Universitat Oberta de Catalunya

A dropout definition for continuance intention and effective re-enrolment models in online distance learning

Doctoral Thesis presented by Josep Grau-Valldosera to apply for the title of Doctor in Education and ICT by the Universitat Oberta de Catalunya

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1 Introduction

1.1 Context: dropout in Higher Education

Dropout in higher education is not a new problem, and in the present context of an expansion of access and scarcity of public budgets, it has acquired renewed relevance. University dropout is becoming a significant issue and should be seen as a failure of the higher education system to create an outcome (graduates) after having invested a considerable amount of resources, usually publicly funded (OECD, 2017). However, the financial costs of dropout are only part of the total costs: Non-pecuniary (or affective) costs –more difficult to measure – are also crucial for dropout students (Beer & Lawson, 2017; Johnes, 1990) and institutional reputation.

Considering the importance of dropout from institutional and personal levels, it is remarkable, and somewhat surprising, that international comparative data on this issue is only partial and not updated, which is mainly due to the lack of periodical data in some countries and also, when data exists, to the differences that generally appear in dropout definitions among higher education systems.

In the report Education at a Glance (OECD, 2010), enrolment data of countries for which data is available is analysed, giving the results shown in Figure 1.1. The average number of students that do not graduate in the higher education program they start is 31%, with high variability (from more than 50% in the USA to 10 % in Japan). These figures depend on how dropout (or completion rate) is defined.

For instance, an OECD report defines completion rate in the following way:

> *"Completion rates are defined as the proportion of new entrants into a specified level of education who graduate from at least a first degree at this level. The rates are calculated as the ratio of the number of students who graduate from an initial degree during the reference year to the number of new entrants in this degree n years before, n being the number of years of full-time study required to complete the degree."*

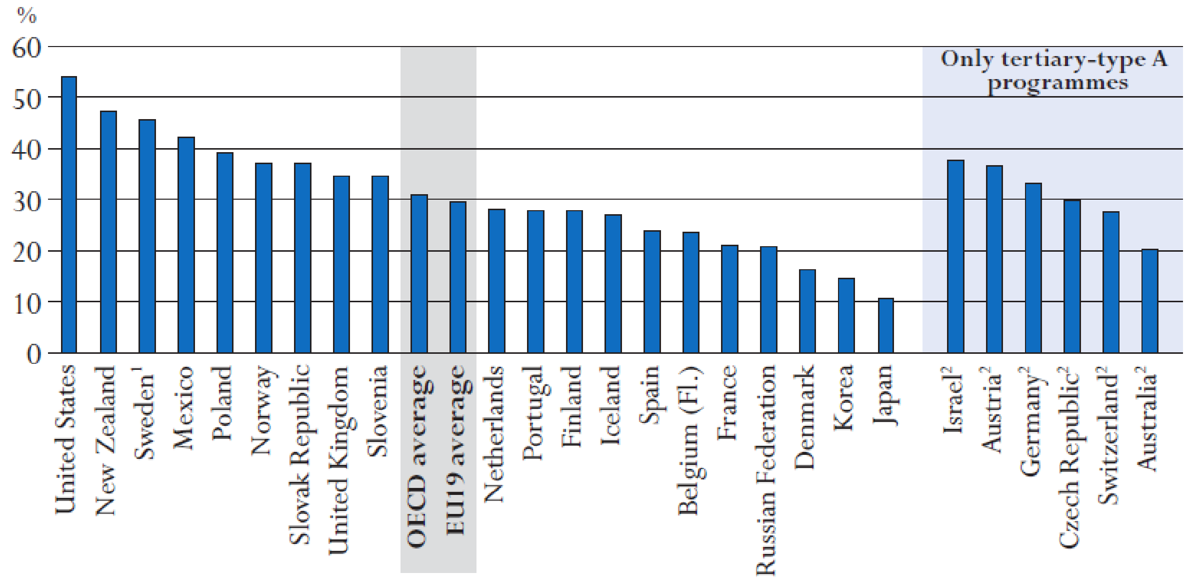


Figure 1.1: Proportion of students who enter tertiary education without graduating from at least a first degree at this level (OECD, 2010.)

Attending to the mentioned OCDE report, it is important to notice that official dropout definitions have to be necessarily simplistic to be quantifiable and generalizable; therefore, they cannot capture all the dimensions that exist behind this very complex phenomenon. For example, a failure from an official or even institutional point of view could not be that from the perspective of the student, who can move to another type of program or take profit from the competences acquired during her year(s) in the program.

Another remarkable result from this report is that non-completion is higher for part-time students than full-time ones:

> *"Full-time students have a better chance of graduating from their courses than part-time students. The largest difference between full-time and part-time students is observed in New Zealand, where completion rates for full-time students who enter tertiary-type A education are 28 percentage points higher than those for students with part-time status".*

It is noticeable that part-time studies are more likely to be offered through distance education.

The report "College Dropout Rate" (CollegeAtlas, 2014) explores the main characteristics of higher education dropout in the US. The main features of US dropout do not differ from the ones given in the OECD report, specifically:

- Full-time and younger students are less likely to drop-out.
- Being unable to balance job, family and school is cited as one of the top reasons to drop out.
- 30% of college first-year students drop-out after their first year at college.

In next section, we will present some data about dropout in online distance learning, taking into account that access to distance education is more open and varied than in traditional face-to-face settings, which implies that more different student profiles exist, each one with their conditions and rhythms.

1.2 Dropout in online distance learning

1.2.1 Dropout in online distance learning systems

After more than 20 years of existence, undergraduate students progressively adopt online distance learning, and there would still be space for more growth, even though it is difficult to find global statistics. A report from EDUCAUSE (Dahlstrom & Bichsel, 2014) notices that most undergraduate US students have used a learning management system in at least one course (83%), although only about half (56%) have used it in most or all of their classes.

As stated by Bawa (Bawa, 2016):

> *"The online delivery system has revolutionized educational technology and has provided easy access to learning for multitudes of students, including many who were unable to go to school before this revolution. Today, online education is one of the top industries in the world, providing support, knowledge, and jobs to a large segment of the world's population. (...) Online learning is also becoming an integral part of corporate training. Organisations that utilise this platform have better chances at business and financial gains, as it provides a positive impact on workplace motivation. Access to electronic data and a self-paced learning environment may increase the interest and value of on-the-job training."*

In parallel with the advantages that online distance learning can offer to institutions and also to students, we have to consider that one of the most significant minuses attributed to distance education is the burden that comes with high dropout rates (Cho & Heron, 2015; Kizilcec & Halawa, 2015; Ryan & Greig, 2017; Stiller & Köster, 2016; Wladis, Hachey, & Conway, 2015). Reed, Wise, Tynan, & Bossu (2013) state that “it has been claimed that no area of research in distance education has received more attention; such is the concern surrounding attrition”. Considering the differences between traditional and online distance learning methodology and their respective student profiles (in the online setting, often adults with work and family obligations in addition to those of education), it should come as no surprise that dropout in online distance learning is both more frequent and of a different nature than with its face-to-face counterpart.

