PONTIFICIA UNIVERSIDAD CATÓLICA DE CHILE
SCHOOL OF ENGINEERING

# OPTIMAL LEARNING EXPERIENCE DESIGN IN BLENDED LEARNING

**PABLO SCHWARZENBERG RIVEROS**

Thesis submitted to the Office of Graduate Studies in partial fulfillment of the requirements for the Degree of Doctor in Engineering Sciences.

Advisor:
**MIGUEL NUSSBAUM**

Santiago de Chile, December, 2017

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**JAIME NAVON**
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*A mi mamá Sonia, que me enseñó las cosas más importantes que he aprendido*
*A mi papá Mario, que me enseñó con su ejemplo*

*Para ti que danzas como una flor en el viento*
*A Claudia, con tu amor y apoyo todo es posible*
*A mi hija Katina*

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Tesis enviada a la Dirección de Investigación y Postgrado en cumplimiento parcial de los requisitos para el grado de Doctor en Ciencias de la Ingeniería

PABLO SCHWARZENBERG RIVEROS

## RESUMEN

Según Dewey (1929) la experiencia es un todo indivisible que relaciona sujeto y objeto, acciones y herramientas, que incluye lo que las personas piensan, creen, hacen y sienten. Esta tesis aborda el diseño de experiencias óptimas de aprendizaje, definiéndolas como aquellas que crean condiciones e inducen emociones que facilitan el aprendizaje. Diseñar una experiencia óptima para todos es complejo, ya que la experiencia de aprendizaje de un estudiante es una interpretación subjetiva que se construye a partir de la interacción con el mundo y que varía a través del tiempo. Un entorno de aprendizaje requiere proveer vías para la expresión de las diferencias individuales y condiciones para que los estudiantes puedan gestionarlas para que pueda promover experiencias óptimas de aprendizaje.

Para identificar los requerimientos de diseño de una experiencia óptima en esta tesis se combinan las teorías del Flow y la Autodeterminación con la literatura del diseño de experiencias de usuario en sistemas de enseñanza basados online y videojuegos. A partir de este análisis se propone un modelo que permite guiar el diseño y la evaluación de la experiencia de aprendizaje de los estudiantes usando un instrumento de medición el cual fue validado en el contexto de la enseñanza superior. Para proveer elecciones y facilitar la adaptación a las diferencias individuales se usó el método de enseñanza Flipped Classroom combinado con un sistema de puntaje como el utilizado en los video juegos. Adicionalmente, se utilizaron técnicas

de aprendizaje de máquinas para permitir que el profesor pueda visualizar el progreso y la experiencia de aprendizaje de sus estudiantes a partir de su actividad en la plataforma en línea.

Esta tesis concluye que la experiencia de aprendizaje puede ser evaluada y correlacionada con el aprendizaje y que las elecciones realizadas por los estudiantes mientras aprenden reflejan e influencian su experiencia de aprendizaje. Esta tesis contribuye una nueva aproximación al diseño y evaluación del uso de la tecnología en clases que usan el método Flipped Classroom, proponiendo que la incorporación de nuevas características debiera enfocarse en mejorar alguna dimensión de la experiencia de aprendizaje para mejorar el aprendizaje. El instrumento de evaluación validado en esta tesis permite establecer una línea base de experiencia de aprendizaje con la que comparar los efectos de la inclusión de una nueva característica y evaluar su impacto, lo que facilita el uso de la investigación basada en el diseño para mejorar en forma incremental implementaciones del método Flipped Classroom. Finalmente se concluye que los resultados que se pueden obtener del uso de la tecnología para la enseñanza dependen de su impacto en la experiencia de aprendizaje de los estudiantes.

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**Palabras claves:** Diseño de experiencias de aprendizaje, Flipped Classroom, Enseñanza de la programación, Motivación, Learning Analytics.

Miembros de la Comisión de Tesis Doctoral
**MIGUEL NUSSBAUM VOEHL**
**JAIME NAVON COHEN**
**MAR PÉREZ SANAGUSTÍN**
**LIOUBOV DROMBOVSKAIA**
**CARLOS ALARIO-HOYOS**
**JORGE VÁSQUEZ PINILLOS**

PONTIFICIA UNIVERSIDAD CATOLICA DE CHILE
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## ABSTRACT

According to Dewey (1929) experience is an indivisible whole that relates subject and object, actions and tools, and includes what people think, believe, do and feel. The subject of this thesis is the design of optimal learning experiences, defined as experiences resulting from conditions and emotions that facilitate learning. Designing an optimal experience for everyone is a complex task, since the experience of each student is dynamic and it is a subjective interpretation of their interaction with the world. To allow the expression and handling of these individual differences, a learning environment must incorporate in their design conditions and choices that promote an optimal learning experience.

To identify the requirements of an optimal experience, we combine in this thesis the theories of flow and self-determination with the design of user experiences in online learning systems and video games. From this analysis, we propose a model to guide the design and evaluation of learning experience using a measurement instrument which was validated in a higher education context. The provision of choice and adaptation to individual differences was implemented using the flipped classroom method combined with game elements and machine learning tools, to enable the teacher the visualization of the progress of their students from their online activity.

This thesis conclude that learning experience can be assessed and correlated with learning outcomes and that the actions performed by the students while learning reflect and influence their learning experience. This thesis contribute a new approach to the design and evaluation of the use of technology in the context of flipped classroom implementations, proposing that the incorporation of new features should focus on improving some of the learning experience dimensions to improve learning. The measurement instrument validated in this thesis allow to stablish a learning experience baseline to compare the influence of a new feature and evaluate their impact, supporting the use of design based research to incrementally improve flipped classroom implementations. We can conclude that the results that can be obtained from the use of technology in teaching depend on their impact on the learning experience of the students.

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**Keywords:** Learning Experience Design, Flipped Classroom, Teaching of Programming, Motivation, Learning Analytics.

Members of the Doctoral Thesis Committee:
**MIGUEL NUSSBAUM VOEHL**
**JAIME NAVON COHEN**
**MAR PÉREZ SANAGUSTÍN**
**LIOUBOV DROMBOVSKAIA**
**CARLOS ALARIO-HOYOS**
**JORGE VÁSQUEZ PINILLOS**

# 1 INTRODUCTION

Emotion and motivation are considered key factors in educational processes, to the point that emotions such as anxiety or frustration can impede learning and decrease student's perception of self-efficacy, while emotions such as joy, awe, and arousal increase the interest and motivation to learn. This thesis defines an optimal learning experience as one that creates conditions that promote learning and emotions that facilitate it. Designing an optimal experience for all is complex, since experience is a personal and subjective interpretation of our interaction with the world, and therefore different for each student. It is for this reason that a learning environment that promotes an optimal experience requires the provision of ways for the expression of individual differences and conditions so that students can manage them. An example of these conditions is the perception of difficulty of an activity. It should be possible to adjust the difficulty to the ability of each student, since an imbalance between these two elements fosters emotions such as anxiety or boredom (Nakamura & Csikszentmihalyi, 2014) that negatively impact learning and academic achievement (Prekrun, 2006; Pekrun, 2010). To manage this and other relevant conditions, this thesis aims to design the learning experience by combining theories that describe the needs that motivate people with the conditions of interaction that foster an optimal experience according to psychology, the design of learning environments, user experiences and video games.

The research questions included in this thesis were tested across six semesters in an introductory level programming course at a Higher Education Institution. This thesis used a design based research approach (Brown, 1992; Barab, 2004; Wang, 2005), where the results of an investigation contribute to the definition and refinement of future research questions, combining knowledge obtained from practical experience with knowledge obtained from the relevant literature.

## 1.1 Optimal Learning Experience Design Framework

### 1.1.1 Experience and Activity

Experience is an indivisible whole that relates subject and object, actions and tools, which includes what people feel, think, believe and do (Dewey, 1929). We can define an experience as a story that emerges from the interaction of a person with the world through action (Hassenzahl, 2013).

According to Hassenzahl (2013), experiences are:

1. Subjective, depending on the person.
2. Holistic, occur in consciousness as a whole that include motivation, cognition and emotion.
3. Located, they occur in a context.
4. Dynamic, they change over time.
5. Valuable, they can meet needs and be positive, or they can be negative but still lead to a valuable purpose.

In order to analyze the elements of the activity from which the experience emerges, and to help the elaboration and testing of research hypotheses we will use the conceptual framework of activity theory (Leonte'ev, 1978; Engeström, 1987; Engeström, 2015). Activity theory states that activity is mediated by both mental and technical tools (Vygotski, 1981), so the relationship between subject and object is not direct but is mediated by these artifacts. An activity can be defined as an interaction with the world which has a purpose and which is realized through actions directed by an objective (Leonte'ev, 1978). The activity is used as the basic unit of analysis of human behavior in a given social context, and what distinguishes one activity from another is its object, which can be understood as its motive. Engeström (2015) consolidated the ideas of Vygotsky and Leonte'v by developing a framework for the analysis of the elements involved in an activity, which can be seen in Figure 1.1.

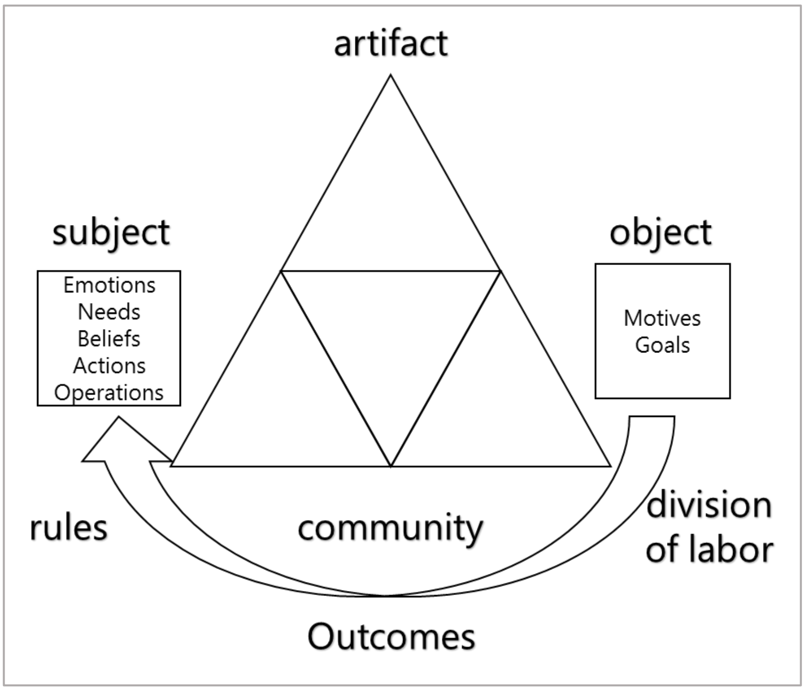


**Figure 1.1:** Activity Theory Framework

This framework incorporates the concepts of community as all the individuals that are involved in the activity, and rules as the conventions that circumscribe the activity and mediate the relationship between the subject and the community. The division of labor mediates the relationship between the object and the community, identifying the actions that are performed by each subject individually and how they contribute to the object in the context of a group. The Activity Theory has been shown to be a framework that is broad and flexible enough to effectively address the design of people's interaction with technology (Kuuti, 1995; Kaptelinin & Nardi, 2006), and also for the analysis of use of technology in the context of learning (Jonassen & Rohrer-Murphy, 1999; Zurita & Nussbaum, 2004; Gedera, 2015; Messenger, 2015; Bligh & Flood, 2017; Gregorcic, 2017). As Figure 1.1 shows, we added to the model proposed by Engeström (2015) a description of the elements of the subject and the object that will be considered for the design of the learning experience mediated by the technology, and also the interconnection between the result of the activity and the subject to represent how through the activity emerges an experience that produces a transformation of the subject. This kind of experience has been conceptualized as an aesthetic experience (Dewey, 1934) and more recently in the context of science teaching as a transformative experience (Pugh, 2011; Pugh, 2017). The subject gives meaning to experience (before, during and after it) through reflection and from past experiences (McCarthy, & Wright, 2004). The dynamic nature of the experience and its personal interpretation allow us to understand how, from the same activity, different experiences emerge for different people, or even for the same person when the activity takes place at different moments of time.

### 1.1.2 Design of an Optimal Experience: Analysis of the subject and the object

We focus on the design of learning activities, so we begin by considering the needs, beliefs and emotions involved in learning. People are naturally curious, with a natural interest in learning and internalizing the knowledge, customs and values of the world around them. This has been the subject of study of the theory of self-determination (Deci & Ryan, 2000) that studies the factors that promote or hinder the natural processes of growth and assimilation in people, analyzing them from the perspective of the motives that give rise to the action. In the educational context, the natural interest to learn is the greatest resource that educators can use to achieve their goals (Niemiec & Ryan, 2009). To foster the natural interest of people and contribute to their well-being, the theory of self-determination identifies three basic needs that an activity must satisfy:

- The need for autonomy: it is related to the person's voluntary behavior, self-initiation and self-regulation.

- The need for competence: it is related to understanding how to reach an objective and to be effective in carrying out the actions required to achieve it (in an educational context it occurs when students are able to overcome the challenges posed during the learning process).
- The need for relatedness: it is related to the development and maintenance of satisfactory relationships with others in a given context.

The satisfaction of the needs of autonomy, competence and relatedness promotes intrinsic motivation. Intrinsic motivation is important in learning, since students tend to learn better and are more creative when they are intrinsically motivated (Niemiec & Ryan, 2009; Hattie, 2013). The learning experience should encourage students to act from their own volition and create a sense of choice in them to foster their autonomy (Reeve, 2006) and promote interaction between teacher and student and between students, to support relatedness (Zainuddin, 2017). Relatedness increase participation, engagement and achievement (Anderson, 2003; Giesbers, 2013; Boelens, 2017). The interaction between students that contribute to the satisfaction of their need of relatedness also allow them to tackle new challenges working with others, using cooperative or collaborative learning approaches. Cooperative work consists of the division of tasks between the participants, each person being responsible for the assigned part; collaboration is a situation in which two or more people learn or try to learn something together, solving a problem with a mutual commitment among the participants (Dillenbourg, 1999). Collaborative activities increase the interaction between students, learning and satisfaction (So, 2008; Kozlov, 2016; Sun, 2017).

The motivation of a student can evolve over time, from extrinsic motivation (originated by external stimuli) to forms of intrinsic motivation, through a process known as internalization. The satisfaction of the needs of autonomy, competence and relatedness facilitates the internalization of learning motivations (Niemiec & Ryan, 2009). At the opposite end of the intrinsic motivation is *amotivation*, which is a state in which people do not see a motive for taking action perceiving their behavior as beyond their control (Legault, 2006). In an academic context, *amotivation* is associated with emotions such as boredom, low concentration in classes, increased perception of stress and dropout in traditional (Vallerand, 1997) and in online and blended learning environments (Vanslambrouck, 2017). The persistence of an individual in doing an activity can be explained by their expectations of success, that are related to the concept of self-efficacy (Bandura, 1977), which is a person's belief in their ability to achieve a goal. These self-efficacy beliefs determine whether or not a task is to be addressed, and determine the effort and perseverance that is applied to it, being a predictor of achievement and satisfaction (Hattie, 2013; Vanslambrouck, 2017).

This relation between the perception of ability and the effort that is put in the accomplishment of an activity suggests that the difficulty of the task should be related to the student's ability and be under his control to adapt it to his beliefs of skill. The balance between challenge and skill is one of the main conditions of an optimal experience as proposed by Flow theory (Csikszentmihalyi, 1990). This theory describes the state of Flow, which is characterized by the complete immersion of the person in the activity that he/she performs, being the activity rewarding by itself and intrinsically motivating (Nakamura & Csikszentmihalyi, 2014). It is possible to conceptualize three conditions necessary to promote an optimal experience (Csikszentmihalyi, 1990):

- There must be a balance between the challenge and the person's perception of his skill.
- The activity must have clear objectives and a sequence of progress.

- The activity should provide immediate feedback.

The presence of this characteristics will be fundamental to characterize the object and establish the rules of an activity that induces an optimal learning experience, because flow has been related to feelings of satisfaction (Karahoca, 2010) and improved learning (Shernoff & Csikszentmihalyi 2003; Esteban-Millat, 2014; Rodríguez-Ardura, 2017). The balance of challenge / ability proposed by Flow theory allows their integration with the theory of self-determination, since the existence and verification of this balance provides a satisfaction to the need for competence. It also links it to the concept of self-efficacy, since past achievement experiences based on successful completion of activities in a specific context should have a positive impact on the perception of self-efficacy of the students. To maintain the challenge / skill balance, the activity must experience a progression over time in line with the progress of skill of the person (Shernoff & Csikszentmihalyi, 2009), because when the difficulty is below the skill of the person emotions of apathy, boredom or relaxation may appear and when the difficulty is above the skill of the person emotions of worry and anxiety are induced (Nakamura & Csikszentmihalyi, 2014).

In conclusion, to create an optimal learning experience it is possible to identify the following conditions:

1. Recognize individual differences by providing options to manage perceptions of self-efficacy, difficulty and value of activity, to promote autonomy.
2. Set clear goals that have a sequence of progress over time.
3. Achieve an adequate balance between the challenge of the activity and the student's ability.
4. Provide timely and effective feedback during the course of the activity.

5. Promote the satisfaction of the need for relatedness by creating a community that connects the teacher with the students and the students with each other to encourage collaboration and learning.

Figure 1.2 summarizes the subject and object analysis performed and incorporates the conditions identified as rules of the activity that must be present in the artifacts. It differentiates between technological and social rules, as proposed in (Zurita & Nussbaum, 2004).

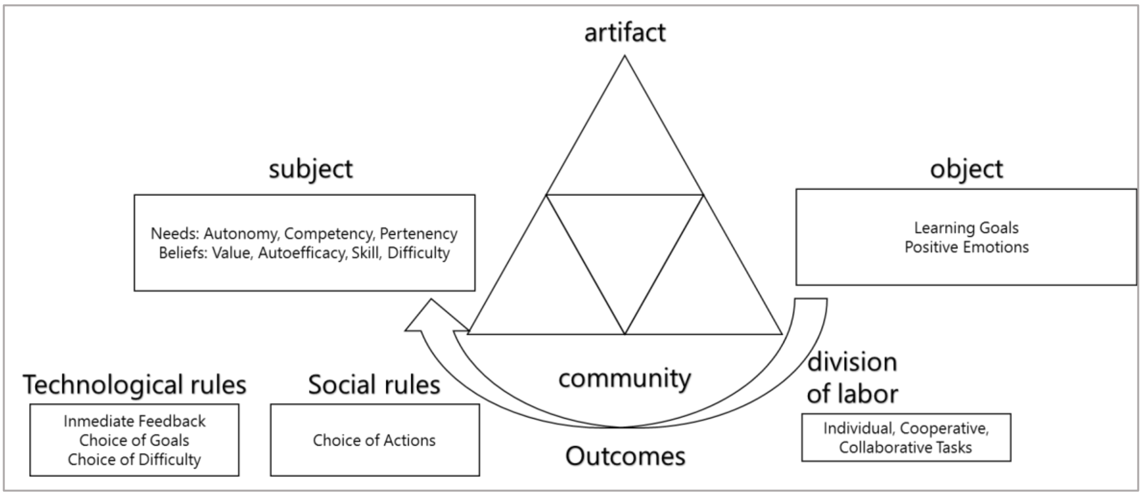


**Figure 1.2:** Subject, Object and rules that promote an optimal experience.

### 1.1.3 Artifacts: methods and technology as mediators of the optimal experience

In order to design an optimal learning experience, we use *blended learning* teaching (Garrison, 2004), in particular we use the *flipped classroom* method (Lage, 2000). In this method, the student learns the content through videos that can be individually reviewed (Gannod, 2008, Bergmann, 2012, Sams & Bergmann, 2012, Bishop, 2013, Campbell, 2014, Kim, 2014) in preparation to the work in class that consists mainly of active learning activities (Prince, 2004). The implementation of the Flipped Classroom usually involves the use of a web platform to provide videos and formative assessments. This allow us to provide feedback to students and give visibility of progress to the teacher. The combination takes advantage of both the possibilities of diagnosis and personalization of online classes and also the advantages of interaction available in a classroom. The flipped classroom promotes self-study of the content through videos, allowing the use of face to face sessions for the realization of active learning activities, combining experiences of individual learning through the online platform with group learning experiences in the classroom. Multiple studies had found that the flipped classroom has a positive effect on academic performance, motivation and student satisfaction (Mason, Shuman & Cook, 2013, Baepler, 2014, O'Flaherty & Phillips, 2015; Thai, 2017; Zainuddin, 2017). This results may be related to a positive learning experience, but the studies does not explain the results obtained using the learning conditions present in the class. Most studies on the flipped classroom include comparisons with traditional lecture-based classes and do not recognize that the conditions, instructional methods, and time on task differ between a flipped and a lecture-based class, and between different implementations of the flipped classroom method. This thesis aim to close this research gap through the following research questions:

**RQ1:** Which elements of student learning and motivation are enhanced in a flipped course?

**RQ2:** Which features of the implementation influence the results that are obtained?

The flipped classroom is particularly beneficial to students with low academic achievement (Baepler, 2014, Gross, 2015). This may be because it provides a highly structured learning environment and promotes active learning, which helps reduce the differences between students with different academic performance (Haak, 2011). However, many students might fail to review and understand the instructional material out of class by themselves because of their lack of self-regulation skills (Lai, 2016). Individual differences in learning can be attributed to a lack of self-regulation among students (Zimmerman, 2002), therefore lower-achieving students should not perform well in an environment requiring higher levels of self-regulation. The effects of the flipped classroom on self-regulation have not yet been comprehensively studied (O'Flaherty, 2015; McLean, 2016). This thesis test the hypothesis that the provision of multiple learning options in the flipped classroom allow students the adaptation of the learning process to their individual needs. The effect of the flipped classroom in choice and how it helps students with different prior academic achievement is studied using the following research questions:

**RQ3:** Does providing choice in the flipped classroom aid the goal-setting process of the students, when compared to lecture-based methods?

