28) themselves.

Self-efficacy. Self-efficacy (Bandura, 1997, 1982, 1986, 2012) refers to beliefs in one's ability to carry out specific actions, how capable people believe they are at dealing with one type of task or another, to "people's judgements of their capabilities to organize and execute courses of action required to attain designated types of performances" (Bandura, 1982, 1986, p. 391). Self-efficacy affects choice of activities, effort, and persistence, and has selective, cognitive, motivational, and affective effects. People's levels of self-efficacy affect their readiness to act (Thorndike, 1913), whether something is satisfying or intolerable, and their approach to achievement (Atkinson, 1957, 1958; Covington & Roberts, 1994; K. Miller et al., 2015), their disposition to avoid failure, to become anxious about failure, and their disposition to approach success, to be disposed to achieve. Self-efficacy may be influenced (Schunk & Pajares, 2005) by previous accomplishments, verbal persuasion, emotional arousal, and vicarious experiences.

Having low or high outcome expectations (Bandura, 1982, 1997, 2012; Schunk et al., 2008, p. 140; Schunk & Pajares, 2005) produces different behavioural and affective reactions in interaction with varying levels of self-efficacy, for example: a) high outcome expectation and high self-efficacy may result in assured, opportune action and high cognitive engagement, whereas b) high outcome expectation and low self-efficacy may result in self-devaluation and depression; or c) low outcome expectation and low self-efficacy may result in resignation, apathy, and withdrawal. Optimal or most adaptive self-efficacy (Bandura, 1997, 2012) are those levels of self-efficacy that slightly exceed actual skills at any given time. Grossly optimistic efficacy beliefs can lead to aversive consequences such as serious injury, death, or needless and debilitating failures. In turn, grossly pessimistic efficacy beliefs limits individuals' potential for learning and cause unnecessary anxiety and further debilitating self-doubts. Individuals with optimal self-efficacy will engage in tasks and careers that foster the development of their skills and capabilities (Bandura, 1997, 2012; Betz & Hackett, 1981, 1983), exert effort in the face of difficulty and persist (Bandura & Cervone, 1983, 1986; Schunk, 1995), and use deeper processing strategies and general cognitive engagement of learning (Graham & Golan, 1991; Pintrich & Schrauben, 1992; Lyke & Kelaher Young, 2006).

The New General Self-Efficacy Scale (NGSE; Chen et al., 2001) was created to measure self-efficacy in a more "trait-like generality dimension" (2001, p. 63). The 8-item scale is scored on a 5-point Likert-type scale from "strongly disagree" (1) to "strongly agree" (5). The NGSE was created to help observe differences among individuals “in their tendency to view themselves as capable of meeting task demands in a broad array of contexts” (2001, p. 63), that is, differences in “the belief that one can mobilize whatever effort it takes to succeed in different undertakings” (Bandura, 1997, p. 53). General Self Efficacy (GSE) is considered to be a motivational trait that describes “one’s belief in one’s overall competence to effect requisite performances across a wide variety of achievement situations” (2001, p. 63), or “individuals’ perception of their ability to perform across a variety of different situations” (p. 63).

According to Chen and colleagues (2001; Eden, 1988, 2001), GSE should not be a substitute or a replacement of task-specific or state-like self-efficacy (SSE). According to Bandura (2006, p. 307; 1997), SSE’s are the most relevant way to measure self-efficacy. The purpose of the NGSE (Chen et al., 2001, pp. 62 - 65) was also to solve construct-validity problems and low test-retest reliability of previous GSE measures such as the Self-Efficacy Scale (SGSE; Sherer et al., 1982). SGSE studies show inconsistencies between GSE and SSE results and limited discriminant validity with measures of self-esteem (2001). Thus, NGSE’s validity (2001, p. 77) is assumed from several studies (n = 639, mostly female U.S. undergraduates ages 18 to 47, and 54 mostly male Israeli managers, 38 years of age on average) that confirmed that in comparison with the SGSE scale, the NGSE is unidimensional, is distinct from self-esteem, captures somewhat different constructs than the SGSE, and results in higher content validity (based on 22 U.S. and 34 Israeli graduate students’ ratings) and somewhat higher predictive validity (of SSE leadership levels). These studies produced relatively high reliability scores (.87, .88, and .85 Cronbach alpha scores) and high test-retest reliability coefficients (.65, .66, and .62).

Bandura specified (2006) that since self-efficacy is “concerned with people’s beliefs in their capabilities to produce given attainments” (2006, p. 307; 1997) and “is not a global trait but a differentiated set of self-beliefs linked to distinct realms of functioning" (p. 307) there is "no all-purpose measure of perceived self-efficacy" (p. 307). Instead, Bandura proposed that "scales of perceived self-efficacy must be tailored to the particular domain of functioning that is the object of interest" (p. 308). Sound efficacy scales should: rely on good conceptual analysis of the relevant domains of functioning (p. 310), be measured against levels of task demands that represent challenges to successful performance (p. 311) and be scored on a large scale (e.g. 0-100). To demonstrate these principles, Bandura produced (2006) a series of self-efficacy scales including a "Teacher Self-Efficacy Scale" designed to "gain a better understanding of the kinds of things that create difficulties for teachers in their school activities. In this scale, 28 items organized into 6 topics invite teachers to rate their degree of confidence from "cannot do at all" (0), to "moderately can do" (50), and "highly certain can do" (100). These topics are efficacy: to influence decision making, instructional, disciplinary, to enlist parental involvement, to enlist community involvement, and to create a positive school climate.

Motivations

Any organism that seeks to attain "its most perfect functioning and the realization of its potentialities" (Fromm, 1993, para. 13), "will try to provide itself with the optimum of needs" (para. 13). Students' actions have purpose, that is, are caused by reasons or motives that determine the direction of their efforts. Students´ predispositions for learning, their motivations for attending the course can be many (Wolters, 2003). Motivation is the willingness of a person to expend a certain amount of effort to achieve a goal under a set of circumstances (Snowman & McCown, 2011, p. 400); the cause for the selection, persistence, intensity, and direction of behaviour (Fulmer & Frijters, 2009); "the process whereby goal-directed activity is instigated and sustained" (Schunk et al., 2008, p. 4); the process responsible for the initiation, intensity, and persistence of behaviour (Usher & D. B. Morris, 2012). Academic motivation (2012) refers to the causes of student effort, goal setting and attainment, to engagement and persistence in activities related to academic functioning and success.

Extrinsic Motives. One way of understanding motivation is that which explains (Skinner, 1953; Thorndike, 1913, 1932; Premack, 1959, 1962, 1971; Goddard, 2017) that when trying to solve a problem by trial and error, an organism will associate its behavioural impulses with the satisfying or annoying states of affairs obtained (Thorndike, 1913, 1932); that is, that the consequences of behaviour are motivating and produce learning (*Law of Effect*; Schunk et al., 2008). An organism may be conditioned (Skinner, 1953, p. 65; Goddard, 2017), its probability of making a response will be modified, based on the consequences of its behaviour: by punishing or reinforcing their behaviour by presenting or removing positive or negative reinforcers. The degree to which a person is interested in doing something is what makes such activity satisfying or annoying (Schunk et al., 2008), that is, a person's readiness to act is determined by the "satisfyingness or intolerability of the action" (*Laws of Readiness*, Thorndike, 1913, p. 125-133). In this regard, for every organism and situation there is an *optimal level of arousal* for performance (Yerkes & Dodson, 1908), an intermediate strength of stimulus (task difficulty) that is most favorable to the acquisition of a habit than a weaker or stronger stimulus: that is, there is an inverted U relationship between arousal and performance (Lewis et al., 2012, p. 1195; Lewis et al., 2008).

Motives (Usher & D. B. Morris, 2012) are causes that produce certain effects, actions or inactions. Motives may be intrinsic, derived from internal conscious or unconscious processes, or extrinsic, the result of external physical or psychosocial forces. Students' actions may be driven by a need to obtain something from their environment, to satisfy a deficiency (e.g. love, thirst, hunger, security, ascendancy). Deficiency needs (Maslow, 1973) are preferred by the deprived person over other satisfactions under certain free choice situations. Absence, presence or restoration of deficiency needs respectively breeds, prevents or cures illness. Subjectively, deficiency needs are characterized by a person's conscious or unconscious yearning or desire, feelings of lack or deficiency, of something palatable that is missing. Safety, belonginess, love, respect, and self-esteem are examples of basic needs (1973). Murray (1936, 1938; C. S. Hall & Lindzey, 1978; Schunk et al., 2008) proposed a taxonomy of 20 needs or "forces that organize perception, apperception, intellection, conation, and action" (Murray, 1938, pp. 123 -124) also thought to be stable personal characteristics. Reiss' (2004, pp. 186 - 187) taxonomy of 16 basic desires is based on the notion that, when satiated to a point of moderation (individually set point, sensitivity, or moderate mean) these 16 drives produce intrinsically valued feelings. In other words, individuals tend to be driven by combinations of these 16 needs in different degrees of sensibility (idiosyncratic optimal levels of arousal).

Intrinsic Motives. Students might also be driven by a need to express something that comes from within, to radiate or express their potentiality, to grow. Growth needs (Maslow, 1973) drive motivation towards the perfection of development, the fulfilment of the person's possibilities, the expression of an eagerness and enjoyment in acquiring new skills. Growth appetites become intensified and heightened by gratification. By experiencing growth, the person rather than coming to rest becomes more active. Growth needs are idiosyncratic and have been ill-defined through concepts such as growth, individuation, autonomy, self-actualization, self-development, productiveness, or self-realization. Self-actualization (1973) refers to the ongoing actualization of one's talents, capacities, potentialities while enjoying life in general and in practically all its aspects and not only in its moments of triumph or achievement.

Even though extrinsic motivations can help modify a person behaviour, it is most desirable to foster the self-reinforcing intrinsic desire to know and understand that active and independent learners have (Seifert, 2004). Intrinsic motivation to learn, what the person expects to get from her or his efforts, is what determines “how sustained an episode [of learning] a learner is willing to undergo” (Bruner, 1960, p. 49) and intrinsic rewards, in the sense of quickened awareness and gains in understanding (i.e. subjective understanding), should be emphasized if one wants to familiarize the learner to increasingly longer episodes of learning (1960). As such, true learning involves “figuring out how to use what you already know to go beyond what you already think” (Bruner, 1983, p. 183), creating a personal interpretation of ideas and experiences, understanding how ideas connect with each other, solving problems on our own, how what we know is relevant to what one is trying to learn. Intrinsically motivated students want to know for the pleasure of knowing, to satisfy their curiosity. Intrinsically motivated or autotelic activity is that which is rewarding in and of itself apart from its end product or any related resulting extrinsic good.

Growth can also be related to the pursuit of one’s distant unattainable goals, those that define one’s purpose of life, to the unceasing trail toward unity integration and synergy within the person, or simply to the expression of the self. Major life goals (Roberts & Robins, 2000) are broad, far-reaching agendas for important life domains. Life goals (2000, p. 1294) are explicit, concrete intentions for future activities and should be powerful predictors of how people structure their life. Life goals (2000, p. 1286) are necessarily desirable outcomes for the individual but do not include desired and feared outcomes. Richards Jr (1966) created a comprehensive life goal instrument to observe major life goals normatively. A set of 35 items helped observe differences in American college freshmen goals and aspirations as a factor in vocational choice and in high-level achievement in culturally significant areas of behaviour. These 35 life goals were considered to be either vocational, social, or personal and helped assess the aspirations of 12,432 freshmen and women in 31 higher education institutions. Orthogonal rotated factors helped identify 9 factors or clusters of students according to their preferred life ambitions: prestige, personal happiness, humanistic-cultural, religious, scientific, artistic, hedonistic, altruistic, and athletic success.

Based on Richards Jr's life goal instrument, Roberts and Robins (2000, p. 1284) organized a set of 38 major life goals by using most of Richards Jr's items with slight modifications in wording (27 items), consolidating and adding others (11 items) to reflect more contemporary issues. Students rate the importance of these 38 life goals on a 5-point scale that ranges from "not important to me" to "very important to me." Based on results from a sample of 672 first- and second-year male and female undergraduates, Roberts and Robins confirmed (based on a varimax rotated principal components analysis on 25 goals) seven internally consistent, reliable, and relatively independent goal clusters (2000, p. 1288): economic, aesthetic, social, relationship, political, hedonistic, and religious.

Motive dispositions. The strength of motivation to perform some act (Atkinson, 1957; Usher & D. B. Morris, 2012, pp. 36 – 37) is a function of the strength of the motive, the expectancy (subjective probability of accomplishing the task successfully), and the value of the incentive (consequence of attainment). People may have different dominant motive dispositions (McClelland & Watson Jr, 1973; McDougall, 1923; Murray, 1936, 1938): achievement, power (personal or social), and affiliation. An *achievement-oriented* person tends to choose tasks of moderate difficulty, relative to their own ability, and tends to choose these privately, for their own sense of personal accomplishment. A *power-oriented* person wants to have impact, to stand out, to be considered important and tends to choose tasks of extreme risk (McClelland & Watson Jr, 1973). A *personal power-oriented* person tends more toward private self-aggrandizing actions (collecting prestige supplies, aggressive thoughts) than toward actual social competition or leadership behaviour, which characterizes *social power-oriented* persons. *Affiliative-oriented* persons (Boyatzis, 1973, p. 270) tend to avoid competition by taking low risks, seeking approval, maintaining relationships, and avoiding rejection or being left alone.

Depending on their motives to learn and their way of learning, students may show different *approaches to learning* (Entwistle, 2007; Entwistle, Kozéki, & Pollit, 1987; J. B. Biggs, 1993, 1988; Entwistle & Waterson, 1988; Marton, 1975). Cognitively, students (J. B. Biggs, 1993, 1988; Andrews et al., 1994; Barattucci, 2017) may want to meet requirements minimally (*surface approach*), have an intrinsic interest in what is being learnt (*deep approach*), or may want to obtain higher grades whether the material is interesting or not to them (*strategic or achieving approach*). Students may organize their efforts towards retention of factual details at the expense of the structural relationships inherent in the data to be learnt (*surface*), to discover meaning by reading widely, being curious, and trying to understand the structural complexity of the task (*deep*) or organizing their efforts by handing in assignments on time and studying per a schedule (*strategic*).

Knowledge of motivational differences enhances prediction of achievement related performances (Atkinson & Litwin, 1960, 1973). Under *achievement stress* (1973, p. 146; Atkinson, 1957, 1958) people will take different levels of risk (set goals per a perceived probability of success), persist (spend more time) and perform (score) differently depending on whether they have a stronger motive to *avoid failure* (a disposition to become anxious about failure under achievement stress) or a stronger motive to *approach success* (a disposition to achieve). As such, four general ways of approaching achievement tasks have been identified (Covington, 1992; & Omelich, 1991; & Roberts, 1994; & Müeller, 2001; Schunk et al., 2008): 1) success oriented, 2) failure avoidance, 3) over striving, and 4) failure acceptance. Persons with a stronger motive to approach success than to avoid failure tend to take more moderate risks, show greater persistence, and attain higher achievement scores. Failure-avoidance motivated persons tend to find all achievement tasks unattractive and tend to perform them inefficiently when pressured or constrained to do so (Atkinson & Litwin, 1973).

Student's beliefs about 'how things are' also have great influence on the types of activities they engage in during a course. Students' beliefs about the nature of ability (Dweck, 2002; Dweck & Master, 2009) or theories of intelligence (Dweck, 1999; Dweck & Elliot, 1983; Dweck & Leggett, 1988; Schunk et al., 2008, pp. 184 - 188) are perceptions about how ability and intelligence change over time. Entity or incremental beliefs impinge on students' goal orientations and lead to "different ways of approaching, engaging in, and responding to achievement situations" (Ames, 1992, p. 261).

Similarly, students' *attributions* (Weiner, 1979, 1985, 1992, 2005; Schunk et al., 2008, p. 82) influence students' expectancies for success, self-efficacy beliefs, affects, and actual behaviour such as choices, persistence, level of effort, levels of achievement, and willingness to help or to provide rewards or sanctions to others. Perceived causes of outcomes' are thought to be related to certain emotions (Weiner, 1986): *stability* (from stable or permanent, to unstable or changeable) to expectancy for success, to feelings of helplessness or hopefulness; *locus* (internal or external) to self-esteem and feelings of pride; and *control* (controllable or uncontrollable) to social affects such as guilt and shame in terms of personal reactions, and to anger, pity or sympathy in relation to others' reactions.

The Test of *Dweck's Model of Achievement Goals* as related to *Perceptions of Ability* (Hayamizu & Weiner, 1991) was created to examine the relationship between individual differences in achievement goal tendencies and perceived causality. The Test of Dweck's Model of Achievement Goals and Weiner's principles of perceived causality (1991) explores the relationship between achievement goals and causal attributions such as persons' implicit theories of intelligence and other causes such as effort, task difficulty, and luck (1991, p. 227). The test consists of a 20-item achievement goals (*Reasons for Studying*) questionnaire and a 5-item perceived qualities of causes questionnaire that asks students to evaluate five causes (ability, effort, task difficulty, professors' instruction, bad luck) that influence their academic achievements on six scales or dimensions (stability, personal or environmental, controllable, temporary, external, responsible).

Dweck's model explains that students' performance should vary according to two types of achievement goals: concerned with increasing their competence (learning goals) or concerned with gaining favorable judgements about their competence (performance goals). A factor analysis on the *Reasons for Studying* 20-item questionnaire helped find these two achievement goal tendencies but with two types of performance goals in Japanese high-school boys and girls (8^{th} grade, $n = 251$; Hayamizu et al., 1989) and American university men and women (ages 18 – 26, $n = 213$; Hayamizu & Weiner, 1991): *a learning goal tendency*, interpersonal oriented reasons for learning or approval seeking and rejection avoidance (*performance 1,* a tendency to learn to gain approval and avoid rejection from teachers and parents), and a tendency to improve actual achievement (*performance 2*, learn to get good grades and advance). Cronbach alpha reliability coefficients for these factors were respectively .89, .78 and .71.

Resources

The material aspects that cause someone's functioning include those biological, physical and social characteristics that describe who the student is, what students have (internal and external resources) or can do (skills or abilities): students' personality, in particular their peripheral mannerisms and opportunistic habits (Allport, 1937); knowledge and abilities, as in cognitive (e.g. crystal and fluid), meta-cognitive (e.g. self-regulation), emotional (e.g. sensibility, empathy, care), or psychomotor abilities (e.g. eye-hand coordination). By definition resources also entail students' developmental reality, for example their degree of cognitive, psychosocial, moral, or physical development, and also their sociocultural capital (*social capital,* Bourdieu as cited in Swartz, 2007) and structures (Bronfenbrenner, 1977, 1979, & 2005), the nested arrangement of formal and informal structures or contexts in which they were brought up and have strived.

To be active is to give expression to one's faculties, talents, and wealth of human gifts (Fromm, 1976), for example, to one's readiness, language, scholastic aptitude, skills and competencies, previous knowledge, and cognitive ability or skills (e.g. categorization, visual/ spatial ability, problem-solving, memory). The ability to think entails the capacity to interpret, to assimilate or accommodate, to simplify, summarize, and categorize experience into abstractions, to reason about abstractions critically, and to store and to be able to remember such experiences and abstractions. The theory of successful intelligence (Sternberg, 2018, 2003, 1999, 1997, 1985, 1984), conceives individual intelligence as "the ability to achieve success in life, given one's personal standards, within one's sociocultural context" (1999, p. 293). This success depends on "one's capitalizing on one's strengths and correcting or compensating for one's weaknesses through a balance of *analytical* (information-processing components or internal representations of objects or symbols applied to analyze, evaluate, judge, or compare and contrast), *creative* (the ability to deal with novel kinds of task and situational demands or coping and automatization of information processing), and *practical* abilities (application of the components of intelligence to experience to purposively adapt, shape, or select environments). Differences in these intelligences produce different intelligence profiles (1984, p. 309), e.g. people that have great capacity for academic tasks (1999, p. 294), people that know how to manipulate their environments to maximum advantage, or people that are extremely creative or able to deal with novelty.

Personality. Every student approaches an educational experience from a uniquely diverse developmental reality. Human development results from "the progressive, mutual accommodation, throughout the life span, between a growing human organism and the changing immediate environments in which it lives, as this process is affected by relations obtaining within and between these immediate settings, as well as the larger social contexts, both formal and informal, in which the settings are embedded" (Bronfenbrenner, 1977, p. 514). Development always "involves selection and a trade-off between alternative pathways and success-failure constellations" (Baltes, 1997, p. 369), and growth should not be considered a unidimensional advance in quantity and quality in functioning but a positive balance of gains and losses for all ages of life (1997, p. 377). Human ontogenesis, the developmental history of an individual within his or her lifetime, has multiple causes (e.g. biological, cultural), dimensions (e.g. biological, cognitive-affective), directions, and functions (1997).

Personalities are formed (Allport, 1937, 1955, 1961) by unique modes of adjusting to and mastering the environment from one's instincts, inheritance (temperament and genes), and disposition to become human. Early affiliative needs set the ground of becoming, *the freedom to* *become*. These early affiliative needs are provided through socialization: dependence, succorance, and attachment. The disposition to become human is composed by conscience, sense of self, and a proprium. This disposition determines the capacities for learning, structure and individuation. *Growth* is caused by reactions to past and present stimuli, what “happens” to us, random inheritance and environment and opportunistic habits such as biological adaptation, tribal conformities, skills, and language. Developing or learning opportunistic habits and courses of behaviour determines the possibilities of behaviour, the number of possible courses of action that can be summoned, it’s statistical degrees of freedom. Growth is also promoted by construction, orientation, intention and evaluation, what we “do,” a person’s propriate activity, those matters of importance to the individual that are also cause of the person’s vital inward unity. Freedom to become is essential for the development of *conscience*.

A childish conscience (Allport, 1955) is guided by fear of punishment or praise, it is a “must consciousness.” In a mature conscience, external sanctions give way to internal sanctions by identification and introjection (1955, p. 73). Experiences of prohibition, fear and “must” give way to experiences of preference, self-respect, and “ought”, and obedience gives way to self-guidance (1955, p. 73). A mature conscience is based on value-related obligations which are based on one’s ideal self-image and value systems, an “ought consciousness.” A healthy adult (1955) selects perceptions, consults conscience, inhibits irrelevant or contrary lines of conduct, drops and forms subsystems of habits depending on whether they are harmonious or dissonant with their commitments. These commitments reflect an organization, a structure of the self. These “*active schemata for conduct*” exert a dynamic influence upon specific choices. As a result, peoples “orientations toward the initiation and regulation of behaviour” (*self-determination theory*; Deci & Ryan, 2008, 2000, 1985, p. 11) may tend towards: *autonomy* (intrinsically self-initiated and choiceful behaviours), *control* (doing things in compliance or defiance of real or imagined external controls or integrated internalizations), or *impersonal* apathy/ alienation (experiencing their behaviour and achieving desired outcomes as something that is beyond their control).

Personality is "the *dynamic organization* within the individual of those *psychophysical systems* that determine his (or her) *unique adjustments* to his (or her) environment" (Allport, 1937, p. 48). "Dynamic organization" refers to the constantly evolving and changing, as motivational and self-regulating, active mental organization. "Psychophysical systems" refer to mental or neural traits or groups of traits in a latent or active condition, e.g. habits, specific and general attitudes, sentiments, and dispositions of other orders. It involves the systems that constitute personality, as determining tendencies, and the adjustive and expressive acts that result in interaction with the environment. These "adjustments" may be reactive, creative, or even passive and the environment may not only be the surrounding physical world but also the constructed, imagined, behavioural or cultural environment.

Personality Traits. The individual personality (Allport, 1961, 1937) is the result of an infinite number of particularly idiosyncratic *individual traits*. Traits are in strict sense only truly individual because "they develop and generalize into dynamic dispositions in unique ways according to the experiences of each individual" (1937, p. 299). As such, there are no two identical persons if at least for a difference in the expression of one individual trait. *Common traits* (Allport & Odbert, 1936; Allport, 1961, 1937; Norman, 1963; R. B. Cattell, 1947, 1957, 1973; R. B. Cattell et al., 1970; H. B. Cattell, 1989; Goldberg, 1981, 1990, 1992; Costa Jr & McCrae, 1985, 1989, 1992, 2008; John, 1990; John et al., 1988; John et al., 1991; Saucier, 1994; H. E. P. Cattell & Mead, 2008; John et al., 2008; Matthews et al., 2009), in contrast to individual traits, are “those aspects of personality in respect to which most mature people within a given culture can be compared” (Allport, 1937, p. 400). Common personality traits are the best obtainable approximations to the structure of personality. A person’s traits indirectly influence or cause behaviour when they produce transient internal conditions or states in interaction with situational factors. Valid measured traits are expected to predict behaviour generally and not specifically, that is, should help predict how groups of people with similar characteristics (and not individuals) act over a series or a set of aggregated relevant situations.

The Sixteen Personality Factor Questionnaire (16PF) was developed by Dr. Raymond Cattell and colleagues (1970). The purpose of this instrument was to “uncover the deep, basic traits that underlie human behaviour” (H. B. Cattell, 1989). The 16PF scales measure temperament: a person’s characteristic style of thinking, perceiving, and acting over a relatively long period of time and in a wide range of different situations. These personality traits are thought to “have a pervasive effect on practically every facet of a person’s overall functioning and way of being in this world.” (1989, p. 2). Temperament, motivation, and ability are the three main factors that influence personality (H. B. Cattell, 1989, p. 3; Schuerger, 2001; H. E. P. Cattell & Schuerger, 2003, p. 2). There are other personality instruments such as the 240-item NEO (Costa Jr & McCrae, 1985, 1989, 1992, 2008; John et al., 2008) or the 100- and 40-item Trait Descriptive Adjectives (TDA; Goldberg, 1990, 1992; Saucier, 1994). Heather Cattell and Mead (2008) argue that the 16PF non-orthogonal primary scale loadings provide more detailed and complex relationships.

The Big Five Inventory (BFI; John et al., 1991; John et al., 2008) is a 44 short-phrase-items instrument designed to canonically represent five trait definitions, 8 to 10 items each: extraversion, an energetic approach toward the social and material world; agreeableness, a prosocial and communal orientation toward others with antagonism; conscientiousness, socially prescribed impulse control that facilitates task and goal directed behaviour; neuroticism, negative emotionality in contrast with emotional stability and even-temperedness; and openness, a description of the breadth, depth, originality, and complexity of an individual's mental and experiential life. Alpha reliabilities of the BFI scales in U.S. and Canadian samples range from .75 to .90 (2008, p. 130). Validity is presumed from high correlations between BFI self-reports and BFI ratings by peers in a sample of 490 male and female participants ages 18 to 80 years from a specific community (2008; DeYoung, 2006) and substantial convergent and divergent relations with other Big Five instruments (John et al., 2008; Rammstedt & John, 2005, 2007). The purpose for creating the BFI was "to create a brief inventory that would allow efficient and flexible assessment of the five dimensions when there is no need for more differentiated measurement of individual facets" (2008, p. 129).

Psychosocial Development. The theory of psychosocial development (Erikson, 1956, 1959, 1982; Snowman & McCown, 2011, pp. 28 - 30), of the epigenesis of the psychosocial personality, conceives the human life cycle as "a gradual unfolding of the personality through phase-specific psychosocial crises" (1956, pp. 74 – 76). Criterions of relative psychosocial health (relatively conflict-free psychosocial arrangements) tend to outweigh criterions of relative ill-health (relatively defective or conflict-laden psychosocial arrangements) in "normal" development (1956, p. 76). Individuals' readiness and society's pressure precipitate the following psychosocial crisis: trust the world to be dependable and safe or fear and mistrust it (trust vs mistrust); be autonomous, willing and able to direct one's own behaviour or feel shame and self-doubt (autonomy vs shame, doubt); feel free to explore and experiment, to have initiative or feel guilty about acting on one's own (initiative vs guilt); learn to enjoy and take pride in producing things well, in trying and persevering or feeling derided or inferior (industry vs inferiority); to experience continuity in the perception of self or failing to establish a sense of stability in various aspects of one's life (identity vs identity diffusion); to establish close and committed intimate relationships and partnerships with other people to the point of being willing to sacrifice or compromise or to feel isolated (intimacy vs isolation); to establish and guide the next generation, to have a positive effect on younger generations or to stagnate and become self-absorbed (generativity vs self-absorption); and to develop integrity, to accept the result of one's life or feel disgust or despair (integrity vs disgust, despair).