Specifically, we have to notice that the existence of a significant rate of early dropout is characteristic of online distance learning institutions (De Santiago Alba, 2011; Oliver, 2007; Tyler-Smith, 2006). Early dropout makes things even worse, since it implies that in many cases students do not have time to acquire knowledge or competencies from the program, which, as we see previously, is more possible in face-to-face programs, particularly in the case of countries where one year of study can provide students with attractive opportunities for employment on the labour market (OECD, 2010). It is also noticeable that some European countries put the focus on early dropout also for traditional programs, due to the fact that transition from the first to the second year of study is considered to be a crucial step in students' educational pathway as well as in face-to-face settings (Vossensteyn et al., 2015).

In the case of Spain, as it appears in the State of the art section, the dropout rate for distance learning is quite higher than that for face-to-face learning: 60.5 % vs. 24%, whereas private distance learning universities (as UOC for example) that are all online have a significantly lower dropout rate than public distance learning ones[1] (53.5 % vs 62.8%, respectively).

Regarding specifically the Universitat Oberta de Catalunya (UOC), we can see that non-enrolment after the two first semesters[2] of the program –enrolment at UOC is bi-annual- is

[1] In Spain, this would be the case of the UNED
[2] In the UOC, the academic term lasts one semester.

reaching an average value of 50% for all the bachelor programs of the last cohort considered with two semesters of history. In Figure 1.2, we can see the evolution of the non re-enrolment rate for consecutive semesters, starting with the 2008-09 cohort (post-Bologna programs). [3]

Focusing our attention on the non re-enrolment rate in the second semester, which is shown in Figure 1.3, we see that non-enrolment has increased clearly through the last 17 cohorts: more than 10 points, from 22 % (for the 2009/2 group) to 32% (for the 2017/1 one). If we take non re-enrolment in the third semester, also shown in Figure 1.3[4], it follows an even more increasing path, reaching a value of 50% in the last cohort analysed (2016/1), as was previously noticed. If we consider that the "official" dropout definition considers the "official" bachelor duration plus two years, we can see that this definition is unsuited to the early non-enrolment behaviour of students in the case of early dropout at UOC.

The other side of the coin would be the students that keep studying and do not follow the non re-enrolment path: the average "real duration" of bachelors at UOC for the students that finally achieve their degree is about 5-6 years, 50% more than the official duration of the program (4 years; that is 8 semesters).

Taking this into consideration, "real" dropout at the end of the "real duration" of bachelors reaches an average value of 80% (Minguillón & Grau-Valldosera, 2013). The focus of this research on the 33% of early non re-enrolment after in the second semester seems justified, as it stands for an important part of total dropout.

1.2.2 A long-term perspective

After justifying the importance of focusing this research into the first two semesters, there still exists the need to connect the high levels of early non re-enrolment with the final number of "definitive" dropout. A dropout definition that allows us to detect early dropout and therefore "anticipate" –and "prevent"- this final dropout would help to make this connection. This

[3] This figure represents the % of non-enrolled students during 1, 2 or 3 semesters over the total of active students of the cohort. This calculus explains the step down of the line in the fourth semester.
[4] There is no data of the 2017/1 cohort because there were not two semesters of history.

definition needs to be based on evidence, specifically on the analysis of the enrolment behaviour of students.

A dropout definition in online distance learning needs to take into account the possibility that distance learning institutions offer -and also, why not say so, the need that students have- of taking a break, that is, of not enrolling during one or more consecutive semesters. This would be a "novelty" about dropout in face-to-face institutions, where dropout is defined arbitrarily from the educational administration considering an "ideal" full-time student. Parallel to the possibility of taking a break, there exists the possibility of re-starting after taking this break: this possibility of re-start depends on the "continuance intention" of students, a concept that has been quite analysed in previous e-learning literature (Cho & Heron, 2015; Hachey, Wladis, & Conway, 2013; Rodríguez-Ardura & Meseguer-Artola, 2014). The analysis of continuance intention, and how this intention ends up in effective re-enrolment or dropout, wants to be one of the main contributions of our research (J. Grau-Valldosera, Minguillón, & Blasco-Moreno, 2018).

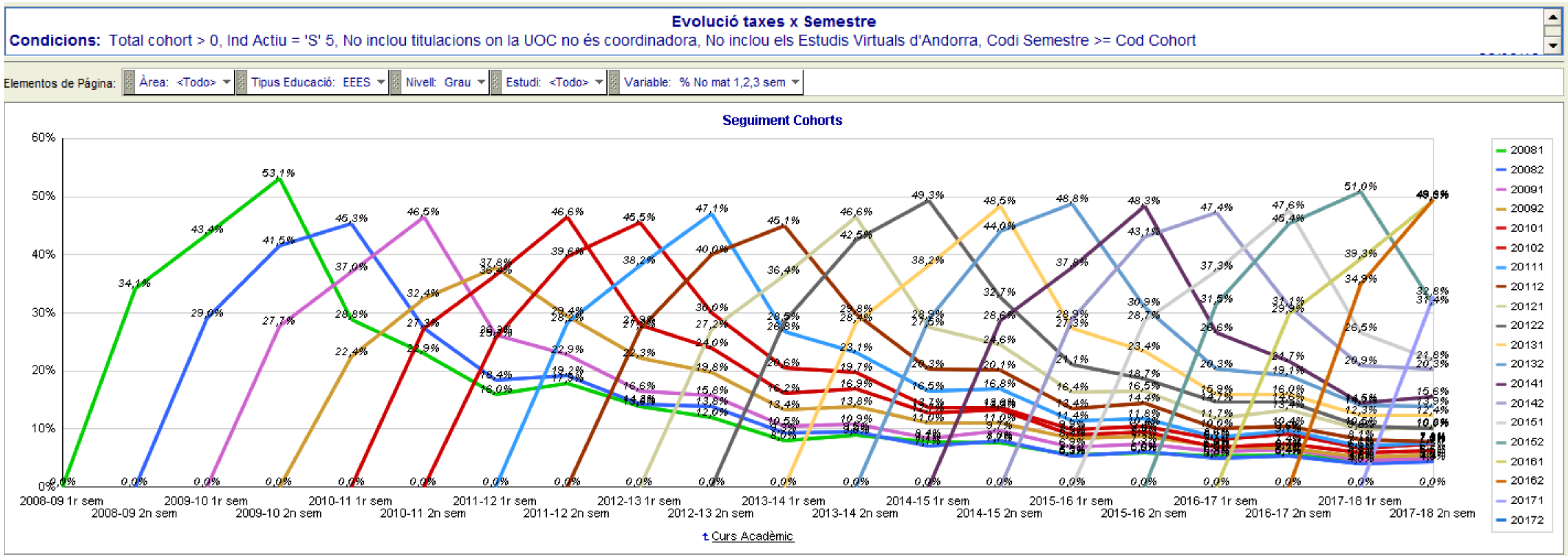


Figure 1.2: Non-enrolment during 1, 2 or 3 consecutive semesters. Source: Academic data-mart UOC.