**RQ4:** Does the influence of choice and clear goals vary among students with different levels of academic achievement?

The Flipped Classroom can be implemented in a variety of ways (Bishop & Verleger, 2013). In this thesis, we considered an implementation based on the rules indicated in Table 1.1, obtained from the analysis of the activity in the context of an introductory programming class, combined with the most common features in flipped classroom implementations (O'Flaherty & Phillips, 2015). This rules frame each of the moments of the learning experience.

**Table 1.1:** Moments and Rules of the Learning Experience

| Pre-class | In-class (optional) | Post-class |
|---|---|---|
| Review videos with lectures and worked examples. | Participate in concept reviews. | Attend weekly laboratory sessions (optional). |
| Answer closed-ended quizzes. | Follow worked examples. | Solve three individual graded programming assignments. |
| Participate in the forum (optional). | Participate in group programming assignments. | Solve online programming assignments. |

### 1.1.4 Design as the elaboration of artifacts that create the conditions for the learning experience

The design of the learning experience was done considering the elements identified in the analysis of the learning activity. These elements are incorporated as conditions and rules that govern the interaction, at the individual, social and technological level during the development of the activity.

1. Autonomy. It is considered in the design, incorporating capacities for the choice of difficulty level, type of activities and sequence of study. The use of flipped classroom is expected to foster students' autonomy perception as they can choose when and how to study.
2. Competence. Competition needs are mainly addressed from the conditions proposed by the Flow theory:
    a. Clear Objective Setting: In the course design, each interaction is considered to have a clear objective that allows it to be used to monitor progress.
    b. Individual adaptation through the Balance Challenge / Skill: The basis of adaptation to individual differences is the recognition of them (Felder & Brent, 2005). Given the dynamic nature of the experience and the evolution over time of students' perceptions and abilities, the needs of each student are dynamic and change over time, requiring the construction and actualization of a student model (Chrysafiadi, 2013), that allow teachers to recognize and handle individual learning needs. However, the use of this model for learning guidance may interfere with the expression of individual differences and with the recognition of them in the future if the model propose fixed trajectories. The approach used in this thesis for the handling of individual differences is to give options to the students that they can use to define their own goals and handle

the balance/skill challenge by themselves, fostering their autonomy and self-regulation.

c. Instantaneous feedback regarding progress: for the feedback of the students an automated formative evaluation mechanism is incorporated in the technological platform, which will provide information for the classification of the students and the management of the learning process by the teacher. The platform provides formative assessment (Shutte, 2008) opportunities to guide the learning and teaching process as well as instant feedback, which increases students' academic performance (Hattie, 2013).

3. Relatedness. The satisfaction of relatedness needs is incorporated in the design essentially through activities of collaborative work in the face-to-face classes, with group and individual objectives that can be adjusted according to the individual needs.

The rules identified in the analysis of the subject and the object of the experience are combined with the rules of the flipped classroom method to promote an optimal learning experience (Figure 1.3).

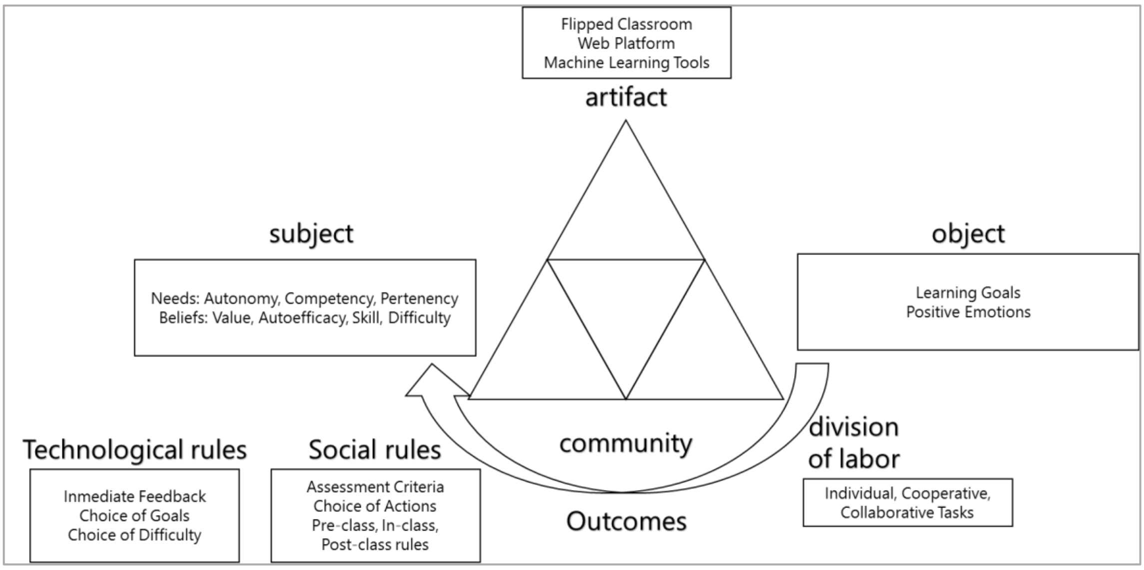


**Figure 1.3:** Optimal Experience Activity Model using the Flipped Classroom method.

### 1.1.5 Is it possible to "Measure" the Experience?

Traditionally, experience has been evaluated using qualitative methods, since it is a personal and subjective interpretation. When approaching the evaluation of the experience from a quantitative perspective we must not forget that the experience is holistic. A quantitative evaluation will necessarily be partial, since it will be focused on those aspects of the experience selected for the analysis. Additionally, the evaluation will be representative of the specific time instant where it is performed, by the dynamic nature of the experience.

The quantitative evaluation will be built around the conditions associated with the Flow concept, which is the most studied in the literature in relation to the evaluation of experiences mediated by technology (Law, 2014), both in the context of the use of web technologies (Chen, 1999, Fu, 2009, Joo, 2012, Esteban-Milat, 2014) and video games (Sweetser, 2005, Kiili, 2005, Kiili, 2012 and Fang, 2013).

This thesis seeks to establish a relationship between the activity theory conceptualization of an optimal learning experience and learning. This relationship has been studied using Flow in face-to-face (Nakamura & Csikszentmihalyi, 2014, Shernoff & Csikszentmihalyi, 2009) and online learning contexts (Fu, 2009, Joo, 2012, Kiili, 2012, Esteban- Milat, 2014), but there are few studies in the context of blended learning and in particular in the context of a flipped class. The model proposed in this thesis aims to provide a consolidated framework that allows to evaluate and design the learning experience from a holistic point of view considering aspects of the subject, object and artifacts involved in the activity.

This thesis propose the hypothesis that there is a duality between experience and activity, activity induces a learning experience and learning experience influence the activity of students in flipped classes. Each student should have a learning experience trajectory during the learning process that should be a consequence of their different motivations and perceptions and reflected in their online interactions. There are multiple models that classify the online activity of students (Kizilcec, Piech & Schneider, 2013; Anderson, 2014; Kahlil & Ebner, 2017), but this classifications lack information about the perceptions of the students which are essential to correctly interpret the results (Gasevic, Dawson, Rogers, & Gasevic, 2016; Gašević, Jovanović, Pardo & Dawson, 2017). To test the proposed hypothesis and provide learning experience information to interpret the online activity of the students this thesis propose the following research questions:

**RQ4:** How can students be classified according to their learning experience at the end of a flipped course?

**RQ5:** Is it possible to build a model that correlates the online engagement patterns of students with their learning experience and academic achievement at the end of a flipped course?

## 1.2 Research Hypotheses

The central hypothesis of this thesis is the duality between experience and activity. Experience can be assessed and correlated with learning outcomes and engagement and the actions performed by the students while learning influence and reflect their learning experience through their choices (Figure 1.4).

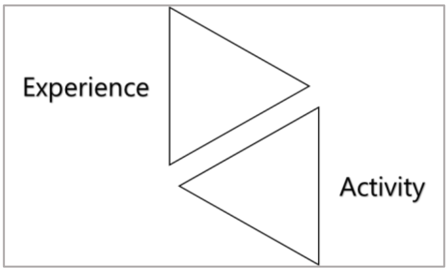


**Figure 1.4:** Duality of Experience and Activity

This central hypothesis will be investigated in the context of learning in a flipped class, through the following research hypotheses that prompt for the research projects presented in this thesis:

1. The learning experience can be measured and correlated with the outcomes of the learning activities in a flipped class.
2. The learning experience in a flipped class emerge from conditions provided by social and technological rules in the activity.
3. The provision of choice in flipped classes influence the learning experience and enable the expression and management of individual differences.
4. There is a duality between experience and activity, activity induces experience classes and experience classes influence activity in flipped courses.

## 1.3 Research Questions

In relation to the hypotheses previously enunciated, the research reported in this thesis has been driven by the following research questions which are tested in the context of the artifacts used in the learning activity (section 1.1.3):

1. Which elements of student learning and motivation are enhanced in a flipped course?
2. Which features of the implementation influence the results that are obtained?
3. Does providing choice in the flipped classroom aid the goal-setting process of the students, when compared to lecture-based methods?
4. Does the influence of choice and clear goals vary among students with different levels of academic achievement?
5. How the students can be classified at the end of a flipped class from the perspective of their learning experience?
6. Is there a model that establish a relationship between the learning experience classification of the students, their academic achievement and their online engagement?

## 1.4 Objectives

The specific research objectives proposed in this thesis are the following:

1. Build a learning experience assessment model and design, test and evaluate a measurement instrument for it.
2. Analyze how the learning experience varies across flipped and traditional teaching methods and different implementations of flipped classes, to establish relationships between class features and the learning experience to inform the design process.

3. Study the influence of the provision of choice in the flipped classroom and how it relates to learning experience.
4. Build a classification model based on the assessment of the learning experience in a flipped class.
5. Build a predictor of the learning experience of the student based on their interaction with the online platform.

## 1.5 Thesis Outline

This thesis is structured in three self-contained chapters, each of them being a paper submitted or published in a refereed journal. One of the papers have been published as the time of this writing. The listing of the subsequent chapters of this thesis is as follows:

II. Schwarzenberg, P., Navon, J., Nussbaum, M., Pérez-Sanagustín, M., Caballero, D. (2017). Learning experience assessment of flipped courses. *Journal of Computing in Higher Education*. https://doi.org/10.1007/s12528-017-9159-8.

III. Schwarzenberg, P., Navon, J. Supporting goal setting in flipped classes. *Interactive Learning Environments,* under review.

IV. Schwarzenberg, P., Navon, J., Pérez-Sanagustín, M., A model for categorizing and predicting learning experience and achievement in flipped courses. *Journal of Computing in Higher Education,* under review.

Chapter II consists of the paper Learning experience assessment of flipped courses. This chapter describes a five dimensional model to assess the learning experience, applicable to face to face and flipped courses. A measurement instrument is derived from the model and validated using a sample of students of an introductory programming class in higher education. After the instrument is validated, it is used to compare the learning experience between face to face and flipped classes to identify similarities and differences. The comparison is also made between two versions of the same flipped class after the inclusion of a rule that require that students achieve a target score choosing between multiple available programming tasks. The correlation of features of the flipped classes with experience and learning is described.

Chapter III consists of the paper Supporting goal setting in flipped classes. This chapter uses a subset of the experience measurement instrument to investigate the relationship between two of their components: choice and the perception of clear goals of students. A comparison is made between face to face and flipped classes regarding this dimensions and a model is constructed to test the influence of choice in the perception of clear goals. The results confirms that the flipped classroom provide a learning experience with meaningful choices that help students to express and manage individual difference by themselves.

Chapter IV consists of the paper A model for categorizing and predicting learning experience and achievement in flipped courses. This chapter focuses in the study of enjoyment and challenge/skill balance as dimensions that allow the classification of the learning experience of students. A Latent Class Model is constructed using those dimensions and the three class solution is analyzed in terms of the learning experience and achievement of the students. The log of online interactions of students is analyzed to find patterns that allow the recognition of learning experience classes from the actions performed for the students in a flipped class. These actions are the results of the choices made by the students while learning.

## 1.6 Thesis Structure

This thesis is structured around the declared research objectives: (1): Build a learning experience assessment model and design, test and evaluate a measurement instrument for it. (2) Analyze how the learning experience varies across flipped and traditional teaching methods and different implementations of flipped classes, to establish relationships between class features and the learning experience to inform the design process. (3) Study the influence of the provision of choice in the flipped classroom and how it relates to learning experience. (4) Build a classification model based on the assessment of the learning experience in a flipped class. (5) Build a predictor of the learning experience class of the student based on their interaction with the online platform. The structure of this thesis is summarized in Table 1.2.

**Table 1.2:** Hypotheses, questions, objectives, papers and results presented in this thesis.

| Hypotheses | |
|---|---|
| H1 | The learning experience can be measured and correlated with the outcomes of the learning activities in a flipped class. |
| H2 | The learning experience in a flipped class emerge from conditions provided by social and technological rules in the activity. |
| H3 | The provision of choice in flipped classes influence the learning experience and enable the expression and management of individual differences. |
| H4 | There is a duality between experience and activity, activity induces experience classes and experience classes influence activity in flipped courses. |
| Research Questions | |
| Q1 | Which elements of student learning and motivation are enhanced in a flipped course? |

| | |
|---|---|
| Q2 | Which features of the implementation influence the results that are obtained? |
| Q3 | Does providing choice in the flipped classroom aid the goal-setting process of the students, when compared to lecture-based methods? |
| Q4 | Does the influence of choice and clear goals vary among students with different levels of academic achievement? |
| Q5 | How can students be classified according to their learning experience at the end of a flipped course? |
| Q6 | Is it possible to build a model that correlates the online engagement patterns of students with their learning experience and academic achievement at the end of a flipped course? |
| Objectives | |
| O1 | Build a learning experience assessment model and design, test and evaluate a measurement instrument for it. |
| O2 | Analyze how the learning experience varies across flipped and traditional teaching methods and different implementations of flipped classes, to establish relationships between class features and the learning experience to inform the design process. |
| O3 | Study the influence of the provision of choice in the flipped classroom and how it relates to learning experience. |
| O4 | Build a classification model based on the assessment of the learning experience in a flipped class. |
| O5 | Build a predictor of the learning experience of the student based on their interaction with the online platform. |
| Papers | |
| P1 | Learning experience assessment of flipped courses. |

| | |
|---|---|
| P2 | Supporting goal setting in flipped classes. |
| P3 | A model for categorizing and predicting learning experience and achievement in flipped courses. |
| Results | |
| R1 | A five dimensional learning experience assessment model applicable to face-to-face and flipped classes. |
| R2 | A learning experience assessment instrument consisting of 14 questions validated in the context of higher education. |
| R3 | An evaluation of characteristics of the flipped classroom method and their correlation with experience and learning to inform the design process of a flipped class. |
| R4 | A model that shows that achievement in a flipped class is higher than in face-to-face classes when taking into account learning experience and previous achievement differences between the students. |
| R5 | A model of the relation between choice, the perception of clear goals and achievement in face-to-face and flipped classes, that shows that the flipped classroom helps students to define their learning goals through the provision of meaningful choices. |
| R6 | A model of the influence of choice in the achievement of students in the flipped classroom which shows that students with low previous achievement benefit more of the increased provision of choice in the flipped classroom. |
| R7 | A latent class model that describe the emergence of three experience classes at the end of a flipped class. Each group is characterized for different perceptions of enjoyment, challenge/skill balance and academic achievement. |

| | |
|---|---|
| R8 | A group of online activity indicators that allow the recognition in a flipped class of the three experience classes and the early detection of students that will drop, fail or pass the course. |
| R9 | A neural network model that recognize with 80% precision, students that will fail the course from their history of online activity in the first third of the semester. |

Figure 1.5 summarizes the connections between hypotheses, research questions, objectives, papers and results presented on this thesis.

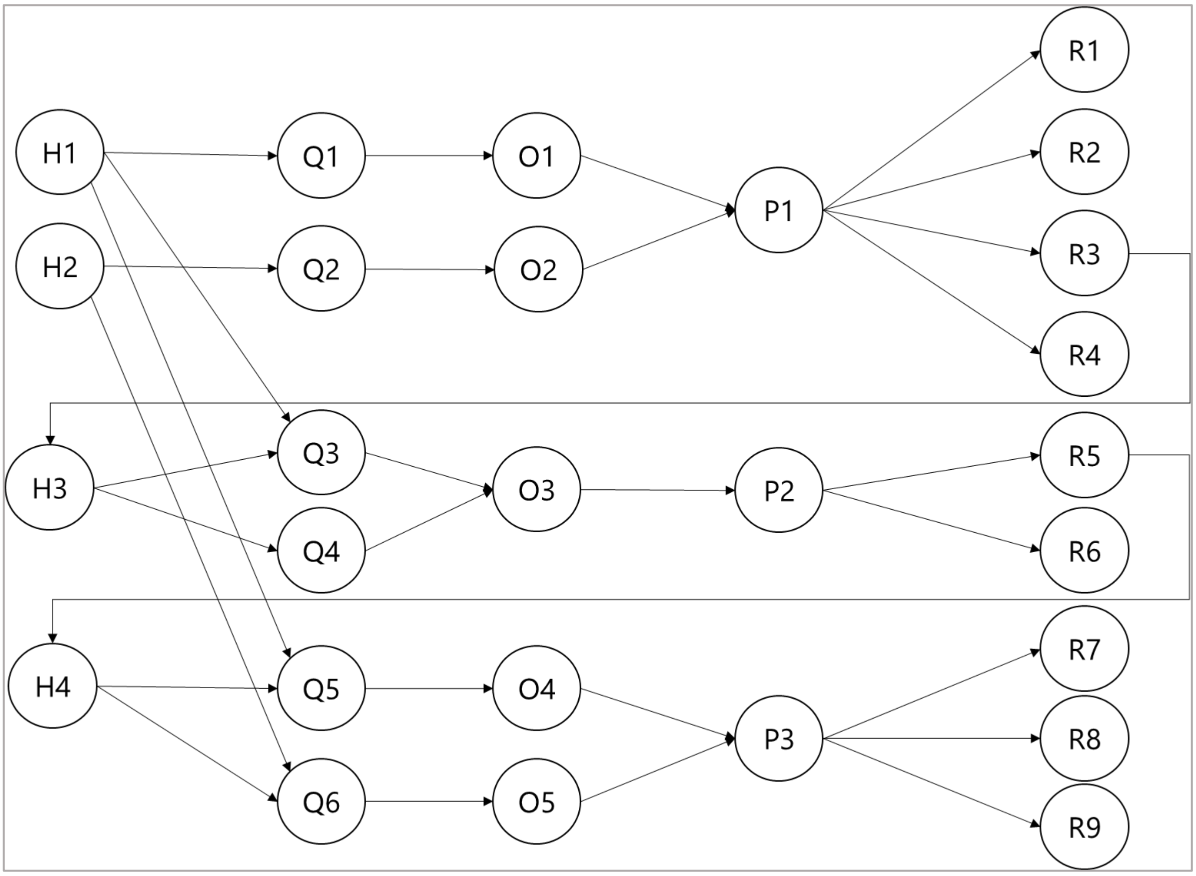


**Figure 1.5:** Relationships between hypotheses, questions, objectives, papers and results.

## 1.7 Conclusions

Following hypothesis H1, “The learning experience can be measured and correlated with the outcomes of the learning activities in a flipped class.”, we can conclude from the results presented in paper 1 that is possible to build a model and an instrument to assess aspects of the learning experience and use them to explain differences between teaching methods (face-to-face or flipped) and between the achievement of students.