The Modified Erikson Psychosocial Stage Inventory (MEPSI; Darling-Fisher & Leidy, 1988, 2015) has been used as an indicator of psychosocial attribute strength in several investigations (2015, p. 1). These attributes arise from progression through Erik Erikson's (1956, 1959, 1982) eight stages of psychosocial development. Rosenthal and colleagues (1981) proposed an inventory for examining the first six of Erikson's stages of psychosocial development (EPSI). The purpose of the EPSI (1981) was to map changes in psychosocial attributes in large samples of subjects in early and late adolescence. The MEPSI (1988) builds on this instrument to measure changes in psychosocial attributes in the adult population. The EPSI and the MEPSI have six and eight subscales respectively. These subscales are based on Erikson's stages and are composed of 12 and 10 short simple statements or items. In both cases, half of the items reflect successful and half unsuccessful resolution of each stage's psychosocial crisis (1981, p. 528; 1988, pp. 747 - 748). All statements are randomly ordered and are followed by a 5-point Likert scale. Lower scores reflect a predominance of negative attributes while the opposite is true for positive attributes.

Validity and reliability of the EPSI (1981) was established on a pilot sample of 58 Melbourne Grade 9 students and a test sample of 622 adolescents (males and females, grades 9 and 11) from nine Melbourne metropolitan high schools. Adequate to high alpha coefficient levels (.64 – .81) were obtained for all six subscales. Validity was considered acceptable based on two criteria: high correlation of most EPSI subscales with relevant subscales of the Psychosocial Maturity Scale (PSM; Greenberger & Sorensen, 1974), and higher scores of older students in each EPSI subscale when comparting Grades 9 and 11.

Psychometric properties of the MEPSI (Darling-Fisher & Leidy, 1988) were based on a convenience sample of 168 adults, men and women ages 19 to 86. High alpha coefficient levels (.75 – .88) were obtained for all eight subscales and for the entire scale (.97). The inventory did not appear to be influenced by situational factors or demographic characteristics. Construct validity claims were derived from four sources: a positive relationship between chronological age and total score, increased scores and decreased variance for increased age in the final two stages of adult development, strong correlations between these two subscales and the first six subscales, and significantly stronger psychosocial attributes for subjects who reported exercising regularly in comparison with those who did not exercise. A secondary analysis (Leidy & Darling-Fisher, 1995) also found the MEPSI to be relatively stable across diverse populations (four samples, younger and older adults with and without chronic diseases).

Self-Regulation Skills. Learners are being active agents in their learning process (Winne, 2006, p. 6) when they *choose* to use cognitive and physical tools, *operate* on raw materials (information), *construct* products (e.g. an idea or knowledge that is stored in memory), and *receive* formative or summative evaluations. Similarly, meaningful learning depends on appropriate active cognitive processing (Mayer, 2012; Sweller, 2012; Sweller et al., 1998) which involves active information *selection*, *organization*, and *integration*. Students that use tools while being active agents in their learning process (Clarebout et al., 2013; Lust et al., 2013; Winne, 2006, p. 7): a) attend to occasions where a tool can be used (cues, signals), b) choose a cognitive tool that is well-matched to the task, c) are capable of using the cognitive tool skillfully (including mediation and utilization efficiencies, and optimal intrinsic and germane cognitive load), and d) are motivated to spend effort to use the tool skillfully, monitor and control its use, accept risks, and acknowledge emotions in relation to mental or external consequences.

Self-regulation studies assume that human behaviour is extensively motivated and regulated by the ongoing exercise of self-regulation (Bandura, 1991, 2012), that people are the predominant cause of their own behaviour (Schunk et al., 2008). Self-regulation refers to the capacity for self-guidance, the management of voluntary action (Karoly, 1993), to the self-generated thoughts, feelings, and actions that are planned and cyclically adapted to attain personal goals (Zimmerman, 1986, 1989, 2008; Schunk & Ertmer, 1999). Self-regulation refers to those processes, internal and/or transactional, that enable individuals to guide their goal-directed activities over time and across changing circumstances or contexts (Karoly, 1993).

Self-regulation (Bandura, 1991, 2012) relies on both discrepancy production and discrepancy reduction; it requires proactive control (goals) as well as reactive control (regulation). Self-regulatory failure (Karoly, 1993) can lead to omission or failure to initiate patterns of goal directed activities, disengagement, premature termination of these activities, and/or to excess or persistence of these activities beyond their useful or necessary lifespan. Self-regulatory failure can be caused by a) sub function deficiencies, b) disruptions in cross-function communication; c) the pursuit of inappropriate or self-defeating standards or goals; d) the absence or underdevelopment of supportive meta-skills; e) the encroachment of natural or imposed boundary conditions; or f) some combination of these.

Academically self-regulated students (Zimmerman, 1986, 1989, 2008; Zimmerman & Labuhn, 2012; Davidson & Sternberg, 2003) are meta-cognitively, motivationally, and behaviourally active participants in their own learning processes. In school settings, students not only self-regulate to increase their knowledge, cognitive, and social skills and resources but also seek to maintain their emotional well-being within reasonable bounds (Boekaerts, 1997; Boekaerts & Niemivirta, 2000). Students with low self-regulation skills find it very hard to make sense or learn actively on their own (Azevedo et al., 2005, 2008). Self-regulated learning (Zimmerman, 1986, 1989, 2008; Zimmerman & Labuhn, 2012) is the feedback loop or cyclical process of: a) forethought processes, task analysis capabilities and levels of self-motivation, b) performance control processes, strategic use of diverse learning tasks and self-observation; and c) self-reflection processes, self-evaluation and causal attributions.

The SRQ was created (Brown et al., 1999) for people to self-report their "ability to develop, implement, and flexibly maintain planned behaviour in order to achieve one's goals" (1999, p. 1). The questionnaire is composed by 63 items which are rated by participants on a 5-point Likert scale that ranges from "strongly disagree" to "strongly agree." This self-report is based on W. R. Miller and Brown's (1991; Brown, 1998) seven-step model of self regulation. This model considers that behavioural self-regulation failure, originally behaviour related to substance abuse, is caused by deficits in receiving information, evaluating information, triggering change, searching for options, formulating a plan, implementing a plan, or assessing the plan's effectiveness. Initial psychometric tests of the SRQ with a sample of college students resulted in high test-retest reliability ($r = .94$, $p < .0001$), internal consistency ($a = .91$), significant discrimination between groups of people with and without self-regulatory related behavioural problems and high inverse correlations with risk-taking and impulsivity behaviours.

Carey and colleagues (2004) created a 31-item short version of the SRQ (SSRQ) based on a principal-factor analysis of the full SRQ. The full SRQ and the SSRQ correlated with an *r* of .96. Neal and Carey later found (2005) a two-factor solution of loadings named “impulse control” and “goal-setting behaviour.” The authors recommend that scores are differentiated in three normally distributed groups: high, intermediate, and low. Following this recommendation, Boechler and colleagues (2016, 2017) found that students with high self-regulation levels were not as satisfied with or engaged with basic instructional content as students with low and intermediate self-regulation (2016) and that introducing more advanced instructional content removed differences in perceptions between students of different self-regulatory capacity (2017).

Chapter 3. Methods

The purpose of this ex post facto (Nunes-Silva, 2010), case study (Yin, 2009, 2012) and primarily applied research (Ary et al., 2019, p. 16; Mertler, 2016) was to describe how higher-education students behaviour changed over time in real-life contexts, explore how trajectories of change differed between students, and explain the relationship between students' characteristics, trajectories of change and levels of achievement. This was attained following a multilevel modelling (Snijders & Bosker, 2012; Heck et al., 2010, 2013), two-level longitudinal data analysis (Singer & Willet, 2003), Spearman correlations (1904) to measure the strength of monotonic relationships between non-normally distributed paired variables, and Pearson correlations (1897) to measure the strength of linear relationships between normally distributed paired variables. Behaviour change was based on students' course-related short-term longitudinal trace data, and students' characteristics on self-reported cross-sectional personality and psychosocial maturity, self-regulation, motivations and beliefs (attributions, expectations, or perceptions). To help further describe the proposed research this chapter is organized into description of participants, measures, data collection procedures, and data analysis.

Participants

A convenience sample of short-term longitudinal interactions with online course components (169,184 records) and cross-sectional characteristics from 118 undergraduate students provided the initial empirical backdrop for this primarily applied ex post facto case study. Six classes from two second year higher-education courses ("A" and "B") instructed between 2016 and 2019 provided the learning context for these students' interactions. Class size in these courses ranged from 12 to 26, with an average size of 19 (*Table 1*). Classes were composed primarily by second year and third-year students, but all classes also had a minority of fourth year and first-year students. The University of Alberta's Research Ethics Board approved the retroactive secondary use of students' course interactions, LMS logs and content on August 24, 2017 (No. Pro00075848, "Optimal Learning and Effective Instruction"). Students information was anonymized, course grades were assessed and the final date to challenge them had passed by the time of the analysis.

Table 1

Learning Contexts

#	Course	Campus	Type	Length	Learners
1	"A." Fall 2016	1	Blended	13 weeks	12
2	"A." Fall 2017	1	Blended	3 weeks	26
3	"A." Fall 2018	1	Blended	3 weeks	20
4	"B." Winter 2018	1	Blended	3 weeks	18
5	"B." Winter 2018	2	Online	13 weeks	23
6	"B." Winter 2019	1	Blended	3 weeks	20
	Total				119

All courses were blended learning with face-to-face lectures except for one ("B2" Winter 2018) in which lectures were fully taught online. All blended courses were elective, and students' program of studies were heterogeneous except for the fully online course that was required for students working on one same program. Starting in the Fall of 2017, campus "1" introduced a new Calendar with a three-week session followed by a more traditional eleven-week block. While the eleven-week session typically consists of three to four courses for most full-time students, during the three-week block, both students and faculty focus on only one course. Four of these courses were taught during three-week course blocks (*Table 1*).

Measures

There were three main sources of information in this study: 1) trace data, 2) selected psychometric instruments, and 3) assessments (*Table 2*). Student actions were observed from course longitudinal trace data: course component selection (choice of activity or behaviour and frequency of occurrence) and time of interaction (date, time). Empirical growth curves and trajectories of change were based on this data. Student characteristics were observed through selected cross-sectional self-report instruments. Students' types of motivations, beliefs, and resources were inferred from these data. The analysis focused on courses 2 and 3 where these data were available. Students' exams and assignment marks, course letter grades and ratings of instruction were used to infer their levels of achievement and satisfaction.

Table 2

Number of Observations Available per Source and Learning Context

Construct	Source	Course #					
		1	2	3	4	5	6
		Trace data					
Actions	LMS log records	14,428	24,546	30,434	30,351	37,422	32,003
		Instruments					
Motivations	Reasons for studying		25	22			
	Major Life goals		26	20			
Beliefs	Self-efficacy (GSE)		25	20			
	Self-efficacy (NGSE)		25				
Resources	Psychosocial MEPSI		24	20			
	Personality BFI		26	20			
	Self-Regulation SRQ			20			

Construct	Source	Course #					
		1	2	3	4	5	6
		Assessments					
Achievement	Course Total	12	26	20	18	23	20
Knowledge	Midterm Exams	12	26	20	18	23	20
Performance	Assignments, Quizzes, & in-class activities	12	26	20	18	23	20
Satisfaction	USRI quantitative data	*8*	*16*	*8*	*10*	*18*	*6*
	USRI qualitative data	*6*	*14*	*8*	*8*	*8*	*4*

Trace data

Students' on-line interactions were conformed into *trace data* files that included information such as: frequency (e.g. number of events), time (e.g. vs. class schedule, other students), and place (e.g. IP address). The number of interactions and their change over time represented student actions in this study (*Table 3*). To allow comparisons, a standardized measure of time was created to indicate percentage of course days elapsed. Days of events were transformed to indicate their relative value to the last (equal to one) and first (equal to zero) day of class. These interactions could also have been categorized by type of component, event, or importance (i.e. essential or supplemental), and timings such as module and assessment period.

Throughout these courses, lecture time was mainly dedicated to three types of activities: 1) explanation of activities, 2) lecture, based on visual slides to summarize important concepts while providing stimulus to facilitate encoding and storage, and 3) learning activities such as polls, discussions, self-reflections, demonstrations, videos, and other collaborative learning activities. Courses 2 and 3 were delivered over a 3-week period with conference meetings every working day of the week.

Table 3

Measures of Student Actions/Behaviour

Measure	Construct	Explains
	Actions/Behaviour	
Trace Data	Selection • Total • Components (e.g. quiz) • Events (e.g. viewed, created) • Importance (e.g. essential)	Quantity of activities selected for learning. Proportion of the course engaged with.
	Time • Daily • Module (e.g. 1, 2, etc.) • Assessment (e.g. Midterm)	Timing of activities selected for learning. When were activities engaged?

Outside of lecture time students were expected to interact with a series of online course components such as: reading and study guides, class slides for note-taking, assignments submitted for formative or summative purposes, and mastery-based practice quizzes (unlimited attempts) that gave students additional opportunities to engage with critical parts of the content and to self-test their understanding. The number and quality of these components varied across course designs (*Table 4*).

Table 4

Number of Course Objects by Module and Assessment Period

Course #	1	2	3	4	5	6
			Course Information			
Main	3	1	2	2	3**	3
Essentials	8	12	7	7	5	10
Assignment 1	6			7	7	5
Assignment 2	13	25	11	5	5	4

Course #	1	2	3	4	5	6
			Course Modules			
Module 1	8	14	6	15	11	10
Module 2	11	8	20	16	8	7
Module 3	4	10	13	11	12	13
Module 4	7	3	13	8	6	11
Module 5	6	17	12	7	11	10
Module 6	3	8	6	5	8	9
Module 7	7	11	9	10	6	8
Module 8	4	3	6	7	5	12
Module 9	4	10	14	5	9	8
Module 10	8	4	7	8	8	5
Module 11	4	3	7		6	7
Module 12	4	2	6		6	
Module 13	7	7	6			
Module 14	3					
Module 15	3					
			Assessment Periods			
1st Midterm	2	2	4*	10*	11*	9*
2nd Midterm	2	3	4*	9*	11*	10*
3rd Midterm		1	4*			
Total	117	144	157	132	138	141

* Online Exam (vs paper-based) ** Online Live Lectures (online meeting space)

Instruments

Interindividual differences in students' trajectories of change were based on students' responses to selected self-report instruments. As part of their learning activities, most students in Courses 2 and 3 chose to experience a series of scale-based self-report instruments related to concepts studied in their course (*Student* characteristics were observed through selected cross-sectional self-report instruments. Students' types of motivations, beliefs, and resources were inferred from these data. The analysis focused on courses 2 and 3 where these data were available.). These instruments were selected for their accessibility, ease of use (short, scale-based, with clear scoring procedures), and for their quality as well-established measures: published evidence of validity and reliability, extensive use in research, or relation to the scholars that defined these constructs.

Table 5

Measures of Student Characteristics, Psychometric Instruments

Instrument	Construct	Explains
	Ideas or Beliefs	
General Self-Efficacy (NGSE; Chen et al., 2001)	Self-efficacy	What are students' perceived levels of self-efficacy? Overall and in specific situations?
The Test of Dweck's Model of Achievement Goals as Related to Perceptions of Ability (Hayamizu & Weiner, 1991)	Perceived causality/ causal attributions	What are students' implicit theories of intelligence and other causes such as effort, task difficulty, and luck? What are students' perceptions of learning activities' stability, personal or environmental responsibility, controllability, and temporality?
	Resources	
The Modified Erikson Psychosocial Stage Inventory (MEPSI; Darling-Fisher & Leidy, 1988, 2015)	Psychosocial attributes	To what degree have students' psychosocial personality developed through relatively conflict-free psychosocial arrangements? What are students' reactions to their readiness and society's pressures through diverse psychosocial crisis?
Big Five Inventory (BFI; John et al., 1991; John et al., 2008)	Personality Traits	What common characteristic traits constitute the structure of the student's personality?

Instrument	Construct	Explains
Self-regulation Questionnaire (SRQ; Brown et al., 1999)	Self-regulation	To what degree is the student capable of control, individuality, regulate behaviour, autonomy, initiate behaviour, be active, free, independent, and think critically?
	Motivations	
Major Life Goals (Roberts & Robins, 2000)	Propriate strivings	What is the student's purpose of life, unique distant unattainable goals, what is the student trying to become or attain?
Reasons for Studying (Hayamizu & Weiner, 1991)	Achievement goals	To what degree are students' achievement goals: intrinsic learning (growth), approval seeking and rejection avoidance, or extrinsic learning (grades).

Assessments

Absolute achievement in this study referred to the fulfilment of course or school requirements, of demonstrating that one possesses certain knowledge or skill regardless of quality or appropriateness of instruction. Marks on written (exams) and performance assessments (assignments), and final course letter grades constituted students' absolute achievement. In all courses, written assessments were used to measure students' knowledge. Except courses 1 and 2, all written tests were based on multiple-option question online tests. Across all course designs, different sets of in-class activities and assignments were used to measure students' ability to apply the required knowledge and skills. Final letter course grades were judgments of student achievement made by the instructor based on a combination of absolute achievement (individual term summary mark) and relative performance in each class. Students' satisfaction, anonymous feedback on the quality of the course and instruction were determined from students' anonymous ratings of instruction (USRI).

Procedures

A series of blended and online undergraduate courses were designed and taught. Students from different undergraduate programs decided to enroll, engage with and complete each course. Students were encouraged to read and meaningfully process all required textbook readings and class materials, expected to attend and actively participate in all class sessions, make sense of what was being discussed during class, think critically and try to make connections between their practical and their newly acquired theoretical knowledge. Students were also encouraged to use assignments and in-class learning activities as opportunities to learn. During lectures, as supplemental non-graded learning activities, students were invited to respond a series of scale-based instruments related to the concepts of their course and to answer short open-ended reflection questions in online discussion forums. Students were invited to maximize their outcomes by organizing their time and energy, to use distributed practice and proper planning to study and work ahead. Exam scores and assignment marks were released to students throughout the course and letter grades at the end. In all cases a Learning Management System (Moodle based LMS) was the main source for course-related online materials and communications.

The instructor/researcher requested permission from the Research Ethics Board for the retroactive secondary use of students' course interactions and content. Once permission was granted, trace data, course content, instruments and assessments were 1) collected, 2) processed, and 3) analyzed. The collection of trace data entailed downloading the database files from the LMS for each course. Students' personal identification information was removed and substituted with random identification numbers. Records of non-student participants such as administrators, instructors, and teaching assistants were removed. Time and date information were processed and transformed from text format into numeric values. A standardized relative measure of time was created for each record according to their course context, to course start and final dates. Each record was categorized according to type of component (e.g. quiz, forum, etc.), event (e.g. viewed, created, submitted), importance (i.e. essential or supplemental), course context (e.g. Module 1, Module 2, etc.), and assessment period (e.g. Midterm 1, Midterm 2). Course and term information and other parameters such as student characteristics and assessment scores were added to each record. All databases were integrated into a main database for analysis.

A similar process was followed for students' assessments, self-reports, and discussion forum reflections: collect, process (anonymize), analyze, and integrate. Self-report instrument data were exported as MS Excel files. Once exported and anonymized each database was coded or scored. Specified instructions were followed to score instrument responses. A database of course content was created by exporting individual records manually from the LMS.

Data Analysis

A multilevel modeling (Snijders & Bosker, 2012; Heck et al., 2010, 2013), two-level longitudinal data analysis (Singer & Willet, 2003, pp. 17 – 137) was conducted in four stages: create a longitudinal data set (*person-period data sets*), a descriptive analysis of individual change over time (*non-parametric and parametric regression*), exploration of differences in change across participants (*ANOVA, ANCOVA, and Maximum Likelihood*), and specification of a two-level multilevel regression model for change (*Mixed Effects Model*). SPSS Statistics 24 (IBM, 2016) and MS Excel for Office 365 (Microsoft, 2019) was used for the quantitative descriptive, exploratory and predictive analyses.

Behaviour change was based on students' course-related longitudinal trace data. Student empirical growth records (*non*-parametric) were based on students' daily change in the cumulative proportion of objects accessed over the duration of each course. Level 1 parametric summaries of students' empirical growth were created estimating a within-person restricted maximum likelihood (REML) regression model with fitted intercept, slope, and residual variance coefficients for each participant (Singer & Willet, 2003, p. 29; Heck et al., 2013, 2010, pp. 141-188). For this purpose, Singer and Willet (2003) suggest using the more parsimonious and easier to interpret linear estimates, but Snijders and Bosker (2012) suggest random functions may be estimated within the framework of a hierarchical linear model using polynomial, piecewise linear, or spline functions.

To explore how trajectories of change differ between students (Singer & Willet, 2003, p. 37), achievement and student characteristics' fixed predictors and random latent variables (Snijders & Bosker, 2012, pp. 46 – 47, p. 60; Heck et al., 2013, 2010, pp. 189-122) were based on students' grades, scores and responses to self-report instruments. Level 2 average observed trajectories were produced for each group using maximum likelihood (ML) with fitted intercepts means (initial status), slope means (rate of change), and interindividual heterogeneity in change in the variability in initial status (intercepts variances), rates of change (slopes variances), and correlation between initial status and rate of change. The fit of successive models was compared using the Akaike Information Criterion (AIC, 1973, 1974, 1981), models that produced the smallest AIC were preferred (Heck et al., 2013, 2010, p. 139). Hypotheses were evaluated using a multivariate Wald test for fixed parameters (Snijders & Bosker, 2012, p. 96, 98), a deviance or likelihood ratio test (differences in deviance values for several models fitted to the same data set) for multiparameter and random latent variables (2012, p. 97), chi-square tests, ANOVA and ANCOVA for random intercepts and slopes (2012, p. 100).

Chapter 4. Results

This section describes the sample, including data collection and sampling decisions, and the results of analyses used to test four research questions: 1. How student interactions changed throughout the course? 2. Is there a relationship between student characteristics? 3. Is there a relationship between students' interaction trajectories and their psychosocial characteristics? 4. What is the shape of students' longitudinal interaction behaviour (change trajectories) and is this change the same for students of varying characteristics? and 5. Is there a relationship between students' characteristics, interactions and achievement? To answer the first question, scatter plots and models of linear change with measurement occasions nested within individuals describe students' growing proportion of course objects accessed across time. For the second and third questions, correlations verify the relationship between students' change parameters and their characteristics. To address the fourth question, multilevel regressions with repeated measures data nested within individuals at Level 1 and differences between individuals at Level 2 describe the shape of students' interaction change trajectories and test if change trajectories are the same for different groups of individuals. Finally, correlations verify the relationship between students' levels of achievement, course total grades, knowledge (exams) and performance (assignments) grades, their change interaction trajectory parameters and psychosocial characteristics.

Data collection

Data collection procedures were conducted as described in previous chapters. However, initial data analysis efforts made evident the need to concentrate the task on a smaller sample. The complete LMS logs for all courses consisted of 169,184 individual interaction records. The system by default provided four types of information for each record: type of event context (i.e. course learning object, e.g. "File: Presentation and Handout Rubric"), type of component (e.g.

"File"), event name (e.g. "Course module viewed"), and description (e.g. "The user with id '123123' viewed the 'resource' activity with course module id '1234567'."). To make this information meaningful, each description needed to be analyzed to identify: user (e.g. "The user with id '123123'"), action (e.g. "viewed"), and course object (e.g. "'1234567'"). Furthermore, contextual course design information such as course module (e.g. "Module 01") or course importance (e.g. "1 Essential") also needed to be added to every course object and record. Considering the size of this task, analyses concentrated on course groups 2 (n = 26) and 3 (n = 20) which had the largest similarities in course design, subject area, and also had the largest amount of student background psychometric information. In total, these 46 students produced 47,624 unique log records of interactions.

Descriptives

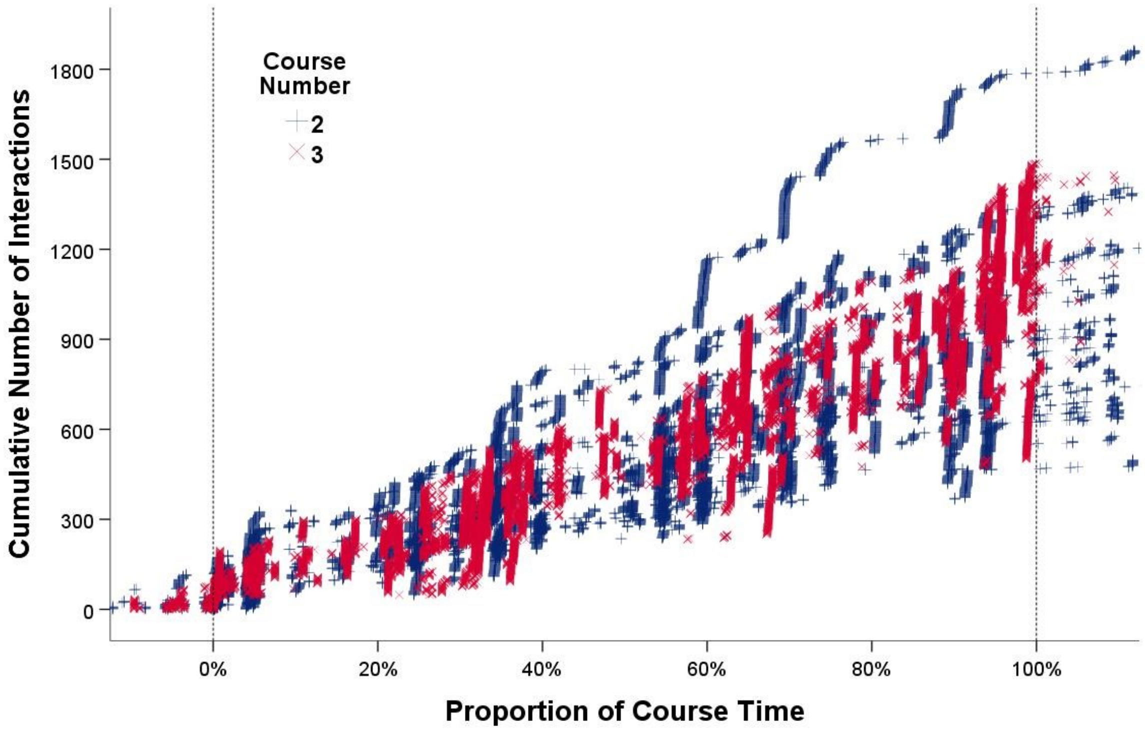
Data included in the analyses were trace data (LMS logs), achievement (course grades), and student characteristics. Sample means, standard deviations, and tests of normality are described next for each interaction, achievement, and psychosocial characteristics constructs.

Trace data

Number of Interactions. Students trace data resulted in 47,624 total LMS log records of interactions with a mean of 558.3 per student (SD = 365.7) and an outlier maximum of 1,919 total interactions (*Figure 1*). Each record's timestamp was transformed into a proportion of time relative to each course's first (0%) and last day of class (100%). The proportion of course time for total number of interactions (47,624) had a mean of 54% (SD = 32.8%), a minimum of -35% and maximum of 263% (298% range). From these interaction records, the proportion of course objects accessed was computed by only taking into account each students' first interaction with each unique course object ($C2_{max}$ = 139, $C3_{max}$ = 132).