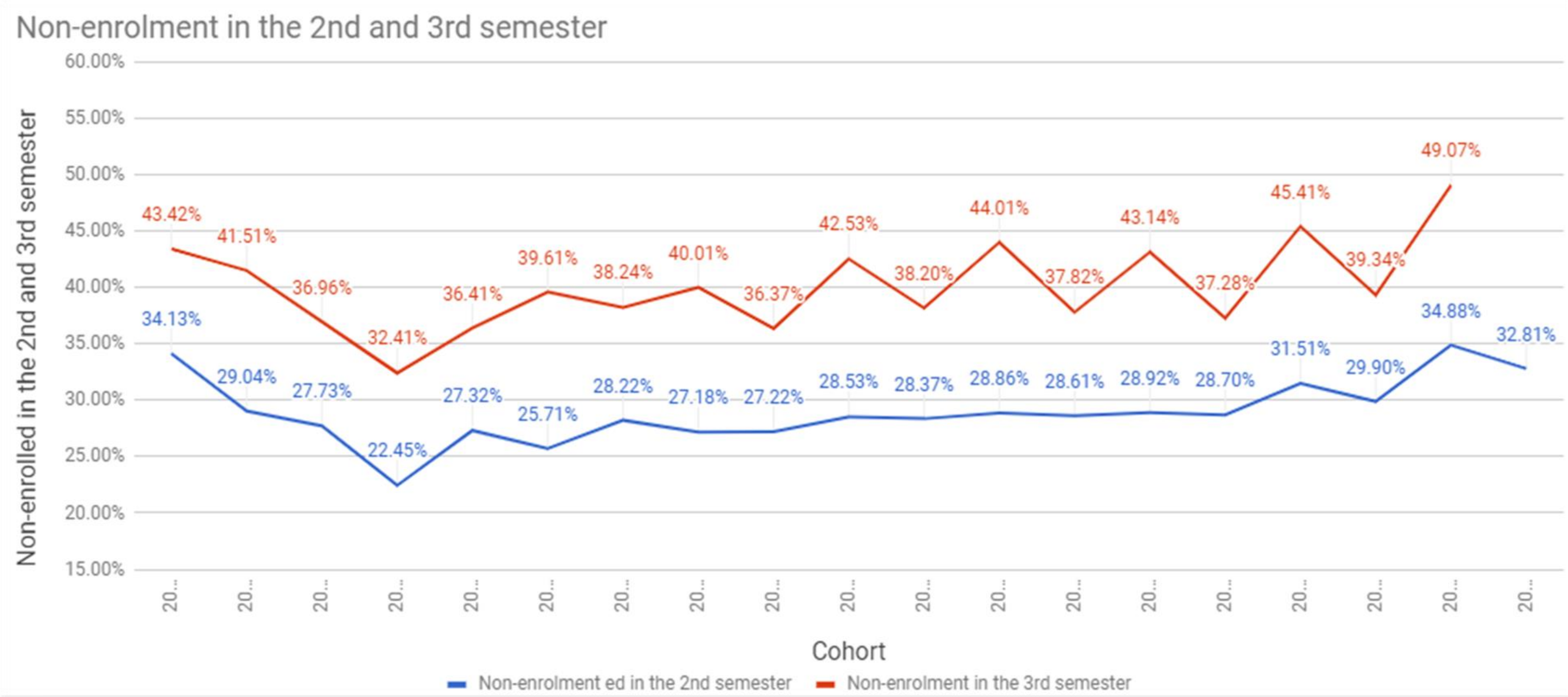


Figure 1.3: Non-enrolment after the 1rst semester. Source: Academic data-mart UOC.

Taking a break in the second semester has strategic importance beyond this specific semester (33% of students, as we have seen previously), as it affects the subsequent continuity of the students throughout all the program. It is essential to notice that, even if only 6.2% of the students that take a break in the second-semester return in the third (J. Grau-Valldosera et al., 2018), a program is a "long-distance race". In most cases, the re-enrolment or break decision is not a spontaneous one and would depend on a previous favourable or unfavourable attitude. This attitude would support a lower or higher level of "continuance intention".

Beer & Lawson (2017) propose an alternative perspective on the problem of student dropout in higher education. In a survey sent to students who had not re-enrolled for two or more consecutive terms, they got 402 responses, representing a 16% response rate. Of those, 24% were internal students and 76% distance learning students. One of the main findings was that the reasons for student attrition that are directly controllable by the university made up only a small proportion of those cited by students in this survey. Also, Lee & Choi (Lee & Choi, 2011), in their review of online course dropout research, detected that university factors were mentioned only in 20% of cases. Nevertheless, we see this as an opportunity and as an issue that deserves to be explored. Our research questions will try to ascertain what happens with students taking a break in the second semester before their eventual dropout/re-enrolment decision in the third semester, and to which extent university policies help to build a positive or negative attitude towards continuance intention. All this without ignoring the analysis of those factors not related to university policies, which are also of great importance.

As a summary to what has been stated so far, our research will focus on finding a dropout definition adapted to an e-learning context, followed by the empirical analysis of early non-re-enrolment and the eventual re-enrolment after one period of break, considering the existence of a previous favourable or unfavourable attitude to re-enrolment. The following section explains these objectives with more detail.

1.3 Research questions

This research focuses on defining dropout in an e-learning context, for measuring student continuance and, more specifically, the re-enrolment of students who have taken a break in the second semester in their higher education programs. Research questions raised in this dissertation are the following:

- RQ1: How can be dropout defined to take into account evidence of enrolment behaviour and "context" of e-learning students (i.e. taking a break)?
- RQ2: Which variables or drivers are behind a clear intention to re-enrol in the next term, and on the same degree or program?
- RQ3: Which variables or drivers are behind the ultimate decision to re-enrol or to extend the break?
- RQ4: Which differences and similarities between we detect for continuance intention and effective re-enrolment?