Following hypothesis H2, “The learning experience in a flipped class emerge from conditions provided by social and technological rules in the activity”, the evidence provided by paper 1 shows that changes in the rules of a flipped class and the addition of features between successive implementations influence the learning experience and the outcomes obtained.

Following hypothesis H3, “The provision of choice in flipped classes influence the learning experience and enable the expression and management of individual differences”, the results of paper 2 shows that the perception of clear goals of the students is influenced by the availability of meaningful choices. These choices help students to elaborate learning goals adjusted to their perceptions and motivations.

Following hypothesis H4, “There is a duality between experience and activity, activity induces experience classes and experience classes influence activity in flipped courses”, we can conclude from the provided in paper 3, that learning experience dimensions are useful to categorize and classify students in groups that achieve different outcomes at the end of the course and that those groups have different engagement patterns in the online platform.

From the validation of hypotheses H1, H2, H3 and H4 we can conclude that the evidence support the central hypothesis of these thesis: Experience can be assessed and correlated with learning outcomes and engagement and the actions performed by the students while learning influence and reflect their learning experience through their choices. This result contribute a new approach to the design and evaluation of the use of technology in the context of flipped classroom implementations, because new features should focus on improving the learning experience targeting some of their dimensions. The measurement instrument validated in this thesis allow to stablish a baseline of the learning experience and assess the influence of a new feature to decide if their inclusion improved the learning experience, supporting the use of design based research to incrementally improve a flipped classroom implementation.

## 1.8 Research Limitations

The main research limitation relate to the assumptions of the studies of this thesis and the characteristics of experience. First, experience is irreducible and holistic, meaning that assessing only some dimensions of it lose information. This limitation manifest first in the omission of the assessment of some aspects of the experience, notably student emotions, which could help clarify the interrelation between motivation and challenge/skill balance and their influence in academic achievement. The second manifestation of this limitation is the focus of the studies in quantitative methods: complementing a quantitative approach with a qualitative one increases the depth of understanding of the results and allows to capture some aspects of the subjectivity of experience through the use of techniques like focus groups, discourse analysis or in-depth interviews. Regarding subjectivity of the experience, the results obtained in this thesis are based in the assessment at the end of the courses, with the risk that student perceptions are greatly influenced by the results obtained in the course (pass, fail). This limitation explains why the majority of experience measurements were obtained from students that passed the course. Another influence of the assessment of the experience at the end of the course is related to the dynamic nature of experience. A measurement at the end of the course may be considered almost a learning experience outcome. Paper 3 try to address this limitation by trying to establish a relationship between actions performed and the declared learning experience at the end of the course. This approach allowed to show the differentiation and convergence of different groups of students along the course and it should be more effective in capturing the dynamic nature of the experience than increasing the interval of learning experience assessment.

The second group of limitations are related to the context of the studies. Our results were obtained in Higher Education and more studies are needed to check the validity of the instruments and models and the relationship between their dimensions in other contexts like schools and with students in another age ranges, because of differences in learning skills and self-regulation, because self-regulation is required to be effective in a flipped classroom setting (Bol & Garner, 2011; Sun, 2016; Zhu, 2016). Perhaps in another contexts the provision of choice must be done in concordance with the inclusion of rules to guide students with less developed self-regulation skills.

Another limitation is the subject used in the studies. All results were obtained while teaching Programming which is a practice oriented subject that greatly benefits from an increased use of active learning. The relation between experience and achievement obtained should be tested in another contexts, for example while teaching subjects with a higher amount of factual or conceptual knowledge.

# 2 LEARNING EXPERIENCE ASSESSMENT OF FLIPPED COURSES

## 2.1 Introduction

The flipped classroom method of teaching inverts the traditional lecture-homework sequence, providing to the students pre-class activities consisting of videos with the contents of the lesson and formative assessment questions that they must answer before class (Bergmann & Sams, 2012; Bishop & Verleger, 2013). The progression from pre-class activities to in-class activities provides opportunities for formative assessment that allow teachers to guide the teaching/learning process (Gross, 2015). According to recent studies (Mason, Shuman & Cook, 2013; O’Flaherty & Phillips, 2015), the flipped classroom has a positive effect on academic performance and student satisfaction (Bergmann & Sams, 2012; Baepler, 2014), and can be particularly beneficial for teaching students with low academic achievement, as showed in contexts like chemistry (Baepler, 2014) or biochemistry (Gross, 2015). The flipped classroom combines a highly structured learning environment, that help reduce the differences between students with different academic backgrounds (Haak, 2011), with active learning, that has proven to be particularly effective for teaching science (Freeman, 2014).

There is huge variation in the way the flipped classroom is implemented (Bishop & Verleger, 2013), without any clear guidelines as to which features produce what results in a particular context (O’Flaherty & Phillips, 2015). To address this need, certain frameworks have been proposed in order to support the design of flipped classroom courses. Kim (2014) proposes nine design principles to create a learner-centered environment. These nine principles are associated with four types of presence: cognitive presence, social presence, teaching presence and learner presence. Y. Chen, Y. Wang and N. S. Chen (2014) propose the FLIPPED model, an acronym for seven principles to guide the use of the flipped classroom in higher education: Flexible environments, Learner-centered approach, Intentional content, Professional educators, Progressive networking activities, Engaging and effective experiences, and Diversified and seamless platforms. While these models propose certain design criteria, they lack ways to assess the impact of specific features of a particular flipped classroom implementation. To guide the design process for a flipped course, it is essential to understand the effects of the chosen implementation on the learning conditions and the student experience. This is particularly important as the literature reports varying effects on engagement and academic performance (O'Flaherty & Phillips, 2015; Bishop & Verleger, 2013), while there is no explanation for these differences based on the learning conditions present in the class. Most studies on the flipped classroom do not recognize that the conditions, instructional methods, and time on task differ between a flipped and lecture-based class. Without information about the learning conditions, we are unable to determine the causes of the effect size for the use of the flipped classroom. This is because part of the effect may be explained by differences in learning conditions and not by the use of the flipped classroom itself. In order to close this gap and further understanding the effects of the flipped classroom method, this study proposes and applies an instrument for assessing the student learning experience and the extent to which factors that may influence the effectiveness of the flipped classroom are present in different contexts. Therefore, the aim of this paper is to answer the following research questions:

- Which elements of student learning and motivation are enhanced in a flipped course?
- Which features of the implementation influence the results that are obtained?

The context of this study is the teaching of programming at the university level. Programming is a subject that most students consider difficult to learn (Jenkins, 2002), because it combines understanding concepts with the acquisition of the skills that are needed to build programs (Koulouri, 2014). There are several studies on applying the flipped classroom method when teaching programming. Campbell (2014) describes an implementation of the flipped classroom that led to significant differences in the students' enthusiasm for the class. This was done by comparing their enthusiasm at the beginning and the end of the semester. In this case, the flipped programming course enjoyed a high level of approval among the students, who performed better academically than a class that was taught using lecture-based methods. Horton and Craig (2015) observed that although performance on a mid-semester exam in a flipped programming class was lower than in a lecture-based class, the students' performance on the final exam was significantly higher. Furthermore, students who did not drop out of the class were more likely to pass than those in the control section. Hayashi (2015) found an increase in the average grade and lowest grades, as well as a decrease in the standard deviation of student performance on the course. None of these studies reports the influence of the flipped classroom on the relevant learning conditions that may explain the differences in academic achievement or student satisfaction that were found.

## 2.2 Activity-based Learning and the Flipped Classroom

From a constructivist perspective, the teacher in the flipped classroom acts as a facilitator, encouraging the students to become involved in the active learning activities. Active learning can be defined as any instructional method that requires the students to do meaningful learning activities, combined with reflection on what they are doing (Prince, 2004). The use of active learning is regarded as the most likely source of learning gains in the flipped classroom (Jensen, 2015). Active learning increases student engagement, helps develop problem-solving skills and increases academic achievement (Hattie, 2013; Prince, 2004). Examples of active learning methods used together with the flipped classroom are Collaborative Learning (Hayashi, 2015) and Problem-Based Learning (McLaughlin, 2014). The effectiveness of these active learning methods has been shown in multiple contexts, such as K-12 education (Wirkala, 2011) and higher education (Freeman, 2014). The success of a flipped classroom implementation largely depends on providing the conditions for active learning, which is the focus of our learning experience assessment model.

## 2.3 Learning Experience Assessment Model

Shernoff and Csikszentmihalyi (2009) propose a model where student engagement is a consequence of the concentration, interest and enjoyment of the students. The level of challenge influence their concentration in the task, relevance and skill influence their interest and control influence their enjoyment. We used this model as a reference for the model presented in this study, which combines theories that describe the factors that motivate people, as well as the conditions that are required in order to produce an optimal learning experience. This model considers that the optimal learning experience is achieved by balancing motivational factors with factors that facilitate learning. The learning experience is a personal one and is therefore expected to differ between students, due to factors such as learning style and learning pace (Felder, 2005).

Assessment of the learning experience will use the conditions described by Flow theory (Csikszentmihalyi, 1990) as flow is the most commonly measured user experience construct (Law, 2014). This theory proposes three conditions required for an optimal experience when carrying out a task:

- The activity must have clear objectives.
- There must be a balance between the perceived challenges of the activity and the students’ perceived skills.
- The activity must provide instant feedback.

These conditions promote concentration and persistence when carrying out a task, as well as fostering intrinsic motivation. Adequate feedback and the presence of a challenge/skill balance in active learning activities is needed for engagement in deliberate practice, which improves performance (Hattie, 2013; Van Gog, 2005), as does the frequency of in-class activities, which promotes spaced practice and increases learning (Hattie, 2013). The presence of these conditions, together with the use of active learning, could partially explain the positive effects of the flipped classroom on learning and student satisfaction, because of their relation with feelings of satisfaction (Karahoca, 2010) and improved learning (Shernoff & Csikszentmihalyi 2003; Esteban-Millat, 2014).

Our analysis combines these conditions with the needs described by self-determination theory (Deci & Ryan, 2000). Self-determination theory studies motivation from the perspective of why people carry out an activity, suggesting that their actions aim to satisfy three basic needs:

- The need for relatedness: this refers to developing and maintaining satisfactory relationships with others in a given context.
- The need for autonomy: this has to do with a person considering that their behavior is voluntary, and that they can initiate and regulate their own behavior.
- The need for competence: this refers to understanding how to meet an objective and be efficient when completing the required tasks, i.e. when students are capable of facing the challenges presented to them.

Satisfying the need for relatedness, autonomy and competence enhances a person's natural interest in an activity, contribute to their wellbeing and boosts intrinsic motivation, which in turn develops learning and creativity among students (Niemiec & Ryan, 2009), as is the case with the conditions described by flow theory (Nakamura & Csikszentmihalyi, 2014).

A combined assessment of the conditions described, may help explain the positive effects of the flipped classroom on satisfaction and learning. In order to carry out this analysis, we propose a Learning Experience Assessment model with five dimensions (Figure 2.1).

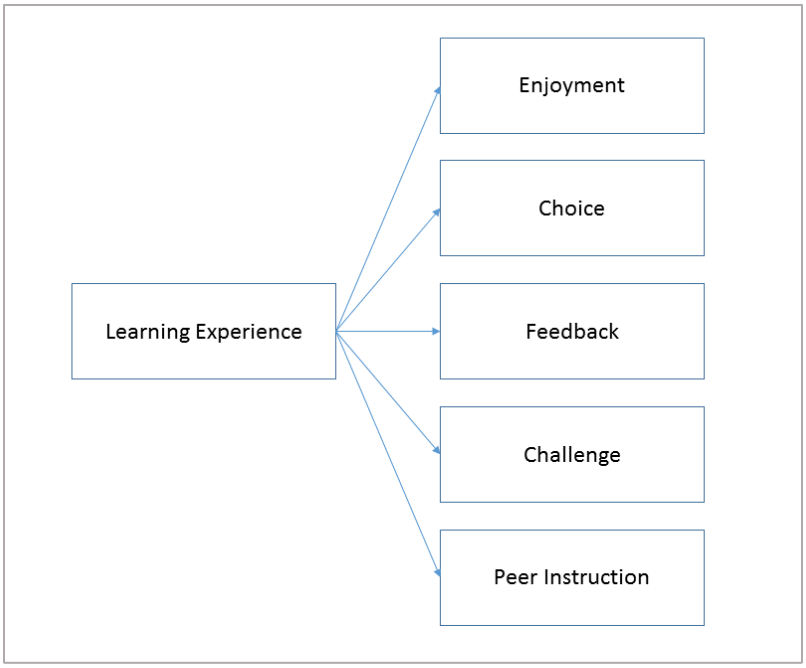


**Figure 2.1**: Dimensions of the Learning Experience model

- Enjoyment: Enjoyment for the task and intrinsic motivation are the expected outcomes of an optimal experience and the satisfaction of the needs described by self-determination theory.
- Choice: The perceived choice relates to the satisfaction of the need for autonomy in self-determination theory (Ryan & Deci, 2000).
- Feedback: This dimension assesses effective feedback, which, according to Hattie (2007), consists of three elements:

  a. Feed Up: Clarity in the definition of the objectives and success criteria.

  b. Feed Back: Clarity in current performance, based on self-assessment.

c. Feed Forward: Clarity in the activities that must be completed in order to progress and set new objectives.

Feedback is one of the factors that has the greatest impact on academic performance among students (Hattie, 2013).

- Challenge: A level of challenge that slightly stretches the student's current level of ability is key to an optimal experience (Csikszentmihalyi, 1990) and learning (Vygotsky, 1978). Challenging objectives have a moderately large effect on academic performance (Hattie, 2013).
- Peer Instruction: Peer Instruction evaluates the extent to which the opportunities provided to the students to interact and learn from each other satisfy their need for relatedness. Peer interaction has a positive effect on student achievement, through mechanisms such as peer tutoring (Hattie, 2013).

## 2.4 Methodology

### 2.4.1 Participants

We conducted the study in an Introductory Programming course at a Chilean University. Table 2.1 and Table 2.2 show the breakdown of the sample for the first and second semester of the study. For the first semester, the sample consisted of eight sections of an Introductory Programming class (each one taught by a different professor). One of the eight sections was chosen at random (F1S1) to be taught using the flipped method. In the second semester, two of the six sections were chosen at random (F1S2 and F2S2) to be taught using the flipped classroom method.

**Table 2.1**: Breakdown of the sample, first semester.

| Section | GPA | | Gender | | Total |
|---|---|---|---|---|---|
| | Mean | SD | Female | Male | |
| L1S1 | 45 | 11 | 18 | 36 | 54 |
| L2S1 | 45 | 11 | 14 | 53 | 67 |
| L3S1 | 44 | 11 | 8 | 33 | 41 |
| L4S1 | 48 | 8 | 16 | 46 | 62 |
| C1S1 | 53 | 9 | 21 | 57 | 78 |
| F1S1 | 54 | 8 | 11 | 62 | 73 |
| C2S1 | 53 | 9 | 21 | 78 | 99 |
| C3S1 | 54 | 8 | 16 | 67 | 83 |
| | | | 125 | 432 | 557 |

**Table 2.2**: Breakdown of the sample, second semester.

| Section | GPA | | Gender | | Total |
|---|---|---|---|---|---|
| | Mean | SD | Female | Male | |
| F1S2 | 51 | 6 | 13 | 20 | 33 |
| F2S2 | 53 | 6 | 17 | 48 | 65 |
| L1S2 | 45 | 16 | 34 | 57 | 91 |
| L2S2 | 50 | 9 | 16 | 59 | 75 |
| C1S2 | 53 | 5 | 27 | 52 | 79 |
| L3S2 | 49 | 7 | 15 | 47 | 62 |
| | | | 122 | 283 | 405 |

To compare student experience and achievement, we selected three sections in the first semester (C1S1, C2S1, C3S1) and one in the second (C1S2) to act as a Control Group (CG). The control group had a similar GPA to F1S1 and F1S2/F2S2, respectively, as we expect that there is a correlation between exam scores and prior achievement (Hattie, 2013). To make the comparison we calculated the z-score for GPA and transformed it to a 0-100 scale (Table 1 and Table 2). Non-significant ANOVAs, $F(3,329) = 0.29$, $p = .83$ for the first semester and $F(2,174) = 1.22$, $p = .3$ for the second, confirmed the homogeneity of the GPA inside the experimental and control group for each semester. The sections marked with L, are lecture-based sections excluded from the comparisons due to their lack of homogeneity with the experimental and control groups.

### 2.4.2 Procedure

We developed the Learning Experience Assessment instrument using exploratory and confirmatory factor analysis. We then used it to analyze the learning conditions of two consecutive semester implementations of a flipped programming course taught by the same professor. We used a quasi-experimental design to compare the flipped section with lecture-based control sections (Table 2.1 and Table 2.2), and compared the factor scores for each group to identify differences in student learning experience and the score achieved on the final exam to analyze the effects on academic achievement. In both semesters, the course topics were the same for all sections, with the same sequence of content presentation and skill development.

The design principles proposed by Clark and Mayer (2011) were followed when creating the online material for the flipped sections. These principles are the multimedia learning principles: Multimedia, Contiguity, Modality, Redundancy, Coherence, Personalization and Segmentation, applied to an e-learning context.

In F1S1, we implemented a flipped classroom using conventional features, Table 2.3, (Bishop & Verleger, 2013; O'Flaherty & Phillips, 2015) to establish a baseline. In the second semester, there were two flipped sections: F1S2 and F2S2, with the latter taught by the same professor as F1S1. All flipped sections used the open source platform OpenEDX (https://open.edx.org/) to deliver the lecture videos and support pre-class activities.

**Table 2.3**: Activities for every course section included in the study.

| Section | Semester | Pre-class activities | In-class activities | Post-class activities |
|---|---|---|---|---|
| F1S1 | First | Videos with Lectures and worked examples.<br>Closed-Ended Quizzes.<br>Forum Participation. | Concept Reviews<br>Q/A Sessions<br>Worked Examples<br>Group Programming Assignments | Laboratory (each week)<br>Three Graded Programming Assignments |
| C1S1<br>C2S1<br>C3S1 | First | None | Lectures<br>Worked Examples | Same as F1S1 |
| F1S2 | Second | Same as F1S1 | Same as F1S1 | Same as F1S1 plus<br>Programming Milestones. |
| F2S2 | Second | Same as F1S1 | Same as F1S1 | Same as F1S1 plus<br>Programming Milestones. |
| C1S2 | Second | None | Lectures<br>Worked Examples | Same as F1S1 plus online forum. |

The content was structured around 10 topics, which were released throughout the semester. The course contained 131 videos with theoretical content and worked examples, with a duration of between three to ten minutes. The pre-class activities consisted of short-answer and multiple-choice quizzes to assess the understanding of the material. The students were provided with feedback on their answers, as well as an explanation of the correct response. The topics included program comprehension, program fixing and questions about how to extend the worked examples presented in the videos. Students were required to participate in the forum every week, by either posting a question about that week's topic or replying to a question posted by their peers. The professor and teaching assistant answered questions and acted as moderators on the forum in order to check the students' answers and the quality of the questions that were posted. For the first semester, these activities accounted for 20% of the final grade for the flipped sections of the course.

In the second semester (S2), we added a feature called Programming Milestones. We based the design of this feature on the concept of experience points used by role-playing games (Adams, 2010). Experience Points are earned upon completion of a given challenge and show the players their progress in the game (Adams, 2010). Throughout the semester, the students had four programming milestones. These milestones required the students to achieve a score of 12 points by solving programming exercises. Each programming exercise awarded points based on the level of difficulty and the course progression. For example, creating a function to test whether a number is prime was awarded one point at the beginning of the semester, but a program to recursively display a Pascal triangle was awarded three points at the end of the semester. The students could choose which programming exercises to do based on their skills and preferences. In this way, the students can select the tasks to accommodate their learning pace. With the addition of Programming Milestones, the pre-class and post-class activities accounted for 30% of the final grade for the flipped sections of the course.

The teacher's in-class activities included concept reviews based on the topics most frequently posted on the forum, as well as Q&A sessions on the optional programming assignments given to the students in class and through the online platform. In the second half of the semester, the students were given weekly group-programming assignments, where they needed to build a program collaboratively in class. Every group had to build part of the solution and join another group in order to assemble the whole solution to the problem. The final solutions could be submitted after class.

In order to pass the course, the students had to sit a final exam, which covered the entire contents of the course. The final exam was the same for all sections and was peer reviewed by all of the professors that taught the class that semester.