Figure 1

Cumulative Number of Interactions Across Time per Student and Course



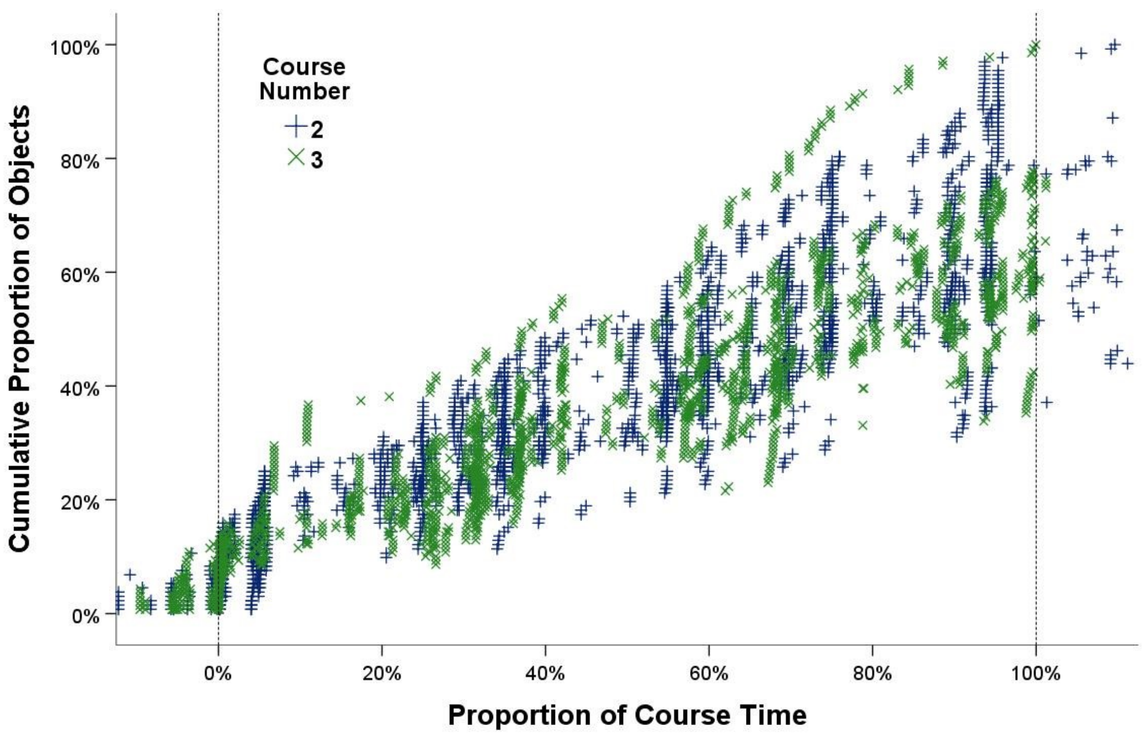
Proportion of Course Objects. This selected trace data resulted in 4,150 records with a mean of 35.3% (*SD* = 21.8%) course objects accessed per student, with maximum proportions of objects accessed per student ranging from 37.9% (C2) and 42.4% (C3) to 100% objects accessed (*Figure 2*). The proportion of time for the sample of unique course objects accessed (4,150) had a mean of 44% (*SD* = 33.7%), a minimum of -35% and maximum of 134% (169% range).

Achievement

Student achievement was observed by students' centered course total grades (46, $M = 0$, $SD = 9.47$, $Min = -34.3$, $Max = 15.6$). Course totals were computed one half by normally distributed students' scores on three written midterm exams (*knowledge*, $M = 0$, $SD = 9.07$, $Min = -31.1$, $Max = 17.9$; $KS = .082$, $p > .05$; $SW = .96$, $p > .05$), and another half by scores on non-normally distributed, highly skewed assignments and online quizzes grades (*performance*, $M = 0$, *SD* = 13.37, *Min* = -46.7, *Max* = 11.7; *Skewness* = -2.09). While written exams (knowledge grades) were conventional summative assessments both performance tasks (performance grades) were implemented following a mastery approach: taking into account each student's higher marks on each assignment while allowing multiple opportunities to submit, receive feedback, improve and resubmit. When grouped by grade similarity students of similar total course grades loaded on groups with higher, lower or both performance and knowledge grades (*Figure 3*).

Figure 2

Cumulative Proportion of Objects Accessed Across Time per Student and Course

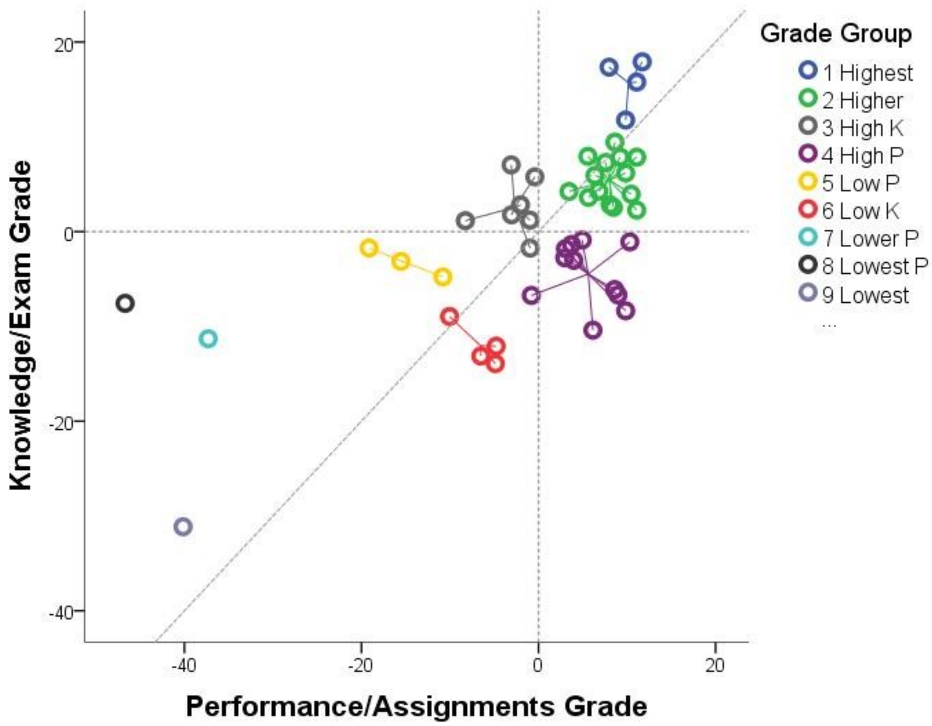


Student Characteristics

Students' psychosocial characteristics were observed through students' responses to six psychometric instruments (*Figure 4 & Figure* 5): Big Five Inventory (BFI), Psychosocial Maturity (MEPSI, *negative-positive resolutions*), Self-Regulation (SRQ), General Self-Efficacy (GSE), Major Life Goals (MLG), and Reasons for Studying (RFS, *extrinsic-intrinsic*).

Figure 3

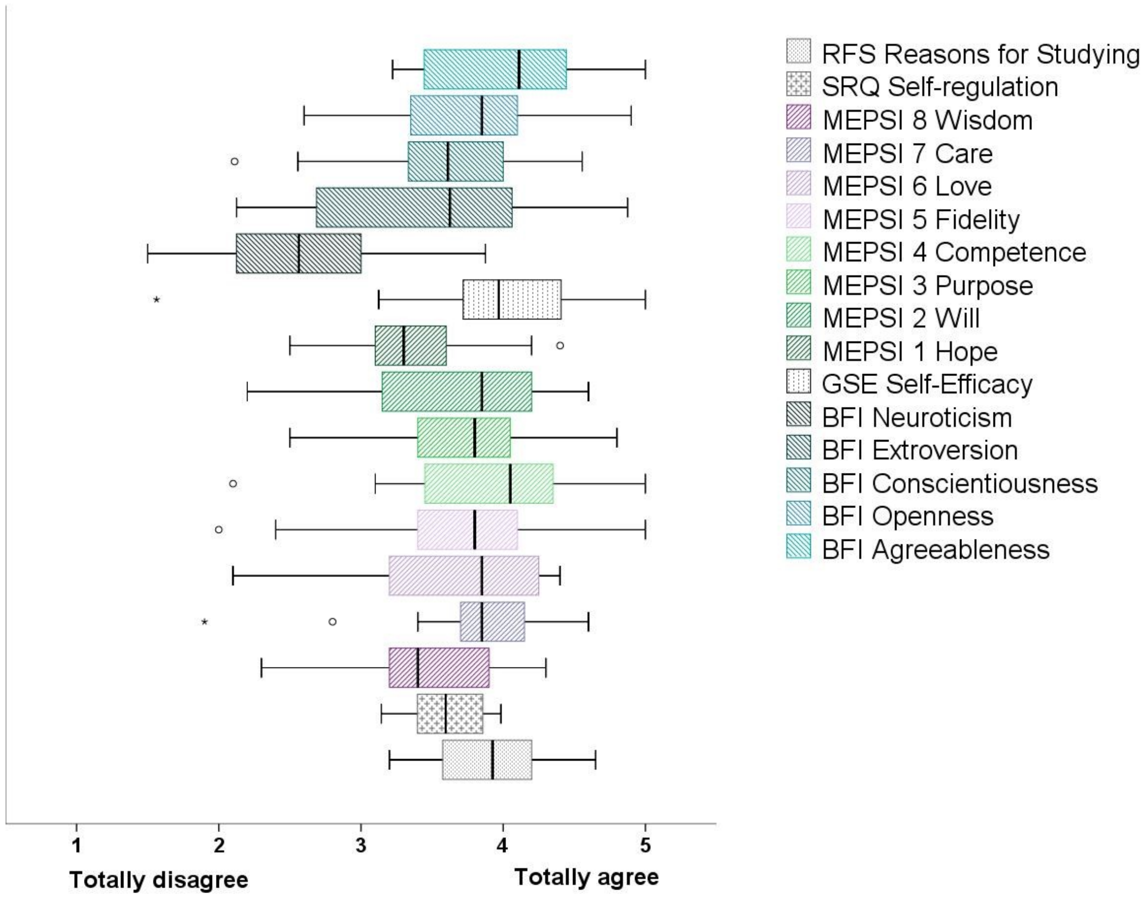
Knowledge (Exams) and Performance (Assignments) Grade Groups



Personality traits. The Big Five Inventory produced 5 trait scales formed by mean responses to 43 items (n = 45) as instructed by its authors: agreeableness (9 items, M = 4.0, SD = .55, α = .79), conscientiousness (9 items, M = 3.7, SD = .63, α = .83), extroversion (8 items, M = 3.5, SD = .74, α = .88), neuroticism (8 items, M = 2.8, SD = .65, α = .77), and openness (10 items, M = 3.3, SD = .48, α = .56; 8 items, M = 3.53, SD = .64, α = .78). Extroversion scores were normally distributed according to the more powerful (Ghasemi & Zahediasl, 2012) Shapiro-Wilk's normality test (SW = .96, p > .05) but not to the more general (2012) Kolmogorov-Smirnov's empirical distribution test (KS = .13, p < .05). All other personality scales were normally distributed according to both tests: agreeableness (KS = .12, p > .05; SW = .96, p > .05), conscientiousness (KS = .08, p > .05; SW = .96, p > .05), neuroticism (KS = .09, p > .05; SW = .98, p > .05), and openness (*8 items*, KS = .12, p > .05; SW = .95, p > .05).

Figure 4

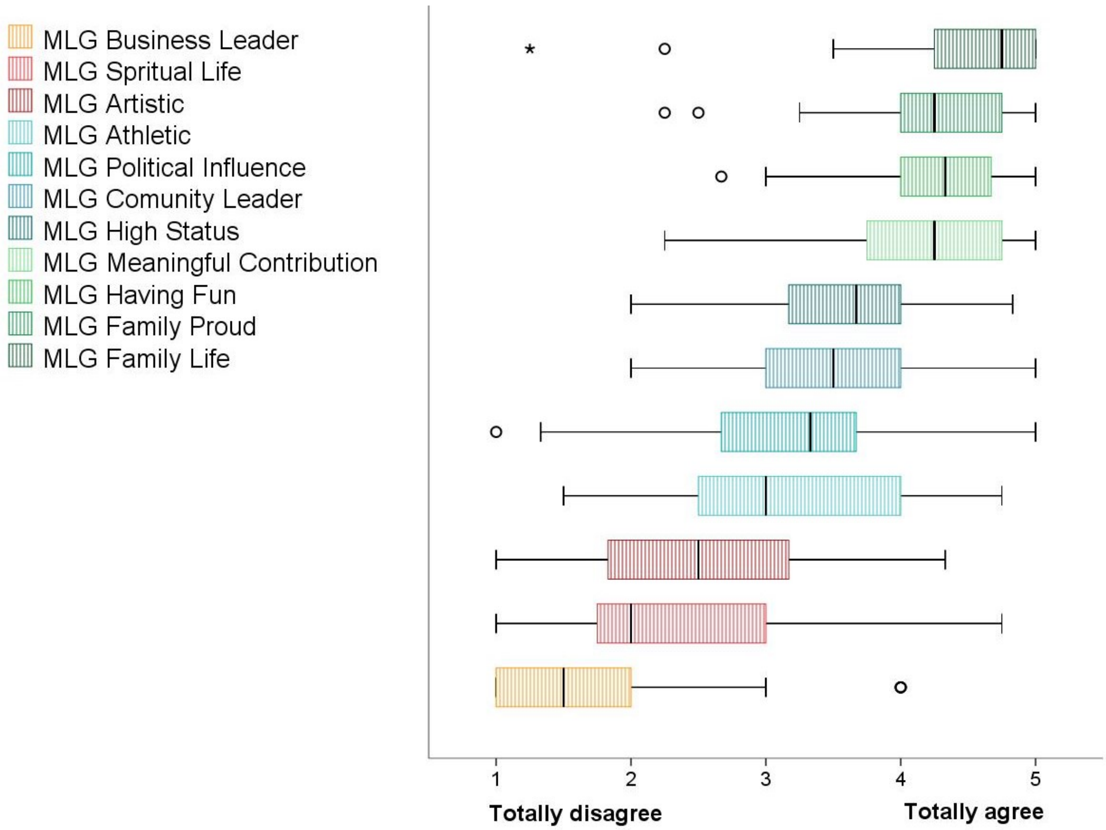
Students' Psychometric Characteristics Scores



Psychosocial maturity. The Modified Erikson Psychosocial Stage Inventory resulted in 8 psychosocial development scales formed by students' mean responses to 80 items (n = 43), 10 for each scale as indicated by its authors: hope (M = 3.5, SD = .51, α = .66), will (M = 3.7, SD = .60, α = .78), purpose (M = 3.8, SD = .51, α = .68), competence (M = 4.0, SD = .66, α = .88), fidelity (M = 3.8, SD = .79, α = .88), love (M = 3.8, SD = .66, α = .80), care (M = 3.9, SD = .56, α = .69), and wisdom (M = 3.6, SD = .57, α = .73). The first 3 and the last scale were normally distributed: 1 hope (KS = .12, p > .05; SW = .96, p > .05), 2 will (KS = .12, p > .05; SW = .96, p > .05), 3 purpose (KS = .12, p > .05; SW = .96, p > .05), and 8 wisdom (KS = .12, p > .05; SW = .96, p > .05). All other scales were not normally distributed.

Figure 5

Students' Major Life Goals Scores



General Self-Efficacy. Scores (n = 44, M = 3.9, SD = .6) were formed by mean responses to 8 items (α = .85) and were normally distributed according to the more general (Ghasemi & Zahediasl, 2012) Kolmogorov-Smirnov's test (.094, $p > .05$) but not to the more powerful (2012) Shapiro-Wilk's (.914, $p < .05$). A visual inspection of scatter plots (*Figure 12*) revealed a single significantly lower score which explained the failed Shapiro-Wilk test. With the outlier removed normality was achieved (KS = .07, SW = .98, both $p > .05$).

Reasons for Studying. Scores (n = 44, M = 3.8, SD = .43, α = .77) were formed by students' responses to 8 intrinsic motivation (*RFS Intrinsic*, M = 4.0, SD = .78, α = .93) and 12 extrinsic motivation items (*RFS Extrinsic*, M = 3.6, SD = .52, α = .73). Only extrinsic RFS and overall scores were normally distributed (KS_{ex} = .066, SW_{ex} = .99; KS = .081, SW = .98, $p > .05$).

Self-regulation. SR Functioning scores (*n* = 20, *M* = 3.6, *SD* = .26) were formed by the sum of students' responses to 63 items (*Cronbach's α* = .82), some reversed according to authors' instructions, and were normally distributed (*KS* = .13, *p* > .05; *SW* = .94, *p* > .05). All SRQ subscales except SRQ planning (*α* = .66) were also normally distributed but with varying internal consistency values: receiving (*α* = .36), evaluating (*α* < .15), triggering (*α* = .33), searching (*α* = .75), implementing (*α* = .71), and assessing (*α* < .22).

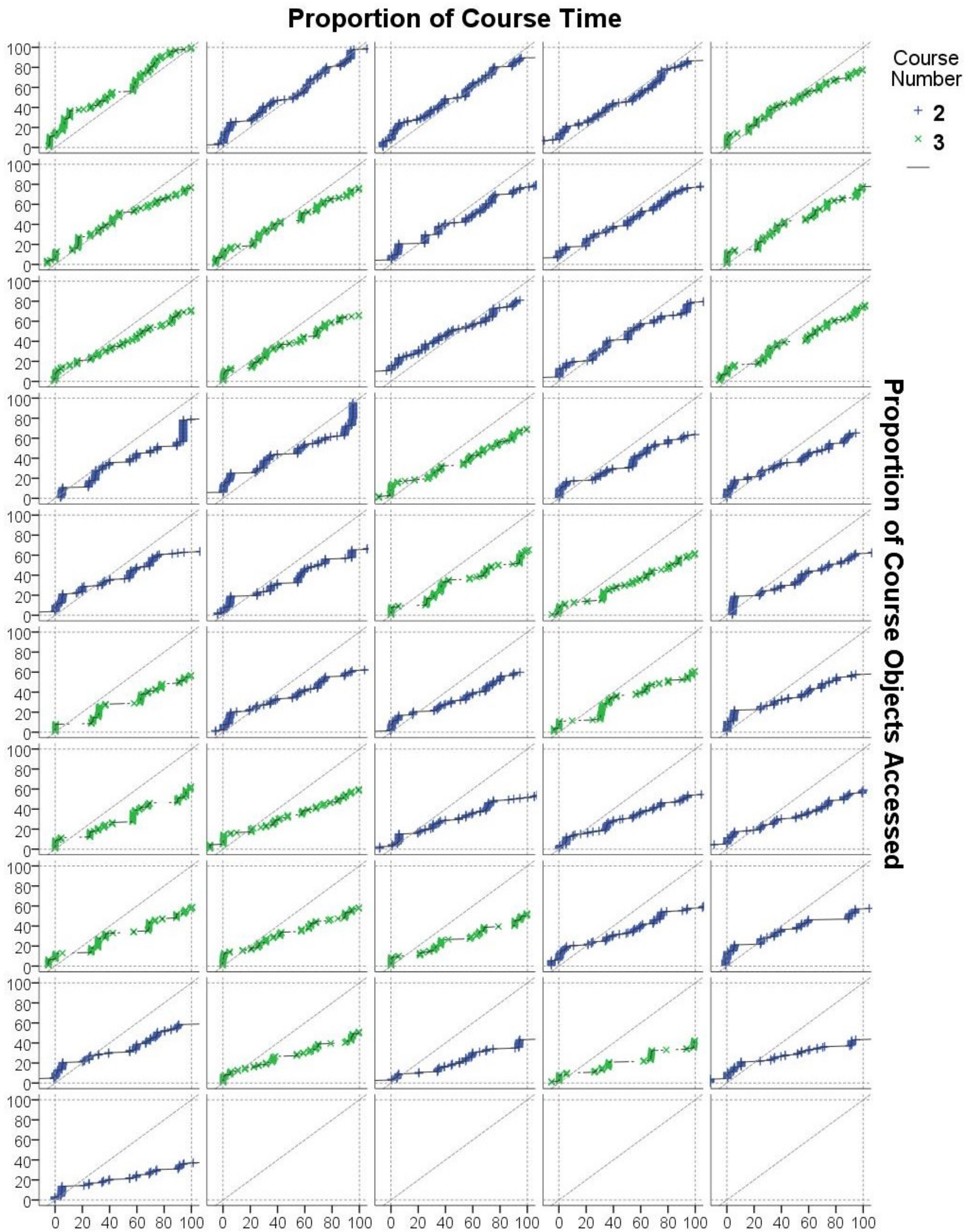
Major Life Goals. Students' mean responses to 40 items measured major life goals (*n* = 45, *min* = 1.0, *max* = 5) grouped into 12 life goals groups: artistic (6 items, *M* = 2.5, *SD* = .88, *α* = .82), high status (6 items, *M* = 3.5, *SD* = .71, *α* = .8), family life (4 items, *M* = 4.5, *SD* = .73, *α* = .78), spiritual life (4 items, *M* = 2.3, *SD* = 1.1, *α* = .82), athletic (4 items, *M* = 3.2, *SD* = .84, *α* = .76), family proud (4 items, *M* = 4.2, *SD* = .62, *α* = .68), meaningful contribution (4 items, *M* = 4.1, *SD* = .67, *α* = .71), having fun (3 items, *M* = 4.3, *SD* = .57, *α* = .66), community leader (2 items, *M* = 3.6, *SD* = .79, *α* = .7), business executive (2 items, *M* = 1.8, *SD* = .82, *α* = .68), and political influence (3 items, *M* = 3.2, *SD* = .77, *α* = .67). Normally distributed MLG goals were artistic (*KS* = .11; *SW* = .97), high status (*KS* = .11; *SW* = .97), political influence (*KS* = .12; *SW* = .96), and athletic (*KS* = .13, *p* = .046; *SW* = .96, *p* > .05).

1. How student interactions changed throughout the course

What was each student's interaction behaviour change throughout the course? To answer this question, first each students' proportion of objects accessed across course time elapsed was mapped on scatterplots to observe students' behaviour change throughout the course (*Figure 6*). Differences between students' patterns of interaction could already be perceived with a visual inspection of plots. Second, linear-change models were computed for each student using linear mixed models' restricted maximum likelihood estimation (*REML*, *Table 14*).

Figure 6

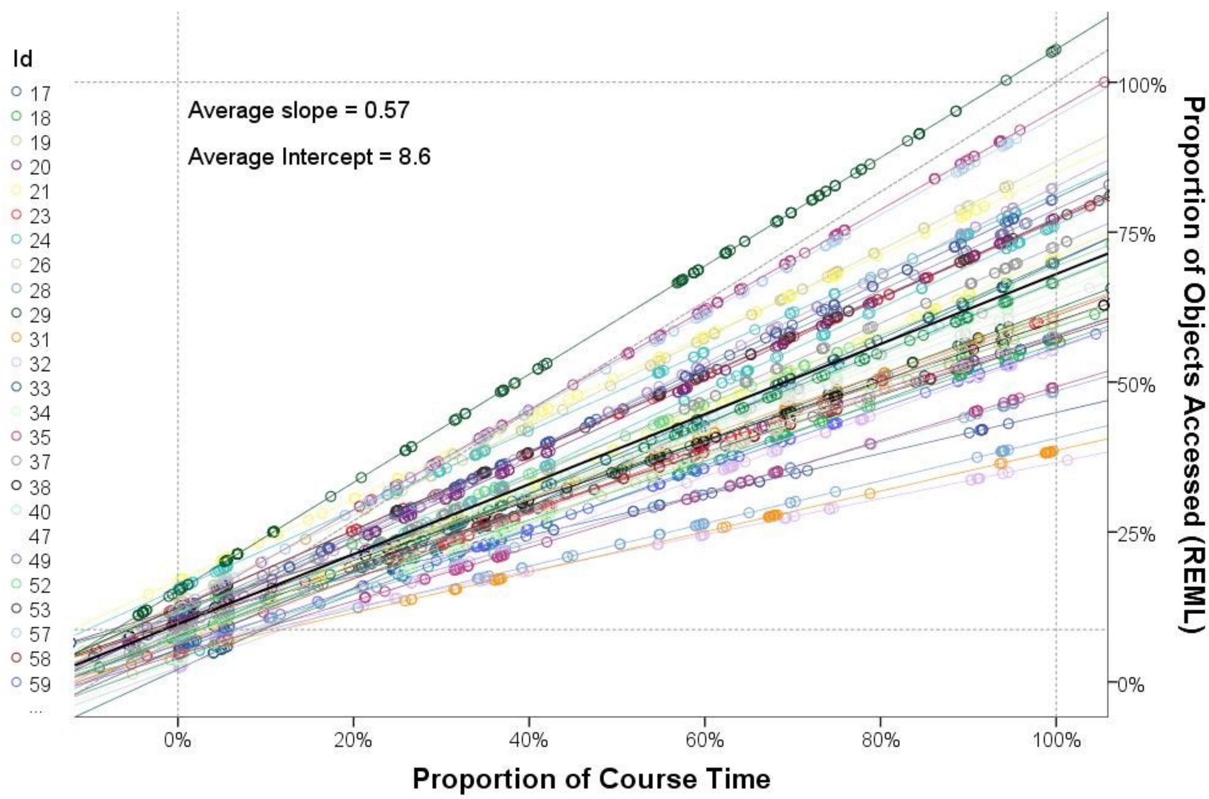
Students' Individual Empirical Interaction Growth Records Ordered by Slope



Each student's REML linear-change interaction trajectory model was formed (*Figure 7*) by an intercept (M = 8.6, SD = 3.44), slope (M = .57, SD = .13), and a residual (*Goodness of Fit,* M = .97, SD = .015). Intercepts ranged from 2.1 to 16.9 proportion of course contents accessed by the first day of class. Intercepts were normally distributed (KS = .07, p > .05; SW = .98, p > .05). Linear-change slopes (rates of change) ranged from .3 to .9 rate of change in the proportion of course contents accessed per unit of proportion of course time (*Figure 7*). Slopes were also normally distributed (KS = .07, p > .05; SW = .98, p > .05).

Figure 7

Students' Linear-Change Interaction Trajectory Models (REML)



2. Relationship between student characteristics

How are student characteristics related to each other? Two-tailed Pearson and Spearman correlations were used to verify the relationship between students' personality traits (*Table 6*), psychosocial maturity (*Table 7*), major life goals (*Table 8*), reasons for studying, self-efficacy, and self-regulation (*Table 9*). Pearson linear correlations were used between normally distributed variables and Spearman rank correlations with non-normal variables.

Personality traits

Conscientiousness. Highly conscientious students were also prone to be more agreeable, autonomous (*will*), to plan and take initiative (*purpose*), to be industrious (*competence*), have a better sense of who they are (*fidelity*), have a greater concern for establishing and guiding the next generation (*care*), and a greater ability to recognize life complexities or feel satisfied with their lives (*wisdom*). More conscientious students also had stronger overall reasons for studying, self-efficacy, self-regulatory overall functioning, receiving, searching and planning skills.

Agreeableness. Students who reported more agreeable personality traits were also less moody, anxious or worrisome (*neuroticism*), had stronger trust in self and others (*hope*), a greater sense that they could handle problems on their own (*will*), self-confidence (*competence*), of who they were and how they fit into society (*fidelity*), a stronger disposition to form reciprocal relationships (*love*), to be productive and creative by caring (care) and to feel they are leading a productive successful life (*wisdom*). More agreeable personalities also had stronger intrinsic reasons for studying, major life aspirations to care for and nurture others (*meaningful contributions*), to take part in public service (*community leader*) and to be influential in public affairs (*political influence*), a stronger belief that they will face any challenge competently (*self-efficacy*), and self-regulatory overall functioning and self-regulating searching skills.