We are especially interested in the analysis of course-program (or institutional) drivers, as they are the ones that the institution can act upon.

1.3.1 A possible generalisation of results

At this point, it seems relevant to consider the possibility of generalising the results of the research carried out with the abovementioned objectives. In many cases, the situation of distance learning institutions is similar to that at UOC, that is, they have an academic system with non-compulsory enrolment and lax or non-existent completion deadlines, allowing the students to start and stop their studies.

Lee and Choi (Lee & Choi, 2011) detected, in their literature review of distance online learning dropout, high heterogeneity of dropout definitions. On the one side, this is positive because it recognises the flexibility that institutions have to define re-enrolment policies adapted to their specific circumstances; on the other hand, this shows the need to find a common definition that allows to benchmark and find synergies between the various research actions carried out by different institutions. Our research pursues this goal.

1.4 Dissertation structure

Figure 1.4 summarises the goals of this dissertation:

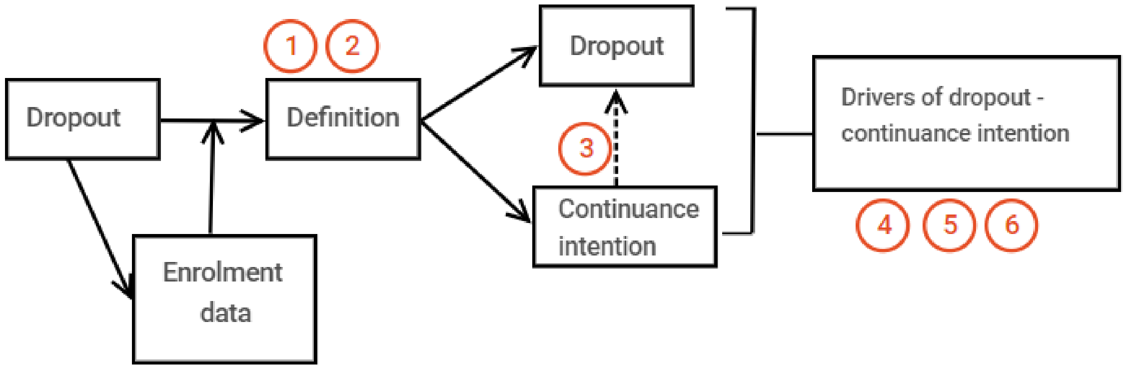


Figure 1.4: Graphical representation of the relation of research objectives with the chapters of the dissertation.

This dissertation is structured as follows:

- In Chapter 2 we find a description of dropout in traditional institutions of Higher Education in Europe and Spain and a literature review of online distance learning dropout and continuance intention,
- Chapter 3 and 4 contain the description of the research carried out, in two major sections:
    - The construction of a dropout definition adapted to the reality of online distance education, which will make it possible to detect which students are at risk of dropout (Chapter 3);
    - The analysis of the drivers behind the decision to continue, a clear intention to re-enrol and an ultimate decision to re-enrol (Chapter 4).
- Then, in Chapter 5, we undertake a discussion of the results that have been reached about the objectives stated in the research questions.
- Finally, the conclusions in Chapter 6 make a synthesis of the work carried out and the main findings achieved. They also undergo a description of the main limitations of the research carried out, possible lines of future research and recommendations to the institution, aimed at getting a better knowledge of the behaviour of students' enrolment patterns in the first two semesters, with the ultimate aim of reducing early dropout.

1.5 Dissertation outputs

Several parts of the research have been submitted and mostly published in international conferences and journals, specifically:

1. *LAK '11: Proceedings of the 1st International Conference on Learning Analytics and Knowledge*. (J. Grau-Valldosera & Minguillón, 2011) (Vol. Banff, Alb). New York, NY, USA: ACM.
2. Minguillón, J., & Grau-Valldosera, J. (2013). When procrastination leads to dropping out: analysing students at risk. *ELC RPS Journal*. Retrieved from http://www.uoc.edu/ojs/index.php/elcrps/article/view/1872
3. Grau-Valldosera, J., & Minguillón, J. (2014). Rethinking dropout in online higher education: The case of the Universitat Oberta de Catalunya. *International Review of Research in Open and Distance Learning*, *15*(1).
4. Blasco-Soplón, L., Grau-Valldosera, J., & Minguillón, J. (2015). Visualisation of enrollment data using chord diagrams. In *GRAPP 2015 - 10th International Conference on Computer Graphics Theory and Applications; VISIGRAPP, Proceedings*.
5. Grau-Valldosera, J., & Minguillón, J. (2017). Differences among online student profiles taking a break: factors for continuance intention and effective re-enrolment vs dropout. Published in O2, UOC institutional repository.
6. Grau-Valldosera, J., Minguillón, J., & Blasco-Moreno, A. (2018). Returning after taking a break in online distance higher education: from intention to effective re-enrollment. *Interactive Learning Environments*. https://doi.org/10.1080/10494820.2018.1470986

The numbers of these articles appear in the context of Figure 1.4.

2 State of the art

2.1 Higher Education dropout in Europe and Spain

We start this section with an approximation to dropout in Higher Education systems in Europe and Spain. For the Spanish reality, we present specific data on distance education dropout and try to distinguish between traditional distance education and online distance education.

2.1.1 Dropout in Higher Education in Europe

Reduction of HE dropout is a priority set out in the Europe 2020 strategy, as mentioned in the report "Dropout and Completion in Higher Education in Europe" of the European Commission (Vossensteyn et al., 2015, p. 92):

> *"In the Europe 2020 strategy, one of the goals is to have at least 40% of 30-34–year-olds complete higher education. Reducing dropout and increasing completion rates in higher education is one of the key strategies for achieving this goal, which is regarded as crucial for creating the high-level skills that Europe's knowledge-intensive economic sectors need as well as for Europe's capacity to innovate and foster productivity and social justice."*

Therefore, dropout is a crucial issue on the European Higher Education policy agenda. The mentioned European Commission study found that study success is regarded as important in three-quarters of the 35 European countries surveyed. In almost half of the nations, it is ranked as high or very high on the policy agenda (see Table 2.1).

Importance of study success	Countries
Very high or high on the agenda	Denmark, England, Estonia, Finland, Flanders (Belgium), France, Greece, Hungary, Italy, Former Yugoslav Republic of Macedonia, Malta, Netherlands, Norway, Serbia, Slovenia, Sweden
On the agenda	Austria, Croatia, Czech Republic, Germany, Ireland, Luxembourg, Montenegro, Poland, Portugal, Romania, Spain, Switzerland
No or little relevance	Bulgaria, Cyprus, Iceland, Latvia, Lithuania, Slovak Republic, Turkey

Table 2.1: Importance of study success in European countries.