### 2.4.3 Instruments and data collection

We developed an instrument to assess the student learning experience using the five dimensions of the Learning Experience Assessment model. For each dimension of the model, we selected groups of items from instruments in the literature checked for reliability and content validity. The initial version of the instrument (Appendix A, Table 2.10) consisted of eighteen 5-point Likert questions, with responses ranging from completely disagree (1) to completely agree (5):

- Enjoyment: We assessed this dimension using three questions adapted from the Intrinsic Motivation Inventory (IMI) (Deci, 1994), which are recognized as the self-reporting scale for intrinsic motivation.
- Choice: We assessed choice using three questions adapted from the Intrinsic Motivation Inventory (IMI) (Deci, 1994).
- Feedback: We included six questions to assess the presence of effective feedback. Three of these questions were focused on the dimensions of Feed Up and Feed Forward, adapted from Fang (2013), while three focused on Feed Back, adapted from Fu (2009) and Fang (2013).
- Challenge: In order to assess the balance between challenge and skill level, we asked about the perceived level of challenge using three questions adapted from Esteban-Millat (2014), where the score given by the students indicated whether or not they found the activity challenging.

- Peer Instruction: We assess this dimension using three questions adapted from Fu (2009).

The initial instrument was administered as part of the mid-term exam of the first semester (n=477, Table 2.4), allowing the students to fill it out voluntarily. This was done to perform the first exploratory factor analysis (Appendix A, Table 2.11) and refine the instrument, removing questions with low reliability and replacing them with others, leading to a definitive version with fourteen questions (Appendix A, Table 2.10). During the final exam in the first semester, we applied the definitive version of the instrument and tested its validity using the data from all of the students that answered the survey (n=422, Table 2.4), including 17 anonymous responses. The second semester, the instrument was applied again in order to collect data and analyze changes in the student experience (Table 2.4).

**Table 2.4**: Student participation in the learning experience survey.

| Section | Total | Mid-term | Final Exam |
|---|---|---|---|
| L4S1 | 54 | 44 | 38 |
| L5S1 | 67 | 40 | 57 |
| L6S1 | 41 | 30 | 27 |
| L7S1 | 62 | 50 | 44 |
| C1S1 | 78 | 64 | 46 |
| F1S1 | 73 | 71 | 63 |
| C2S1 | 99 | 97 | 83 |
| C3S1 | 83 | 81 | 64 |
| Total First Semester | 557 | 477 | 422 |
| F1S2 | 33 | | 29 |
| F2S2 | 65 | | 64 |
| C2S2 | 79 | | 52 |
| Total Second Semester | 177 | | 145 |

The sample sizes fulfilled the recommended criteria for exploratory factor analysis (Field, 2012). A Kaiser-Meyer-Olkin index of 0.81 with indexes for each question above 0.5 (Appendix, Table 12), confirmed the adequacy of the data for exploratory factor analysis (Field, 2012). Bartlett's Sphericity test was significant ($\chi^2$ (91) = 2693.26, $p < .001$), suggesting that the correlation between the items is adequate for conducting exploratory factor analysis. The oblique rotation method *oblimin* was used to obtain factor scores because the expected correlation between factors such as enjoyment and feedback (Csikszentmihalyi, 1990) or enjoyment and choice (Ryan & Deci, 2000). The results obtained at the end of the semester appear in Table 2.5, organized by question and dimension using the coding taken from Table 2.10 (Appendix A).

**Table 2.5**: Factor loadings, reliability and validity of the definitive instrument.

| Item | Standardized Factor Loadings | | | | |
|---|---|---|---|---|---|
| | Peer Instruction | Choice | Enjoyment | Challenge | Feedback |
| c1 | | 0.76 | | | |
| c2 | | 0.91 | | | |
| c3 | | 0.70 | | | |
| f1 | | | | | 0.76 |
| f2 | | | | | 0.65 |
| f4 | | | | | 0.40 |
| b1 | | | | 1.00 | |
| b2 | | | | 0.65 | |
| e1 | | | 0.52 | | |
| e2 | | | 0.84 | | |
| e3 | | | 0.70 | | |
| p1 | 0.89 | | | | |
| p2 | 0.91 | | | | |
| p3 | 0.84 | | | | |
| Explained Variance | 0.17 | 0.14 | 0.12 | 0.10 | 0.10 |
| Cronbach's alpha | 0.91 | 0.85 | 0.78 | 0.80 | 0.70 |
| CR | 0.91 | 0.85 | 0.78 | 0.87 | 0.71 |
| AVE | 0.78 | 0.66 | 0.54 | 0.79 | 0.45 |

Factor loadings (Table 2.5) were greater than or equal to 0.4 and can be considered significant for the sample size (Stevens, 2009). A reliability analysis of the scales (Appendix A, Table 2.13) obtained a Cronbach's alpha greater than or equal to 0.7 for each one. We verified the reliability and convergent validity of the scales by calculating their composite reliability and average variance extracted. The composite reliability (CR) was calculated using the standardized factor loadings (all significant, $p<.05$, Table 2.5). This returned results above the recommended limit of 0.7 (Hair, 2010) for each of the scales. The average variance extracted (AVE) obtained for each factor (Table 2.5) was above the recommended minimum value of 0.5 (Hair, 2010), except for Feedback. We decided to keep Feedback in the model, despite having an AVE that is slightly below the recommended value. This decision was made based on the effect that feedback has on motivation and academic performance. To obtain the factor scores for the students, Thurstone's regression approach was used, because it produces the strongest correlations between factors and factor scores (Tabachnick, 2013). In order to aid the interpretation, the factor scores were transformed to a 0-100 scale, mean=50, standard deviation=10, (Table 2.6).

## 2.5 Results

To answer the research question, Which elements of student learning and motivation are enhanced in a flipped course?, the scores for the experimental group and control group from both semesters were compared doing ANOVAs on exam and factor scores (Table 2.6), excluding anonymous responses to the experience survey.

**Table 2.6**: Mean Exam and Factor scores for experimental and control groups.

| | N | Exam Score | Peer instruction | Choice | Enjoyment | Challenge | Feedback |
|---|---|---|---|---|---|---|---|
| F1S1 | 62 | 53.3 | 55 | 52 | 48 | 50 | 48 |
| C1S1 | 33 | 55.5 | *48 | 50 | 50 | *45 | 51 |
| C2S1 | 82 | 53.0 | *51 | 51 | *52 | 53 | *52 |
| C3S1 | 62 | 52.3 | *49 | 49 | 48 | 51 | 48 |
| F1S2 | 27 | 56.2 | 48 | 52 | *49 | *48 | 52 |
| F2S2 | 62 | 56.4 | 52 | 55 | 53 | 52 | 53 |
| C1S2 | 49 | 54.7 | 53 | 52 | 52 | 52 | 53 |

In Table 2.6, significant differences ($\alpha$=.05) with baseline sections for each semester (F1S1 for the first and F2S2 for the second) are highlighted with *. The mean of peer instruction is significantly lower in C1S1, C2S1 and C3S1. The effect size (Cohen's d) was d=.25 and the power of the test was .9. There were no difference in peer instruction between F1S1 and F2S2 (same professor): $F(1,122) = 2.19$, $p = .14$, and between F2S2 and F1S2 (different professors): $F(1,87) = 2.94$, $p = .09$. Student perception of the feedback increased significantly in F2S2: $F(1,122) = 11.7$, $p < .001$, after the introduction of programming milestones and in comparison with the students in F1S1. This was also the case for enjoyment of the course, $F(1,122) = 11.79$, $p < .001$. The achieved power of the test was 0.79 and the effect size on feedback and enjoyment was d=.25.

We standardized the GPA and final exam scores for each semester in order to test for differences in achievement (Table 2.6). We conducted an ANCOVA on exam scores for each semester using GPA as a covariate. The effect of GPA on exam scores was significant in both semesters: $F(1,234) = 68.34$, $p < .001$, $r = .47$ and $F(1,134) = 26.15$, $p < .001$, $r = .40$. We did not find any significant differences in exam scores for the first semester $F(3,234) = 1.47$, $p =$

.22. In the second semester, F2S2 achieved a significantly higher score compared to C1S2, $F(1,108) = 4.20$, $p = .04$, d = .19, but this was not the case for F2S1, $F(1,73) = 3.77$, $p = .06$. Figure 2a shows a boxplot of the GPA within each section. We divided each section into two groups, above (A) and below (B) GPA mean, to plot the final exam scores (Figure 2.2b).

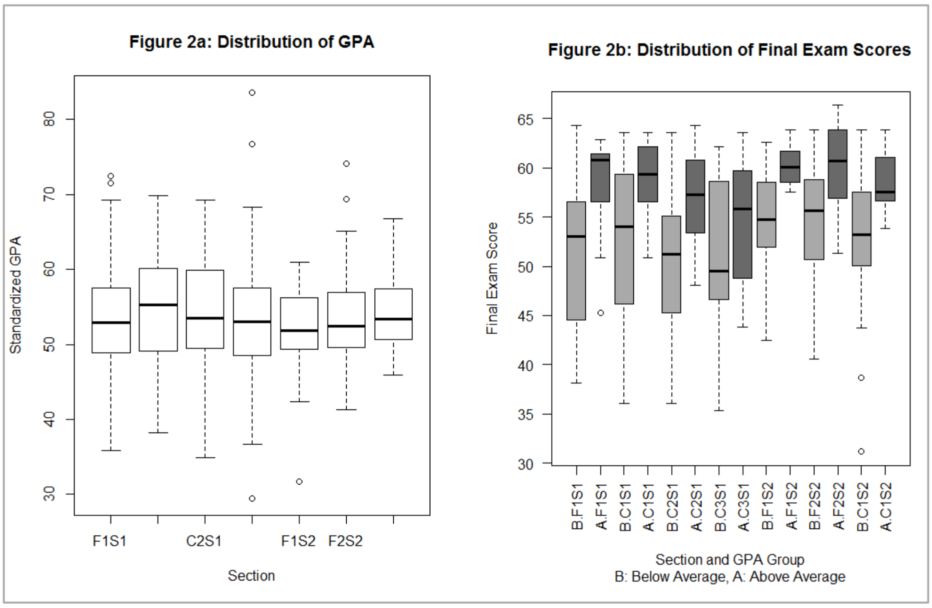


**Figure 2.2:** GPA Distribution of groups

To answer the research question: Which features of the implementation influence the results that are obtained?, we conducted a multiple regression analysis (Pedhazur, 1997) for experience scores on achievement. To assess the effect of the flipped classroom on final exam scores, we added this as a predictor using dummy coding (Pedhazur, 1997), assigning 0 to lecture-based courses and 1 to flipped courses. We also included a dummy variable called semester in the analysis (0: first semester, 1: second semester). The purpose of this was to control variations in achievement that were related to contextual differences between semesters, such as the level of difficulty of the course or the students' academic load. Table 2.7 shows the Pearson correlations between experience and achievement, with the dichotomous variable 'flipped'.

**Table 2.7:** Correlations (p<.05) of experience with achievement and method.

| | Final Exam | Flipped |
|---|---|---|
| Enjoyment | 0.36 | |
| Choice | 0.27 | 0.12 |
| Feedback | 0.38 | |
| Challenge | -0.18 | |
| Peer instruction | | 0.11 |
| GPA | 0.44 | |
| Final Exam | | 0.11 |

We recorded participation indicators for students in flipped classes, including the total amount of videos viewed (median=62), online questions answered (median=40), messages posted in the forum (median=9) and points earned in milestones (median=48). We used Kendall's tau to investigate their correlation with achievement and experience (Table 2.8). We decided to do this given that the participation indicators were count data (Field, 2012).

**Table 2.8:** Kendall τ Correlations (p<.05) with participation.

| | Video | Quiz | Forum | Milestone |
|---|---|---|---|---|
| Enjoyment | | | 0.12 | 0.16 |
| Choice | | | | |
| Feedback | | | | 0.18 |
| Challenge | | | | |
| Peer Instruction | | | 0.12 | 0.21 |
| GPA | 0.15 | 0.21 | 0.27 | 0.32 |
| Final Exam | | 0.16 | | 0.23 |

Table 2.9 shows the regression model for final exam achievement on experience. The fit of the model did not increase when adding choice: $F(1,369) = 0$, $p = .99$ or peer instruction: $F(1,369) = 3.55$, $p = .06$ as predictors.

**Table 2.9:** Multiple Regression Model for Achievement.

| | $R^2$ | B | SE B | 95% CI | β |
|---|---|---|---|---|---|
| | *0.40 | | | | |
| Constant | | *25.48 | 2.82 | 19.94, 31.01 | |
| Enjoyment | | *0.15 | 0.04 | 0.07, 0.23 | 0.21 |
| Feedback | | *0.15 | 0.04 | 0.07, 0.22 | 0.20 |
| Challenge | | *-0.14 | 0.03 | -0.19, -0.08 | -0.21 |
| GPA | | *0.37 | 0.04 | 0.29, 0.44 | 0.40 |
| Semester | | *1.47 | 0.61 | 0.27, 2.68 | 0.11 |
| Flipped | | *1.40 | 0.59 | 0.22, 2.57 | 0.10 |
| * $p < .05$ | | | | | |

To assess the assumptions of normality, linearity and homoscedasticity, figures 2.3a, 2.3b and 2.3c show the analysis of the residuals of the model (Tabachnick, 2013). The analysis did not reveal any significant deviations in the assumptions, which suggests that our model may be generalized beyond our sample (Field, 2012).

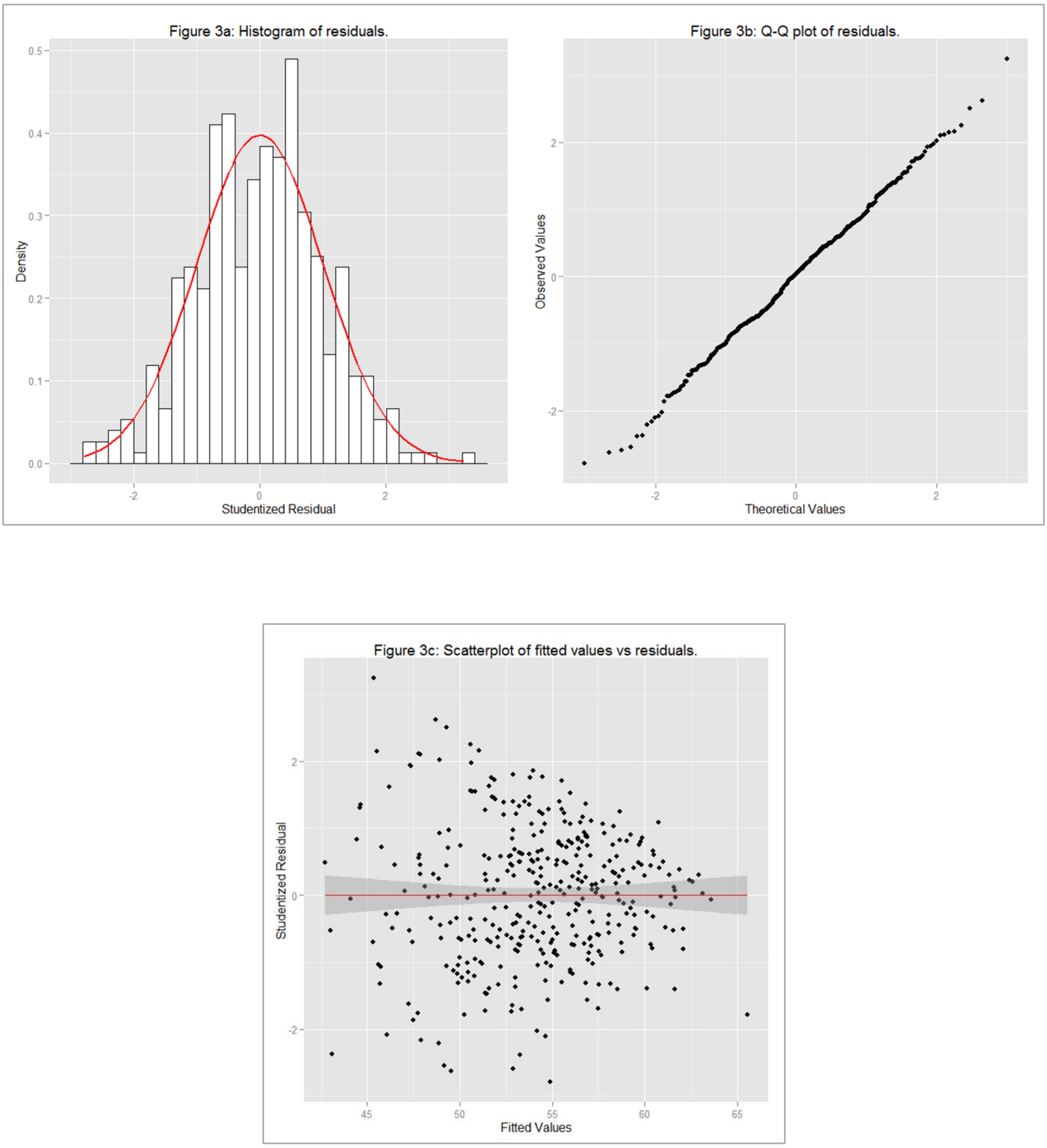


**Figure 2.3**: Regression Analysis

## 2.6 Discussion

The instrument proposed in this study allowed for the identification of similarities and differences in the student learning experience between flipped and lecture-based sections of a programming course. The results suggest that in-class activities and online forum posting relate to the perception of opportunities for peer instruction between the students in flipped classes, because peer instruction score correlated with online forum activity. The in-class Q&A sessions guided by the teacher allowed the students to interact with each other, creating a learning environment that fostered peer learning. The teacher encouraged students to exchange strategies for solving the programming assignments. The students collaborated by building the solutions to the in-class group programming exercises and by answering questions about these assignments on the forum. The difference in perceived opportunities for peer instruction between the flipped and lecture based section holds, even though laboratory sessions, where students could practice and work together, were included in every section. It is widely acknowledged that peer instruction has a positive effect on academic performance, both for the instructor and the learner (Hattie, 2013) but we did not find a correlation between peer instruction and achievement. We found a significant correlation between the use of the flipped classroom and the perception of choice of the students (Table 2.7). GPA and feedback were significant predictors of achievement (Table 2.9), as expected (Hattie, 2013). We also observed differences in achievement between the two semesters during which the study took place. In the second semester, the students scored between 0.27 and 2.68 points higher on the final exam, when fixing the effect of GPA and student experience (Table 2.9). In both semesters, the flipped classroom students scored between 0.22 and 2.57 points higher on the final exam (between 0.03 to 0.39 standard deviations of exam score), when fixing the effect of GPA and student experience. The use of the flipped classroom increased achievement ($\beta$=0.10) when compared to lecture-based courses, when fixing the effect of student experience and GPA. In the first semester, C2S2 scored higher in enjoyment and feedback than F1S1, but not in achievement (Table 2.6). The differences in enjoyment and feedback did not influence the overall performance of the students in F1S1, because flipped classes are able to compensate for small differences in experience and prior achievement given their positive effect on achievement. The flipped classroom effect and the student experience explain why F2S2 achieved higher scores on the final exam compared to C1S2. The use of programming milestones, which increased the perception of feedback and enjoyment in F2S2 over F1S1, contributed to this result. This is because of the increased practice and the effect of feedback on achievement (Hattie, 2013). Programming milestones had a significant correlation with exam scores (Table 2.8). To better interpret the effect size, we obtained an approximate Pearson equivalent of r=0.35 for this correlation. This was done using Kendall's formula (Walker, 2003), and suggests there is a medium-size effect on achievement. In the flipped classes, the online activity correlates with GPA, and online participation correlate with the perception of enjoyment, feedback and opportunities for peer instruction of the students (Table 2.8). Our results support that the improvements obtained in flipped classes are related to the use of active Learning (Haak, 2011), because of the correlation between achievement and indicators of practice such as milestone scores, and increased pre-class preparation (Gross, 2015), represented by the students' level of online activity.

## 2.7 Conclusions, Limitations and Future Work

In this study, we presented an instrument to assess the student learning experience with the aim of understand differences in flipped and lecture-based programming courses. Concerning the research question: Which elements of student learning and motivation are enhanced in a Flipped Classroom course?, previous research had found that interaction and collaboration between students increase their engagement with the class (Shernoff &

Csikszentmihalyi, 2009) and influence the achievement of the students (Hattie, 2013) providing opportunities to learn from peers. We observed that the flipped classroom, precisely, increases the opportunities for peer instruction when in-class activities promote active learning and the students interact via an online forum. Our results suggest that the effect of the flipped classroom on learning experience is dependent on their implementation. A flipped classroom implementation that promotes a better learning experience and active learning helps students with different prior achievement, reducing the effect of individual differences on achievement. This result within the context of teaching Computer Programming replicated the results obtained in the context of teaching Chemistry (Baepler, 2014) and Biochemistry (Gross, 2015).