Extroversion. Students with stronger extroversion also had stronger confidence in themselves (*will*), better psychosocial ability to plan and take initiative (*purpose*), sense of identity, of who they were and what they believed in (*fidelity*), were less afraid of being rejected and less prone to be isolated (*love*), and more prone to feel they were leading a successful life (*wisdom*). Extroverted students also had greater aspirations to have an exciting lifestyle (*have fun*), to have an influential and prestigious career with a high standard of living and wealth (*high status*), to become a community leader, and to be in good physical condition, and also had stronger self-regulatory searching, planning, but weaker evaluating skills (*Table 6*).

Table 6

Correlations between Personality Traits and Other Characteristics

Measure	*n*	Ext.	Agr.	Con.	Neu.	Ope.
			Personality Traits			
Extroversion	45		.16	.07	-.22	.19
Agreeableness	45	.16		.40**	-.43**	.25
Conscientiousness	45	.07	.40**		-.22	-.03
Neuroticism	45	-.22	-.43**	-.22		-.23
Openness	45	.19	.25	-.03	-.23	
			Psychosocial Maturity			
1 Hope	42	.18	.32*	.28	-.24	.16
2 Will	42	.43**	.49**	.52**	-.49**	.26
3 Purpose	42	.49**	.28	.48**	-.34*	.10
4 Competence	42	.21	.42++	.76++	-.17	.22
5 Fidelity	42	.38+	.35+	.42++	-.24	.19
6 Love	42	.65++	.47++	.30	-.08	.18
7 Care	42	.16	.46++	.45++	-.31+	.18
8 Wisdom	42	.40**	.51**	.45**	-.33*	.25
			Motives			
Reasons for Studying	43	.06	.14	.43**	-.06	.30
Intrinsic	43	.18	.38+	.26	-.52++	.48++
Extrinsic	43	-.03	-.29	.15	.46**	-.06

Measure	*n*	Ext.	Agr.	Con.	Neu.	Ope.
			Major Life Goals			
Family Life	45	.04	.13	.24	.08	-.02
Family Proud	45	.15	.05	.27	.19	.25
Having Fun	45	$.47^{++}$	-.04	-.09	-.07	.03
Meaningful Contribution	45	.02	$.39^{++}$	.24	-.16	.29
High Status	45	$.34^{*}$	-.04	.13	.20	.09
Community Leader	45	$.35^{+}$	$.44^{++}$	.27	-.28	.21
Political Influence	45	-.14	$.35^{*}$	.12	-.18	.24
Athletic	45	$.42^{**}$	-.15	-.08	.00	-.04
Artistic	45	.21	.05	-.12	-.25	$.77^{**}$
Spiritual	45	.08	.20	.02	$-.34^{+}$	$.42^{++}$
Business Leader	45	.06	-.09	-.06	-.20	.14
			Beliefs			
Self-Efficacy	43	.28	$.43^{++}$	$.44^{++}$	-.25	.25
			Self-regulation			
Self-regulation	20	.35	$.50^{*}$	$.56^{**}$	-.25	.38
Searching	20	$.58^{**}$	$.68^{**}$	$.45^{*}$	-.38	$.46^{*}$
Receiving	20	.13	.38	$.64^{**}$	-.26	.23
Implementing	20	.27	.33	.38	-.36	.23
Triggering	20	.29	.41	.39	-.03	.34
Planning	20	$.55^{+}$	.27	$.51^{+}$	-.15	.27
Evaluating	20	$-.54^{*}$	-.44	-.18	.38	$-.54^{*}$
Assessing	20	.02	.38	.11	.07	$.45^{*}$

** Pearson correlation (2-tailed) is significant at .01, * at .05.

$^{++}$ *Spearman rank correlation (2-tailed) is significant at .01,* $^{+}$ *at .05.*

Neuroticism. Students higher in neuroticism also had stronger extrinsic reasons for studying and weaker intrinsic reasons for studying, less desire to devote attention to their spiritual life as a life goal, less confidence in their ability to handle problems, were less prone to take initiative or risks, to be creative and desire to guide the next generation (*care*), to feel they were leading a productive successful life (*wisdom*), and were also less prone to be agreeable.

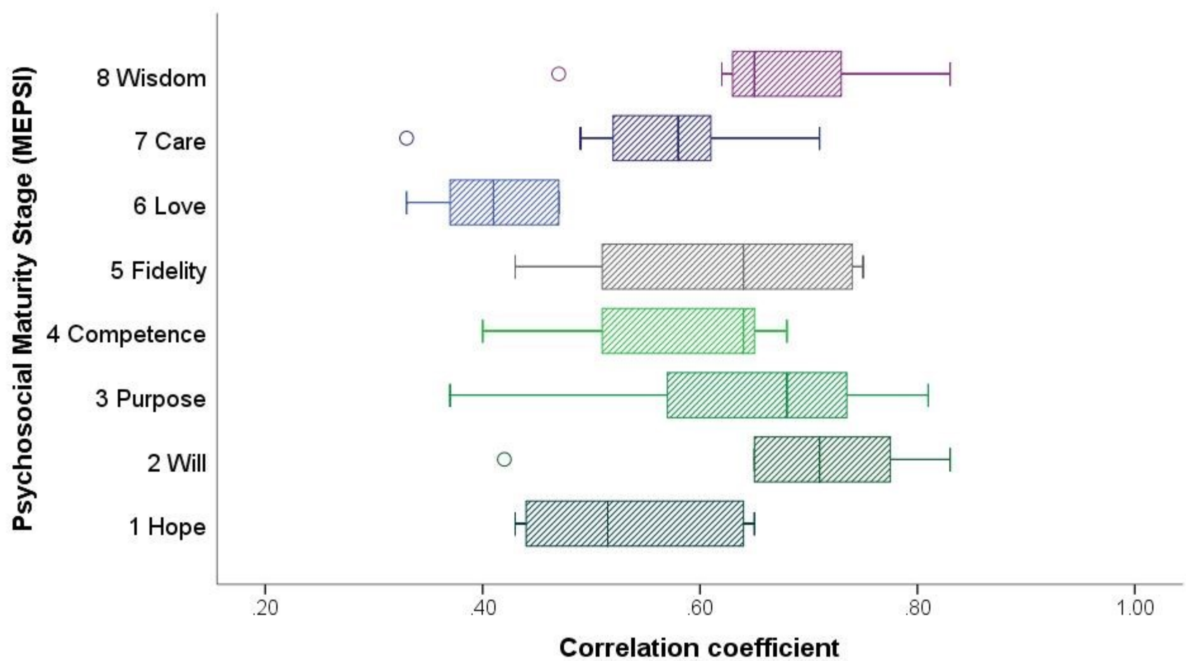
Openness. Students with higher openness also had stronger intrinsic reasons for studying, aspirations to produce good artistic work and to participate in religious activities (*spiritual life*), and SR searching, assessing but weaker evaluating SR skills.

Psychosocial maturity

All psychosocial indicators were significantly related with each other except for stages 1 Hope (*Trust*) and 6 Love (*Intimacy*) whose relationship was non-significant. Associations between the eight indicators of psychosocial attribute strength ranged from very strong (r = .83, p < .01) to weak (r = .33, p < .05). While stage 2 had the strongest correlations, stage 6 had the weakest (*Figure 8*). Psychosocial indicators were also related to other characteristics (*Table 7*).

Figure 8

Psychosocial Maturity Attributes' Intercorrelation Coefficients



Stage 1 Hope. The degree to which a person trusts the world to be dependable and reliable was moderately related to all other maturity stages ($r_{avg} = .49$) and was most strongly related to stages 2 (*will*) and 8 (*wisdom*). Students with a stronger sense of trust in the world also tended to have a stronger sense of self-sufficiency and that they were leading a successful life. Students with a stronger sense of trust in others were also prone to be more agreeable.

Stage 2 Will. The measure of a person's self-sufficiency was strongly correlated to all other stages ($r_{avg} = .69$) and was very strongly related to stages 3 (*purpose*) and 8 (*wisdom*). Students with stronger self-sufficiency were also prone to plan and initiate activities more independently and believe they were leading a happy productive life. Students' capacity to be autonomous was moderately related to all personality traits: conscientiousness, agreeableness, extroversion, and negatively to neuroticism but not to openness. Stage 2 was also related to self-regulatory searching, implementing and overall skills, intrinsic and overall reasons for studying, self-efficacy, self-regulatory planning, becoming a community leader and having a spiritual life as major life goals, and negatively to self-regulatory evaluating.

Stage 3 Initiative. The degree to which a person purposefully acts independently was strongly correlated to all other stages ($r_{avg} = .64$) and was most strongly related to stages 2 (*will*) and 5 (*fidelity*). Students with a stronger capacity to take initiative also tended to be more autonomous and have a more defined sense of who they are and what they believe in. Students with a stronger disposition to plan and undertake activities also had stronger self-regulatory skills, planning, searching, receiving, and implementing but lower evaluating skills. Stage 3 was also positively related to stronger general self-efficacy, to more extroverted and conscientious personality traits, intrinsic reasons for studying, aspirations to become a community leader as a major life goal, and to lower neuroticism.

Table 7

Correlations between Psychosocial Maturity Stages and Other Characteristics

Measure	*n*	1	2	3	4	5	6	7	8
					Psychosocial Maturity				
1 Hope	43		.65**	.54**	.44**	.43**	.27	.49**	.64**
2 Will	43	.65**		.81**	.65**	.74**	.42**	.71**	.83**
3 Purpose	43	.54**	.81**		.68**	.75**	.37*	.60**	.72**
4 Competence	43	.44++	.65++	.68++		.64++	.40++	.58++	.65++
5 Fidelity	43	.43++	.74++	.75++	.64++		.47++	.55++	.74++
6 Love	43	.27	.42++	.37+	.40++	.47++		.33+	.47++
7 Care	43	.49++	.71++	.60++	.58++	.55++	.33+		.62++
8 Wisdom	43	.64**	.83**	.72**	.65**	.74**	.47**	.62**	
					Motives				
Reasons for Studying	42	.26	.42**	.27	.41**	.41**	.32*	.22	.34*
Intrinsic	42	.08	.60++	.43++	.42++	.47++	.28	.31+	.44++
Extrinsic	42	.07	.01	-.03	.11	.13	.15	.04	-.00
					Major Life Goals				
Family Life	42	.21	.22	-.01	.15	.18	.33+	.11	.31+
Family Proud	42	.05	.19	.08	.37+	.17	.43+	.23	.24
Having Fun	42	.05	.16	.21	-.057	-.04	.40++	-.13	.20
Meaningful Contr.	42	-.07	.29	.07	.30	.26	.41+	.11	.44++
High Status	42	-.16	-.08	.10	.23	.09	.37*	-.11	.10
Community Leader	42	.16	.49++	.49++	.48++	.48++	.33+	.31+	.53++
Political Influence	42	.24	.24	.16	.26	.12	.04	.07	.44**
Athletic	42	.01	.04	.22	.10	.14	.28	-.08	.01
Artistic	42	.01	.10	.02	.05	-.01	.04	.00	.13
Spiritual Life	42	.07	.39+	.14	.15	.14	.09	.45++	.17
Business Leader	42	-.06	.19	.25	-.01	.05	.05	.09	.21

Measure	*n*	1	2	3	4	5	6	7	8
				Beliefs					
Self-efficacy	42	.19	.58++	.59++	.63++	.45++	.33+	.41++	.45++
				Self-regulation					
Self-Regulation	20	.40	.63**	.60**	.66**	.62**	.41	.52*	.67**
Searching	20	.41	.69**	.57**	.55*	.54*	.53*	.52*	.73**
Receiving	20	.18	.39	.54*	.51*	.38	.22	.33	.44
Implementing	20	.33	.65**	.51*	.36	.54*	.35	.53*	.48*
Triggering	20	.25	.36	.39	.67**	.42	.36	.26	.61**
Planning	20	.33	.55+	.72++	.57++	.58++	.50+	.46+	.48+
Evaluating	20	-.15	-.45*	-.58**	-.27	-.30	-.34	-.30	-.36
Assessing	20	.25	.13	.16	.45*	.37	-.03	-.09	.35

** Pearson correlation (2-tailed) is significant at .01, * at .05.

++ *Spearman rank correlation (2-tailed) is significant at .01, + at .05.*

Stage 4 Competence. The reported strength of self-confidence, industry, diligence, perseverance at tasks, and putting work before pleasure was moderately correlated to all stages (r_{avg} = .58) and was strongly related to stages 2 (*will*), 3 (*purpose*), 5 (*fidelity*), and 8 (*wisdom*). Students with stronger self-confidence also reported acting more independently, purposefully, having a better-defined sense of identity, and feeling more satisfied with their lives. A stronger disposition to bring productive situations to completion was related to higher conscientiousness, self-efficacy, self-regulatory triggering, overall SR, planning, searching, and receiving skills, aspirations to become a community leader as a major life goal, self-regulatory assessing, intrinsic reasons for studying, and aspirations to make their family proud as a major life goal.

Stage 5 Fidelity. The degree to which students reported having a well-defined identity, a sense of who they were, what they believed in and what they could be, was strongly correlated to all stages (r_{avg} = .62) and was strongly related to stages 2 (*will*), 3 (*purpose*), and 8 (*wisdom*). Students with a stronger sense of self also reported a stronger capacity to be autonomous, take initiative, and to feel accomplished and satisfied with their lives. A stronger sense of identity was also found to be related to stronger self-regulatory planning, searching, and implementing skills, aspirations to become a community leader, intrinsic reasons for studying, self-efficacy, overall reasons for studying, and a more conscientious, extroverted, and agreeable personality.

Stage 6 Love. The capacity and willingness to form intimate, reciprocal relationships, was the least correlated of all stages (r_{avg} = .39) but was still moderately related to stages 5 (*identity*), and 8 (*wisdom*). Students with stronger dispositions to form intimate, reciprocal relationships also reported having a better-defined sense of self and satisfaction with their lives. Students with a stronger capacity for intimacy, a weaker disposition towards isolation, also reported having extroverted and agreeable personalities, stronger self-regulatory searching and planning skills, aspirations to make their family proud, make meaningful contributions, have fun, attain high status, become a community leader, and to have a family life as major life goals, and were also prone to have stronger self-efficacy and overall reasons for studying.

Stage 7 Care. The degree to which someone feels productive and accomplished by contributing to society and helping guide future generations was moderately correlated to all other stages (r_{avg} = .55) and was strongly related to stage 2 (*will*). Students who were more willing to help society move forward also tended to be more self-sufficient. A stronger disposition to care was also related to stronger self-regulatory implementing, searching, overall and planning skills, to having a more agreeable and conscientious personality, stronger general self-efficacy, aspirations to have a spiritual life and to become a community leader, intrinsic reasons for studying, and to lower neurotic personality traits.

Stage 8 Wisdom. The degree to which a person feels satisfied with their life was strongly correlated to all other stages (r_{avg} = .67) and was most strongly related to stages 2 (*will*) and 5 (*fidelity*). Students who felt more accomplished and satisfied with their life also tended to be more self-sufficient and had a stronger sense of who they were. Stage 8 was also related to stronger self-regulatory searching, overall and triggering skills, aspirations to become a community leader, to having a more agreeable personality, self-regulatory implementing and planning skills, general self-efficacy, a more conscientious personality, aspirations to make meaningful contributions, stronger intrinsic reasons for studying, aspirations to have political influence, a more extroverted personality, overall reasons for studying, aspirations to have a family life, and was inversely related to neuroticism.

Major Life Goals

Most major life goals were significantly related to each other, to personality traits, psychosocial maturity attributes, and other characteristics (*Table 8*).

Family Life. Students who aspired to have a satisfying marriage or relationship, to have children, or to be a good parent, partner, husband or wife (*Family Life*) also aspired to make their parents proud, to have harmonious relationships with their parents and siblings, or to be well read and feel a real purpose in life (*Family Proud*), to promote or ensure the welfare of others, care for and nurture others, or to have the time and means to relax and enjoy life (*Meaningful contribution*), and to have new and different experiences or an exciting lifestyle (*Have Fun*).

Have Fun. Students who desired to *have fun* also had stronger *athletic* aspirations. Students with stronger *athletic* aspirations or aspirations to *have fun* were also prone to have somewhat more extroverted personalities.

Family Proud. Students who wished to make their family proud also aspired to make *meaningful contributions* and to have a high-status career, an influential and prestigious occupation, a high standard of living and wealth, or to being well-known or well-liked (*High Status*). Students with aspirations to have a *family life*, to make their *family proud*, or to have *high status* also reported stronger extrinsic reasons for studying.

Table 8

Correlations between Major Life Goals

Measure	*1*	2	3	*4*	5	*6*	7	8	9	*10*	*11*
1 Family Life		$.40^{++}$	$.31^{+}$	$.32^{+}$	.28	-.05	-.04	-.04	-.01	.03	.11
2 Family Proud	$.40^{++}$		.26	$.36^{+}$	$.44^{++}$	.02	.12	.24	.19	.17	-.03
3 Having Fun	$.31^{+}$	.26		.16	$.43^{++}$	.11	.12	$.41^{++}$	.17	.01	.10
4 Meaningful C.	$.32^{+}$	$.36^{+}$	.16		.26	.28	$.38^{++}$	.05	.21	.07	.23
5 High Status	.28	$.44^{++}$	$.43^{++}$	.26		.12	$.32^{*}$	$.57^{**}$	.20	-.25	.20
6 Community L.	-.05	.02	.11	.28	.12		$.30^{*}$	.21	.05	.29	.08
7 Political Inf.	-.04	.12	.12	$.38^{++}$	$.32^{*}$	$.30^{+}$		.10	.19	-.08	.15
8 Athletic	-.04	.24	$.41^{++}$	.05	$.57^{**}$	.21	.10		.07	-.12	.20
9 Artistic	-.01	.19	.17	.21	.20	.05	.19	.07		$.51^{++}$	.13
10 Spiritual Life	.03	.17	.01	.07	-.25	.29	-.08	-.12	$.51^{++}$		.01
11 Business L.	.11	-.03	.10	.23	.20	.08	.15	.19	.13	.01	

** Pearson (2-tailed) is significant at .01, * at .05.

$^{++}$ Spearman rank correlation (2-tailed) is significant at .01, $^{+}$ at .05.

High Status. Students with *high status* aspirations also reported higher self-efficacy and a slightly more extroverted personality. Students with aspirations to attain *high status* also aspired to *have fun*, to become an outstanding athlete, be in good physical condition, being well-known or obtain awards or recognition (*Athletic*), and to keep up to date with political affairs, be influential in public affairs, or to promote or ensure the welfare of others (*Political Influence*).

Political Influence. Students who aspired to have *political influence* also aspired to make *meaningful contributions* and to become a community leader or take part in volunteer community and public service (*Community Leader*).

Community Leader. An aspiration to become a *community leader* was also related to higher self-efficacy and a slightly more extroverted personality. Students who desired to have *political influence*, aspired to make *meaningful contributions*, or aspired to be a *community leader* were prone to have somewhat more agreeable personalities.

Meaningful contributions. Students who aspired to make *meaningful contributions* were also prone to have stronger intrinsic reasons for studying. Stronger aspirations to have *political influence* or to make *meaningful contributions* were also moderately related to higher self-regulatory functioning skills.

Artistic. Students who aspired to produce good artistic work, to become accomplished in one of the performing arts, or to be creative and invent or develop something useful (*Artistic*) were also prone to devote attention to their spiritual life or participate in religious activities.

Spiritual Life. Students with stronger *artistic* and *spiritual life* aspirations were also somewhat more likely to have more open personalities and intrinsic reasons for studying. Students with *spiritual life* aspirations also tended to report slightly lower neuroticism.

Other characteristics

General self-efficacy. The belief that one can handle any situation competently, was associated with many other student characteristics with correlations ranging from weak ($r = .32$) to strong ($r = .66$). Students with higher self-efficacy beliefs were prone to have stronger self-regulation skills, to be more industrious (*competence*), have stronger searching and planning self-regulation skills, intrinsic reasons for studying, to report being more purposeful (*initiative*) and autonomous (*will*), to have stronger receiving and implementing self-regulation skills, to be less prone to compare themselves to others (*SR evaluating*), to have stronger overall reasons for studying, a better-defined sense of identity (*fidelity*), satisfaction with their life (*wisdom*), a more conscientious and agreeable personality, disposition to care for others (*generativity*), to form intimate, reciprocal relationships (*love*), aspire to be a *community leader* and to have *high status*.

Table 9

Correlations between Reasons for Studying, Self-efficacy, and Self-regulation

Measure	*n*	RFS	I-RFS	E-RFS	GSE	SRQ
			Motives			
Reasons for studying	44		$.60^{++}$	$.69^{**}$	$.46^{++}$	.21
Intrinsic RFS	44	$.60^{++}$		-.05	$.59^{++}$	.29
Extrinsic RFS	44	$.69^{**}$	-.05		.13	.07
			Major Life Goals			
Family Life	43	$.39^{*}$	.09	$.36^{*}$	.07	.37
Family Proud	43	$.47^{**}$	.14	$.45^{**}$	.27	.16
Having Fun	43	.13	.18	.07	.17	.12
Meaningful Contribution	43	$.38^{*}$	$.42^{++}$	.04	.25	$.53^{*}$
High Status	43	$.35^{*}$	.06	$.46^{**}$	$.32^{+}$	.38
Community Leader	43	.01	.27	-.24	$.33^{+}$	.27
Political Influence	43	.25	.15	-.01	.14	$.45^{*}$
Athletic	43	.06	.01	.15	.29	.23
Artistic	43	.27	$.34^{+}$	.01	.16	.22
Spiritual Life	43	.23	$.34^{+}$	-.09	.24	-.06
Business Leader	43	-.05	.07	-.16	.13	.23

Measure	n	RFS	I-RFS	E-RFS	GSE	SRQ
			Beliefs			
Self-Efficacy (GSE)	44	$.46^{++}$	$.59^{++}$	.13		$.66^{++}$
			Self-regulation			
Overall (SRQ)	20	.21	.29	.07	$.66^{++}$	
Searching	20	.07	.39	-.14	$.61^{++}$	$.84^{**}$
Receiving	20	.11	.11	.01	$.57^{++}$	$.78^{**}$
Implementing	20	.26	.31	.09	$.55^{+}$	$.81^{**}$
Triggering	20	.15	.25	-.03	.43	$.61^{**}$
Planning	20	.20	.07	.14	$.60^{++}$	$.68^{++}$
Evaluating	20	.13	$-.53^{+}$	.43	$-.47^{+}$	-.19
Assessing	20	-.11	.12	-.16	.26	$.65^{**}$

** Pearson (2-tailed) is significant at .01, * at .05.

$^{++}$ *Spearman rank correlation (2-tailed) is significant at .01, $^{+}$ at .05.*

Reasons for Studying. Students with higher reasons for studying also aspired to make their *family proud*, reported stronger self-efficacy, conscientiousness, autonomy (*will*), better-defined identities, industriousness, aspirations to have a *family life*, make *meaningful contributions*, to have *high status*, to being more satisfied with their life (*wisdom*) and open to reciprocal relationships (*love*). Stronger ***extrinsic reasons for studying*** were related to stronger neurotic personality traits, aspirations to have *high status*, make one's *family proud*, and to have a *family life*. In contrast, stronger ***intrinsic reasons for studying*** were related to more agreeable and openness traits, higher self-efficacy, being more autonomous (*will*), purposeful (*initiative*), industrious (*competence*), a better-defined identity (*fidelity*), disposition to care for others (*generativity*), and feeling accomplished in one's life (*wisdom*). Higher intrinsic reasons for studying were also related to having *artistic* aspirations, a desire to pay attention to one's *spiritual life* and to making *meaningful contributions*, as well as being less likely to follow others (*SR evaluating*) or to have neurotic personality traits.

Self-regulation. Although reflective of a smaller sample (20), self-regulatory functioning skills were also related to several other characteristics such as having more agreeable and conscientious personality traits, stronger self-efficacy, and positive psychosocial attributes: will (*autonomy*), purpose (*initiative*), competence (*industry*), identity (*fidelity*), care, and ego integrity (*wisdom*), as well as *meaningful contributions* and *political influence* aspirations.

3. Relationship between interaction trajectories and characteristics

Two-tailed Pearson and Spearman correlations tested whether there was a relationship between students' linear-change parameters (intercepts and slopes) and student characteristics (*Table 10*). Intercepts, the initial proportion of course objects accessed by the first day of class, were related to slopes and conscientiousness. Slopes, the rate at which the proportion of course objects accessed increased over time, were positively related to general self-efficacy, political influence life goal, psychosocial hope, will, purpose, competence, and fidelity, conscientious personality, overall and intrinsic reasons for studying, and self-regulatory overall functioning, implementing, receiving, and assessing. These relationships are described in more detail in the following sections.

Table 10

Correlations between Interaction Trajectories and Student Characteristics

Measure	*n*	Intercept	Slope
Interaction Trajectories			
Intercept	46		.43**
Slope	46	.43**	

Measure	*n*	Intercept	Slope
	Motives		
Reasons for Studying	44	.01	$.40^{**}$
Intrinsic	44	-.03	$.39^{++}$
Extrinsic	44	-.02	.09
	Major Life Goals		
Political Influence	45	-.15	$.30^{*}$
Meaningful Contribution	45	-.22	.27
Family Life	45	.22	.16
Family Proud	45	-.02	.16
Community Leader	45	.07	.10
Athletic	45	-.18	.09
High Status	45	-.02	.09
Artistic	45	-.26	-.02
Spiritual Life	45	-.07	-.03
Having Fun	45	.02	-.10
Business Leader	45	-.27	-.10
	Beliefs		
Self-Efficacy	44	.00	$.38^{+}$
	Psychosocial Maturity		
1 Hope	43	.16	$.31^{*}$
2 Will	43	.15	$.35^{*}$
3 Purpose	43	.21	$.37^{*}$
4 Competence	43	.25	$.51^{++}$
5 Fidelity	43	.09	$.34^{+}$
6 Love	43	.01	.12
7 Care	43	.14	.21
8 Wisdom	43	.14	.30

Measure	n	Intercept	Slope
		Personality Traits	
Conscientiousness	45	.34*	.43**
Agreeableness	45	.19	.28
Openness	45	-.15	.05
Extroversion	45	.03	-.09
Neuroticism	45	.11	-.20
		Self-regulation	
Overall	20	.42	.61**
Searching	20	.28	.37
Receiving	20	.33	.50*
Implementing	20	.17	.56*
Triggering	20	.44	.31
Planning	20	.40	.34
Evaluating	20	-.17	-.11
Assessing	20	.42	.48*

** Pearson correlation (2-tailed) is significant at .01, * at .05.

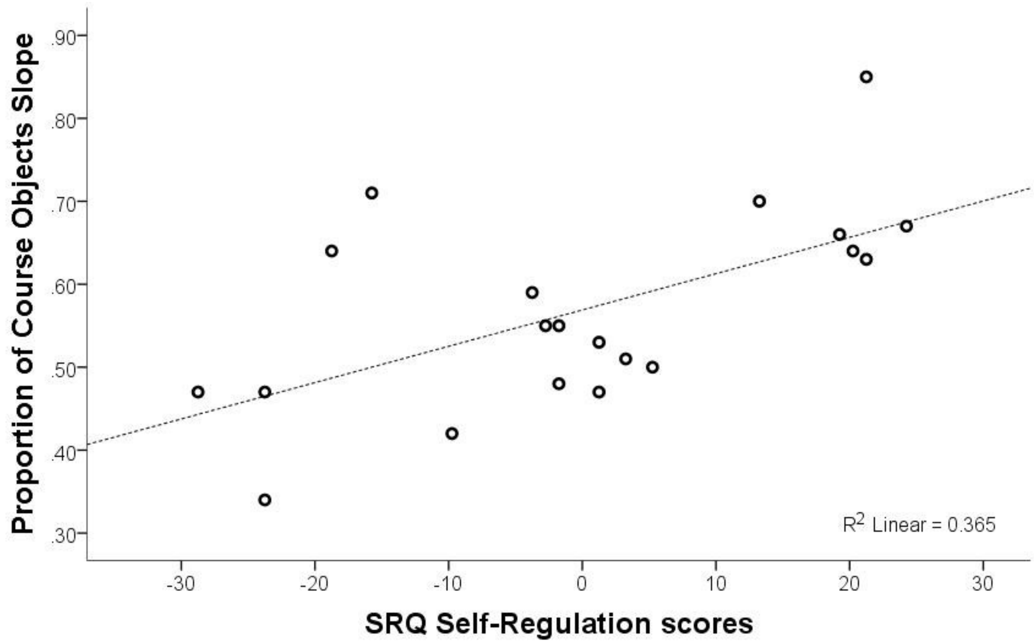
++ *Spearman rank correlation (2-tailed) is significant at .01, + at .05.*

Self-regulation

There were strong linear correlations between students' self-regulation functioning scores and their rate of change in the proportion of course objects accessed ($r = .60$, $n = 20$, $p < .01$) but not their intercepts ($r = .42$, $n = 20$, $p = .063$). Students with stronger self-regulation capacity engaged with larger proportions of course objects (*Figure 9*). Three normally distributed self-regulation subscales were positively related ($n = 20$, $p < .05$) to students' change slopes: implementing the plan ($r = .56$), receiving relevant information ($r = .50$), and assessing the plan's effectiveness ($r = .48$). Students who did not get easily distracted from their plans, who usually kept track of their progress toward their own goals, and who rewarded themselves for progress towards their own goals also engaged with larger proportions of objects during the course.