Even the aim behind this dropout reduction is the same that the one existing in the OECD from a global perspective, there exist some specificities in Europe. For instance, concerning the different definitions of study success: national governments and higher education institutions use different orientations or measures to guide their policy-making concerning study success:

- Completion: to complete the study program with a degree.
- Time-to-degree: to complete the study program within a reasonable period.
- Retention or dropout: the aim to have students re-enrolling in a study program until they complete their degree and to reduce the likelihood they drop out before completing their program.

Depending on the focus of each country, policy-making will prioritise certain strategies and actions to achieve the specific objectives included in each of these orientations. This needs of a particular measure for evaluating achievement.

This diversity of criteria, together with the non-existence of a joint strategy of student success data collection from member states, has resulted in a significant gap of European data in this area, and therefore also in non-completion / drop-out data, as was stated in the mentioned European Commission report (Vossensteyn et al., 2015, p. 92) :

> *"However, systematic monitoring of study success is not a widespread practice within Europe. This demonstrates that tracking study success is not yet a prominent issue in most countries – at least not at the national level. Some countries leave policy initiatives mainly to higher education institutions. When looking at available data, the current study has found that cross-country overviews of completion rates, let alone other orientations of study success, are rare and do not provide a solid basis for comparing the performance of countries in the various understandings of study success."*.

2.1.2 Dropout in Higher Education in Spain: tackling the (online) distance education dropout

The definition of Higher Education dropout rate and "program change" rate are defined in Spain (Ministerio de Educación, 2016) as follows:

- Dropout rate: Percentage of students from a new enrolment cohort in undergraduate studies that are not enrolled in the study in the following two semesters.
- Program change rate: Percentage of students from a new enrolment cohort in undergraduate studies enrolled in another study in the two following courses.

Using the data described in the previous sections, we show the ratios of dropout in Spain in Table 2.2. The main conclusions that we can derive from the analysis of Higher Education dropout in Spain are:

- The dropout rate for distance learning is quite higher than that for face-to-face learning: 60.5 % vs 24%, whereas the rate of change are similar between the two modalities,
- Private distance learning universities, that are all online[5], have a significantly lower dropout rate than public distance learning ones (53.5 % vs 62.8%, respectively).
- Arts and Humanities is the knowledge area with higher levels of dropout, regardless of ownership (public/private): 50%, as shown in Table 2.3.

Grado. Abandono

Tasas globales de abandono y cambio del estudio en Grado por tipo de universidad. Cohorte de nuevo ingreso de 2009-2010

	Total		Univ. Públicas		Univ. Privadas	
	Abandono del estudio	Cambio de estudio	Abandono del estudio	Cambio de estudio	Abandono del estudio	Cambio de estudio
Total	**32,0%**	**10,9%**	**32,7%**	**11,2%**	**29,0%**	**9,8%**
Presencialidad de la universidad						
Univ. Presenciales	24,0%	11,2%	25,1%	11,4%	18,2%	10,4%
Univ. No presenciales	60,5%	9,8%	62,8%	10,3%	53,5%	8,3%

Table 2.2: Dropout in Spanish Higher Education by modality (face-to-face, distance) and ownership (private, public). (Ministerio de Educación, 2015).

[5] Private online universities are: UDIMA-Universidad a Distancia de Madrid, UNIR-Universidad Internacional de La Rioja, UI1-Universidad Internacional Isabel I de Castilla, VIU-Universidad Internacional Valenciana and UOC-Universitat Oberta de Catalunya. Public distance universities are represented by only one university: UNED-Universidad Nacional de Educación a Distancia.

Tasas globales de abandono y cambio del estudio en Grado por rama de enseñanza. Cohorte de nuevo ingreso de 2009-2010

	Total		Univ. Públicas		Univ. Privadas	
	Abandono del estudio	Cambio de estudio	Abandono del estudio	Cambio de estudio	Abandono del estudio	Cambio de estudio
Total	**32,0%**	**10,9%**	**32,7%**	**11,2%**	**29,0%**	**9,8%**
Rama de enseñanza						
Ciencias Sociales y Jurídicas	29,4%	10,8%	28,9%	11,1%	31,5%	9,7%
Ingeniería y Arquitectura	31,6%	11,6%	36,4%	12,9%	14,8%	7,2%
Artes y Humanidades	46,0%	11,6%	45,9%	11,7%	47,9%	11,3%
Ciencias de la Salud	29,4%	8,5%	29,2%	7,9%	30,0%	11,0%
Ciencias	29,8%	16,7%	29,9%	16,6%	29,3%	21,4%

Table 2.3: Dropout in Spanish Higher Education by knowledge area. (Ministerio de Educación, 2015).

The report also provides data (attending to the official criteria) about dropout in the first year (that is, attending to the official definition), and not-enrolling in the second and third year:

- Ratios are also quite high both for face-to-face and distance learning universities.
- The proportion of the first-year dropout over total dropout [6] is higher for face-to-face and “traditional” distance learning institutions (about two thirds) than for online distance learning institutions (about a half). These results appear in Table 2.4.
- Arts and Humanities is also the knowledge area with higher dropout in the first year, but differences are lower than the ones seen in total dropout rates. It seems than Arts & Humanities’ students drop out more in the following courses than those of other programs (Table 2.5).
- It is remarkable that a negative relationship exists between the admission note and the dropout rate (the lower the admission note, the higher the dropout rate, see Figure 2.1).

[6] Taking into account that we are considering different cohorts of students.

Tasas de abandono y cambio del estudio en primer año en Grado por tipo de universidad. Cohorte de nuevo ingreso de 2010-2011

	Total		Univ. Públicas		Univ. Privadas	
	Abandono del estudio en 1º año	Cambio del estudio en 1º año	Abandono del estudio en 1º año	Cambio del estudio en 1º año	Abandono del estudio en 1º año	Cambio del estudio en 1º año
Total	**21,2%**	**8,1%**	**22,1%**	**8,4%**	**15,9%**	**6,0%**
Presencialidad de la universidad						
Univ. Presenciales	16,2%	8,3%	16,9%	8,6%	11,5%	6,4%
Univ. No presenciales	41,7%	6,9%	44,7%	7,4%	28,9%	4,8%

Tasas de abandono y cambio del estudio en primer año en Grado por tipo de universidad. Cohorte de nuevo ingreso de 2011-2012

	Total		Univ. Públicas		Univ. Privadas	
	Abandono del estudio en 1º año	Cambio del estudio en 1º año	Abandono del estudio en 1º año	Cambio del estudio en 1º año	Abandono del estudio en 1º año	Cambio del estudio en 1º año
Total	**22,5%**	**8,0%**	**23,3%**	**8,3%**	**17,8%**	**6,2%**
Presencialidad de la universidad						
Univ. Presenciales	17,2%	8,3%	17,8%	8,5%	13,3%	6,5%
Univ. No presenciales	42,8%	6,8%	45,7%	7,2%	29,3%	5,2%

Table 2.4: Dropout in Spanish Higher Education after the first course by modality (face-to-face, distance) and ownership (private, public), for 2010-11 and 2011-12 cohorts (Ministerio de Educación, 2015).