Concerning the research question: Which features of the implementation influence the results that are obtained?, the student experience in flipped classes is the result of in-class activities, online participation and out-of-class activities, such as programming milestones. Programming milestones provided deliberate practice opportunities that were spaced across the semester and influenced learning. This feature allowed students to choose the next problem that they wanted to solve and to create their own strategy that met the course requirements, instead of the standard practice of sending a fixed sequence of assignments for the students to complete. This result shows that class features influence student experience and explain differences in achievement between flipped classroom implementations. When flipping a course, our model predicts an improvement in student achievement when the learning experience is similar to lecture-based offerings. The expected improvement in achievement increases when features of the flipped classroom implementation improve student experience. Our results suggest that the design of a flipped class should consider the effect of different implementation features and select the most appropriate ones for a particular context. We designed our instrument to help the design process and the selection and assessment of implementation features. We expect that the relationships between learning experience, achievement, and flipped classroom that are proposed in our study are generalizable to other implementations because they are grounded in theory. In topics involving non-technical or humanities content, the use of the flipped classroom may allow the use of face to face sessions for case studies and discussion between students, which could lead to increased opportunities for feedback and increased enjoyment of the course. Only the use of the instrument proposed and the testing of the model in other contexts, can confirm if our findings are generalizable.

It remains as future work to investigate causal relationships between experience factors that could explain the flipped classroom effect on achievement. To answer this question, we need a larger sample size of flipped classroom students to apply techniques such as structural equation modeling. Our model only partially accounts for differences in the social context of the classroom. This is because the application of multilevel regression techniques to cluster the students at the classroom level requires a larger number of groups (n>20) than those included in our study (Hox, 2010).

## 2.8 Appendix A:

**Table 2.10:** Refinement of the Measurement instrument

| Dimension | Item | | Question |
|---|---|---|---|
| Choice | F | c1 | I feel that the structure of the course allows me to choose the activities that I want to in order to learn. |
| | D | c2 | I complete the course activities (classes, laboratory sessions, assignments, quizzes, etc.) because it is obligatory. |
| | A | c2 | The course provides options for me to choose how I want to learn. |
| | F | c3 | I have been able to choose the activities that I think will help me learn. |
| Feedback | F | f1 | I am fully aware of what I must learn in order to pass this class. |
| | F | f2 | I am fully aware of the activities that I must complete during the course in order to learn. |
| | D | f3 | The course objectives are clearly defined. |
| | F | f4 | I am aware of how much I am retaining of what is being taught in this course. |
| | D | f5 | As I am completing the activities I have a clear idea of how I am doing on them. |
| | D | f6 | I feel that I receive appropriate and timely feedback on my progress. |
| Challenge | F | b1 | Understanding the content of this course is a challenge for me. |
| | F | b2 | Applying the content of the course to develop a program is a challenge for me. |
| | D | b3 | I feel that I have the skills that are needed to face the challenges presented by this course. |
| Enjoyment | F | e1 | I have enjoyed the experience of taking this class. |
| | F | e2 | I find it satisfying to apply what I have learnt in class to create my own programs. |
| | F | e3 | One of my motivations for taking this class is seeing my programs work. |
| Peer Instruction | F | p1 | I feel that the structure of the course allows me to interact with my peers and receive help from them. |
| | F | p2 | I feel that the structure of the course favors a discussion and exchange of ideas with my peers. |
| | F | p3 | I feel that the structure of the course allows me to learn from my peers. |

F: item was the same in initial and definitive version, A: item added on definitive version, D: item deleted on definitive version.

**Table 2.11**: Factor Loadings and Reliability of the Instrument (Initial Version).

| Item | Standardized Factor Loadings | | | | |
|---|---|---|---|---|---|
| | Peer Instruction | Choice | Enjoyment | Challenge | Feedback |
| c1 | | 0.38 | | | |
| c2 | | -0.11 | | | |
| c3 | | 1.00 | | | |
| f1 | | | | | 0.75 |
| f2 | | | | | 0.68 |
| f3 | | | | | 0.62 |
| f4 | | | | | 0.34 |
| f5 | | | | | 0.21 |
| f6 | | | | | 0.17 |
| b1 | | | | 0.88 | |
| b2 | | | | 0.84 | |
| b3 | | | | -0.09 | |
| e1 | | | 0.87 | | |
| e2 | | | 0.69 | | |
| e3 | | | 0.54 | | |
| p1 | 0.87 | | | | |
| p2 | 0.89 | | | | |
| p3 | 0.88 | | | | |
| | | | | | |
| Cronbach's alpha | 0.91 | 0.58 | 0.77 | 0.64 | 0.76 |

**Table 2.12**: MSA Index for each question on the instrument.

| | c1 | c2 | c3 | f1 | f2 | f3 | b1 | b2 | e1 | e2 | e3 | p1 | p2 | p3 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| MSA | 0.86 | 0.81 | 0.86 | 0.85 | 0.85 | 0.88 | 0.5 | 0.53 | 0.9 | 0.81 | 0.82 | 0.79 | 0.78 | 0.83 |

**Table 2.13**: Reliability of scales of the final version of the instrument.

| Item | Reliability | Item-Total |
|---|---|---|
| | Without tem | Correlation |
| c1 | 0.78 | 0.72 |
| c2 | 0.76 | 0.75 |
| c3 | 0.83 | 0.68 |
| f1 | 0.54 | 0.58 |
| f2 | 0.61 | 0.53 |
| f4 | 0.68 | 0.47 |
| b1 | 0.66 | 0.66 |
| b2 | 0.66 | 0.66 |
| e1 | 0.76 | 0.57 |
| e2 | 0.64 | 0.66 |
| e3 | 0.70 | 0.61 |
| p1 | 0.87 | 0.83 |
| p2 | 0.85 | 0.85 |
| p3 | 0.90 | 0.79 |

# 3 SUPPORTING GOAL SETTING IN FLIPPED CLASSES

## 3.1 Introduction

The Flipped classroom is a form of blended learning that combines computer-based, individual instruction outside the classroom with active and group learning activities inside the classroom (Bergmann, 2012; Bishop, 2013). The individual instruction outside the classroom is usually web-based and combines videos and quizzes on the content. Self-regulation is recognized as a key element for successful learning in a flipped classroom setting (Bol & Garner, 2011; Sun, 2016; Zhu, 2016). Zimmerman (1989) defines academic self-regulation as the extent to which learners are meta-cognitively, motivationally, and behaviorally active in achieving their learning goals. Self-regulation is important in flipped classes because it is linked to how learners utilize the online materials in order to set learning goals and monitor their progress (Bol & Garner, 2011.) Many students might fail to review and understand the instructional material out of class by themselves because of their lack of self-regulation skills (Lai, 2016). Self-regulating strategies such as goal-setting, planning, effort and time management are essential for academic performance. Furthermore, students with better self-regulation skills tend to perform better on academic tasks (Pintrich, 1990). The use of the flipped classroom model improves academic achievement (O'Flaherty, 2015), while the effect is apparently greater among lower-achieving students (Baepler, 2014; Gross, 2015). The flipped classroom shifts the responsibility of knowledge acquisition to the learner, however, lower-achieving students tend to have less developed self-regulation skills (Pintrich, 1990) and individual differences in learning can be attributed to a lack of self-regulation among students (Zimmerman, 2002). Therefore lower-achieving students should not perform well in an environment requiring higher levels of self-regulation. The positive effects of the flipped classroom among lower-achieving students may be attributed to the fact that it aids some aspect of self-regulation for certain students. The purpose of our study is to investigate whether the flipped classroom provides any support to the self-regulation process of students.

### 3.2 Self-regulation, clear goals and the flipped classroom

According to Zimmerman (2003), self-regulatory processes can be represented using a cyclical model composed of three phases: forethought, performance and self-reflection. Self-regulation is a self-oriented feedback loop (Zimmerman, 1990), in which students monitor the effectiveness of their learning methods and react to feedback, guided by their learning goals. The response from students to the feedback that is received may involve adopting strategies to reduce the gap between their goals and outcomes, or increasing their goals based on the outcomes that are observed (Zimmerman, 1990; Bandura, 1989). Forethought phase processes are used to prepare for learning and are intended to enhance it. Performance phase processes are employed while learning and are intended to facilitate self-control and self-monitoring of one’s performance. Finally, self-reflection phase processes occur after learning and are intended to optimize reactions to outcomes and influence subsequent forethought processes and beliefs (Zimmerman, 2013). The forethought phase is composed of task analysis processes and self-motivation beliefs. Goal setting is a key form of task analysis which refers to deciding on the intended outcomes of a learning effort. High self-regulated (proactive) individuals organize their goals hierarchically, setting specific, proximal and challenging goals for themselves that allow them to reach more distal outcome goals. In contrast, low self-regulated (reactive) individuals set vague, distal or unchallenging goals for themselves (Zimmerman, 2013). Effective goal setting allows students to plan more effective strategies to aid their learning. Furthermore, realistic goals help students monitor their progress and adopt a different approach if the current approach had been ineffective (Schunk, 1990). Because task analysis processes require personal initiative and persistence, they also require high levels of self-motivation beliefs: self-efficacy, outcome expectations, intrinsic interest or valuing and goal orientation (Zimmerman, 2003). There is evidence to suggest that student goal setting is closely linked to key sources of self-motivation. Furthermore, evidence also indicates that certain properties of goals, such as proximity and challenge, influence performance, self-reflection and self-motivation (Zimmerman, 2003). In terms of motivation, self-regulation is considered a continuum by self-determination theory (Deci, 1996). This continuum ranges from a person undertaking an activity freely because they find it interesting or important, to a person undertaking an activity because they feel forced to do so by an external agent. In this sense, actions can be distinguished between those that are intrinsically motivated and those that are extrinsically motivated. Intrinsic motivation is fostered by social contexts that can satisfy the basic psychological needs of autonomy, competence and relatedness (Deci, 1996). Such contexts are characterized by the provision of choice, optimal challenge, informational feedback, interpersonal involvement and acknowledgment of feelings (Deci, 1996). To be intrinsically motivating a target goal must provide an optimal challenge by being optimally discrepant from one's skill level (Csikszentmihalyi, 1990). Goals must be challenging but attainable in order to enhance academic performance (Hattie, 2013), self-regulated learning and achievement beliefs (Schunk, 1990). Providing choice appears to be indispensable if self-regulation is to be supported (Zimmerman, 2002), as well as to accommodate different self-motivation beliefs during the student goal-setting process. In our study we aim to answer the following research questions:

1. Does providing choice in the flipped classroom aid the goal-setting process of the students, when compared to lecture-based methods?

2. Does the influence of choice and clear goals vary among students with different levels of academic achievement?

The effects of the flipped classroom on self-regulation have not yet been comprehensively studied (O'Flaherty, 2015; McLean, 2016). McLean (2016) studied an implementation of the flipped classroom with a basic medical sciences course. In his study, the students reported that they gained independent learning skills, while the use of the flipped classroom enabled them to use time management strategies and learn at their own pace when completing the pre-class activities, suggesting that the use of the flipped classroom had an effect on time management skills. Sun (2016) found that, when compared to distance learning, the use of the flipped classroom enhances the self-regulation of help-seeking among students. Lai (2016), in a study involving 44 fourth grade math students, proposed a flipped classroom model that supports self-regulation. The aim of doing so was to improve the students' effectiveness by helping them to set learning goals and create plans, as well as to monitor and evaluate their learning performance. The students set their learning goals before completing the out-of-class activities. The students with higher levels of self-regulation increased their level of achievement with the self-regulated flipped classroom. However, there were no differences in achievement for students with low self-regulation skills. As clear goals are essential for self-regulation (Ridley, 1992), we further investigate ways to improve the goal-setting process for students learning with the flipped classroom method. This study is conducted within a university-level programming course and involves a larger sample of students than the previously highlighted studies, to allow the investigation of causal relationships between choice, the use of the flipped classroom and the students' perception of clear goals while learning.

## 3.3 Methodology

### 3.3.1 Providing support for goal-setting in the flipped classroom

We implemented a conventional flipped classroom model (Bishop, 2013; O'Flaherty & Phillips, 2015). To design the online learning materials, we followed the multimedia learning principles (Multimedia, Contiguity, Modality, Redundancy, Coherence, Personalization and Segmentation), adapted to an e-learning context by Clark and Mayer (2011). Table 3.1 shows the breakdown of the pre-class, in-class and post-class activities for the course. In table 3.1 activities marked with an asterisk were exclusive to the flipped classroom sections, and the rest were shared with the lecture based sections.

**Table 3.1:** Breakdown of activities used in the course.

| Pre-class activities | In-class activities | Post-class activities |
|---|---|---|
| Videos with lectures and worked examples*<br><br>Closed-ended quizzes*<br><br>Forum participation | Concept reviews<br><br>Q/A sessions<br><br>Worked examples | Laboratory (every week)<br><br>Three graded programming assignments<br><br>Programming milestones* |

We used the open source platform OpenEDX (https://open.edx.org/) to deliver the lecture videos and formative assessment quizzes for the pre-class activities. The content was structured around 10 topics, which were released throughout the semester. The course contained 131 videos with theoretical content and worked examples. Each video lasted between three to ten minutes and included closed-ended questions to assess comprehension of the content. Feedback was also given on the students’ responses, as well as an explanation of the correct response. A forum was made available to the students for them to ask questions about the topics covered during the course. These questions were answered by other students, in addition to the teaching assistants and the professor.

To help students self-regulate and support their goal-setting process, we added a feature to our flipped classroom implementation based on the concept of experience points used in role-playing games (Adams, 2013). Experience Points are earnt by completing selected challenges and show the player their progress in the game (Adams, 2013). The game’s progression mechanisms encourage the players to take on increasingly difficult challenges so as to advance in the game. In our flipped classroom implementation, the game is the course, with the associated learning objectives and progression. We divided our introductory programming course into four levels called Programming milestones. Each level required the students to obtain 12 learning points within a three week period by solving programming exercises aligned with the learning goals for that level. Each programming exercise awarded learning points based on the level of difficulty and the course progression. For example, creating a function to test whether a number was prime was awarded one point at the beginning of the semester. However, a program to recursively solve the eight queens problem was awarded three points at the end of the semester, therefore requiring the students to increase their level of effort as the course progressed. For each level, the exercises scored between 1 to 3 points. Students had multiple ways of achieving the required score for a given level, such as only solving exercises worth 1 point, or combining exercises of different levels of difficulty. The students can choose their proximal goal (the next exercise to be solved) based on their self-motivation beliefs. The course met twice a week through 1-hour face-to-face sessions. The first session in the week was used to address misconceptions, solve questions and show worked examples. In the second session, the students were allowed to solve programming exercises together with their peers and with the help of the teaching assistants and the professor.

The aim of dividing the course into levels and including learning points was to set challenging goals and provide students with an expected performance level. These are both conditions that influence achievement (Hattie, 2013). The aim of the flexible structure of the course levels was to allow all of the students to learn and achieve the learning goals for each level, as well as for the course as a whole.

### 3.3.2 Research Model

In order to investigate our first research question, regarding the influence of choice in the flipped classroom on the student goal-setting process, we constructed a research model with the following research hypotheses:

H1: The use of the Flipped Classroom increases the students' perception of choice while learning. The flipped classroom and online learning environments allow for greater learner choice because students can progress at their own pace (Bergmann, 2012; McLean, 2016) and control the sequence in which the online materials are navigated (Bol & Garner, 2011).

H2: The students' perception of choice helps the goal-setting process, increasing the students' perception of clear goals while learning. Challenging goals influence achievement. However, challenge is a term that is relative to current student performance and understanding (Hattie, 2013). Better self-regulation is characterized by the setting of proximal, challenging and specific goals (Zimmerman, 2013). Furthermore, providing a choice of proximal goals should help students with the goal-setting process as it provides multiple pathways to regulate their learning.

H3: Perceived choice, clear goals and the use of the flipped classroom influence academic achievement among students. The influence of perceived choice is greater on motivation than on learning (Hattie, 2013). However, motivation also influences achievement (Hattie, 2013), thus suggesting that choice has both direct and indirect effects on achievement. Clear and challenging goals improve achievement (Hattie, 2013) and help self-regulation (Zimmerman, 2013). Multiple studies support the positive effects of the flipped classroom on academic achievement, for a review see O'Flaherty (2015).

A research model was constructed based on these hypotheses (Figure 1).

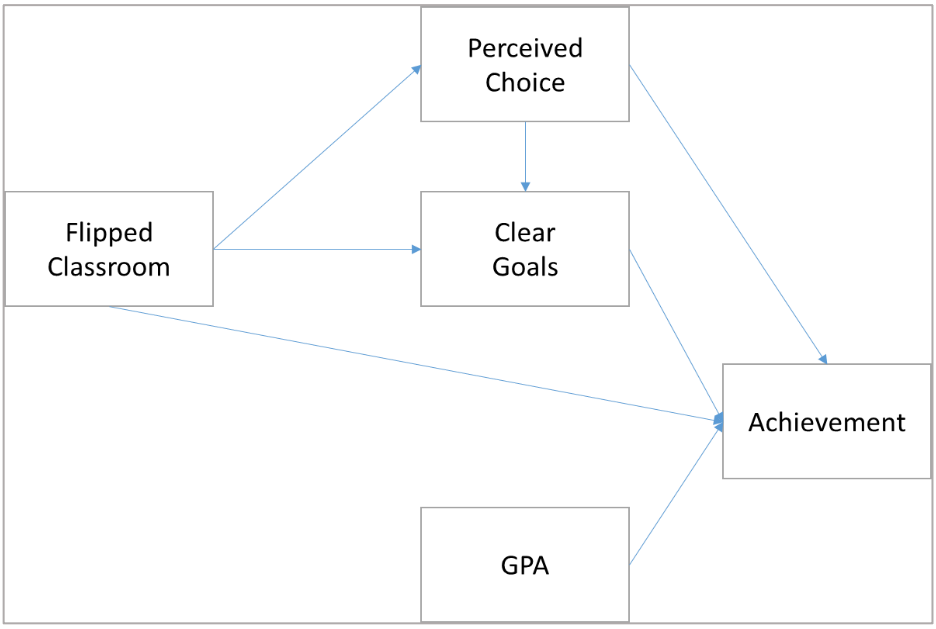


**Figure 3.1**: Research model for the study

To control for differences in previous academic achievement among the students, and because of their correlation with academic achievement (Hattie, 2013), we also added student GPA to the research model.

### 3.3.3 Participants

The study was conducted over a whole semester with an Introductory Programming course. Table 2 shows the breakdown of the sample of the study, which consisted of six sections, each one taught by a different professor. At the beginning of the semester, two of the six sections were chosen at random (F1 and F2) to be taught using the flipped classroom method.

**Table 3.2:** Breakdown of the sample.

| Section | GPA | | Gender | | Total |
|---|---|---|---|---|---|
| | Mean | SD | Female | Male | |
| F1 | 51 | 6 | 13 | 20 | 33 |
| F2 | 53 | 6 | 17 | 48 | 65 |
| L1 | 45 | 16 | 34 | 57 | 91 |
| L2 | 50 | 9 | 16 | 59 | 75 |
| L3 | 53 | 5 | 27 | 52 | 79 |
| L4 | 49 | 7 | 15 | 47 | 62 |
| | | | 122 | 283 | 405 |

### 3.3.4 Experimental Procedure

The course topics were the same for all sections, with the same sequence of content presentation and skill development. In order to pass the course, the students had to sit a final exam, which covered the entire contents of the course. The students' scores on the final exam were used to assess the influence on achievement. The final exam was the same for all sections and was peer reviewed by all of the professors that taught the class that semester.

To promote student participation in the flipped sections, 30% of the final grade for the course was awarded based on the completion of pre-class activities (online quizzes) and accumulation of learning points. The online quizzes evaluated comprehension of the content and examples presented in the videos. The programming exercises used in the laboratory sessions were common for all sections of the course. Learning points were awarded in the flipped section for solving exercises proposed in the laboratory sessions, as well as additional exercises set during class sessions.

### 3.3.5 Instruments and data collection

To assess the students' perception of choice and clear goals while learning, a measurement instrument was constructed by adapting five questions from existing instruments. Responses were rated by the students using a five-point Likert scale. Choice was assessed using three questions adapted from the Intrinsic Motivation Inventory (IMI) (Deci, 1994). The perception of clear learning goals was used to evaluate the student goal-setting process. To assess the perception of clear goals two questions were adapted from Fu (2009). Table 3.3 shows the items included in the measurement instrument used in this study.