Figure 9

Relationship between Self-regulation and Interaction Trajectory Slopes

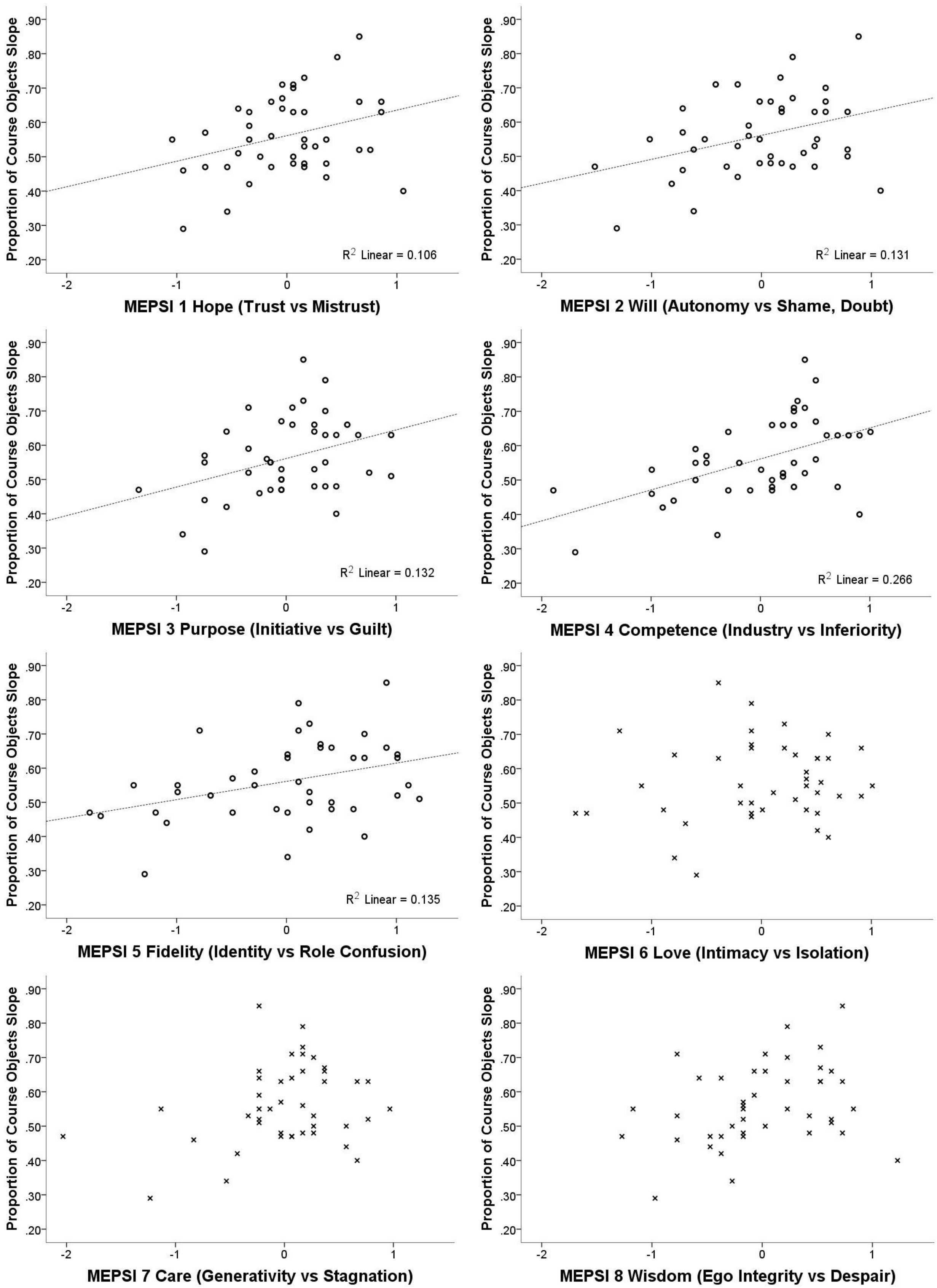


Psychosocial maturity

There were weak positive correlations between students' slopes and their scores on stages 1 (*Hope*, $r = .31$), 2 (*Will*, $r = .35$), and 3 (*Purpose*, $r = .37$). There were also moderate and weak positive Spearman rank associations between slopes and scores on the non-normally distributed stages 4 (*Competence*, $r = .51$, $p < .01$) and 5 (*Fidelity*, $r = .34$). Students who engaged with larger proportions of course objects also reported stronger sense of trust in the world (*hope*), of self-sufficiency (*will*), capacity to purposefully act independently (*purpose*), of self-confidence (*competence*), and a well-defined sense of who they were (*fidelity*, *Figure 10*).

Figure 10

Relationship between Psychosocial Maturity Levels and Interaction Trajectory Slopes

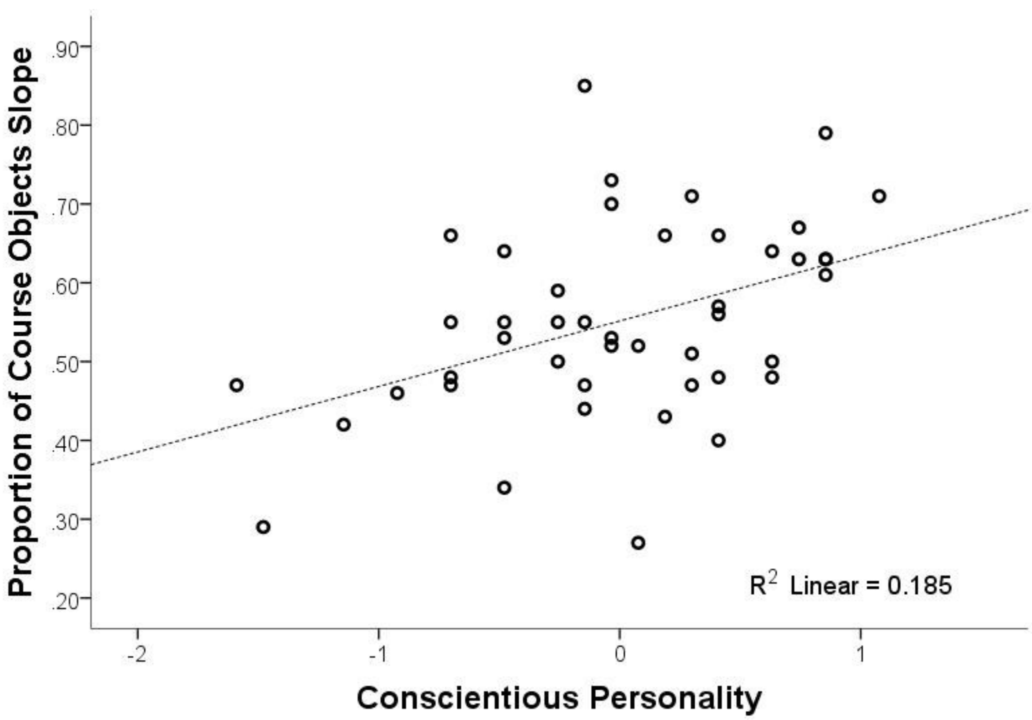

Proportion of Course Objects Slope
R2 Linear = 0.106
MEPSI 1 Hope (Trust vs Mistrust)
R2 Linear = 0.131
MEPSI 2 Will (Autonomy vs Shame, Doubt)
R2 Linear = 0.132
MEPSI 3 Purpose (Initiative vs Guilt)
R2 Linear = 0.266
MEPSI 4 Competence (Industry vs Inferiority)
R2 Linear = 0.135
MEPSI 5 Fidelity (Identity vs Role Confusion)
MEPSI 6 Love (Intimacy vs Isolation)
MEPSI 7 Care (Generativity vs Stagnation)
MEPSI 8 Wisdom (Ego Integrity vs Despair)

Personality traits

There were weak and moderate positive correlations (n = 45, p < .05) between students' conscientiousness and their linear-change intercepts (r = .34) and slopes (r = .43, p < .01). Students with stronger conscientious personalities, who are likely to be more responsible, diligent, careful, efficient or organized also accessed a larger proportion of objects by the first day and engaged with larger proportions of objects throughout the course (*Figure 11*).

Figure 11

Relationship between Conscientious Personality and Interaction Trajectory Slopes

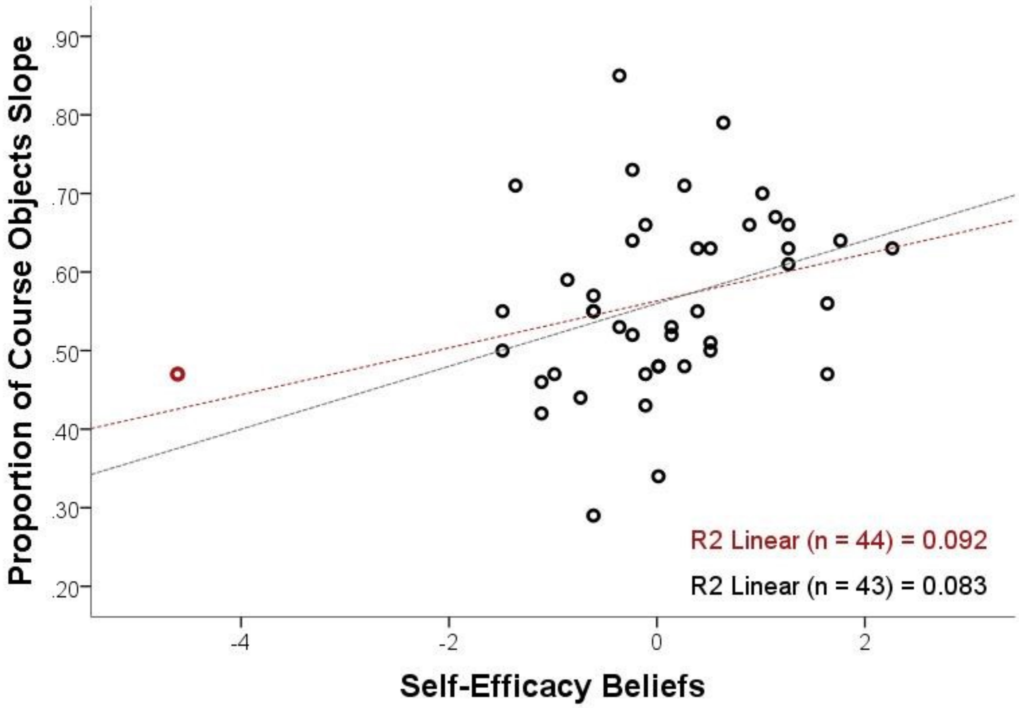


Self-efficacy

There was a weak, positive correlation (n = 44, p < .05) between students' self-efficacy and their linear-change slopes (*Spearman* r = .36). Students with stronger general self-efficacy, who believed they would do well in every situation, also had slightly higher rates of change in the proportion of course objects accessed (*Figure 12*).

Figure 12

Relationship between Self-efficacy and Interaction Trajectory Slopes



A visual inspection of Figure 12 revealed a single significantly lower score (marked in red on the left side of the chart). This outlier explains why the distribution had not been considered normal according to the Shapiro-Wilk's test of normality. With the outlier removed normality was now achieved (KS = .07, SW = .98), the Spearman rank correlation was still significant (n = 43, r = .33, $p < .05$) and a Pearson correlation was confirmed on one side of the distribution (n = 43, r = .29, $p < .05$, *1-tail*; r = .29, p = .061, *2-tailed*).

Other characteristics

Major Life Goals. There was a weak positive relation between students' aspirations to have political influence as a life goal and their slopes (r = .3, n = 45, $p < .05$). Students who had a stronger desire to promote or ensure the welfare of others, to keep up to date with or being influential in public affairs also accessed higher proportions of the course (*Figure 13*).

Figure 13

Relationship between Political Influence Life Goal and Interaction Trajectory Slopes

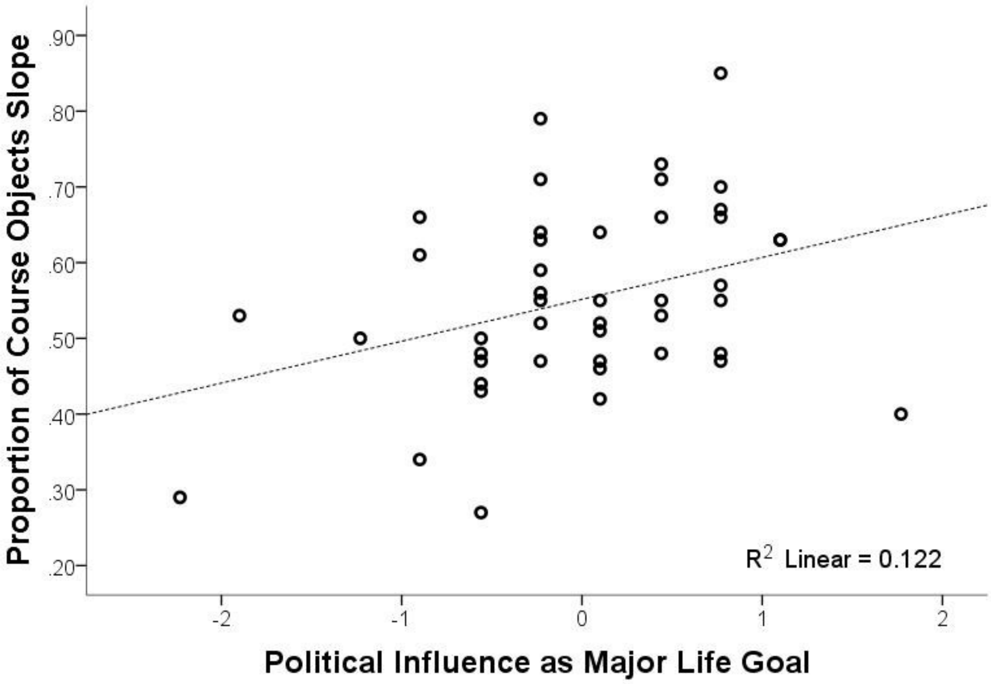
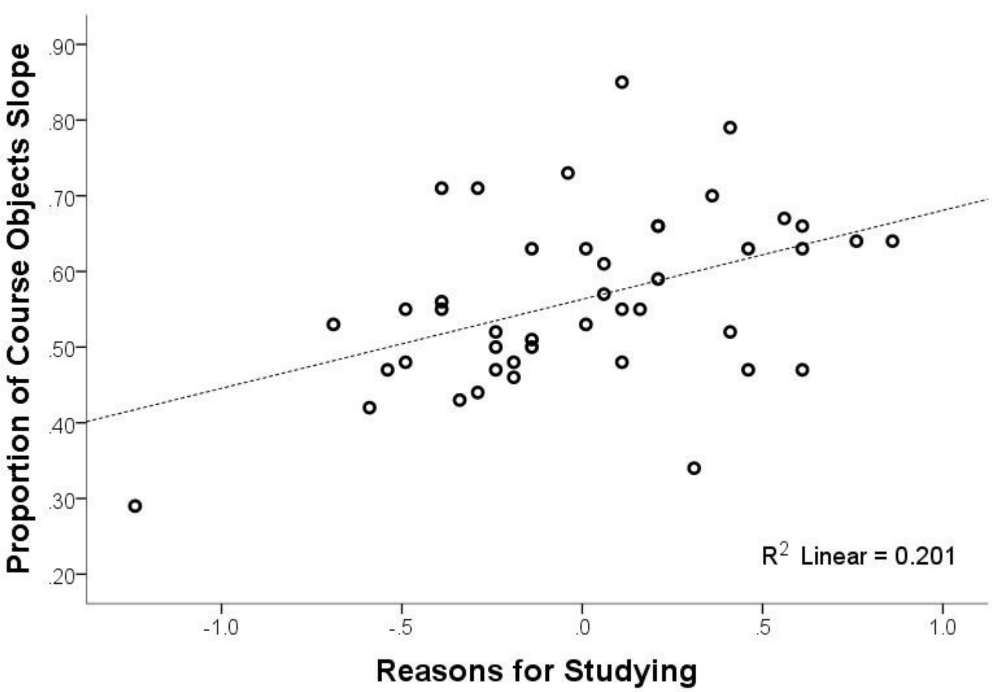


Figure 14

Relationship between Reasons for Studying and Interaction Trajectory Slopes



Reasons for studying. There was a moderate positive relation between students' reasons for studying and their slopes ($r = .4$, $n = 44$, $p < .01$). There was no relation for extrinsic reasons ($r = .09$, $p = .57$) and a weak relation for students' intrinsic reasons (*Spearman* $r = .39$, $p < .05$). Students with stronger overall reasons (both extrinsic and intrinsic) and stronger intrinsic reasons also had higher rates of change in the proportion of course objects accessed (*Figure 14*).

4. Student characteristics predict longitudinal interaction behaviour

Multilevel regressions were estimated to predict the shape of students' change trajectories and verify if this change was the same for students of varying characteristics (*Table 11*). Repeated measures longitudinal data was used on level 1 with students as subjects on level 2. Longitudinal analyses focused on students' interactions before, during and after the course (proportion of course time $_{max}$ = 112%). The estimation method was Maximum Likelihood (ML) to allow comparison between nested models (Heck et al., 2010, 2013).

The Akaike Information Criterion (AIC) index was used to compare models. Higher model quality (Heck et al., 2010), a better trade-off between goodness of fit and simplicity, was assumed with lower AICs. A diagonal residual variance structure was used to describe random effects, the relationship between intercepts and slopes. More complex structures were also explored, e.g. autoregressive or unstructured. However, their AIC estimates did not outperform diagonal structures. Thus, when present in the following models, random effects analyses assume: 1) different variances across measurement occasions with 2) heterogenous variances for each measurement occasion in the diagonals of the matrix (intercepts variances and slopes' variances), and 3) no covariances between occasions (between intercepts and slopes). Intraclass Correlation Coefficients (ICC; Heck et al., 2010, 2013) were calculated using the formula σ^2_s / $(\sigma^2_s + \sigma^2_e)$, to indicate the proportion of total variance explained by random effects variance.

Table 11

Interaction Trajectories' Multilevel Model Estimates (& Standard Deviations)

Parameter	Model 0 Null	Model 1 Time	Model 2 Time^2	Model 3 Time^3	Model 4 A. Period	Model 5 Conscient.	Model 6 Conscient.
				Fixed			
Intercept	33.7 (1)	8.8 (0.7)	8.5 (0.7)	8.4 (0.7)	7.5 (0.7)	7.5 (0.7)	10.4 (1.0)
Time		0.6 (0.1)	0.6 (0.2)	0.6 (0.2)	0.6 (0.2)	0.6 (0.2)	0.6 (0.2)
A. Period					1.4 (0.5)	1.4 (0.5)	1.4 (0.5)
Conscient.						1.9 (0.9)	
Higher							0 (0)
High							-3.6 (1.1)
Low							-3.8 (1.2)
Lower							*-4.0 (1.4)***
				Random (variance)			
Residual (occ.)	424.6 (3.1)	10.6 (0.5)	9.1 (0.5)	8.7 (0.4)	8.1 (0.4)	8.1 (0.4)	8.1 (0.4)
Intercept	46 (3.3)	10.7 (1.5)	10.4 (1.5)	9.9 (1.5)	11.3 (1.6)	9.9 (1.5)	8.9 (1.4)
Time Slope		.02 (0.1)	.02 (0.1)	.03 (0.1)	.02 (0.1)	.02 (0.1)	.02 (0.1)
Time^2 Slope			.01 (0.1)	.05 (0.1)	.05 (0.1)	.10 (0.1)	.10 (0.1)
Time^3 Slope				$.02^{-8e}$ (*)	$.02^{-8e}$ (*)	$.02^{-8e}$ (*)	$.02^{-8e}$ (*)
A. Period Slope					2.9 (0.9)	2.9 (0.9)	2.9 (0.9)
ICC	9.8%	50.2%	53.3%	53.6%	63.8%	61.4%	59.5%
AIC	36,014	21,444	20,973	20,900	20,700	20,697	20,696

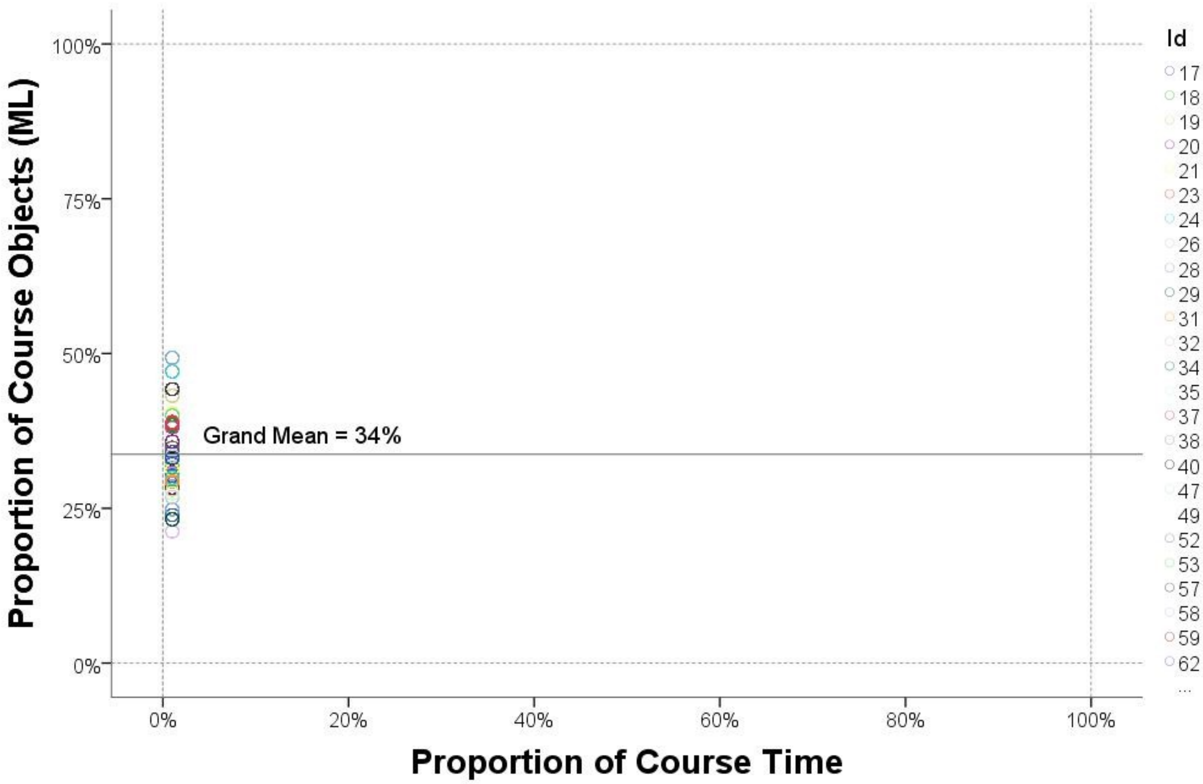
* Standard deviation = $.08^{-4e}$ ** *Non-significant, p > .05*

Model 0 – No predictors

A null model was defined with no fixed or random predictors to verify if the average proportion of course objects accessed varied across students (*Figure 15*). Students' average proportion of objects was 34% (*SD* = 1, *t* (45.2) = 31.72, *p* < .001) and was significantly different between students (random variance; *Wald Z* = 4.3, *p* < .001). The average proportion of course objects accessed was significantly different between students, that is, it may not be said that all students interacted with a similar average proportion of objects throughout their courses.

Figure 15

Model 0 – Average Proportion of Course Objects Across Students



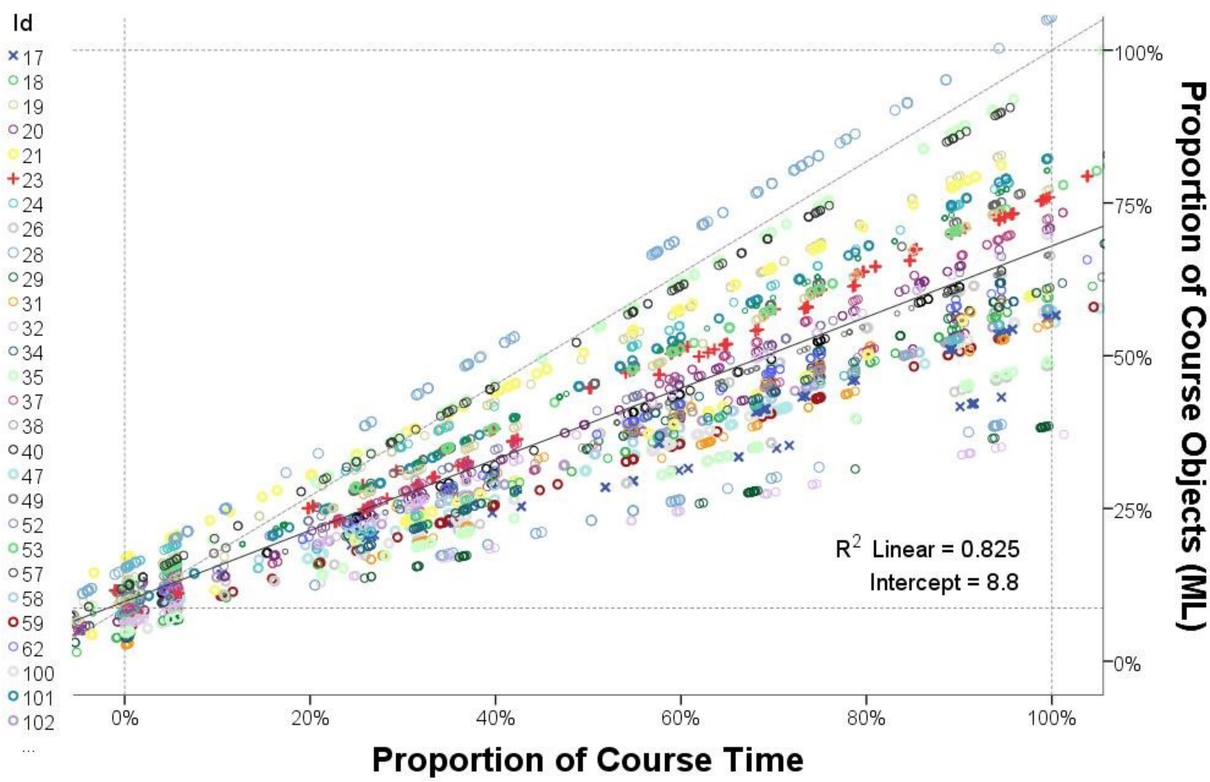
The AIC for the null model was 36,014 with 3 parameters (fixed effects intercept, random effects intercept, and residual). On Figure 15, the fixed intercept is the grand mean (*M* = 33.78, *SD* = 1.0) and students' individual average proportion of objects are each shown in different colours (random intercepts). Differences between students' individual intercepts accounted for 9.8% of the total variance (ICC). Since this proportion was higher than 5%, the null model suggested further multilevel modeling was justified (Heck et al., 2010, p. 6). The random residual parameter (*M* = 425.7, *SD* = 3.1) also indicated there was significant variance to be explained (*Wald Z* = 44.69, *p* < .001).