Tasas de abandono y cambio del estudio en primer año en Grado por rama de enseñanza. Cohorte de nuevo ingreso de 2011-2012

	Total		Univ. Públicas		Univ. Privadas	
	Abandono del estudio en 1º año	Cambio del estudio en 1º año	Abandono del estudio en 1º año	Cambio del estudio en 1º año	Abandono del estudio en 1º año	Cambio del estudio en 1º año
Total	**22,5%**	**8,0%**	**23,3%**	**8,3%**	**17,8%**	**6,2%**
Rama de enseñanza						
Ciencias Sociales y Jurídicas	21,8%	7,2%	22,4%	7,5%	18,5%	5,8%
Ingeniería y Arquitectura	24,5%	10,3%	25,6%	10,9%	16,3%	5,3%
Artes y Humanidades	29,3%	8,8%	29,4%	8,9%	26,2%	6,7%
Ciencias de la Salud	17,4%	6,0%	17,8%	5,7%	15,8%	7,3%
Ciencias	24,5%	11,0%	24,6%	11,0%	19,1%	10,4%

Table 2.5: Dropout in Spanish Higher Education in the first course by knowledge area. (Ministerio de Educación, 2015).

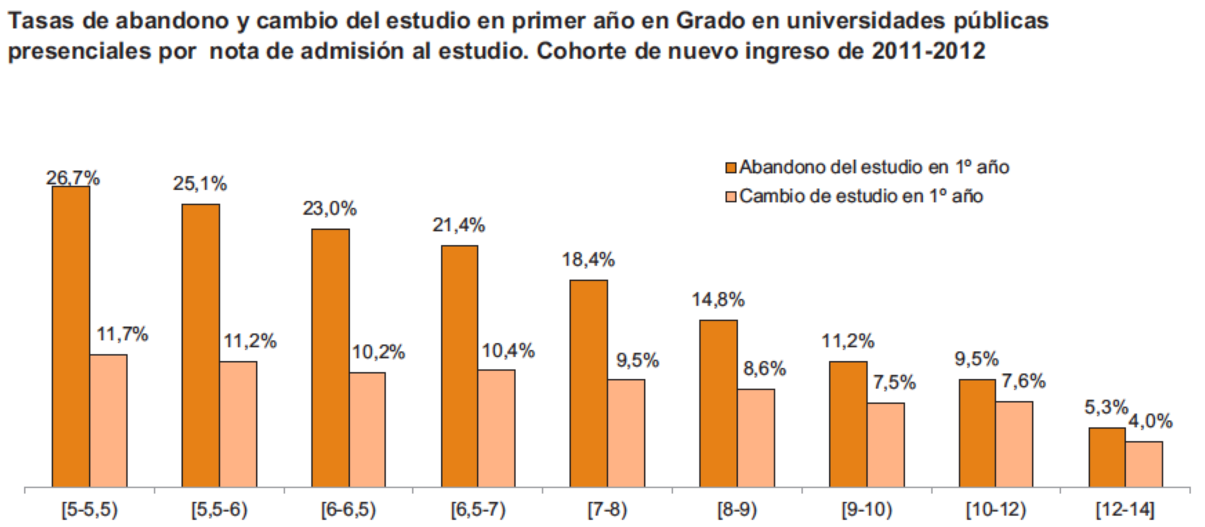


Figure 2.1: Dropout in Spanish Higher Education in the first course by admission note. (Ministerio de Educación, 2015).

Table 2.6 below shows a synthesis of the indicators mentioned in this section. In the light of all these data, it would seem that dropout (both total rates and early rates) are effectively an important issue, also, in Spanish HE.

	Dropout 1st year	**Total dropout**	**1st-year dropout / total dropout**
Distance universities (global)	42 %	60.5 %	69 %
- **Distance Public / Traditional (UNED)**	45 %	63 %	71 %
- **Distance Private Online**	29 %	53 %	54 %
Face-to-face universities	16 %	24 %	67 %
Total universities	22 %	32 %	70 %

Table 2.6: Selection of official statistics on 1st year and global dropout in Higher Education in Spain (Ministerio de Educación, 2015).

Besides considering the data, we think an effort should be made to capture the real magnitude of this problem. This magnitude should be considered in terms of lack of effectiveness and efficiency of the higher education system (in a context of scarce resources), as well as in terms of a permanent feeling of frustration of those who have not been able to complete the program they started. This figures justify the large amount of academic literature in dropout, as it can be seen in ISI Web of Knowledge (WoK) and Scopus, where a simple search[7] returns 8476 results in ISI WoK (considering a search by subject) or 9022 in Scopus (considering a search by Title, Abstract o Keyword).

In the following section, we will analyse the most relevant literature about dropout in higher education.

2.2 Literature review

After more than 20 years of existence, online distance learning has been adopted by more than 50% of higher education students (Dahlstrom, Brooks, Grajek, & Reeves, 2015). Over these two decades, both the positive and negative aspects of its application have appeared. On the positive side, online distance learning, and information and communication technologies in general, seems to be a vital driver of the (r)evolution of teaching and learning systems. The correct management of online distance learning systems allows for more widespread access to quality, personalized education (Lane, 2012), taking advantage of the huge possibilities it offers in terms of creativity, for example through gamification (Matusevscaia & Matusevscaia, 2016; Tomé Klock et al., 2015), and putting a cap on costs (Castillo Merino & Sjöberg, 2008; OECD, 1998).

Nevertheless, negative perceptions of online distance learning also exist, as stereotypes inherited from the "non-digital distance education era". A few examples are poor or irregular quality (Bates, 2004), lack of interaction with professors and other students (M. Cole, Shelley, & Swartz, 2014) or significant difficulties regarding teaching and learning the content (Tyler-Smith, 2006). In the latter case, there is a lack of "touch-and-see" experimentation, although some exciting initiatives have appeared in areas like STEM (Potkonjak et al., 2016) – specifically, chemistry (Saxena & Satsangee, 2014)- or medicine (Makransky et al., 2016).