**Table 3.3:** Measurement instrument used in the study.

| Dimension | Item | Question |
|---|---|---|
| Perceived Choice | c1 | I feel that the structure of the course allows me to choose the activities that I want to in order to learn. |
| | c2 | I have been able to choose the activities that I think will help me learn. |
| | c3 | The course provides options for me to choose how I want to learn. |
| Clear Goals | g1 | I am fully aware of what I must learn in order to pass this class. |
| | g2 | I am fully aware of the activities that I must complete during the course in order to learn. |

The measurement instrument was applied at the end of the semester together with the final exam. The participation of the students was voluntary and 299 valid responses were obtained

(Table 3.4). The sample size was adequate for structural equation modelling, because the ratio between the number of cases (299) and the number of parameter estimates in the research model (Figure 3.1) was over 20, while the total sample size was over 200 (Kline, 2015).

**Table 3.4:** Responses to end of semester survey.

| Section | Total | Participation |
|---|---|---|
| F1 | 33 | 29 |
| F2 | 65 | 64 |
| L1 | 91 | 70 |
| L2 | 75 | 46 |
| L3 | 79 | 51 |
| L4 | 62 | 39 |
| Total | 405 | 299 |

Data analysis was performed using R version 2.15. With the collected data, we validated scale reliability, obtaining a Cronbach's alpha of 0.84 for choice and 0.82 for clear goals, suggesting that the scales are reliable (Field, 2012). We conducted a confirmatory factor analysis using Structural Equation Modelling to validate factor structure. The measurement model that was tested included choice and clear goals as latent variables and the questions on the measurement instrument as indicators. The maximum likelihood estimation method was used to address the lack of multivariate normality in the data (Hair, 2010). We obtained a model with a good fit ($\chi^2$ (4) = 2.41, p=0.66; GFI=0.90, RMSEA=0.00, SRMR=0.01), with all factor loadings above 0.7 (Table 3.5). The Composite Reliability (CR) was calculated using the standardized factor loadings (Table 3.5), with the results for each scale above the recommended limit of 0.7 (Hair, 2010). To establish convergent validity, we calculated the Average Variance Extracted (AVE) for each scale (Table 3.5), obtaining values above the recommended minimum of 0.5 (Hair, 2010).

**Table 3.5:** Result of the confirmatory factor analysis.

| Indicator | Standardized Loadings | |
|---|---|---|
| | Perceived Choice | Clear Goals |
| c1 | 0.85 | |
| c2 | 0.81 | |
| c3 | 0.74 | |
| g1 | | 0.87 |
| g2 | | 0.80 |
| CR | 0.84 | 0.82 |
| AVE | 0.64 | 0.70 |

From the confirmatory factor analysis we concluded that our scales were reliable for testing our research model. Exam scores (on a scale of 1 to 7, with 4.0 the minimum passing grade) were used to assess the effect on academic achievement. The mean exam score was 4.51, with SD=1.40. The exam scores were standardized in order for them to be analyzed.

## 3.4 Results

To answer the research question "Does providing choice in the flipped classroom aid the goal-setting process of students, when compared to lecture-based methods?", the research model (Figure 3.1) combined with the measurement model (Table 3.5) was tested using Structural Equation Modelling (SEM). To estimate the model we used a maximum likelihood estimator with bootstrapping. This decision was made because of the robustness for handling data with a distribution that is not multivariate normal (Hair, 2010). To assess the effects of the use of the flipped classroom, a dummy coded variable was added to the model, with a value of 0 for lecture-based courses and 1 for flipped classroom courses. The proposed research model had a good fit ($\chi 2$ (15) = 18.58, p=0.23; GFI=0.99, RMSEA=0.03, SRMR=0.05, AIC=5706.52). All paths were significant ($p<0.05$), except the path between the use of the flipped classroom and clear goals ($p=0.89$). This suggests that there is no direct effect of using the flipped classroom on the students' perception of clear goals. The non-significant path was removed, obtaining a model with a good fit ($\chi2$ (16) = 18.60, $p=0.29$; GFI=0.99, RMSEA=0.02, SRMR=0.05, AIC=5704.54). Table 3.6 shows the parameter estimates for the structural model.

**Table 3.6:** Parameter estimates for the Structural Research Model.

| Parameter Estimate | | Estimate | Std. Error | Standardized |
|---|---|---|---|---|
| From | To | | | coefficient |
| GPA | Achievement | 0.90 | 0.16 | 0.49** |
| Clear Goals | Achievement | 0.37 | 0.10 | 0.24** |
| Perceived Choice | Achievement | 0.33 | 0.10 | 0.22** |
| Flipped Classroom | Achievement | 0.31 | 0.13 | 0.10* |
| Flipped Classroom | Perceived Choice | 0.53 | 0.11 | 0.26** |
| Perceived Choice | Clear Goals | 0.52 | 0.07 | 0.54** |
| *significance p<0.05 | | | | |
| **significance p<0.01 | | | | |

The model explains 46% of the variance of exam scores ($R^2=0.46$). Perceived choice explains 30% of the variance of clear goals. The use of the flipped classroom increased the students' perception of choice ($\beta=0.26$), thus supporting the first research hypothesis (H1). Perceived choice increased the students' perception of clear goals ($\beta=0.56$), thus supporting the second research hypothesis (H2). The perception of choice had an overall effect on achievement of 0.35. This includes a direct effect of $\beta=0.22$ and an indirect effect mediated by the students' perception of clear goals ($\beta=0.13$). The use of the flipped classroom had an overall effect of $\beta=0.19$, with a small direct effect of $\beta=0.10$ and small indirect effects mediated by the students' perception of choice ($\beta=0.06$) and clear goals ($\beta=0.03$). The direct and indirect effects of perceived choice, clear goals and the use of the flipped classroom on achievement supported the third research hypothesis (H3). Figure 2 shows the final research model with standardized loadings, including their measurement and structural components.

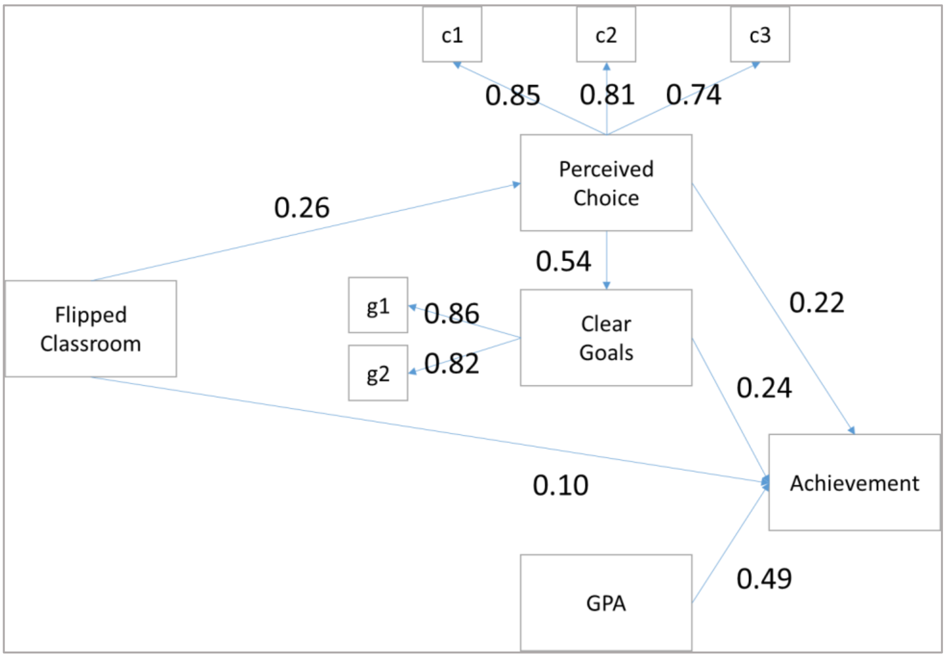


**Figure 3.2:** Research model with standardized loadings.

Students in the flipped classroom sections scored between 0 and 124 learning points across the four levels of the course, with a median of 48 learning points. The learning point score correlated with the perception of clear goals ($r=0.26$, $p<0.05$), but there was no significant correlation with perceived choice ($p=0.13$).

To answer the research question "Does the influence of choice and clear goals vary among students with different levels of academic achievement?", a Quantile Regression analysis was conducted (Koenker, 1978). Quantile Regression is used in various research fields such as Biology (Cade, 2003) and Educational Research (Robinson, 2011) when the answer to a research question involves the modelling of a conditional quantile of a response variable. Ordinary linear regression models estimate the conditional mean of a response variable as a function of their predictors, while quantile regression is a way of estimating the conditional quantiles of a response variable (Hao, 2007). Because the second research question involves studying the variation of the effect of choice and clear goals among students with levels of academic achievement above or below the mean, we are more interested in the lower (0.25 percentile) or upper tail (0.75 percentile) of the distribution rather than in its central location. Figure 3.3 shows a histogram of final exam scores for the data used in the study.

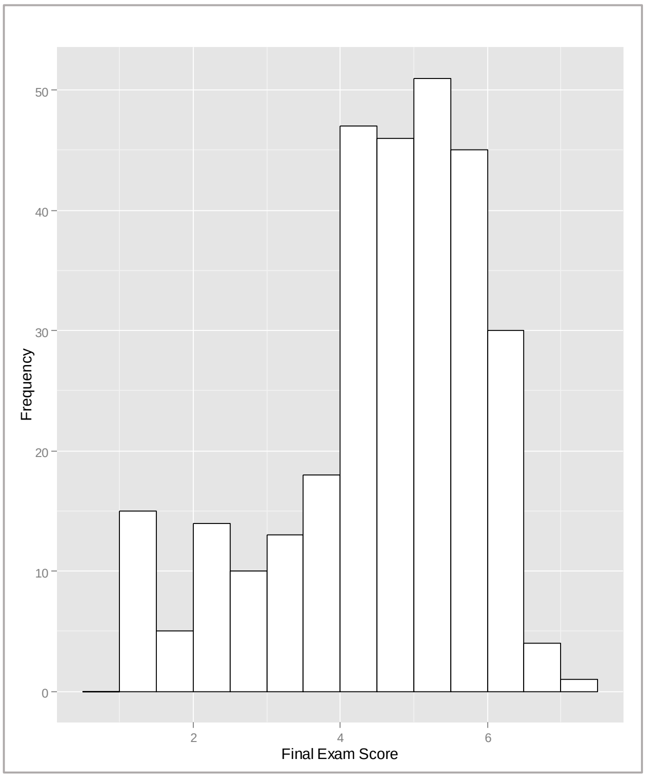


**Figure 3.3:** Histogram of exam scores.

The distribution of exam scores is slightly asymmetric (Figure 3.3), with a skew of -0.87 and a kurtosis of 0.16. Quantile regression analysis is appropriate when the response distribution is asymmetric (Figure 3.3), because the conditional mean does not always correctly model central location shifts (Hao, 2007).

To estimate the quantile regression model at percentiles 0.25, 0.5 and 0.75, the students' scores for the variables *perceived choice* and *clear goals* were calculated from the model used in the confirmatory factor analysis. Table 3.7 shows the results of the quantile regression for GPA, clear goals and perceived choice with the students' exam score at percentiles 0.25, 0.5 and 0.75.

**Table 3.7:** Quantile Regression Analysis.

| Variable | Percentile 0.25 | | | Percentile 0.5 | | | Percentile 0.75 | | |
|---|---|---|---|---|---|---|---|---|---|
| | Estimate | Std. Error | β | Estimate | Std. Error | B | Estimate | Std. Error | β |
| Intercept | **3.82 | 0.10 | | **4.52 | 0.09 | | **5.23 | 0.08 | |
| GPA | **0.99 | 0.12 | 0.71 | **0.91 | 0.12 | 0.65 | **0.56 | 0.11 | 0.40 |
| Clear Goals | *0.28 | 0.14 | 0.20 | *0.24 | 0.10 | 0.17 | **0.23 | 0.08 | 0.16 |
| Perceived Choice | **0.40 | 0.13 | 0.29 | 0.20 | 0.11 | 0.14 | **0.23 | 0.08 | 0.16 |
| *significance p<0.05 | | | | | | | | | |
| **significance p<0.01 | | | | | | | | | |

To test for significant differences between percentiles ANOVAs were conducted between each of the models (Hao, 2007). The slopes of the models differ: percentile 0.25 – percentile 0.5, $F(4,595)=3.26$, $p<0.05$; percentile 0.5 – percentile 0.75, $F(4,595)=8.03$, $p<0.01$, percentile 0.25 – percentile 0.75, $F(4,595)=7.33$, $p<0.01$.

The direct effect of perceived choice on achievement was greater among students with an exam score in the 0.25 percentile ($\beta=0.29$) that in higher-achieving students, with an exam score in the 0.75 percentile ($\beta=0.16$). The direct effect of clear goals on student achievement was almost constant, with a slightly greater effect among students in the 0.25 percentile, with a $\beta=0.20$. Figure 8 shows the variation of each regression coefficient across the percentiles of the distribution of final exam scores.

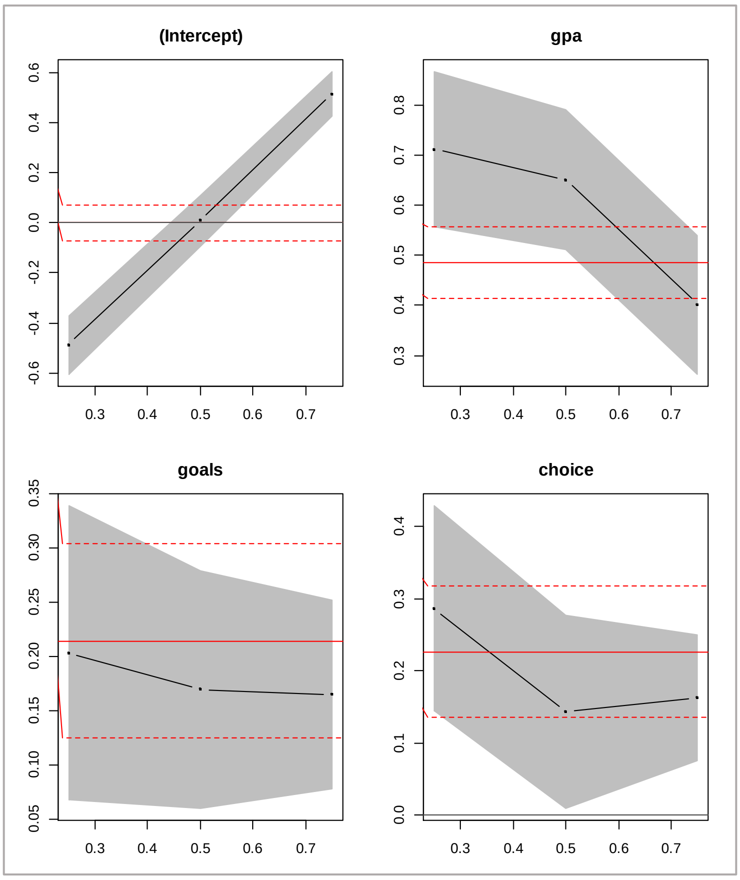


**Figure 3.4:** Quantile Regression coefficients.

## 3.5 Discussion

Students in the flipped classroom sections of the course perceived higher levels of choice than students in lecture-based sections (β =0.26, a medium effect, Table 3.6). In the flipped classroom, the pre-class, in-class and post-class activities were designed to provide choices that were aligned with the learning objectives and progression of the course. In terms of practice activity choices, all of the students in our study were given similar possibilities, because most of the programming exercises were shared across sections in laboratory sessions. Perceived choice had a large effect on the students' perception of clear goals while learning (β=0.54, Table 3.6). This result suggest that providing meaningful learning choices that are aligned with the learning goals and progression of the course helps students with their goal-setting process. The use of the flipped classroom increases the students' perception of clear goals, when compared with lecture-based courses (β=0.14). The effect of choice on learning and motivation is complex. Our results suggest that the effect of choice is partially mediated by their effect on self-motivation beliefs, as well as the support of processes in the forethought phase of self-regulation such as goal-setting. Patall (2010) found that choices increase motivation when they are aligned with students' interests and goals and that choice has positive effects on self-motivation beliefs (interest, perceived competence and value) when the task proposed to the student is not interesting (Patall, 2013). Flowerday (2015) found that interest, and not choice, had a direct influence on learning. However, we found a direct effect of choice on academic achievement (β=0.22, a small to medium effect, Table 3.6). This effect can be explained because the choices provided in the flipped classroom were a combination between option and action choices. These choices involve the initiation and regulation of student behavior (when to study a topic, when to attend a face to face class session, how many and what programming tasks to do to earn learning points, etc.) and are perceived as autonomy-supportive (Reeve, 2003; Patall, 2010). Providing choices that promote the experience of autonomy enhances motivation and achievement, as proposed by self-determination theory (Ryan & Deci, 2000).

We found that the effect of choice on achievement was greater among lower-achieving students (Table 3.7), result that helps to explain the observed effects of the flipped classroom on lower-achieving students (Baepler, 2014; Gross, 2015). Providing the students with meaningful learning choices allowed them to set proximal goals based on their perception of self-efficacy, and when the feedback received was positive, the students' self-efficacy beliefs are improved and they feel confident enough to set more challenging goals that improve their learning (Hattie, 2013).

## 3.6 Conclusion

Concerning the first research question, "Does providing choice in the flipped classroom aid the goal-setting process of students, when compared to lecture-based methods?" we found that choice helps the goal setting process of all students. In the flipped classroom, the increased choices provided in comparison with lecture based methods, raised the perceptions of clear goals while learning of the students. The flipped classroom provided more meaningful choices for learning than lecture-based courses, because the choices offered by the flipped classroom allowed students to organize their learning and control what, when and where to learn, by combining option and action choices. Meaningful choices, aligned to the learning objectives and progression of the course, influenced the students' perception of clear goals while learning and improved their academic achievement. Our findings suggest that choice improves self-regulation as it aids the student goal-setting process. Instructional designers may take advantage of the increased choices provided by the flipped classroom to improve self-regulation and achievement, embedding a rule system into the course structure to promote alignment between the students' learning goals and the learning goals and progression of the course. Our proposed mechanism, the idea of learning points, established a clear indication of the need to increase effort with regards to course progression, encouraging students to solve more challenging exercises towards the end of the course. This guidance is important because students with less effective self-regulation strategies might only complete exercises that are too easy for the expected level of the course and fail to meet the assessment criteria and expected learning outcomes for the course. The increased perception of choice in the flipped classroom, and their effect in achievement, complement the effect of active learning in the results obtained from flipped classroom use.

Concerning the research question “Does the influence of choice and clear goals vary among students with different levels of academic achievement?” we found that the effect of choice is higher among first quartile students, contributing to the understanding of the positive effects on achievement of the flipped classroom. Instructional designers may take advantage of this result providing a range of practice activities with different levels of difficulty that help this students to gain confidence and sustain their effort in the course.

One of the limitations of this study is that we did not take into account differences in interest for programming among the students. These differences could narrow the perceived choices of the students and explain differences in behavior in the course. We focused our analysis on choice and its influence on the perception of clear goals as an outcome of self-regulation. We did not included an auto report measure of student self-regulation in our model, such as the one proposed by the MSLQ (Pintrich, 1991) or Barnard (2009), to control for differences in self-regulation strategies among the students. The inclusion of these dimensions in future versions of the proposed model, combined with an analysis of learning logs as described by Lai (2016), may help to further clarify ways to improve student self-regulation using the flipped classroom and increase the effectiveness of the goal-setting support mechanism that is provided.

# 4 A MODEL FOR CATEGORIZING AND PREDICTING LEARNING EXPERIENCE AND ACHIEVEMENT IN FLIPPED COURSES

## 4.1 Introduction

One of the many advantages of the flipped classroom method (Bishop & Verleger, 2013) is that students can work at their own pace interacting with an online platform (O'Flaherty & Phillips, 2015), while teachers can get regular updates on student progress by analyzing their online activity. This information can be difficult to analyze in large classes, especially when there is a wide range of activities for the students to choose from. Teachers need tools that allow them to analyze this large volume of information and detect which groups need their support (Ferguson, 2012; Gasevic, Dawson & Siemens, 2015).

Within the context of massive open online courses (MOOCs), various studies have been conducted in order to classify a student's activity and predict their future behavior or final grade (Kizilcec, Piech & Schneider, 2013; Anderson, 2014; Kahlil & Ebner, 2017). Online courses often lack formal assessments that provide feedback on their progress to students and teachers. This therefore justifies the use of Learning Analytics models (Siemens & Gasevic, 2012). In blended formats such as the flipped classroom, the online interaction is complemented with face-to-face classes and formal assessments, allowing the lecturer both, to monitor their students' progress and give them feedback on their learning. The advantage of this pedagogical model is that it facilitates the analysis of the correlation between these two types of interaction and academic performance (Andergassen, Mödritscher & Neumann, 2014; Conijn, Snijders, Kleingeld & Matzat, 2017). Moreover, having information on student perceptions is essential if their online activity wants to be interpreted correctly (Gasevic, Dawson, Rogers, & Gasevic, 2016; Gašević, Jovanović, Pardo & Dawson, 2017).