Model 1 – Linear Time

Model 1 was defined to answer two questions: was there a change in the proportion of course objects accessed over time and, was this change the same for different students? To answer these questions, for each student each successive measurement was defined by a growth interaction trajectory with an estimated initial proportion of course objects accessed (*intercept*), a rate of change in this proportion across linear time (*slope*), and individual measurement deviations from these parameters. To observe linear change in time, the variable "proportion of course time" was coded 0% for the first day of classes and 100% for the last.

Figure 16

Model 1 – Linear Interaction Trajectories Across Students



This model indicated the average change in the proportion of course objects could be significantly explained in terms of a linear interaction trajectory with an overall average initial proportion of 8.8 by the first day of classes (*intercept, SD* = .7, *t* (45.12) = 17.7, $p < .001$) and an average linear growth rate of .57 per unit of time (*slope, SD* = .2, *t* (45.02) = 29.71, $p < .001$). In this model, differences between students' individual trajectories of change were also significant, their individual trajectories varied significantly both in the proportion of course objects accessed by the first day of class (*Wald Z* = 4.6, $p < .001$) and the average rate at which their proportion of course objects grew for every unit of linear time (*Wald Z* = 4.71, $p < .001$).

On Figure 16, intercepts are not grand interaction means as in Figure 15 but linear interaction trajectories of change intercepts: the overall average initial proportion of course objects accessed (*mean intercept*, *M* = 8.8, *SD* = .7) and each student's individual and significantly different initial proportions (*random intercepts*). The effect of time can also be observed on the overall average trajectory slope (*fixed effect*, *M* = .6, *SD* = .1) and on each students' varying linear trajectories of change (*random slopes*).

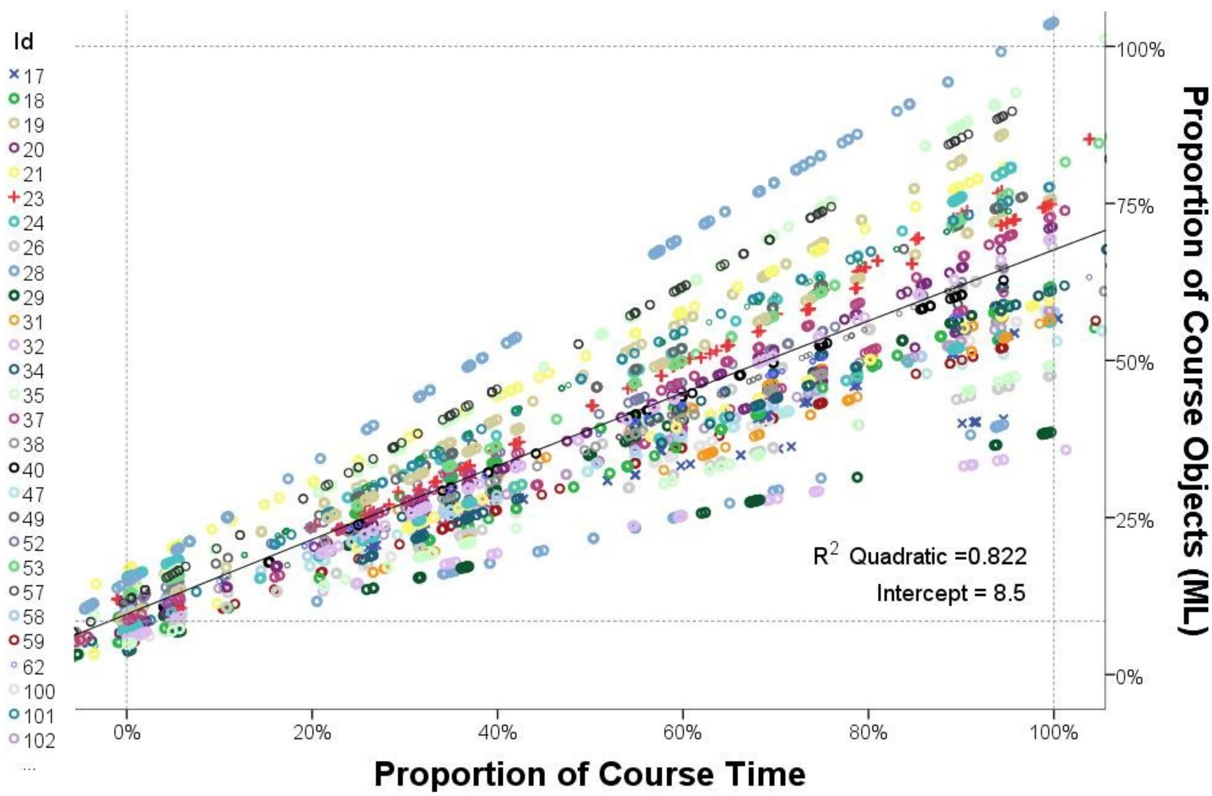
The effect of linear time, of students' linear trajectories of change, accounted for 50.2% of the variance (ICC). That is, the rate at which students' initial proportion of course objects accessed grew across linear time explained half the differences in the proportion of course objects accessed. The AIC for model 1 was 21,444 with 5 parameters (model 0 and fixed and random effects of linear time). The remaining variance was also significant (49.8%, *Wald Z* = 44.4, $p < .001$), could still be explained by factors other than average and individual differences in students' initial and increasing proportion of course objects per linear unit of time.

Model 2 – Quadratic Time

Model 2 was designed to verify if there was a quadratic change (acceleration or deceleration) in the proportion of course objects accessed and if the quadratic change was the same for different students. Quadratic time was computed by multiplying the proportion of course time by itself (*time*time*). The fixed effect of quadratic time on the overall average trajectory of change was also tested but was found to be non- significant and was not further included in this or future models (*fixed effect*, M = -.01, SD = .13, t (45.96) = .64, p = .426). This meant students' average interaction trajectory could not be significantly described in terms of quadratic changes in time. Instead, students' general average change in the proportion of course objects accessed could be better described with a linear trajectory of change across time.

Figure 17

Model 2 – Quadratic Interaction Trajectories Across Students



However, quadratic changes in students' interaction trajectories varied significantly between individuals (random effect, *Wald Z* = 4.37, $p < .001$). That is, differences in students' varying trajectories of interaction could be better explained by considering changes in students' rates of change in the proportion of course objects accessed across time. That curved (quadratic) estimated individual trajectories, student's varying patterns of acceleration or deceleration in the proportion of course objects accessed, could further explain differences in students' interactions. On Figure 17, random effects of quadratic time can be appreciated in students' declining (e.g. id=17) or increasing (e.g. id=23) curved patterns.

With a linear average trajectory of change (fixed effect) and quadratic random effects of quadratic time in students' growth rates, model 2 accounted for 53% of the total variance (ICC). The AIC was 20,973 with 6 parameters (model 1 parameters plus random effects of quadratic time), a significantly better AIC than model 1. The unexplained random variance was also significant (*Wald Z* = 44.2, $p < .001$), that is, could still be explained by factors other than the average linear trajectory of change in the proportion of course objects and differences in students' individual quadratic interaction trajectories, their intercepts and slopes.

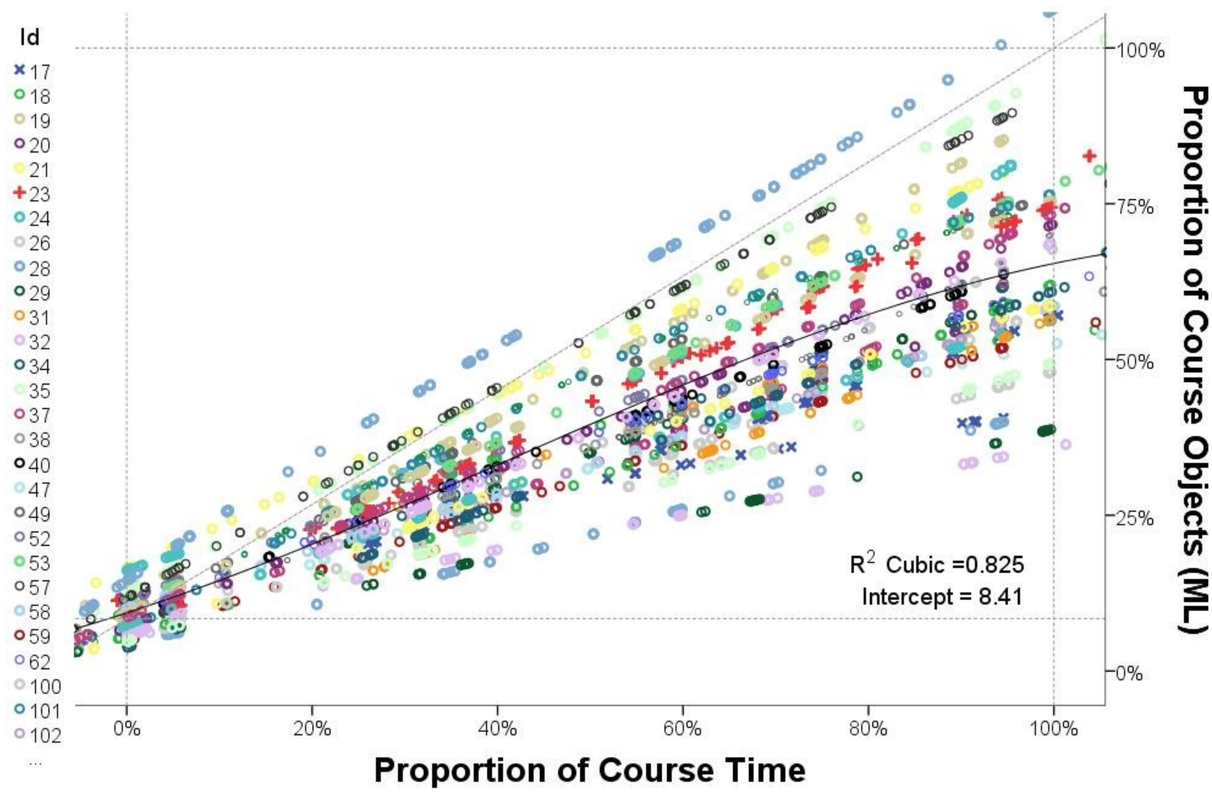
Model 3 – Cubic Time

Model 3 was defined to predict students' cubic changes (acceleration and deceleration) in the proportion of course objects accessed over time and resolve if cubic changes in the rate of interaction trajectories were the same for different students. Cubic time was computed by multiplying the proportion of course time by itself twice (time*time*time). Similar to quadratic effects in model 2, there was a non-significant general fixed effect of cubic time in this model ($M = -.01^{-4e}$, $SD = .001$, $t\,(29.44) = -.535$, $p = .597$). This meant students' general average trajectory of change in the proportion of course objects accessed could still be better described as a linear trajectory and general fixed effects of cubic time were not included in further calculations.

However, cubic changes in the proportion of course objects accessed varied significantly between students' individual trajectories of change (random effects, *Wald Z* = 3.03, $p < .01$). That is, differences in students' varying trajectories of interaction could be better explained by describing acceleration and deceleration patterns in the rate at which students' individual proportions of course objects accessed grew. That cubic estimated individual trajectories could further explain differences in students' interactions. These random effects of cubic time can be appreciated in students' increasing and declining interaction trajectory patterns (*Figure 18*).

Figure 18

Model 3 – Cubic Interaction Trajectories Across Students



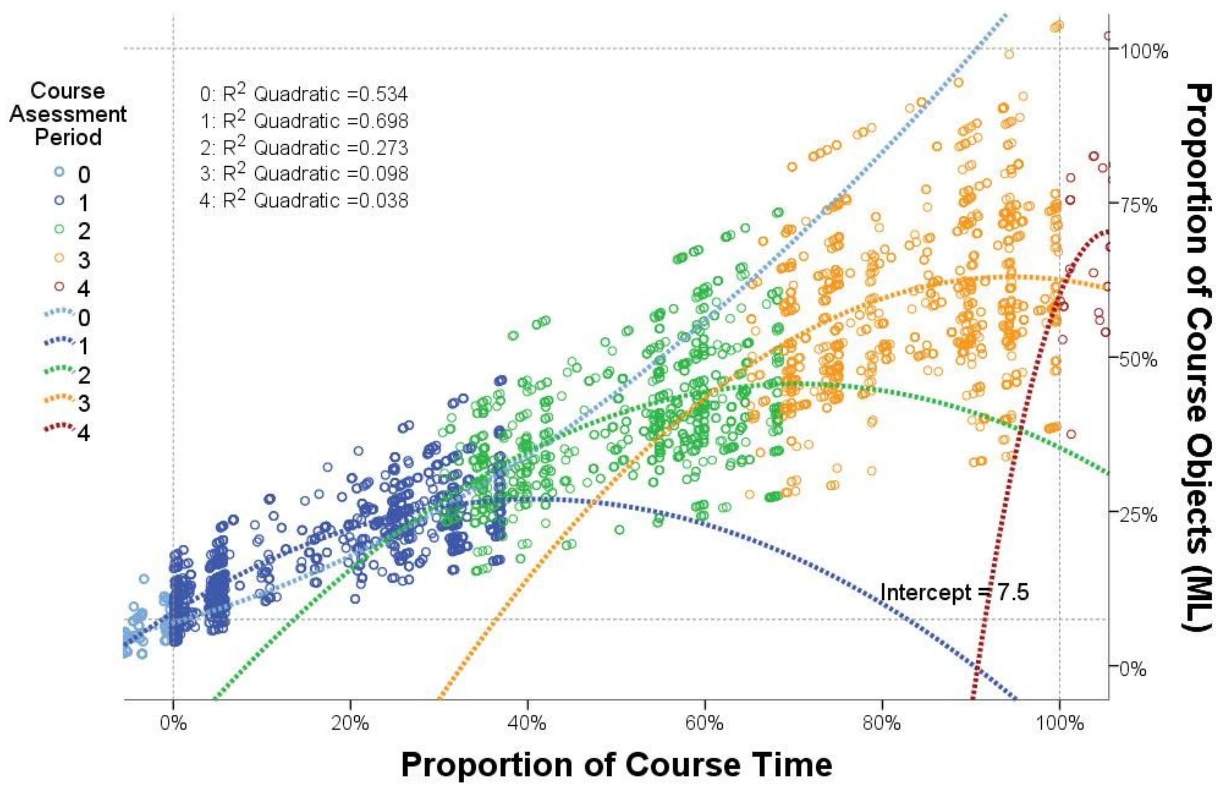
The AIC for Model 3 was 20,900 with 7 parameters (model 2 parameters plus random effects of cubic time). Model 3, with a general linear average trajectory and individual students' cubic interaction trajectories accounted for 54% of the total variance. The unexplained random variance was still significant (*Wald Z* = 43.4, $p < .001$), that is, could still be explained by factors other than the average linear trajectory of change in the proportion of course objects and acceleration and deceleration differences in students' individual interaction trajectories.

Model 4 – Assessment Periods

Model 4 was defined to predict changes in the proportion of objects across assessment periods, whether trajectories were the same across periods and if trajectories were the same for students. For this purpose, each course interaction data was classified with a dummy variable to indicate whether each course object belonged to the first (Period = 1), second (Period = 2), or third (Period = 3) course assessment period. Interactions before (Period = 0) and after the course (Period = 4) were also classified (*Figure 19*).

Figure 19

Model 4 – Interaction Trajectories Across Assessment Periods



The general average trajectory of change in the proportion of objects accessed was significantly different between assessment periods with an average initial proportion of 7.5 (*SD* = .7, *t* (46.6) = 14.3, *p* < .001), an average slope change of 0.6 for per unit of linear time (*SD* =

.2, t (44.6) = 24.4, $p < .001$), and an average slope change of 1.4 ($SD = .5$, t (48.94) = 4.55, $p < .001$) per assessment period. On the average, students progressively interacted with larger proportions of objects as the course progressed through its assessment periods.

Individual student trajectories were also significantly better explained by observing differences in students' trajectories between assessment periods (*random effects*, *Wald Z* = 3.55, $p < .001$). This means that students' individual interaction trajectories varied significantly across time, with different acceleration and/or deceleration patterns across different assessment periods. The AIC for this model was 20,700 with 9 parameters (model 3 parameters plus fixed and random effects of assessment period). Model 4, with a significantly increasing general linear average trajectory and significantly different average trajectories across assessment periods, and with students' individual linear, quadratic, and cubic differences across assessment periods, accounted for 64% of the variance. Since random variance was also significant (*Wald Z* = 43.1, $p < .001$), other factors than average and individual differences between assessment periods could still further explain differences in students' interaction trajectories.

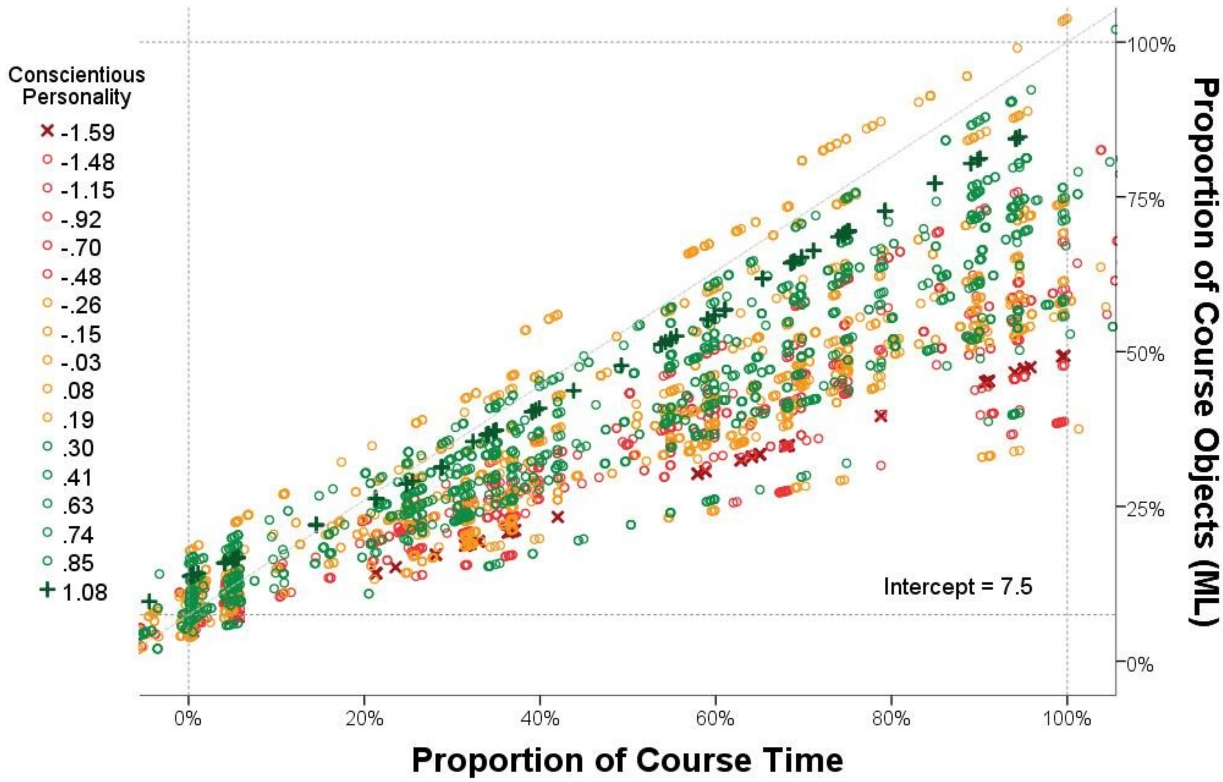
Model 5 – Conscientious Personality

Model 5 was designed to predict students' growth in the proportion of course objects accessed across assessment periods, students and conscientiousness trait scores. This model intended to answer whether students' average interaction trajectories were the same across varying degrees of students' conscientiousness. To answer this, fixed effects of students' conscientiousness scores were added to Model 4. The average rate of change in the growing proportion of course objects varied significantly across time, assessment periods and between students of varying conscientiousness levels with an average slope change of 1.9 ($SD = .9$, t (45.8.) = 2.37, $p < .05$) per higher conscientiousness score unit. As it may be observed in Figure

20, on the average, as students' conscientiousness levels increased so did the rate at which their proportion of course objects accessed increased across time and assessment periods.

Figure 20

Model 5 – Interaction Trajectories Across Conscientiousness Scores



The AIC was 20,697 with 10 parameters (model 4 parameters plus fixed effects of conscientiousness). Random and fixed effects in model 5 accounted for 61% of the variance. But the remaining random variance was still significant (*Wald Z* = 43.1, $p < .001$), that is, other factors than average differences in conscientiousness scores, time and assessment periods, and individual acceleration or deceleration patterns could further explain differences in interactions.

Model 6 – Conscientious Personality Groups

This model was also designed to answer whether students' growth rates in the proportion of course objects accessed was the same across different conscientiousness levels. While Model

5 introduced conscientiousness scores as fixed effects covariates, Model 6 introduced conscientiousness groups as fixed effects factors: lower (*M* = -1.4, *SD* = .2), low (*M* = -.5, *SD* = .2), high (*M* = .13, *SD* = .21), and higher (*M* = .8, *SD* = .13). The average growth rate in the proportion of course objects accessed across linear time and assessment periods was significantly different between these conscientiousness groups (t (3, 46.28) = 3.65, $p < .05$).

Figure 21

Model 6 – Interaction Trajectories Across Conscientiousness Groups

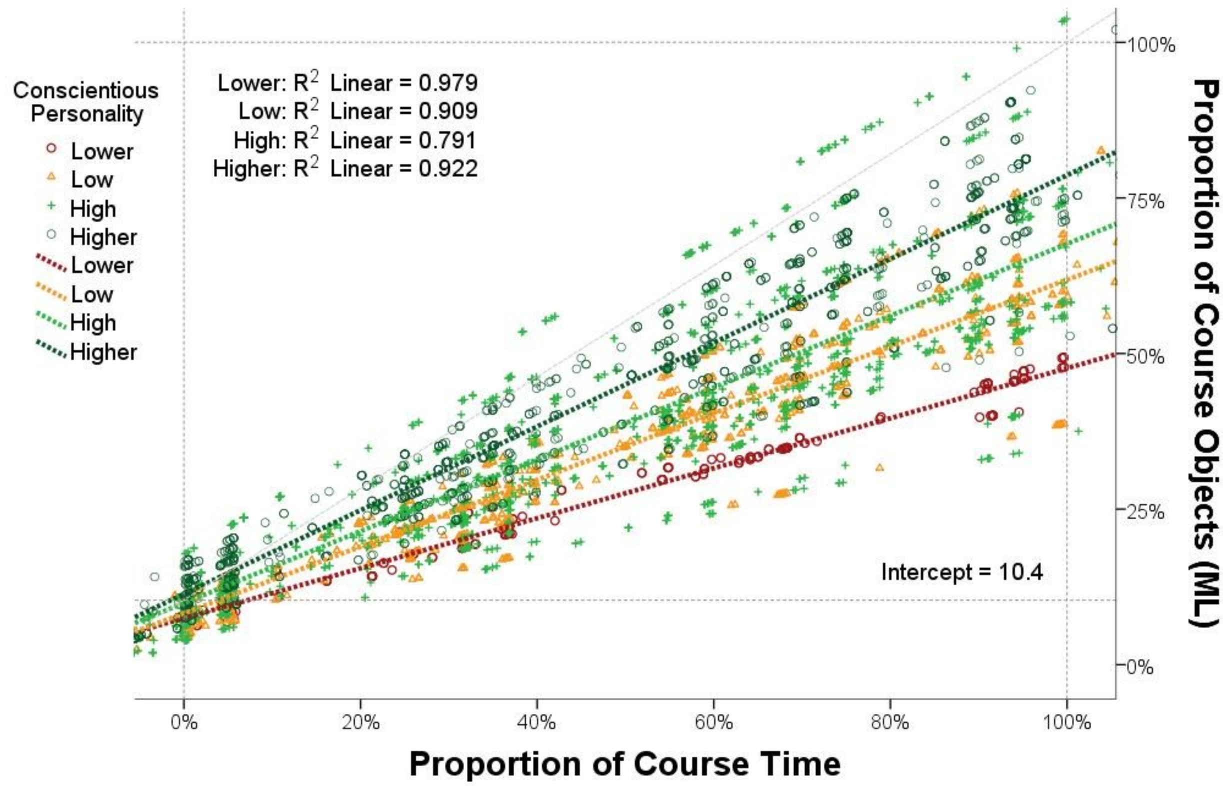
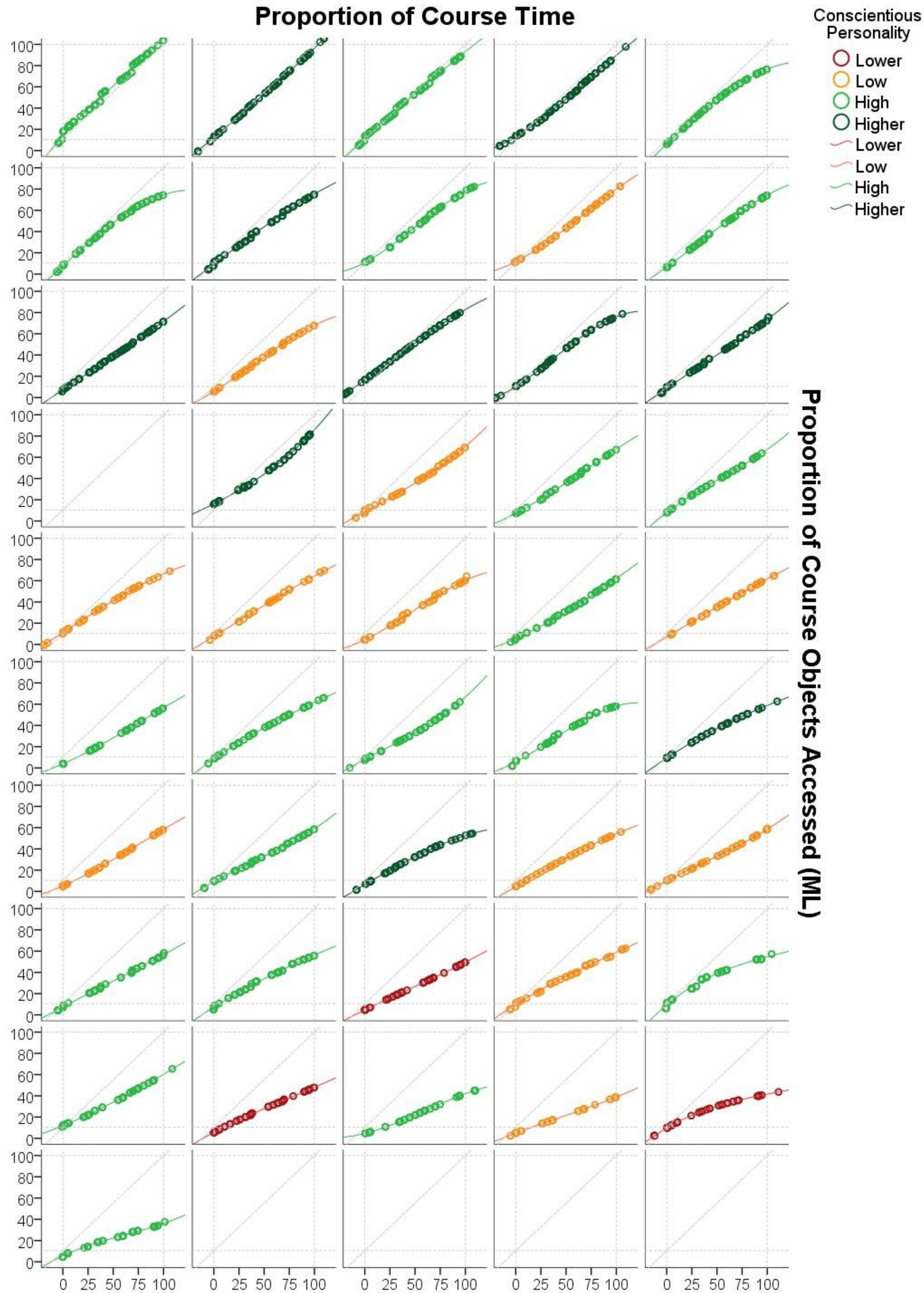


Figure 21 shows these differences with average linear predicted interaction trajectory trends for each group, especially between the lower conscientiousness average trend (red) and the higher conscientiousness average trend (dark green). The AIC for this model was 20,696 with 12 parameters (model 4 plus 3 conscientiousness group factors).