One of the most significant drawbacks attributed to distance education is the burden that comes with high dropout rates (Cho & Heron, 2015; Wladis, Conway, & Hachey, 2015). A significant proportion of early dropout is characteristic of online distance learning institutions: for

[7] Using "(dropout OR retention) AND higher education", as search query as of 10th May 2019

example, almost 50% of first-year students at the National Distance Education University (UNED) in Spain (De Santiago Alba,2011 and Table 2.6) or the Open University in the UK (Simpson, 2004) wind up dropping out. Early dropout rates are also high, up to 80%, in (relatively) new formats like MOOCs (Diver & Martinez, 2015; Kolowich, 2013), although this may be a reflection of trial and error since the cost of signing up is very low. However, despite these figures, there are actions that can be carried out to fight against early dropout and to engage learners from the first steps of the course. Some examples of these actions could be a Web-based tool developed to support an inquiry-based learning approach characterised by strong learning scaffolds, proposed by Oliver (2007), or the “optimisation” of cognitive overload, that is, the amount of information given to new students within the first weeks of the course start, as explained in Tyler-Smith (2006).

However, it is interesting to note that in certain contexts such as blended learning, degree completion is higher than in full face-to-face settings (Deschacht & Goeman, 2015; Montgomery, Hayward, Dunn, Carbonaro, & Amrhein, 2015; Shea & Bidjerano, 2014). Therefore, it would seem that e-learning is not negative *per se*, but depends on the way each institution implements it.

Based on the Spanish higher education system’s official definition of “dropout”, calculated as not enrolling for two consecutive years (Ministerio de Educación, 2015), previously described, we can see that dropout rates reach a value of 42.8% in the first year and 6.8% in the second year (a total of 49.6% after the second year) for distance education institutions. At face-to-face institutions, these values are 17.2% for the first year and 8.3% for the second, for a total of 25.5% (see bottom of Table 2.4, data for the 2011-12 cohort). In other words, one out of two distance education students drops out after their second year, while “only”[8] one out of four do so at traditional institutions.

Probably one of the shortcomings of the straight comparison of dropout rates between distance and face-to-face universities is that it does not consider the specificities of online distance learning students and higher education providers. We should take into account that higher

[8] Anyway, there is an important increase from 2009-10 cohort, from 19,8 % of dropout, to 2011-12 cohort, with a value of more than 25%), so these figures need to be always put into context, i.e. taking into account socio-economical factors.

education institutions engaged in online distance learning consider the specific needs of their students and, therefore, recognise their will to take a break, for instance. In many cases, they have an academic system with non-compulsory enrolment and lax or non-existent completion deadlines, allowing the students to start and stop their studies. As has been commented previously, there are exceptions, such as the Open University (UK) and Athabasca University (Canada), which establish a maximum time limit by which students must pass all undergraduate qualifications. In the latter case, the recommendation is that students remain active (enrol each academic period) on the program they have begun; otherwise, they are required to pay a fee to restart. Table 2.7 shows some similarities and differences of leading providers of online distance learning gathered through an e-mail questionnaire sent in May 2019. These differences and, above all, the common points are those that would condition the applicability of the results obtained in the UOC to other institutions, as all these specificities shape enrolment patterns and should be taken into account when analysing dropout.

2.2.1 The need for a dropout definition

It should be noted that university dropout, both in face-to-face and online learning institutions, is a multidimensional phenomenon that needs to be correctly defined before any thorough analysis of its causes can be carried out. One of the authors who has put great emphasis on creating a university dropout framework is Vincent Tinto (1975). Tinto stressed the importance of reaching a good definition of university dropout, which he saw as essential as detecting the causes of this dropout:

> *"Despite the very extensive literature on dropout from higher education, much remains unknown about the nature of the dropout process. In large measure, the failure of past research to delineate more clearly the multiple characteristics of dropout can be traced to two major shortcomings: namely, inadequate attention given to questions of definition and to the development of theoretical models that seek to explain, not simply to describe, the processes that bring individuals to leave institutions of higher education. (p. 89)"*

	Does your university have access requirements?	The academic period is annual or semi-annual?	Is there a limit to the number of consecutive periods during which a student may be "taking a break"?
Open University of the Netherlands	Mín 18 years old	They do have an academic year, but students enrol courses throughout the year.	Regarding 'taking a break' there are no limits. Rights connected with a course enrolment (e.g. taking an exam) last for one year.
University of Jyväskylä, Open University, Finland	Open Universities do not offer degrees. As a student, you can complete your courses/studies at the Open University, but to you have to apply to a degree in faculty	The academic year of the University of Jyväskylä consists of the autumn semester and the spring semester, which are both divided into two teaching periods. Then we also have summer period as a kind of extra period. At the Open University, they do not follow those periods; our studies are flexible (almost always) available	At the Open University a student "pay" one course or larger module and gets a certain period to complete this course or module. A student can individually build his/her timetable. If she/he is not able to complete the course during the period, she/he can "pay" it again to get a new opportunity. Still, there are some time limits for studies accepted to be a part of the bigger module or degree. Sometimes a student might need to update her/his studies.
Athabasca University, Canada	Athabasca University programs' are made to work for students regardless of their level of experience, previous grades or degrees	Most of Athabasca University's graduate programs use an online grouped study format. Generally, group study courses follow a traditional semester system; for example, courses which begin in September will end in December.	Establish a "reasonable" maximum time limit by which all undergraduate qualifications must be passed.
Open University UK	For most of The Open University's undergraduate degrees, no formal qualifications are required, and no entrance test is required.	In general, undergraduate courses start in October or February. The start dates for short courses and postgraduate courses are more flexible	Establish a "reasonable" maximum time limit by which all undergraduate qualifications must be passed.
FernUniversität in Hagen	Access at regular degree programs requires university entrance qualification Since 2012; there exists a separate track in Germany for people with vocational qualifications, who are allowed in a selected number of degree programs	Semi-annual	The German term is "leave of absence." There is no limitation to the number of consecutive semesters; however, students have to (reapply) for a leave of absence period every semester and also fill out a form suggesting reasons (for example, job-related),
UOC	Same entry requirements than the rest of the universities in the public system.	Semi-annual	No limits established.

Table 2.7: Similarities and differences of prominent providers of online distance learning.

The difficulty of defining dropout was, therefore, already acknowledged in traditional face-to-face education. Another article of Tinto (Vincent Tinto, 1982) is dedicated to this objective, stressing the different possible definitions of dropout depending on the individual or institutional perspective.

Besides an academic perspective, we can consider a policy one: in Europe, depending on their orientation and policy focus, governments and higher education institutions employ different definitions for each of these phenomena, namely completion and dropout. For example, many countries regard completion within the nominal (stipulated) study period plus one extra year as an indication of study success. Realising that the transition from the first to the second year of study is a crucial step in students' educational pathway, other countries focus on retention (or dropout) in higher education during the first year.