This study proposes a predictive model to detect students' who are at risk of failing the course that combines data of students' online activity with classifications based on their perceptions at the end of the course. The analysis starts with the construction of a model for classifying the students according to their learning experience and academic performance. Indicators of online activity are then developed and used to determine whether they can differentiate between the different groups included in the classification model throughout the course. The result is a model that provides teachers with information that they can use to design timely interventions based on the needs of each group of students.

### 4.1.1 Engagement Patterns in Online Courses

Different alternatives have been explored within the field of Learning Analytics for deducing students' personal characteristics based on their interaction with online platforms. Kizilcec, Piech and Schneider (2013) used k-means clustering to group together patterns of interaction with video lectures and assessments in three MOOCs. These authors identify four different engagement trajectories:

- Completing: students who complete the majority of assessments on the course.
- Auditing: students who complete few assessments and spend most of their time watching the video lectures.
- Disengaging: students who start the course with an engagement pattern similar to the Completing group but then have a marked decrease in their activity until practically disappearing. This drop in activity usually occurs in the first third of the course.
- Sampling: students who only watch videos during one or two assessment periods, usually at the beginning of the course.

Anderson (2014) identified five engagement patterns of MOOC students instead of four:

- Viewers: students who watch the video lectures but complete few of the assignments, if any.
- Solvers: students who complete the assignments in order to get a grade but watch few of the video lectures, if any.
- All-rounders: students who balance watching the video lectures with completing the assignments.
- Collectors: students who download the course materials but complete few of the assignments. They may or may not watch the video lectures.
- Bystanders: students with a very low level of activity in the course.

The highest achieving students on the course were those classified as Solvers or All-rounders. The study by Anderson (2014) also showed that the students' behavior on the online platform (the course forum) can be influenced using a system of badges and levels. Similarities can be observed between the classifications used in these two studies. In both there are groups of students who focus on watching the video lectures, while other groups focus on completing the assignments. In both cases, the students who focus on practice activities achieve better results. In another study, Kahlil and Ebner (2017) compared classifications based on online activity with classifications used for grouping students in face-to-face classes. Their findings suggest that factors of extrinsic motivation are not enough for ensuring student engagement in a MOOC and that conditions for fostering intrinsic motivation must be incorporated in order to achieve engagement. These studies have been based on developing models by looking at online activity at the end of the course. However, there are no models in the literature applied to blended learning context in order to classify the students' while the course is still in progress.

### 4.1.2 Active Participation, Motivation and Academic Performance

The models used to classify students in online courses are based on their level of interaction with the course content. However, this type of classification does not take into account the students' perceptions, which are essential if the results are to be correctly interpreted (Gasevic, Dawson, Rogers, & Gasevic, 2016; Gašević, Jovanović, Pardo & Dawson, 2017). Variables relating to the students' learning experience, such as motivation and perceived challenge, have an effect on academic performance (Hattie, 2013). These variables are therefore important for understanding the results that are obtained. Moreover, the students' level of online activity is influenced by their perception of the quality and usefulness of the course material (Hone, 2016), their motivation for signing up for the course (Ho, 2014), and their emotions and experience during the learning process (Dillon, 2016; Schwarzenberg, Navon, Nussbaum, San-Agustín & Caballero, 2017). By only considering engagement patterns, a student may be classified as a Disengager or Bystander given their low level of activity, however, that same level of activity may be the average in another course. This suggests that student perceptions should be taken into account in order to interpret their engagement patterns more accurately.

Within the context of the flipped classroom, studies have found that the results can primarily be attributed to the use of active learning (Jensen, 2015). Online activities classifiable as active participation (Agudo-Peregrina et al., 2014) such as sending assignments, should therefore be more closely linked to motivation and academic performance than passive activities, such as watching video lectures, because they promote the practice of the skills and the application of the content. According to Hattie (2013), active learning can influence student engagement, academic performance and intrinsic motivation. The relationship between students' experience and engagement suggests that patterns of online activity should differ among groups of students with different learning experiences.

This study aims to characterize groups of students by classifying them according to their assessment of the learning experience at the end of the course using self-reported data. Since engagement is influenced by motivation (Barba, Kennedy & Ainley, 2015), and engagement patters are the result of students' perception and motivation, this classification can be used to understand their online engagement. This bidirectional influence leads us to our first research question:

**RQ1:** How can students be classified according to their learning experience at the end of a flipped course?

### 4.1.3 Models for predicting academic performance based on patterns of interaction

Patterns of interaction in online courses have been used to predict students' results. Agudo-Peregrina, Iglesias-Pradas, Conde-González and Hernández-García (2014) studied how effectively academic performance can be predicted by analyzing interactions in blended and online courses. In order to do so, they distinguish between classifications of interactions based on the agent (student-student, student-teacher and student-content), classifications based on the frequency of use (most used, moderately used and rarely used) and classifications based on the mode of participation. Within the latter group, they distinguish between active and passive interaction (e.g. completing an assignment vs. simply viewing the material). The authors conclude that classifications based on the agent explain better academic performance on online platforms, particularly student-teacher and student-student interactions. This is also true for interactions involving active participation. However, they did not find any significant correlation between interaction with the online platform and academic performance for blended courses.

Most of the classification systems that can be found in the literature include time spent watching video lectures as one of their variables. However, there is not a direct relationship between viewing course material and academic performance. Instead, there is a relationship between completing learning activities and academic performance (Agudo-Peregrina et al., 2014). Students who actively participate, such as Anderson's (2014) Solvers and All-rounders, complete more exercises on the online platform and do better on the course. Conijn, Snijders, Kleingeld and Matzat (2017) analyzed the effectiveness of various indicators of online activity for predicting academic performance in 17 blended courses (N=4,989). They found that the strength and quality of the predictors varied considerably across the courses. Of the variables they analyzed, performance on midterms was the only variable that consistently correlated with performance on the final exam for each course. The number of quizzes passed also correlated with academic performance in 75% of the courses, while the number of assignments completed revealed a positive correlation in 3 of the 6 courses that included such assignments. Having identified the best predictors, the authors built regression models to predict student performance on the final exam. The effectiveness of these models varied greatly across the courses, explaining between 8% and 37% of the variance in each case. The authors concluded that new data sources and additional theoretical elements must be incorporated in order to predict student performance based on their online activity in blended courses.

Therefore, prior literature suggests the need to incorporate additional variables, like the learning experience variables proposed in this study, to enhance the interpretation of their interaction with the online platform. Doing so will also help us understand the differences in academic achievement and learning experience of the students. The lack of models that incorporate such elements leads us to our second research question:

**RQ2:** Is it possible to build a model that correlates the online engagement patterns of students with their learning experience and academic achievement at the end of a flipped course?

## 4.2 Methodology

### 4.2.1 Context and Participants

The study was conducted with a university-level programming course taught using the flipped classroom method. The data was collected over 5 semesters, from 7 courses and a total of 509 students, mostly first year undergraduates. Table 4.1 shows the breakdown of each of the courses included in this study.

**Table 4.1**: Breakdown of the classes included in the study.

| Course | Gender | | Total |
|---|---|---|---|
| | **Female** | **Male** | |
| 1 | 12 | 21 | 33 |
| 2 | 17 | 49 | 66 |
| 3 | 13 | 69 | 82 |
| 4 | 24 | 68 | 92 |
| 5 | 26 | 60 | 86 |
| 6 | 10 | 63 | 73 |
| 7 | 21 | 56 | 77 |
| | 123 | 386 | 509 |

### 4.2.2 Procedure

The open source platform OpenEDX (https://open.edx.org/) was used to publish the course material and assessments. The activities included in the course are detailed in Table 4.2.

**Table 4.2**: Course activities included in the analysis of the students' online activity.

| **Pre-class activities** | **In-class activities** | **Post-class activities** |
|---|---|---|
| 131 videos with lectures and worked examples | Concept reviews | Laboratory (each week) |
| Closed-ended quizzes | Worked examples | 53 automatically-graded online exercises |
| | Group programming assignments | 3 manually-graded assignments (three-week projects) |

Students had to complete and submit the automatically-graded exercises at four checkpoints throughout the semester. The exercises were characterized by eight criteria describing the algorithmic skills and knowledge required to successfully complete them (Table 4.3). Because each exercise require a combination of algorithmic skills and knowledge, the categorization was codified using an 8-bit number in which a 1 or a 0 indicates the presence or absence of each criteria (Figure 4.1).

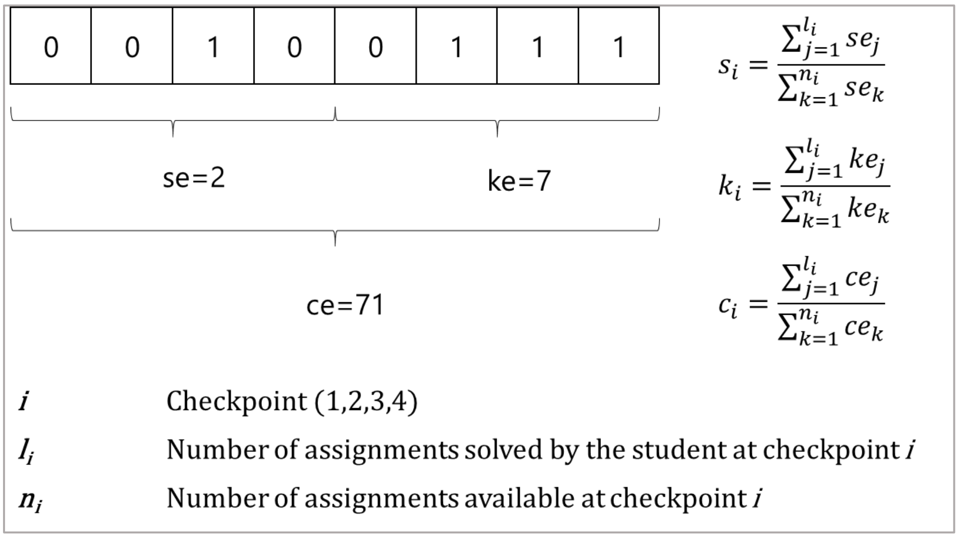


**Figure 4.1**: Example of the coding of an exercise.

**Table 4.3**: Coding used for classifying automatically-graded online exercises

| Bit | Criteria | Name | Description |
|---|---|---|---|
| 8 | Algorithmic Skill | Recursive Algorithm | The student must design a recursive algorithm. |
| 7 | Algorithmic Skill | Level 3 Algorithm | The student must design an algorithm to combine data from several data structures. |
| 6 | Algorithmic Skill | Level 2 Algorithm | The student must represent information using a data structure. |
| 5 | Algorithmic Skill | Level 1 Algorithm | The student must design an algorithm that does not require a data structure but that cannot be directly deduced from the wording of the problem. |
| 4 | Knowledge | Classes | The student must know how to define a class with attributes and methods. |
| 3 | Knowledge | Collections | The student must know how to add, remove and search for elements within a data structure (strings or lists). |
| 2 | Knowledge | Advanced Control Flow | The student must know how to define a loop and determine its characteristics based on the problem. |
| 1 | Knowledge | Simple Control Flow | The student must know how to define variables, combine them using comparison operators, and use them to build conditional expressions, as well as in input/output instructions. |

To analyze the interaction patterns of the students we developed coverage indicators (Figure 4.1) that measure the level of completion of the activities available at each checkpoint. The skill ($s_i$) and knowledge ($k_i$) coverage indicators were calculated using the score for skill (se) and knowledge (ke) of each exercise, represented by the first and last four bits of the 8-bit number associated to the exercise. The checkpoint coverage indicator ($c_i$) was calculated using the whole 8-bit number of the exercise (ce). Along the semester there were four checkpoints where the coverage indicators were calculated. Table 4.4 shows the frequency of each checkpoint, as well as the total points available for skill and knowledge.

**Table 4.4**: Breakdown of the assessment checkpoints.

| Checkpoint | Week | Number of exercises available | Total points available for skill | Total points available for knowledge |
|---|---|---|---|---|
| 1 | 6 | 16 | 4 | 42 |
| 2 | 9 | 15 | 34 | 91 |
| 3 | 12 | 16 | 33 | 191 |
| 4 | 16 | 6 | 53 | 38 |

Furthermore, each exercise was assigned another score depending on its level of complexity and the stage of the course. The students had to reach a score of 15 points at each checkpoint and could choose which exercises to complete to meet this requirement. The achievement of this score accounted for 10% of the final grade of the students. The other components of the grading policy of the course included three programming projects (30%), two quizzes (30%) and a final exam (30%).

### 4.2.3 Instruments

An instrument for evaluating the learning experience in a flipped course was used to assess the students' perception of the course. This instrument had been previously validated by the authors (Schwarzenberg et al., 2017) and evaluates the students' experience based on enjoyment (intrinsic motivation), choice, feedback, challenge and peer instruction. Given that choice, feedback and peer instruction are more closely related with the structure of the course itself, only enjoyment and challenge were used for this study. These are also the two dimensions which the lecturer can influence more directly while the course is in progress. The instrument for evaluating the learning experience was administered at the end of each semester and participation was entirely voluntary. Table 4.5 shows the number of responses received each semester.

**Table 4.5**: Student responses to the learning experience survey.

| Class | Gender | | Total | Total | Response Rate % |
|---|---|---|---|---|---|
| | Female | Male | Responses | Students | |
| 1 | 11 | 16 | 27 | 33 | 82 |
| 2 | 16 | 46 | 62 | 66 | 94 |
| 3 | 11 | 53 | 64 | 82 | 78 |
| 4 | 21 | 62 | 83 | 92 | 90 |
| 5 | 19 | 36 | 55 | 86 | 64 |
| 6 | 10 | 50 | 60 | 73 | 82 |
| 7 | 15 | 43 | 58 | 77 | 75 |
| | 103 | 306 | 409 | 509 | 80 |

The students were classified using Latent Class Analysis (LCA), a statistical method that allows groups to be identified within a population using categorical variables (Lanza, Flaherty & Collins, 2003). Unlike k-means clustering, the number of groups is not defined a priori. Instead, it is determined by comparing different models that are generated using quality criteria, such as the Bayesian Information Criterion (BIC) or the likelihood ratio ($G^2$). In order to conduct LCA, models with between 1 and 6 classes were evaluated and compared using the Bayesian Information Criterion (BIC) (Lanza, Flaherty & Collins, 2003). The model with the lowest BIC score was then chosen as the final model. Figure 2 shows a graph comparing the models that were evaluated.

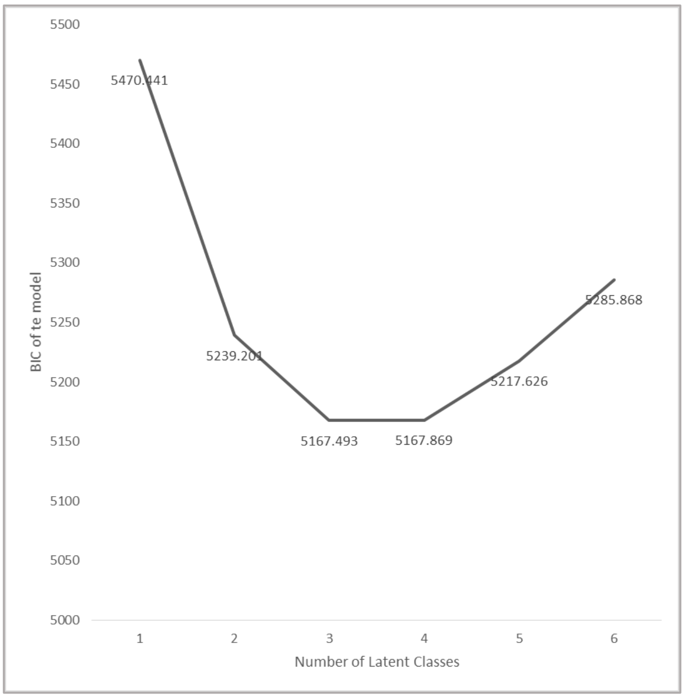


**Figure 4.2**: Comparison of the Latent Class models

The model with three latent classes was chosen as the final model as it had a slightly lower BIC and was simpler than the model with four latent classes. A breakdown of the final model can be found in Table 4.12 (see Appendix A). This breakdown includes the probability of a student belonging to each class based on their responses to the learning experience survey.

### 4.2.4 Data Collection

The data that was gathered in each of the five semesters of the study was taken into consideration when classifying the students (Table 4.1). Only the students from the last two classes (n=150) were considered when establishing relationships between their classification, academic performance and online activity. This is because these students had access to the same set of exercises and detailed information was available on their online activity (sequence in which they completed the exercises and number of successful and failed attempts, for example). The data for the students in Table 4.6 was used to analyze online activity. This includes the 150 students from classes 6 and 7 who completed the course, as well as 21 students who dropped out. Although not all of the students answered the survey, most students who passed the course did. The response rate among students who passed the course was 91.7%, while for students who dropped out it was 26.7%.

**Table 4.6**: Breakdown of the data on online activity.

| **Class** | **Student status in the course** | | | | | | | | | **Total** |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Dropout** | | | **Failed** | | | **Passed** | | | |
| | **Survey** | | | **Survey** | | | **Survey** | | | |
| | **No** | **Yes** | **Total** | **No** | **Yes** | **Total** | **No** | **Yes** | **Total** | |
| 6 | 14 | 0 | 14 | 6 | 2 | 8 | 7 | 58 | 65 | 87 |
| 7 | 7 | 0 | 7 | 16 | 6 | 22 | 3 | 52 | 55 | 84 |
| | 21 | 0 | 21 | 22 | 8 | 30 | 10 | 110 | 120 | 171 |

The data was analyzed in two stages. The first stage focused on discovering engagement patterns that could detect which students would drop out of or fail the course. The second stage was to identify the students from each of the groups in the classification model, as the majority of the students who answered the learning experience survey passed the course. For the results to be more generalizable, we used the coverage indicators (Figure 4.1) to analyze the online activity instead of the number of exercises completed or the total score achieved by each student. We created a total coverage indicator using all of the information from each semester (sf, kf and cf). The online data that was collected (Tables 4.7 and 4.8) includes the indicators for skill (s1, s2, s3, s4) and knowledge (k1, k2, k3, k4) at each checkpoint, as well as the overall indicators at the end of the course (sf, kf).

**Table 4.7**: Students' online activity at each of the checkpoints and by course status.

| **Status** | **n** | **s1** | **k1** | **s2** | **k2** | **s3** | **k3** | **s4** | **k4** | **sf** | **kf** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Dropout | 21 | 0.25 | 0.39 | 0.12 | 0.14 | 0.02 | 0.04 | 0.00 | 0.00 | 0.10 | 0.14 |
| Failed | 30 | 0.32 | 0.46 | 0.37 | 0.42 | 0.19 | 0.26 | 0.07 | 0.08 | 0.24 | 0.30 |
| Passed | 120 | 0.54 | 0.67 | 0.50 | 0.57 | 0.46 | 0.53 | 0.38 | 0.41 | 0.47 | 0.55 |

**Table 4.8**: Online activity for each of the classes included in the model.

| **Class** | **n** | **s1** | **k1** | **s2** | **k2** | **s3** | **k3** | **s4** | **k4** | **sf** | **kf** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 36 | 0.56 | 0.68 | 0.49 | 0.57 | 0.44 | 0.51 | 0.37 | 0.40 | 0.46 | 0.54 |
| 2 | 43 | 0.49 | 0.63 | 0.48 | 0.56 | 0.43 | 0.52 | 0.32 | 0.35 | 0.43 | 0.52 |
| 3 | 39 | 0.59 | 0.74 | 0.56 | 0.64 | 0.55 | 0.62 | 0.47 | 0.51 | 0.54 | 0.63 |

Table 4.9 shows the value of the checkpoint coverage indicator by learning experience class and checkpoint (c1, c2, c3, c4).

**Table 4.9**: Checkpoint coverage indicator for each of the classes included in the model.

| **Class** | **n** | **c1** | **c2** | **c3** | **c4** | **cf** |
|---|---|---|---|---|---|---|
| 1 | 36 | 3.75 | 4.03 | 4.08 | 325.08 | 1036.83 |
| 2 | 43 | 3.09 | 3.21 | 3.65 | 284.56 | 986.14 |
| 3 | 39 | 4.15 | 4.05 | 4.44 | 417.79 | 1259.28 |

### 4.2.5 Classifier Development

In order to identify students at risk of failing using the information from the first checkpoint, a classifier was developed based on neural networks. The neural network (Figure 4.3) was implemented using Python 3.5.2 and TensorFlow (https://www.tensorflow.org/).