Figure 22

Students' Individual Cubic-Change Interaction Trajectory Models (ML)


Proportion of Course Time
Proportion of Course Objects Accessed (ML)
Conscientious Personality
Lower
Low
High
Higher
Lower
Low
High
Higher
0 25 50 75 100
0
20
40
60
80
100

Differences in student average growth rates across conscientious personality groups accounted for 60% of the total variance and the remaining random variance was significant (*Wald Z* = 43.1, $p < .001$). Multilevel analyses presented in this section were computed to figure the shape of students' interaction trajectories and if this change was the same for students of different conscientiousness groups. Multilevel models (*Table 11*) explained that on average the change in students' trajectories of course objects accessed was linear (Models 1-3) with different rates of change for different course assessment periods (Model 4). However, random parameters in these models also specified that individual student trajectory differences could be further explained by differences in linear, accelerating and/or decelerating rates of change across time (*Figure 22*). Furthermore, once the shape of students' trajectories was established by taking into account these individual linear, quadratic, or cubic effects of time across assessment periods, multilevel models confirmed students' differences in conscientiousness scores (Model 5) and conscientiousness groups (Model 6), significantly explained structural (average) differences between students' interaction trajectories across linear time, assessment periods, and each other.

5. Relationship between characteristics, interactions and achievement

How are students' characteristics and trajectories of change related to their achievement? Two-tailed Pearson and Spearman correlations were used to answer these questions. Students' slopes (REML), major life goals and psychosocial maturity were found to be related to course total and exam grades. The following sections describe these results in more detail.

Table 12

Correlations between Interaction Trajectories and Achievement

Measure	*n*	*Course Total*	Knowledge	*Performance*
Intercept	46	*.03*	.09	*-.16*
Slope	46	*.27*	.38**	*.19*

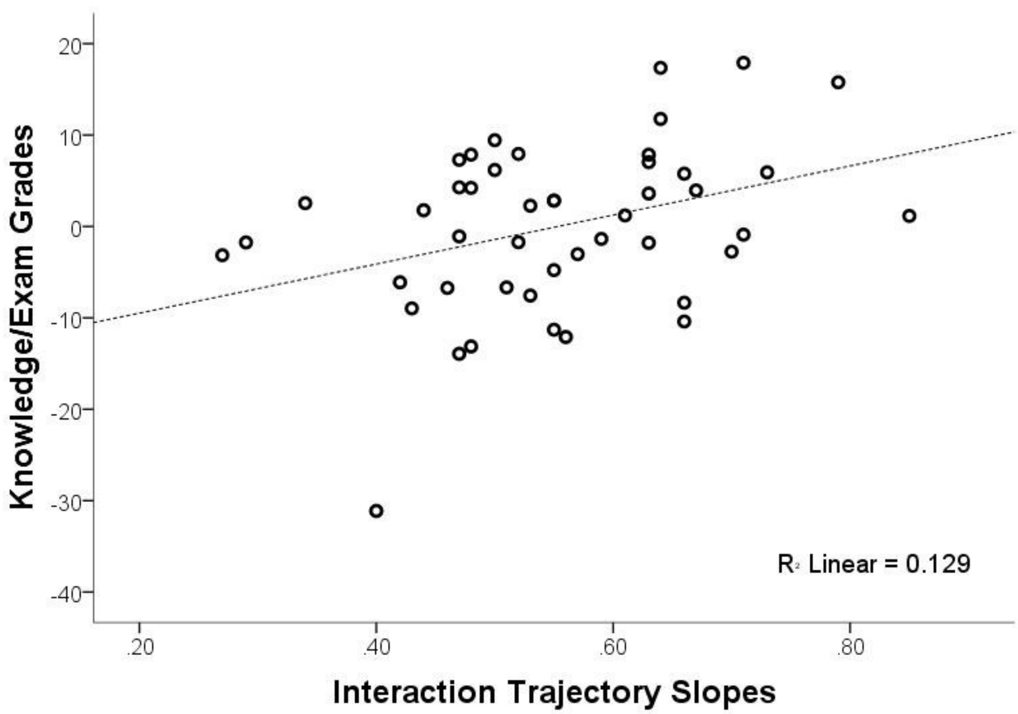
** Pearson correlation (2-tailed) is significant at .01

Interaction behaviour

How are students' interaction trajectories related to achievement? Although there was a moderate relationship between intercepts and slopes ($r = .43$, n = 46; *Table 10*), students' initial proportion of course objects accessed (*intercepts*) were not related to any type of student achievement (*Table 12*). However, students' slopes, the estimate linear rate of change in the proportion of course objects accessed per unit of time were found to be significantly related to knowledge but not to course total or performance grades (*Figure 23*).

Figure 23

Relationship between Interaction Trajectory Slopes and Achievement



With intercepts held constant, the relationship between slopes and achievement was also significant (*Knowledge partial* $r = .38$, 43, $p < .05$; *Course Total partial* $r = .34$, 43, $p < .05$). Students with higher rates of change in the proportion of objects accessed also attained higher exam (knowledge) and course total grades, regardless of initial proportion of objects accessed.

Student characteristics

How are students' characteristics related to achievement? No significant relations were found except for negative associations between three students' major life goals, psychosocial maturity stage 6 love (*intimacy* vs *isolation)*, and their course and exam grades (*Table 13*).

Table 13

Correlations between Student Characteristics and Achievement

Measure	*n*	*Course Total*	Knowledge	*Performance*
		Achievement		
Course Total	*46*		.95^{++}	.76^{++}
Knowledge grades	*46*	.95^{++}		.60^{++}
Performance grades	*46*	.76^{++}	.60^{++}	
		Motives		
Reasons for Studying	44	.14	.09	.21
Intrinsic	44	.11	.08	.25
Extrinsic	44	.05	.01	.06
		Major Life Goals		
Family Life	*45*	-.36^{+}	-.34^{+}	-.26
Family Proud	45	-.12	-.13	-.08
Having Fun	*45*	-.45^{++}	-.43^{++}	-.27
Meaningful Contribution	*45*	-.33^{+}	-.33^{+}	-.08
High Status	45	-.09	-.19	.06
Community Leader	45	-.03	-.07	-.06
Political Influence	45	-.01	-.05	.09
Athletic	45	-.08	-.08	-.02
Artistic	45	-.06	.08	-.10
Spiritual Life	45	.20	.22	.09
Business Leader	45	-.15	-.19	.01

Measure	*n*	*Course Total*	Knowledge	*Performance*
		Beliefs		
Self-Efficacy	44	.14	-.03	.23
		Psychosocial maturity		
1 Hope	43	-.10	-.14	-.24
2 Will	43	-.02	-.17	-.03
3 Purpose	43	.07	-.08	-.02
4 Competence	43	.18	.16	.10
5 Fidelity	43	-.02	-.08	.02
6 Love	*43*	-.41⁺	-.48⁺⁺	-.21
7 Care	43	.20	.15	.02
8 Wisdom	43	-.13	-.27	-.15
		Personality		
Extroversion	45	-.18	-.22	-.06
Agreeableness	45	-.07	-.15	.03
Conscientiousness	45	.14	.04	.18
Neuroticism	45	-.04	-.01	-.21
Openness	45	.00	-.05	.05
		Self-regulation		
Overall functioning	20	-.18	-.18	.03
Searching	20	-.21	-.21	.04
Receiving	20	-.12	-.14	.10
Implementing	20	-.22	-.20	.06
Triggering	20	-.15	-.12	.06
Planning	20	-.03	-.06	.20
Evaluating	20	.04	.09	-.05
Assessing	20	-.19	-.04	-.18

++ *Spearman rank correlation (2-tailed) is significant at .01*

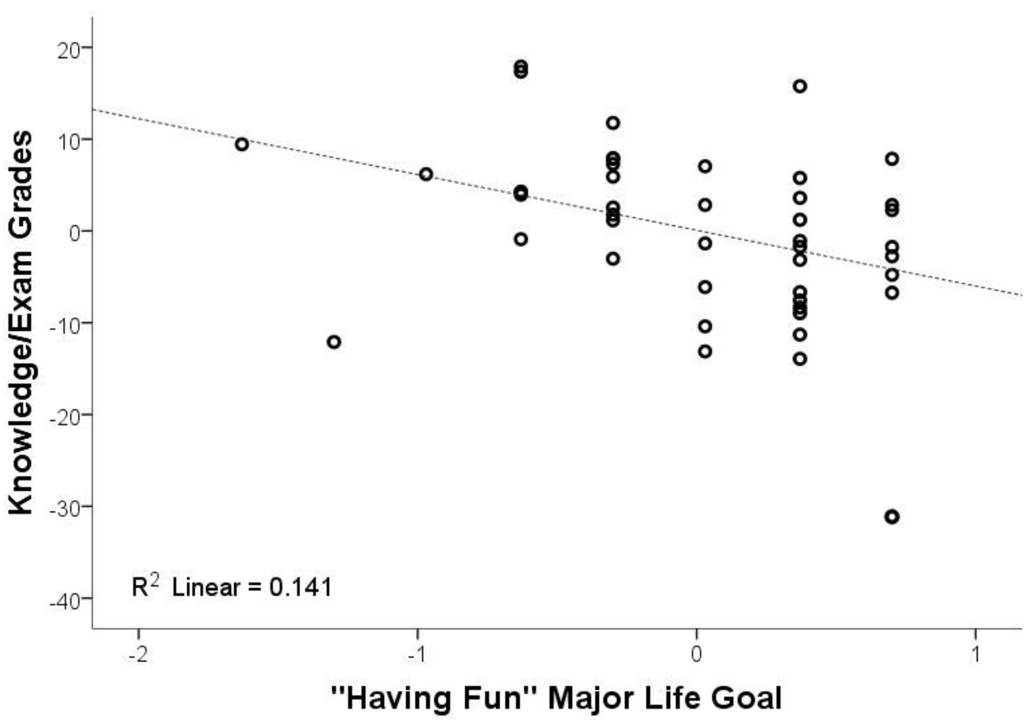
\+ *Spearman rank correlation (2-tailed) is significant at .05*

Major Life Goals

Three students' life goals were negatively related to students' achievement (*Spearman*, $n = 45$, $p < .05$). Course total grades were moderately and weakly negatively related to *having fun* ($r = -.45$), *family life* ($r = -.36$) and *meaningful contribution*s ($r = -.33$) as life goals. Knowledge grades were also negatively related to *having fun* ($r = -.43$), *family life* ($r = -.34$) and *meaningful contributions* ($r = -.33$) as life goals. Students with aspirations to have new and different experiences, or an exciting lifestyle attained moderately lower course total and knowledge grades (*Figure 24)*. Students who prioritized having a satisfying marriage, children, being a good parent, partner, husband or wife, or who aspired to make meaningful contributions to their field of study, promote or ensure the welfare of others, care for and nurture others, and have the time and means to relax and enjoy life also attained slightly lower course total and knowledge grades.

Figure 24

Relationship between "Having Fun" Major Life Goal and Achievement



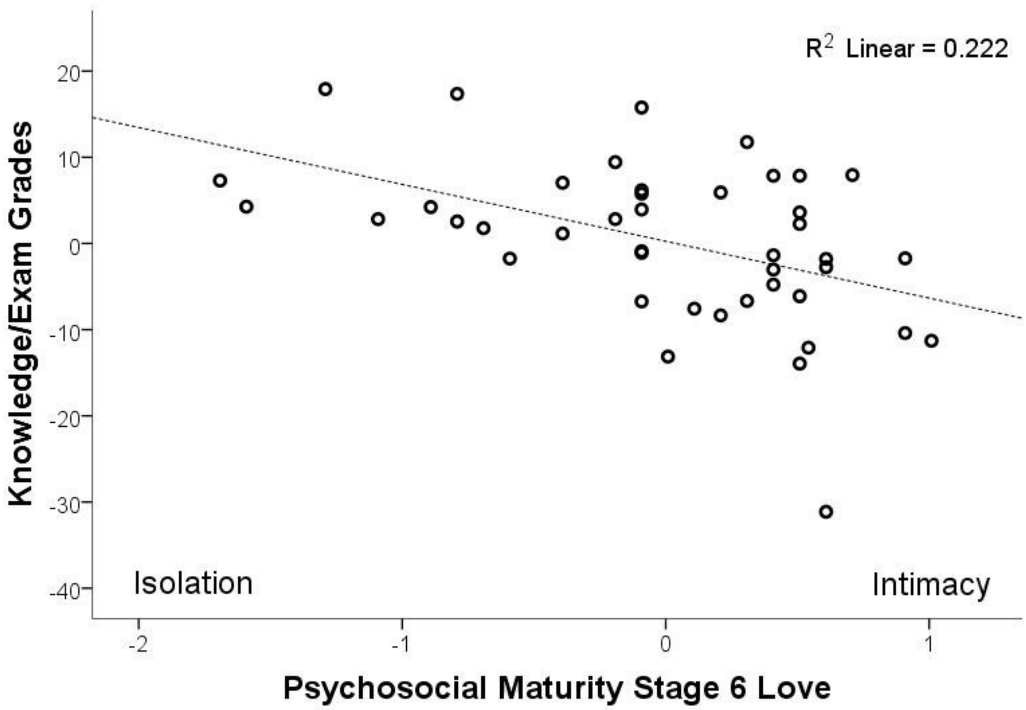
Spearman correlations were also used to verify if these three life goals were related to other student characteristics (*Table 6, Table 7, Table 8,* & *Table 9*). Having fun as a life goal was moderately related to more extroverted personalities (r = .47, p < .01), aspirations to achieve high status (r = .43, p < .01) and athletic life goals (r = .41, p < .01), and weakly related to being open to intimate, reciprocal relationships (*intimacy,* r = .39, p < .01) and having a *family life* (r = .31, p < .05). Aspirations to have a *family life* were also moderately related to a desire to make one's *family proud* (r = .40, 45, p < .01), weakly to extrinsic (r = .36) and overall reasons for studying (r = .39, 43, p < .01), being open to intimate, reciprocal relationships (*intimacy,* r = .33, 42) and to feeling satisfied with one's life (*wisdom,* r = .31), and aspiring to make *meaningful contributions* (r = .32). Finally, aspirations to make *meaningful contributions* were moderately related to self-regulation overall (r = .53, 20, p < .05), receiving (r = .48), and searching skills (r = .47), to being open to intimate, reciprocal relationships (*intimacy,* r = .41, p < .01) and to being satisfied with one's life (*wisdom,* r = .44, p < .01), intrinsic (r = .42, 43, p < .01) and overall reasons for studying (r = .38), having a more agreeable personality (r = .39, p < .01), and aspirations to have *political influence* (r = .38, p < .01) and to make one's *family proud* (r = .36).

Psychosocial maturity

Students' MEPSI Stage 6, which measures the degree to which students have resolved to form close, honest, loving relationships with other people (intimacy) or to have few or no friendships or close relationships (isolation), was moderately and negatively related to course (*Spearman* r = -.41, 43, p < .05) and knowledge grades (*Spearman* r = -.48, p < .01). Students with higher course and knowledge grades also had a stronger tendency to keep what they thought or felt to themselves, to not get too involved with people, to have less close, honest, and loving relationships, or to find it less easy to make close friends (*Figure 25*).

Figure 25

Relationship between Psychosocial Maturity Stage 6 and Achievement

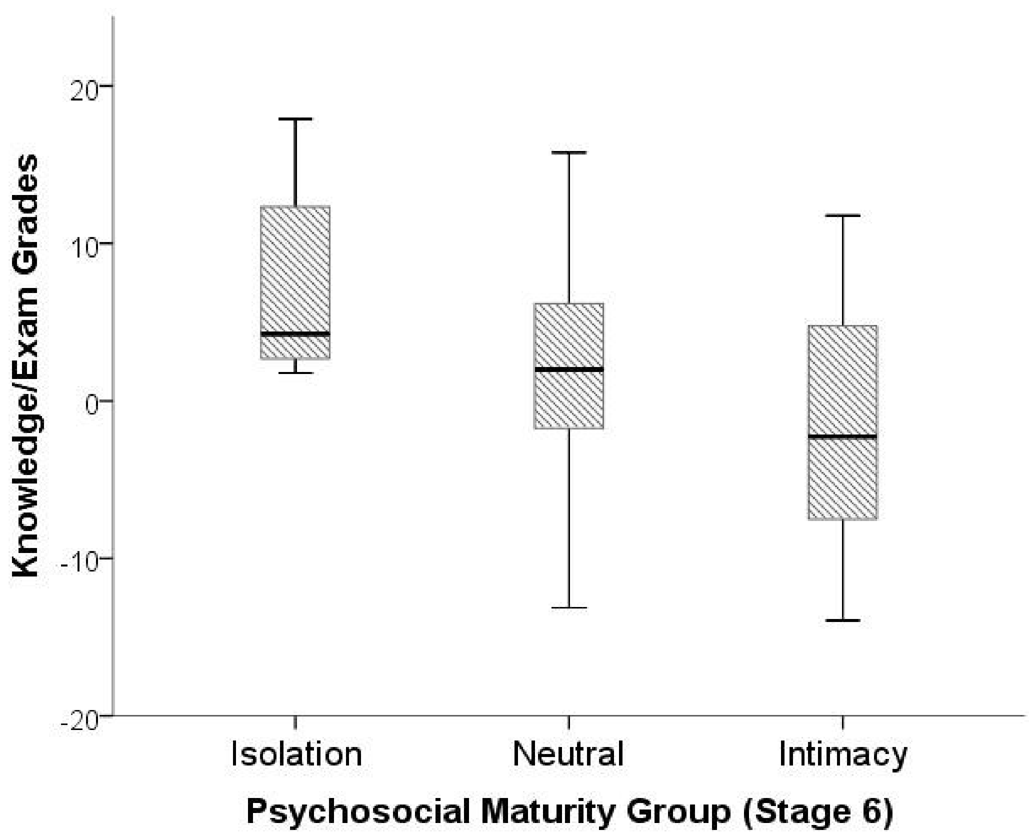


Spearman correlations were also computed to verify if this psychosocial stage was also related to other student characteristics. Students' intimacy-isolation resolutions were positively and strongly related to students' extroversion ($r = .64$, $n = 42$, $p < .01$), moderately to students' agreeableness ($r = .47$, $p < .01$), self-regulatory searching ($r = .53$, $n = 20$, $p < .05$), planning ($r = .5$), weakly to self-efficacy ($r = .33$, $n = 42$), general reasons for studying ($r = .32$, $n = 42$), and making one's family proud ($r = .37$) and having fun as life goals ($r = .31$). Students with stronger inclinations to keep what they thought or felt to themselves, to not show too much of themselves or to get too involved with people or to find it less easy to make close friends, who also tended to obtain higher course and knowledge grades also reported being much more introverted (less extroverted), moderately less agreeable, had weaker self-regulatory searching and planning skills, less aspirations to make their family proud or have fun as major life goals, and also reported having weaker self-efficacy and overall reasons for studying.

An analysis of variance further confirmed that students of different stage 6 psychosocial resolutions obtained significantly different exam grades, F (2, 39) = 4.42, p = .02, but not total grades, F (2, 39) = 2.09, p = .14. Bonferroni post hoc tests specified that knowledge grades were higher for students with an *isolation* type of resolution (M = 7.3, SD = 6.6) compared to grades of students with an *intimacy* type of resolution (M = -1.8, SD = 7.5), but not to grades of students with more neutral or no resolution at this stage (M = 1.5, SD = 7.5; *Figure 26*)

Figure 26

Achievement Differences between Psychosocial Maturity Groups



Chapter 5. Discussion

This section describes the major findings in this study, why these findings are important, how they contribute to and or fill existing gaps in the field, unexpected findings and alternative explanations, acknowledge its limitations, and suggestions for further research.

Major findings

This study used course trace data to gain a deeper understanding on how and why students were able to thrive, to learn how students were actively engaged and made the most out of their course. Restricted maximum likelihood (REML) linear regressions described students' patterns of interaction, correlational analyses tested the association between these trajectories' intercepts and slopes, students' characteristics and achievement. Maximum likelihood (ML) multilevel longitudinal regressions on students' interaction data explained why students were more engaged than others during different parts of the course. Pearson and Spearman correlations tested the relationship between students' characteristics, interaction trajectory parameters, and achievement. As expected, results showed 1) interindividual differences in students' linear and longitudinal trajectories of interaction, 2) that these differences were related to a variety of students' characteristics: motivations (reasons for studying and major life goals), beliefs (self-efficacy), and resources (personality traits, psychosocial maturity and self-regulatory skills); and 3) associations between some students' characteristics (major life goals and psychosocial maturity) and interaction trajectory slopes with achievement (course total and knowledge grades).

In particular, this study found that students were able to be productively engaged, that in terms of number of activities accessed the instructional designs and delivery were more effective or worked best for students with more conscientious personalities, positive psychosocial maturity resolutions (stages 1 through 5), stronger overall and intrinsic reasons for studying, aspirations to have political influence as a major life goal, self-efficacy beliefs and self-regulatory skills (overall functioning and implementing, receiving, and assessing self-regulatory skills). The multilevel analysis found that students' longitudinal interactions could be described linearly on the average and in quadratic or cubic terms individually, that these patterns of interaction varied between course assessment periods and that these could be significantly explained by differences in students' conscientiousness. Finally, this study also found that students were able to thrive academically, that in terms of achievement these courses were more effective or worked best for students with an isolation type of psychosocial resolution and for students that gave less importance to "*having fun*", making "*meaningful contributions*" such as promoting or ensuring the welfare of others, or to have a "*family life*" as major life goals.

Findings of this study contribute to three bodies of knowledge: 1) knowledge that allows instructors and practitioners to better translate data into actionable knowledge; 2) insights related to those student characteristics and learning environment conditions that elicit optimal active and independent performance in students; and 3) a demonstration of a practical way in which this information may be used to make iterative improvements to instructional practices.

These results are important because there is a need to improve LMS data analysis claims about students LMS observed behaviours (Conijn et al., 2017; Gašević et al., 2015; Lukarov et al., 2015; Reiman et al., 2014; Lodge & Lewis, 2012) to better process, analyze and translate data into actionable knowledge for teachers and researchers (Howard et al., 2018); because teachers need to make sure that students are in condition to learn actively and independently (Patrick et al., 2012; Tanner, 2012; Weimer, 2013) and because there is a need for a parsimonious theory of performance, of student characteristics and learning environment conditions that elicit optimal performance in students (Pardo et al., 2015; Corno et al., 2002); and because there is a need for instructors who observe students' behaviours and continuously ask what motivates these behaviours to understand them (Prizant & Fields-Meyer, 2015; Clark, 2016), instructors who may be analytical about their own practice and make iterative instructional decisions based on evidence (Tanner, 2011), who are engaged in sustained and intentional processes of identifying and checking the accuracy and validity of their teaching assumptions (Brookfield, 2017).

Actionable knowledge

Trace data studies have usually based their analyses on "how many times" students interact with course objects, on the frequency or number of interactions. Considering that human behaviour is a highly complex phenomenon and recognizing that LMS activity logs only capture certain aspects of such complexity (e.g. Motz et al., 2019, p. 301) this study did not focus on students' total number of interactions (e.g. "how many" clicks) but on extracting and observing a more specific layer of behavioural information compounded in LMS logs.

LMS activity logs capture only certain interaction behaviour information (e.g. who, what, when, where but not why or how) which is then synthesized and compounded into general abstractions such as frequencies or accumulated amounts (e.g. "how many," "how often," etc.). Although imperfect or incomplete these compounds of abstract behaviour information have been processed in many creative ways by learning analytics scholars to find patterns which summarize how instructional designs and instructional practices unfold and become a reality for students (e.g. Romero et al., 2008). The issue with this type of summary data is that some points (i.e. cross-sectional aggregates or totals) although equal in value could have been caused by completely opposite reasons. For example, high interaction numbers may represent deep germane engagement for a group of students but may also have been caused by problematic or non-germane interactions for others. Low interaction numbers may also come from germanely engaged learners (e.g. Sutton, 2001; Rourke & Anderson, 2004; Garrison & Cleveland-Innes, 2005) or represent disengaged behaviours. The analyses conducted and the results obtained in this study suggest there is promise in sorting out and filtering out meaningful layers of behaviour information in LMS logs. For instance, "how much" of the course was accessed by students, the number or proportion of unique objects that students interacted with, which in this study was related to students' achievement and characteristics. Unless a learner possesses the required knowledge beforehand or obtains it from other sources, learning may only begin to be presumed to have been promoted or caused by the online activities or resources when at least there is evidence that the learning objects or activities were accessed.

Just as this layer of information was translatable into actionable knowledge in this study, many more layers of such meaningful aspects of the teaching and learning relationship may be potentially unraveled to improve the description of learning situations with LMS data. For example, which significant indicators (You, 2016) or interactions (Agudo-Peregrina et al., 2012, 2014) have actual influence on students' academic performance. The analyses on the proportion of unique objects accessed in this study show there is promise in continuing to explore more meaningful ways to summarize LMS activity logs to represent more fine grained aspects of "what happened," of how students behaved during their course beyond the "total number of interactions."

Translating learning interactions data into actionable knowledge is however, an even more complex task. Even though traditional trace data studies have found associations between achievement and the frequency or number of times students interacted with learning objects (e.g.

Beer et al., 2010; You, 2015; Yeung et al., 2017; Ricker, 2019), or have characterized different patterns of number of interactions into "how" students learnt (Fincham et al., 2018; Gašević et al., 2017; Pardo et al., 2016; Pardo et al., 2015), substantial differences are usually found, for example in the sign and size of the effects of different predictors related to number of interactions (Conijn et al., 2017, p. 26). One of the most obvious reasons for this variance are the differences between course designs (2017), because "what constitutes the behavioural components of 'engagement' will be contingent on course structure" (Motz et al., 2019, p. 300). The longitudinal differences in patterns of interaction between course periods confirm this assertion. Moreover, as this study demonstrates and others have predicted (e.g. Corno et al., 2002; Watson et al., 2020), differences in such components will also be contingent on students of which characteristics interact with such course structures.

Theory of Performance

In a learner-centred environment (Weimer, 2013; Baeten et al., 2010) active learning is expected to be promoted when students are engaged in the hard, messy work of learning, are motivated and empowered, when collaboration is encouraged, when reflection about learning is promoted, and when explicit learning skills instruction is included (2013). There is plenty of evidence that active learning increases student performance (e.g. in STEM, Freeman et al., 2013), that cognitively active learning engages students productively in the process of learning and higher order thinking (Deslauriers et al., 2019), but also that students' perceptions of learning, instructor's effectiveness, and enjoyment or satisfaction tend to be lower (2019). Student resistance might be caused in part by instructors or peers behaviours (Seidel & Tanner, 2013) but also because understanding the requirements and expectations of a learner-centered active-learning class presents a real challenge to students (Fisher et al., 2017) with some having a love/ hate relationship with activity in the classroom (Strayer, 2012). Some students might even perceive the lack of lecture and an increased expectation for personal responsibility for their own learning outside of class time as unfair or unreasonable (Wilson, 2013, p. 198).

Findings in this study suggest that one of the reasons why students resist, why it is difficult to foster students' active and independent learning and observe this type of behaviour through data is because this form of learning is deeply related to the process of *individuation* (Allport, 1955), to the essence of what constitutes a person, to who the person is and who the person is trying to become. The associations found in this study between student characteristics, interaction behaviours and achievement suggest that the complex ways in which students differ in response to instruction demands and opportunities are deeply related to their "idiosyncratic ways of achieving definiteness and effectiveness in their self-image and in their relationships with others and with their contexts" (Allport, 1955, p. 28). When students are required to be active and independent, they are not only incited to acquire or develop new knowledge and skills, students are also challenged to *become* self-aware, self-critical and self-enhancing (*becoming*; Allport, 1955, pp. 24 – 28). As such, students are not only cognitive systems that may be productively engaged but human beings "continually seeking to realize their own possibilities and uniquely express and realize their unique hierarchy of interests and long-range goals" (1955).

To learn actively and independently students need to be able to share the responsibility for learning, value learning, be motivated to learn and view learning and personal improvement as realistic and their primary goal (Patrick et al., 2012). Student's motivations, beliefs, and resources are related to these enabling conditions. As this study shows, for students to share responsibility for learning it was conducive for them to have more conscientious and agreeable as well as lower neuroticism personality traits. For students to share responsibility for learning it was also conducive to have more positive psychosocial maturity attributes such as a stronger tendency to be more autonomous, purposeful, or industrious. This study also found, as many others have (Karoly, 1993; Bandura, 1982, 1991; Schunk et al., 2008; Zimmerman 1986, 1989, 2008; Zimmerman & Labuhn, 2012; Davidson & Sternberg, 2003; Schunk & Ertmer, 1999; Karoly, 1993; Deci & Ryan, 2008, 2000, 1985) that students are better able to share the responsibility for learning if they have a stronger capacity to manage their self-generated thoughts, feelings, and actions that are planned, performed, evaluated and cyclically adapted to attain their goals over time and across changing circumstances or contexts (*self-regulatory functioning skills*). Some long-range goals were also found to be positively associated with the proportion of the course engaged and some long-range interests were counterproductive for the intensity with which students seized learning opportunities.

To be able to value learning, to be motivated to learn and view learning and personal improvement as realistic (Patrick et al., 2012) it was favourable for students to have a stronger sense of who they were and what they believed in (*identity, psychosocial maturity*), to believe in themselves and what that they were capable of (*self-efficacy*), and to be more satisfied with their life choices and accomplishments (*ego integrity, psychosocial maturity*). It was also important for students to have strong motivations to learn, especially stronger intrinsic reasons for studying, in combination with extrinsic reasons or by themselves. These findings confirm that for students to "use their human powers productively" (Fromm, 1976), to be active not just by expending energy (e.g. number of clicks), their activity needs to be "an expression of a positive intrinsic interest, to have an inner relation and satisfaction in what they are doing, a relation to what they think the goal of living is, to what makes their life meaningful, to what they seek from life" (Fromm, 1976, pp. 76-84). The hierarchy of major life interests expressed by the cohorts studied was surprising to discover and it was clear that some of the things that students valued the most could have been elicited as practical applications of the knowledge and skills offered through the course (e.g. examples used) and learning activities (e.g. assignments or quizzes). Connecting learning activities to students' long-range aspirations should help students find value in learning not only to achieve immediate academic goals but also to become aware how these promote their growth and help them achieve their long-range goals.

Many studies have sought to find predictive factors of student success, and more recent studies have focused especially on the impact of motivational factors and self-regulatory skills (e.g. Mitra & Beenen, 2019; Lazarides et al., 2020; Seiver & Troja, 2014; Y. Lee et al., 2013; Aragon & Johnson, 2008; Dabbagh, 2007; Kerr et al., 2006). Future studies should benefit from considering all four dimensions observed in this study: student motivations (e.g. goals), beliefs (e.g. self-efficacy), resources (e.g. abilities or skills), and behaviours (e.g. interactions). There is also a growing recognition that students' performance and satisfaction are affected by a broader range of factors such as learning outcomes or instructional designs as well as learner characteristics (Gering et al., 2018; Glazier, 2016; Kauffman, 2015). For example, Joosten and Cusatis found (2019) that in online learning environments, *course design* and *organization* positive and significantly influence students' perceptions of learning and satisfaction; that so does providing students with clear directions and information to manage their expectations and their interactions with the course (*learner support*, 2019), as well as having an instructor whose role is to connect to students and connect them to the course, to enhance their learning by showing interest in their learning, maintaining a productive dialogue, keeping students engaged, encouraging exploration of new concepts in discussions, providing reminders and detailed feedback on assignments, and communicating ideas and expectations timely and effectively (*student interactions with the instructor,* 2019). The reason why these instructional factors have a significant impact on learning is because they help recognize and treat students as human beings. Through these and other similar instructional interventions students are given the freedom to understand the demands and opportunities that the learning activities present and are allowed to independently decide to use them to grow, to realize their own possibilities through learning, and uniquely express and realize their own unique hierarchy of interests and long-range goals, to the extent that the quality of the course design and instruction and their own resources, beliefs, and motivations can afford it.

Considering the findings of this study, a practical recommendation for any instructor would be to consider getting to know their student cohorts better by learning who their students are and what they are trying to become to better understand their teaching and learning relationships. It should also be beneficial for these relationships that students learn more about the person who designed and is willing to guide and evaluate their learning to promote their growth. Instructors should share with students who they are, how they have become who they are, what they are trying to attain as well as how they have planned to achieve their aspirations. It would also be beneficial for students and instructors to reflect on what they think about themselves, what are their strengths and how well they have developed key learning skills required for the course, what are their long-term ambitions (major life goals) and how these are related to their goals for the course. As this study showcases, there is great value when these insights derive from psychometrically valid measures and other more practical ways (e.g. surveys, discussions, writing or video assignments, among others) can also be used to foster students' reflection in these areas. Such efforts should help students realize where they start their learning journey and, if continued throughout the course, how much they gain through their efforts. As a by product instructors will also gain an opportunity to know their students and identify areas were the distance between course expectations and what the student or students bring to the course present opportunities for improvement and growth. The key aspect would be to figure out a pedagogically sound way to involve students in the process of identification, diagnosis, planning, execution, observation, and reflection on their motivations, beliefs, and resources as they complete course tasks, achieve course milestones, and develop required knowledge and skills. In such way, the course would not only demand but promote students' active and independent learning, would help students "develop learning skills they will need across a lifetime of learning and the confidence to use them" (Weimer, 2013, p. 11). Before proceeding to the last major finding, two unexpected findings related to the theory of performance require a more detailed discussion: the associations found between conscientiousness, interactions, and achievement, and the associations found between students' psychosocial intimacy-isolation maturity attributes and achievement.

Conscientiousness, interactions and achievement. Results showed an expected relationship between conscientiousness, students' initial proportion of activities accessed and the rate of change in this type of interactions, but student conscientiousness was not associated to students' levels of achievement. Conscientious students are usually reliable, hardworking, self-disciplined, persevering (Colquitt & Simmering, 1998; Costa Jr & McCrae, 1985, 1989, 1992, 1995, 2008; McCrae & Costa Jr, 1987), and are expected to engage in active learning behaviours such as searching for new knowledge and new ways to improve performance (Bakker et al., 2012, p. 556; Baeten et al., 2010; Simmering et al., 2003; Taris et al., 2003). However, even when conscientiousness was related to differences in interactions in this study and interactions were positively related to students' achievement, there was no significant association between conscientiousness and achievement. This result contradicts studies which found conscientiousness to be significantly related to student achievement (P. E. Morris & Fritz, 2015; Furnham et al., 2013; Poropat, 2009; O'Connor & Paunonen, 2007; Wolfe & Johnson, 1995), to be a salient trait of highly successful students (Eilam et al., 2009, p. 429).

The association between conscientiousness and achievement has varied in the literature from small to quite substantial with no clear explanation for this variance (O'Connor & Paunonen, 2007, p. 976). It is possible that one of the causes for this variance are the differences in teaching and assessment strategies used, that it will be especially stronger in situations where performance is highly dependant on students' hands-on engagement in coursework. For instance, a very strong relationship was found between conscientiousness and achievement in an inquiry-based science project (Eilam et al., 2009) and conscientiousness more strongly predicted coursework marks than examination marks in another setting (P. E. Morris & Fritz, 2015, p. 197). In this study, course teaching and assessment strategies were less focused on inquiry-based hands on experiences and more on helping students germanely interact with texts to acquire an advanced conceptual understanding.

A second reason for these differences might also have to do with the differential effects of teaching and assessment strategies on students with higher degrees of conscientiousness and other characteristics such as performance or learning goal orientations. Extremely high levels of conscientiousness have been found to have a detrimental effect on grades (O'Connor & Paunonen, 2007, p. 976; Cucina & Vasilopoulus, 2005) and the effect of conscientiousness on academic performance has also been found to be mediated through more proximal characteristics such as self-efficacy or test anxiety (Conrad & Patry, 2012). Highly conscientious students have a predisposition to maintain high levels of effort in the face of difficulties and this also makes them more vulnerable to experience feelings of tension or frustration to achieve the goal (Cianci et al., 2010). High levels of tension are likely to have a negative effect on performance on tasks that require concentration, information processing, and learning (2010, p. 621). The detrimental effect of higher conscientiousness on tension and performance is amplified when highly conscientious students try to demonstrate their competence to others (have a performance goal vs a learning goal) and receive negative feedback, information which indicates poor performance (Cianci et al., 2010). Moreover, students' highly conscientious tendencies to be thorough, careful, and meticulous may interfere with performance of tasks that have to be performed under time pressure (Yeo & A. Neal, 2004; Tett et al., 1999), although might surpass less conscientious students' performances and transitions to transfer contexts with more time and practice (2004; Colquitt et al., 2000).

In this study, conscientiousness significantly explained students' breadth of interaction during the three-week courses but was not related to students' achievement. It is possible that more conscientious students were not able to deeply process all the required content while being thorough, careful, and meticulous in such a short period of time. Their performance could also have been hindered by higher levels of tension especially if they were focused on obtaining higher grades or completing all the proposed activities instead of using them to further their understanding. This calls for a revision of the breath of concepts that may be processed during the course, the number of activities offered, and also to find ways to better support students' self-regulatory processes by finding ways to communicate to students the learning activities' purpose (essential vs non-essential), assumptions and expectations (e.g. performance vs learning) and the type of information they receive when engaging with them (summative vs formative feedback).

Student psychosocial maturity and achievement. Students with an isolation type of psychosocial developmental resolution unexpectedly tended to obtain higher grades than those with an intimacy type of resolution. In *normal* development (Erikson, 1956, 1959, 1982; Snowman & McCown, 2011, pp. 28 – 30) criterions of relative psychosocial health such as the relatively conflict-free *intimacy* psychosocial arrangement should tend to outweigh criteria of relative ill-health such as the relatively defective or conflict-laden *isolation* psychosocial arrangement (Erikson, 1956, p. 76). In the two courses analyzed, isolating oneself from others academically favoured some students, that is, a stronger instructional focus on deep conceptual understanding favoured isolated identities vs relationship committed identities who were also more extroverted, agreeable, and sought to make their family proud and have fun as life goals. These results contradict studies which found social ties and friendships to be positively related to academic achievement (Brook & Willoughby, 2015; Woolf et al., 2012; Gouguen et al., 2010; Swenson et al., 2008; Buote et al., 2007; Tokuno, 1986) and studies in which lower academic achievement was related to being prone to be withdrawn or have greater difficulty forming new friendships or social connections (Brook & Willoughby, 2015; B. K. Biggs et al., 2012; Goguen et al., 2010; Strahan, 2003). If this had been true in courses 2 & 3, students who had resolved to establish close and committed intimate relationships and partnerships with other people would have obtained higher grades than those who had psychosocially resolved to feel isolated, to not establish close and committed intimate relationships and partnerships.

One of the reasons for this unexpected contradictory result might be the varying contextual demands caused by varying assumptions of how learning is expected to unfold, how much information is expected to be processed or taken in, and which learning activities are designed and implemented to facilitate this learning. The key assumption in one of the contrasting studies (Brook & Willoughby, 2015) was that feelings of social distress and avoidance in the university context prevented socially anxious individuals from taking advantage of the learning opportunities that were designed to bolster academic success, especially interactions with others, developing intimacy within new friendships, and engaging professors and teaching assistants in discussion (2015, p. 1140). In courses 2 & 3, teaching and learning interactions, lectures, discussions, quizzes, assignments and other teaching and learning interactions were not designed to be the primary source of learning. Instead, these activities were designed to foster, support, reinforce, clarify or deepen students' primary germane engagement with course texts, the textbook and a collection of scholarly articles (Paas et al., 2003; Van Merriënboer et al., 2006; Ayres, 2006; Mayer et al., 2005, p. 257). Nevertheless, student evaluations of teaching in these courses reflected that discussions were an asset to their learning, especially for students in Course 3 who commented that one of the aspects they found most valuable was that "class time provided a lot of interesting discussions," and that "[the instructor] made the course very discussion-based which was refreshing since I find that three-week terms are often lecture heavy; (…) [that] even when students didn't initially speak to answer questions, some answers given by peers was enough to spark discussion and promote meaningful learning."

Extraneous load refers to contextual elements that demand mental processing or distract mental resources away from learning (Debue & Van de Leemput, 2014, p. 2). It is possible that students with an isolation type of psychosocial resolution obtained higher grades because their developmental dispositions made them less prone to be distracted, to dedicate less resources to extraneous demands from committed relationships, being more outgoing, socially confident or unable to spend time alone, or from having a stronger preference for having harmonious relationships with their parents and siblings, or for having fun, seeking new and different experiences, or an exciting lifestyle as a life goal.

Intrinsic cognitive load results from differences between students' levels of expertise and the demands of the learning tasks (Debue & Van de Leemput, 2014, p. 2). In their course evaluations, students commented that one of the aspects of the course or instructor that they found least valuable was "the amount of info in the course within the three-week[s]," "the amount of time we had to grasp course concepts. Although the goals were clearly defined, it was difficult to keep on top of reading and quizzes and studying," that "as a three week course it is understandably condensed and I was able to keep up with the pace, but I feel it was difficult to take opportunities to go beyond the material and use the resources given for extra information," or that "it felt like I knew the material, but did not have time to process/digest the content and relate the content to applications in the classroom." This means that the quantity of information and how students were required to process it caused high levels of intrinsic cognitive load regardless of students' motivations to learn. With such an intense demand, fewer students were better equipped to engage in deeper, germane processing, those who were not committed to close relationships or partnerships, who did not have to manage extraneous demands, sacrifice or compromise studying time or higher degrees of attention to course texts. This finding indicates there is an opportunity to find a proper balance in the amount of information that students are required to process and how they are required to process this information.

Reflective teaching

"Critical reflection is the sustained and intentional process of identifying and checking the accuracy and validity of our teaching assumptions" (Brookfield, 2017, p. 3). When experienced teachers are engaged in reflective practice and dialogue (Darling-Hammond, 2000), the end goal is to be analytical about one's own practice and make iterative instructional decisions based on evidence from the students (Mandinach, 2012; Tanner, 2011, p. 333). The following considerations derive from a reflection on whether the way in which the learning situation was arranged was able to get the best from my students, whether the data analyzed and the results discussed above can ensure that the course design and instruction facilitated an optimal functioning as originally envisioned.

One of the patterns that spoke the most to me as the instructional designer and instructor of these courses was to observe on students' longitudinal patterns of interaction that excluding one or two exceptions almost everyone in the class showed consistently strong initial patterns of interaction. At first it seems that everyone was trying their best to fully learn and understand but as the courses progressed, students with stronger sets of motivations, beliefs, and skills or resources started showing more positive patterns of interaction while others were progressively being left behind, especially during the second and third parts of the course. Observing these patterns and reflecting on the findings discussed above made me wonder whether my courses were designed to challenge students with a series of tasks that only some would be able to complete because they were better equipped (had the required or expected skills, attitudes or dispositions) or whether the courses could have been better designed to provide better opportunities to uplift oneself.

Student feedback and course assessments indicate that students indeed learnt and appreciated the opportunities that the courses offered to improve themselves as learners. For instance, students strongly agreed that they increased their knowledge of the subject areas (median student evaluations of 4.4/5 in course 2 and 4.6/5 in course 3) and reported being motivated to learn more about the subject areas (average score of 4.5/5 in course 2 and 4.6/5 in course 3). However, the behavioural data observed, and the associations discussed above suggest that although good for most perhaps the current design of the course and its instructional practices might need to be rethought and refocused to better ensure success for all.

First, a more concise set of outcomes for the course would need to be defined. To promote significant learning, Fink (2013) recommends most courses to have at least four and no more than seven important issues, topics, or themes. Second, instructional activities will be planned considering that the amount of work required to complete a set of learning tasks depends on how students approach studying the materials (Lawless, 2000). For instance, students "who seek to learn the subject" may spend longer time on activities than students "who seek to pass the course" (2000). For this reason and considering the differences in students' motivations, beliefs, and resources observed in this study, at least two paths towards completion should be designed to offer differentiated paths or opportunities for students: 1) a streamlined set of activities that would be compulsory for all students and would be aimed at students who wish to focus their learning solely on completing a set of learning activities and 2) a set of additional tasks that would seek to develop self-directed learning skills of those who wish to be challenged. The main expected consequence would be the acquisition of concepts and constructs for the first set of activities, and development of learning skills and self-confidence in these skills for the second.

The streamlined set of activities should be designed to challenge students just a bit further of what experience has shown can be appropriately expected from them. Potential reading workload will be estimated using Chambers' criteria (1992). Chambers proposed reading speed criteria was: 100 words per minute for "an easy read," 70 words per minute for "fairly straightforward read," and 40 words per minute for "dense or difficult read." Accommodations would also need to be embedded in the design after considering Universal Design for Learning

(*UDL*; T. Hall et al., 2003; Meyer et al., 2014) and differentiated instruction principles (Tomlinson, 2014, 2015). Additional sets of resources or guides should also be ready for students who master the required content quickly and wish to expand their expertise or knowledge further, but students will no longer be expected to study them, or will these resources be a main part of the course. Since deep learning can occur when one or two issues are addressed through selected readings and interactive strategies (Ascough, 2002), course redesign will follow the recommendation “often less is better” (2002). Similarly, but in relation to the use of media, Clark and Meyer (2018) also recommend that “less is often more, and leaner media can be more effective for learning than rich media” (2018, p. 266). Palloff and Pratt (2003) also suggest it would be good practice to build in time off for students and instructor in the time budget for the course. The second set of extra academic challenges, with careful consideration for students’ workload would focus on activities to help students diagnose their strengths and areas of opportunities for growth, to help them set learning goals, track their performance and workload, and reflect on their own achievements.

To promote active learning during synchronous interactions perhaps what is needed is to bring germane processing and consideration of key constructs and concepts to the forefront. As such, instructional strategies and practices need to be rethought to help the class be productively and germanely engaged. Instructional interactions should be more productive if based on a set of intellectual challenges, on critical questions that foster a need to know, opportunities to put their newly acquired knowledge into practice, and a reference for students to assess whether they have acquired or developed the required knowledge. Peer and instructor based instructional interactions should provide students with opportunities to test and expand their actual levels of mastery while figuring these streamlined intellectual challenges.

Instructional time would require at a minimum: a bridge to motivate students and frame the conversations, discussion of previously completed diagnostic pretests, diverse strategies and activities to promote dialogue and discussion on those topics that require more elaboration, post discussion tests to help students diagnose which areas might require further work, and discuss planning for the next session. Readings, activities, and quizzes would be kept to a minimum and would be offered to support the need to know. The most important instructional function will be to motivate students, for example by helping them make more explicit connections between what they know and what they are expected to know (e.g. conceptual understanding), and what they might gain beyond the acquisition of knowledge (e.g. transfer or application of knowledge).

Improving the teaching and learning relationship, a teacher's instructional practices and course design entails asking many complex questions, with plenty of possible answers and consequences for teaching and learning. The analysis of students' interactions, their characteristics and achievement has provided an interesting opportunity to check the accuracy and validity of my teaching assumptions. These data, results, and discussion, together with students' feedback have made me realize that my course designs although beneficial, could be improved by shifting the focus from a demanding set of outcomes and expectations, to a more streamlined set of outcomes and a clearer and better laid out path to get the best from my students, to ensure that the course design and instruction promotes students' optimal functioning.

Study limitations

This study was situated in a local context and focused on a local issue, to investigate the phenomenon of student active and independent learning within the real-life context of two blended learning three-week undergraduate courses. It was designed to determine the consequences of or the antecedents of the differences in students' interactions with two course blended learning designs that sought to foster students' active and independent learning. This study was conducted after variation in students' interactions had already been determined in the natural course of events. Two instruments that were planned to observe students' characteristics, students' beliefs of possible causes of student academic failure and a measure of moral development were not included because a significantly lower number of students were able to complete them adequately. Students decided to enroll in this course and as such, random selection of the participants was not possible. Finally, case studies are generalizable to theoretical propositions and not to populations or universes. Thus, no statistical generalization may be inferred from the results to the general higher-education population. Instead, this study advances theoretical knowledge through modelling, but the associations found must be replicated in more contexts before they may be analytically generalized.

Further research

Several possibilities for future research emerge from this study. The most immediate would be to implement the design and instructional changes envisioned and contrast students' interactions, characteristics, and achievement. It would also be interesting to compare more courses taught by the same instructor across different contexts and types of classrooms. Together with other multifaceted sources of information, this type of analysis may further support this instructor's ongoing educational development as a reflective teacher.

Analyses of student interactions, characteristics, and achievement could also be used to examine different types of courses such as courses with known difficulties, award-winning, mandatory or elective, of different pedagogical approaches, from different disciplines, directed towards different years in program, of different class sizes, durations (e.g. 3-week vs 13-week courses), or even across institutions with multilevel analyses. Such research would help characterize instructional designs, instructor characteristics, their cohort compositions, behavioural interactions, and describe what types or characteristics of instruction benefit or hinder what types of students the most. With students' interactions, characteristics, and achievement there is also potential for fine grained analyses of specific learning objects' interactions, objects of different importance (e.g. essential, required, or optional; Boechler et al., 2017), or type (quizzes, multimedia resources, assignments) to analyze whether particular resources make a difference or not in students' learning interactions, or for students with varying sets of skills and motivations.

There is also potential for LMS activity logs to be improved to reduce the time required to process logs and facilitate analyses that may translate these data into actionable knowledge. For instance, improving how events are tagged and classified. Description of events need to be separated into its components in a more standardized manner to facilitate analyses. Longitudinal analyses would also be easier to conduct if activity logs also recorded the outcome or outcomes of students' interactions (e.g. relative or absolute points or grades obtained, including scores in dimensions evaluated by rubrics). Formative feedback loops could also be better recorded to better represent these chains of interaction in teaching and learning. For example, when a student receives information (accesses the resource), processes it, responds (submits, interacts), is evaluated, receives such evaluation, responds to it, and so on. Such improvements would require instructors' contextual inputs to feed LMS log systems with more information on the interaction expectations from the course design to better categorize captured events.

Although the analyses in this study focused on observing the effects of instructional interactions, they could also be used to help students learn more about their strengths and limitations in learning by contrasting their past, current, and future interactions with different types of courses, observing their motivational, belief, and resource characteristics, and the academic and practical results they obtain. This type of analysis could also focus on specific student cases within course cohorts to better understand students' modes of engagement in light of their hypothesis, goals, interactions, and results. There is also further opportunity in continuing to explore and combine different types of qualitative and quantitative data to better explain "how" and "why" students interacted and learned through different learning activities in different contexts. It would be productive to continue exploring other instruments and validate other practical forms of observation for classroom use to observe students' motivations, beliefs, and resources. Furthermore, it would also be practically useful to design and validate a formative instrument for students, a "person-in-situation readiness to learn" instrument to help observe key motivational, belief, or student resources to inform instructors practice. Finally, reflections on the significance of findings of this study, on the sustained and intentional process of identifying and checking the accuracy and validity of this instructor's teaching assumptions could also be improved by paying attention to peer and student reactions to findings and this instructor's reflections.

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Appendix

Table 14

Students' Linear-Change Interaction Trajectory Parameters (REML) and Achievement

	Interaction Trajectory Parameters			Achievement *	
ID	Intercept	Slope	Goodness of Fit	Course Total	Knowledge
			Course 2		
35	12.01	0.83	0.99	15.6	15.8
57	12.13	0.82	0.98	7.6	5.9
19	13.09	0.74	0.98	2.6	-0.9
53	12.38	0.65	0.96	-2.8	-10.4
23	12.31	0.65	0.98	4.5	5.8
21	16.89	0.68	0.99	5.4	3.6
49	11.19	0.68	0.98	4.5	7
33	2.11	0.68	0.95	1.5	-1.8
24	15.52	0.66	0.95	1.5	1.2
26	6.46	0.6	0.97	1.1	-3
40	8.78	0.58	0.98	-8.2	-12.1
52	11.55	0.58	0.97	-6.3	-4.8
34	7.89	0.57	0.97	-21	-11.3
29	7.34	0.55	0.97	-22.4	-7.6
62	9.61	0.54	0.97	8.4	7.9
37	7.3	0.54	0.98	-7.8	-1.7
31	10.17	0.51	0.96	10.6	9.4
47	7.32	0.48	0.97	-10	-13.1
59	5.4	0.5	0.98	5.4	4.2
58	9.8	0.47	0.99	6.8	4.3
38	10.31	0.5	0.97	-3	-6.7

	Interaction Trajectory Parameters			Achievement *	
ID	Intercept	Slope	Goodness of Fit	Course Total	Knowledge
18	11.86	0.47	0.93	1.1	1.8
20	12.19	0.46	0.96	-8.3	-9
28	5.07	0.36	0.95	-34.3	-31.1
17	10.72	0.34	0.93	-0.5	-1.7
32	6.46	0.3	0.94	-7.3	-3.1
Course 3					
113	15.2	0.9	0.97	-4.1	1.1
101	8.78	0.74	0.98	14	17.9
104	10.2	0.7	0.98	-1.9	-2.8
107	9.87	0.68	0.99	5.1	3.9
110	7.02	0.69	0.98	-2.5	-8.3
108	6.89	0.64	0.99	9.5	11.8
116	5.55	0.65	0.98	12.1	17.4
119	8.4	0.64	0.99	6.9	7.9
103	7.7	0.59	0.98	-0.8	-1.4
117	3.52	0.58	0.97	3.5	2.8
106	4.17	0.56	0.98	-0.6	2.8
115	2.37	0.53	0.96	4.3	2.3
109	6.24	0.55	0.95	-1.9	-6.7
100	3.9	0.54	0.97	6.2	6.2
102	8.91	0.49	0.99	7.7	7.9
105	7.44	0.49	0.97	-11.8	-13.9
111	8.04	0.5	0.98	2	-1.1
118	4.57	0.45	0.98	6	7.3
112	6.21	0.42	0.98	-1.7	-6.1
114	4.78	0.34	0.96	3.5	2.5

* Students' centered course total and knowledge/exam grades