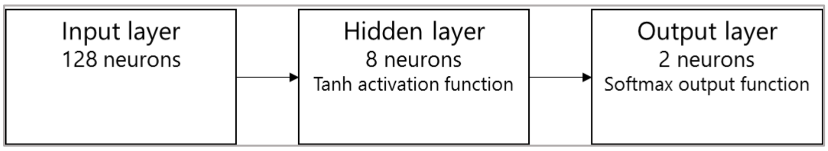


**Figure 4.3**: Neural Network Architecture.

The data was divided into a training set (n=128) and a test set (n=43), while maintaining the proportion of students from each group (Table 4.7). The student's activity was coded as a sequence of 128 integers, with 16 exercises and 8 integers per exercise. As the majority of students did not complete the 16 exercises, the sequences were completed with zeros until reaching the maximum length. The vector [0,0] was used to represent the Dropout and Failed groups, while the vector [0,1] was used for the Passed group. The network was trained for 300 iterations using the conjugate gradient method with a learning rate of 0.08. To reduce overfitting we added dropout to the network with a probability of retention of 0.5. The best classifier had an accuracy level of 0.84 with the test data and 0.80 with the training data. Figure 4 shows the convergence graph for the network.

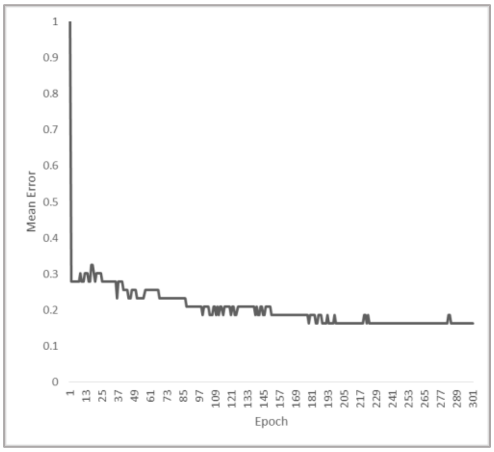


**Figure 4.4**: Convergence graph for the classifier.

## 4.3 Results

To answer our first research question, **RQ1: How can students be classified according to their learning experience at the end of a flipped course?**, the students' perception of enjoyment and challenge were used to characterize the students in each of the three classes of learning experience that were identified using Latent Class Analysis. The students' perceptions were obtained from the learning experience survey, while their academic performance was compared using a standardized final grade (Table 4.10).

**Table 4.10**: Characterization of the three classes included in the model

| Class | Students | Final Grade | | Enjoyment | | Challenge | |
|---|---|---|---|---|---|---|---|
| | | **Mean** | **SD** | **Mean** | **SD** | **Mean** | **SD** |
| 1 | 118 | 0.00 | 1.00 | 0.53 | 0.49 | 0.87 | 0.41 |
| 2 | 162 | -0.36 | 0.96 | -0.85 | 0.83 | -0.01 | 0.93 |
| 3 | 129 | 0.46 | 0.85 | 0.59 | 0.38 | -0.78 | 0.78 |

There are statistically significant differences across the three classes of student in terms of their final grade, $F(2,406) = 27.35$, $p < 0.001$, with an effect size (Cohen's f) $f = 0.57$ and a power of 1. There were also statistically significant differences in Enjoyment across the classes, $F(2,406) = 256$, $p < 0.001$, with a difference between classes 1 and 2, as well as classes 2 and 3 ($p<0.05$), while there was no difference between classes 1 and 3. Finally, there were statistically significant differences in Challenge across all of the classes, $F(2,406) = 143.9$, $p < 0.001$, with an effect size (Cohen's f) $f = 0.64$ and a power of 1. In order to complement the characterization of the classes, the number of video lectures watched by the students in classes 6 and 7 was also analyzed. Figure 5 shows that the students in class 1 tended to watch fewer videos. However, this difference is not significant, $F(2,115) = 1.224$, $p=0.2979$.

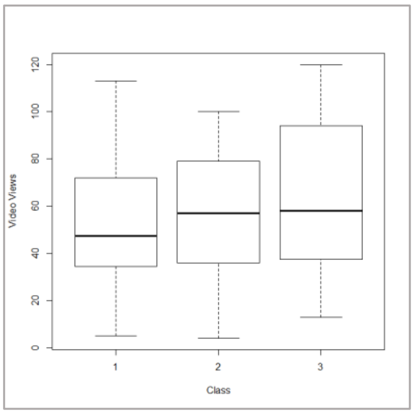


**Figure 4.5**: Videos watched by each class included in the model

Given that the number of videos watched is relatively low (Figure 4.5, less than 50%), we use the term “Solvers” to refer to all three classes of students. However, we also give each class a qualifier in order to distinguish between them (Figure 6).

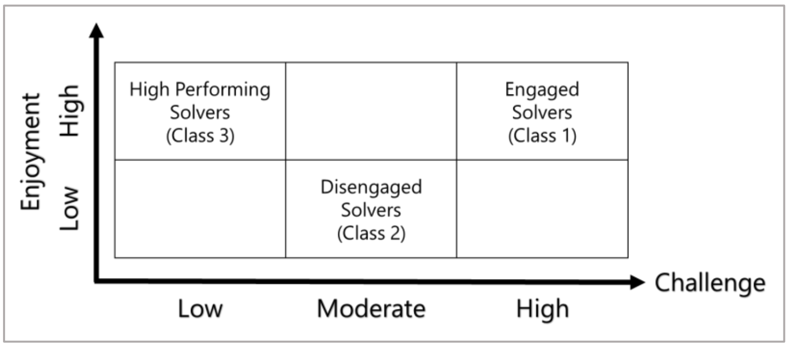


**Figure 4.6**: Motivation levels among the classes included in the model

Therefore, the analysis shows that we identify three types of students: High Performing Solvers, Engaged Solvers and Disengaged Solvers. The first group (Engaged Solvers) is characterized by a high level of enjoyment and perception of challenge (class 1 in the model). The second group (Disengaged Solvers) corresponds to class 2 in the model and is characterized by a low level of enjoyment and a moderate perception of challenge. The final group (High Performing Solvers) is characterized by a high level of enjoyment and a low perception of challenge. This is most likely due to the high level of skill reached by these students, as shown by their performance on the course (Table 4.10).

To answer our second research question, **RQ2: Is it possible to build a model that correlates the online engagement patterns of students with their learning experience and academic achievement at the end of a flipped course?** , we started the analysis testing for differences in the coverage indicators between the classes that represent the status of the students at the end of the course (Table 4.7). There was a strong correlation between the indicators for online activity and the student's final grade, with $r=0.78$, $p<0.001$ for the skill coverage indicator sf and $r=0.79$, $p<0.001$ for the knowledge coverage indicator kf.

Statistically significant differences were found between the students' activity at each checkpoint ($p<0.05$) and at the end of the course, both for sf, $F(2,168) = 70.63$, $p<0.001$ with an effect size $f=0.69$, as well as kf, $F(2,168) = 76.8$, $p<0.001$ with an effect size $f=0.67$. At the first checkpoint there were statistically significant differences between classes for the skill coverage indicator (s1), $F(2,168) = 22.03$, $p<0.001$, and for the knowledge coverage indicator (k1) $F(2,168) = 44.32$, $p<0.001$. However, the Dropout and Failed groups cannot be distinguished either by s1 ($p=0.47$) or k1 ($p=0.48$). From checkpoint 2, there are statistically significant differences among all of the groups for both skill ($F(2,168) = 42.37$, $p<0.001$ at s2) and knowledge ($F(2,168) = 44.32$, $p<0.001$ at k2). These differences remain at checkpoint 3, with $F(2,168) = 62.5$, $p<0.001$ for s3 and $F(2,168) = 70.68$, $p<0.001$ for k3. Despite the differences among the groups at checkpoint 4, with $F(2,168) = 33.71$, $p<0.001$ for s4 and $F(2,168) = 39.21$, $p<0.001$ for k4, the Dropout and Failed groups could not be distinguished by either the indicator for skill (s4, $p=0.6$) or the indicator for knowledge (k4, $p=0.51$). The correlation between the indicators s and k is very strong ($r=0.98$, $p<0.001$).

Once engagement patterns that could distinguish between passing and failing students had been determined, the students were classified based on their learning experience (Tables 4.8 and 4.9). A correlation was found between the indicator sf and Enjoyment ($r=0.32$, $p<0.001$), as well as between kf and Enjoyment ($r=0.30$, $p=0.001$) and between kf and Challenge ($r=-0.21$, $p=0.02$).

Table 4.11 shows the results from the ANOVA that were conducted in order to compare the value of each indicator between the three learning experience classes (Engaged Solvers, Disengaged Solvers and High Performing Solvers). The p-values for statistically significant differences between classes ($\alpha=0.05$) are also shown.

**Table 4.11**: Comparison of indicators between classes at each checkpoint.

| **Checkpoint** | **Indicator** | **Class Differences** | | | | |
|---|---|---|---|---|---|---|
| | | **F(2,115)** | **p** | **1-2** | **1-3** | **2-3** |
| 1 | s1 | 2.622 | 0.07 | | | |
| | k1 | 4.629 | 0.011 | | | 0.008 |
| | c1 | 16.26 | <0.001 | 0.002 | | <0.001 |
| 2 | s2 | 3.296 | 0.04 | | | 0.048 |
| | k2 | 3.578 | 0.03 | | | 0.039 |
| | c2 | 11.8 | <0.001 | <0.001 | | <0.001 |
| 3 | s3 | 6.029 | 0.003 | | 0.01 | 0.007 |
| | k3 | 5.042 | 0.008 | | 0.01 | 0.027 |
| | c3 | 8.669 | <0.001 | | | <0.001 |
| 4 | s4 | 3.191 | 0.04 | | | 0.038 |
| | k4 | 3.697 | 0.03 | | | 0.022 |
| | c4 | 3.216 | 0.04 | | | 0.037 |
| Total | sf | 7.446 | <0.001 | | 0.03 | <0.001 |
| | kf | 8.508 | <0.001 | | 0.008 | <0.001 |
| | cf | 6.99 | 0.001 | | 0.018 | 0.001 |

It is possible to differentiate between the different classes of learning experience using the indicators. This is because they are able to distinguish between high performing students (class 3) and the other classes at the third checkpoint. They are also able to distinguish between classes 1 (Engaged Solvers) and 2 (Disengaged Solvers), as well as classes 2 (Disengaged Solvers) and 3 (High Performing Solvers), by the first and second checkpoints using the overall indicators c1 and c2. These differences can distinguish between students with high levels of enjoyment (classes 1 and 3) and students with low levels of enjoyment (class 2). The students' level of skill (s1, s2, s4, sf) and knowledge (k1, k2, k3, k4, kf) vary depending on whether they drop out of, fail or pass the course. The effectiveness of the indicators for detecting which class the student will belong to by the end of the course evolves over time in both cases (Figure 4.7 and Figure 4.8).

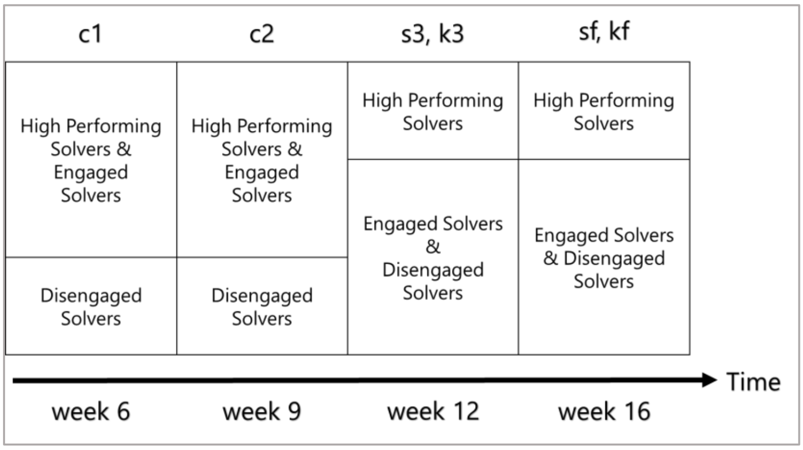


**Figure 4.7**: Ability to identify a student's experience based on their level of activity.

Initially, it is only possible to distinguish between highly motivated and unmotivated students (Figure 4.7). Later in the course, however, it is possible to differentiate between students who perceive the level of challenge to be low (High Performing Solvers) in comparison to the rest of the students (Engaged Solvers and Disengaged Solvers) (Figure 4.7).

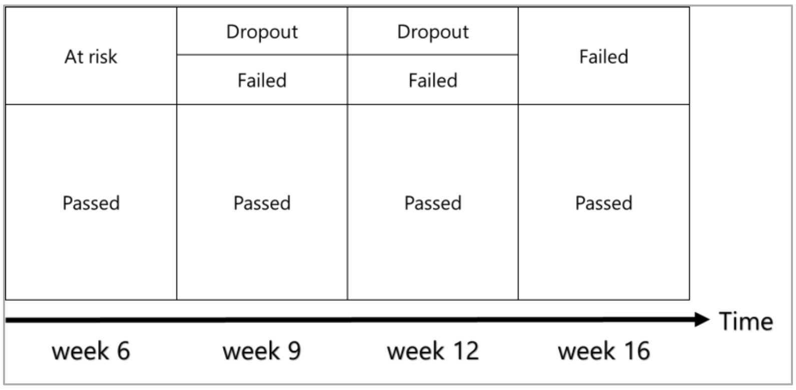


**Figure 4.8**: Ability to identify a student's final status based on their level of activity.

## 4.4 Discussion

The model based on the different classes of student experience (Figure 6) allows characterizing the students in the course and identifying actions that could be taken with each of them. The information generated by the model suggests that Engaged Solvers could be provided with a suggested sequence of increasingly-complex activities, based on their current skill level. This should help them adjust their perception of the challenge/skill balance by defining progressive learning goals. This is because the learning goals should be challenging yet attainable in order to have a positive impact on academic performance (Hattie, 2013).

The same strategy can be used to motivate the students in the second group (Disengaged Solvers), as their low level of enjoyment and moderate perception of challenge may point towards a problem with self-regulation. This is because reactive students with underdeveloped self-regulation skills tend to set vague, distant or unchallenging goals (Zimmerman, 2013). The setting of unchallenging goals may explain the low level of motivation among these students (Nakamura & Csikszentmihalyi, 2014; Hattie, 2013), which can be manifested in emotions such as boredom (Pekrum, 2014). The issue is then further compounded as a lack of interest makes it difficult to set effective goals as the goal-setting process requires personal initiative and persistence (Zimmerman, 2003). Increasing the difficulty level of the exercises completed by this group of students should therefore increase their motivation and enjoyment of the course. Finally, we may infer that the High Performing Solvers are proactive students with well-developed self-regulation skills. These students are characterized by organizing their goals hierarchically, setting specific and challenging yet achievable goals that allow them to achieve a high grade by the end of the course (Zimmerman, 2013). For this group, it may be best not to intervene in their self-regulation process and instead propose optional exercises that will allow them to enhance their understanding of the content and master the skills taught by the course.

Significant differences were found in the students' patterns of online problem solving. This was the case when classifying them according to their status at the end of the course, as well as their level of motivation and perception of challenge. This is coherent with the fact that the student's final outcome on the course is the result of their learning experience and process (Schwarzenberg et al., 2017). The correlations between enjoyment, challenge and academic performance are similar in strength but with opposite signs. Therefore, when a student scores highly on both variables the effects may compensate each other and the results may be similar to students with lower levels of motivation or a lower perception of challenge. This compensation is also observed with the students' level of activity, meaning that classes 1 and 2 cannot be accurately distinguished using the overall indicators. However, differentiating by motivation can allow efforts to be focused on the Disengaged Solvers in order to boost their motivation and performance from week 6. This intervention can then be extended to the Engaged Solvers in order to help them manage the increasing level of difficulty towards the end of the course.

It is important to identify and apply these strategies early on as by the sixth week of the course the students who are at risk of failing can already be identified (Figure 4.8). Although it is not possible to differentiate between students who will drop out or fail the course, it is possible to differentiate between those who will pass or fail based on their online activity. Week 6 is approximately a third of the way through the course, which coincides with the point at which students most often drop out of a MOOC (Kizilcec, Piech & Schneider, 2013). In the case of the course analyzed in this paper, identifying at-risk students in week 6 gives the lecturer three weeks to intervene before the students finally drop out of the course at week 9, which is when activity among students who drop out tends to decrease, dropping to almost zero by week 12 (Table 4.7). This decrease in activity among students who fail the course is consistent with previous results in the context of MOOCs (Sharma, 2015).

### 4.5 Conclusions, Limitations and Future Work

Three classes of student were identified in a course that was taught following the flipped classroom approach. Indicators of online activity were then determined, allowing the students to be differentiated at several points throughout the course. With regards to our first research question, **RQ1: How can students be classified according to their learning experience at the end of a flipped course?** , we found that the students can be classified into three groups based on their learning experience (High Performing Solvers, Engaged Solvers and Disengaged Solvers). Belonging to one of these classes is then an indicator of the student's academic performance by the end of the course. With regards to our second research question, **RQ2: Is it possible to build a model that correlates the online engagement patterns of students with their learning experience and academic achievement at the end of a flipped course?**, we found that the classes based on learning experience, as well as those related to the students' academic performance (Drop Out, Failed or Passed), can be differentiated using indicators of online activity. This allows the lecturer to design interventions in order to boost student motivation or adjust the challenge/skill balance of the activities done by each student. For students who fail the course, the predictive model accurately identified over 80% of at-risk students based on their online activity from week 1 to week 6. In this case, the information is available five weeks before getting the results from the first formal assessment on the course. Early detection allows remedial measures to be taken in good time, considering that the students who will drop out of the course no longer register activity by week 12. The ability to generalize this method of prediction must be validated in order to determine whether similar patterns can be detected in other blended courses using a system based on the skills and knowledge required by the student to pass the course, such as the system presented in this study.

One of the limitations of this study is the relatively small sample size (n=171) for the students' online activity. More data must therefore be gathered in order to confirm the effectiveness of the indicators of online activity used in this study. The neural model that was developed must also be refined using additional data so as to confirm its effectiveness. Alternatively, data augmentation techniques (Goodfellow, 2016) could be used to verify its generalization ability. Nevertheless, the level of accuracy seen in this study still makes it a useful tool for targeting remedial teaching activities. Although the students' level of motivation could be diagnosed by week 6 by analyzing their online activity, further data is required in order to build a more generalizable predictive model. Another limitation of the study is that, despite being dynamic, the learning experience is only evaluated at the end of the course. Evaluating the experience at midway points, such as the checkpoints, may allow us to verify the way in which the composition of the groups evolve over time. As future work, we plan to use the indicators of online activity that are proposed in this study (based on the skills and knowledge required in order to solve an online problem) to differentiate between the different classes of learning experience that are present in the flipped classroom in programming classes and other subjects. As these indicators also allow the predictive models to take into account the number of exercises completed by a student, it is important to assess how these exercises help students acquire the skills and knowledge that they needed in order to meet the learning objectives of a course.

**Appendix A: Statistical Models**

**Table 4.12**: Latent Class Model

| Question | Class | Prob(1) | Prob(2) | Prob(3) | Prob(4) | Prob(5) |
|---|---|---|---|---|---|---|
| e1 | 1 | 0.0276 | 0.0289 | 0.1271 | 0.2228 | 0.5935 |
| | 2 | 0.1065 | 0.1899 | 0.3352 | 0.3283 | 0.0401 |
| | 3 | 0.0000 | 0.0071 | 0.0257 | 0.2960 | 0.6712 |
| | | | | | | |
| e2 | 1 | 0.0136 | 0.0000 | 0.0421 | 0.1591 | 0.7852 |
| | 2 | 0.0683 | 0.1407 | 0.2781 | 0.4372 | 0.0757 |
| | 3 | 0.0000 | 0.0118 | 0.0208 | 0.1942 | 0.7733 |
| | | | | | | |
| e3 | 1 | 0.0000 | 0.0000 | 0.0238 | 0.0154 | 0.9609 |
| | 2 | 0.0359 | 0.1435 | 0.2347 | 0.4826 | 0.1032 |
| | 3 | 0.0000 | 0.0000 | 0.0000 | 0.2026 | 0.7974 |
| | | | | | | |
| b1 | 1 | 0.0000 | 0.0000 | 0.0296 | 0.1309 | 0.8396 |
| | 2 | 0.0310 | 0.0686 | 0.1578 | 0.4209 | 0.3216 |
| | 3 | 0.0540 | 0.2185 | 0.4380 | 0.2894 | 0.0000 |
| | | | | | | |
| b2 | 1 | 0.0000 | 0.0000 | 0.0000 | 0.1044 | 0.8956 |
| | 2 | 0.0305 | 0.1116 | 0.1306 | 0.3955 | 0.3319 |
| | 3 | 0.0548 | 0.2249 | 0.3029 | 0.3872 | 0.0302 |

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