Another noticeable issue, related to the shortage of data on HE dropout in the European Union report (Vossensteyn et al., 2015), is that there is also a lack of systematic knowledge, data and indicators on study success in Europe:

> *"Although many studies are focusing on factors that may have an impact on the study success of individual students, research on study success policies and their effectiveness is rare, particularly research taking an international comparative perspective."*

A critical step for gaining better knowledge in this issue, attending to the same report, would be expanding and harmonising data:

> *"Our inventory of existing national data collections demonstrates that only 12 out of 35 European countries regularly report a national indicator of completion. Even fewer countries report on retention and dropout rates and time-to-degree. A recent report on computing and collecting data on completion rates and average duration in higher education concludes that the monitoring of study success and its calculation method need to be harmonised across Europe (ICON and QUANTOS, 2015). Only this would allow meaningful comparisons to inform the various stakeholders interested in higher education. The same need for systematic knowledge, data and indicators are also felt in Australia and the U.S.A."*

Last but not least, the report concludes that a clear definition of study success (and, reciprocally, dropout) is the first step towards a more effective policy design.

Considering the specific case of Spain, the "Conferencia de Rectores de las Universidades Españolas" (CRUE, Conference of Spanish University Vice-Chancellors) has established an arbitrary definition of the dropout rate. This definition applies to both brick-and-mortar and online universities (Ministerio de Educación, 2015) as the percentage of students who have not enrolled for either the academic year when they should theoretically finish their course or for the following academic year, with respect to the total number of students who enrolled on this course in the initial semester. It is easy to see that this definition does not capture the high numbers of early dropout seen at UOC. We can affirm, then, that the official definition of dropout in Spain does not reflect the particular peculiarity of UOC and, by extension that of online distance higher education in general.

2.2.2 Theoretical backgrounds for examining online learners

Bawa (2016), in a literature review on retention in online courses, address a complete analysis of which are the theoretical backgrounds for examining online learners. This analysis is important to determine the contexts within which online learning environments and learners are placed, taking into account especially the group of adult students, protagonists of distance higher education and normally "digital immigrants". We can classify these theories in various categories, depending on the matter they elaborate on. Specifically, as shown in Table 2.8. Those categories are learner, institution (pedagogical approaches that make up the online learning environment), or faculty.

As was stated previously, course-program or institutional drivers are very important, as they are the ones that the institution can act upon. Anyway, student and "external" factors are also essential to explain dropout, as they account for 40% and 15% of total factors (Lee & Choi, 2011). This will be seen at the end of this section.

Learner related theories	Institution-related theories (pedagogical approaches)	Faculty-related theories
Marginalisation or social exclusion have been used in literature to explain the decisions of learners to select or reject the online platform (Ball, Davies, David, and Reay (2002)) **Motivational theories of self-determination and self-efficacy are also pertinent to examining learners within online environments. Self-determination is defined as action generated by one's own mind or free will, with no influence from outside situations or entities (Wehmeyer, Abery, Mitaug, & Stancliff, 2003).** **Socio-cognitive views and models (Bandura, 1986; Zimmerman & Schunk, 1989) describe how self-efficacy beliefs of learners determine their abilities to persist and self-regulate.**	**Constructivism and andragogy** are closely related concepts and a huge factor in determining the content, structure, and climate of online learning environments. Chu and Tsai (2009) studied the factors that influence adult learners to select online programs/courses. They concluded that even though adult learners have concerns about their Internet efficacies, they find the constructivist approach of self-directed learning prevalent in online environments very attractive. **Cognitivism and related theories** are critical to understanding online education, particularly when viewed through the lens of globalised content creation and management, as is required in many online learning programs that have International students. **Siemens's (2014) theory of "Connectivism"** provides a new spin on traditional learning theories by addressing the technological and digital aspects of learning. Traditional theories rely on the belief that learning takes place within people and that it is a social process.	**Culturally unaware faculty** not prepared to cope with the rapid evolution of online learning environments.

Table 2.8: Theoretical backgrounds for examining online learners (Bawa, 2016).

2.2.3 Dropout and procrastination

Dropout in online distance learning can be related to the concept of procrastination. This would be one of the "student factors" to take into account if we want to understand dropout fully. Academic procrastination is defined "as intentionally deferring or delaying work that must be completed" (Schraw, Wadkins, & Olafson, 2007). Additionally, they note the fact that "although research in this domain has yielded mixed results, most studies report negative correlations between procrastination, grades, learning, and completion of course work" (Howell & Watson, 2007).

Understanding procrastination in the sense of taking a break of one or more semesters, it can be observed that this is not uncommon at distance universities (due to their relaxed enrolment requirements), as students have more opportunities to decide how many subjects they take each semester and their pace. According to Michinov et al. (2011), it is interesting to pair the concept of "taking a break" with that of procrastination, translating the temporal dimension from the subjects to that of the degree. As time (of inactivity) is the *leitmotiv* behind any ad-hoc definition for dropout, some of the variables that can eventually be related to dropout as descriptors or even as causes would also be related to the time-factor "macro-variable". For example, time management skills were detected as predictors of persistence studies in a questionnaire of 60 items (Holder, 2007), while the tendency towards procrastination/disengagement "is often associated with deficiencies in the processes of self-regulation", and would also be a factor that can affect the learning and performance and that can potentially cause dropout (Michinov, Brunot, Le Bohec, Juhel, & Delaval, 2011). Other variables like time availability or time constraints (Romero, 2011) would be more external, that is, more imposed by the environment (Lee & Choi, 2011).

As will be introduced in later sections, Grau-Valldosera and Minguillón (2011), a new definition of dropping out is fully explained for online higher education (using UOC as a case study), taking into account the aforementioned issues; that is, the particular features of students and also the possibility of taking breaks procrastinating at semester level. This definition falls into the category "Time personalisation (rhythms, adaptive time, acceleration, etc.)" defined by Gros et al. (2010), where time factor in e-learning is analysed. Using this definition, we can establish a line between those students just taking a break and those starting a long pause that leads them into dropping out. To analyse the procrastination behaviour of students, a "long-term" perspective of enrolment and break behaviour is needed.

Taking this into consideration, it is interesting to see that the results of the review of research on online learning dropout by Lee and Choi (2011), reveals that so far research has focused mainly on analysing the causes of dropout on a "short term" / course[9] level and does not take a whole program perspective (that is, a group of parallel courses). Additionally, the authors affirm, in various points of their paper, that there is a need for a standard definition of dropout also from an academic point of view, besides the official definitions established by the educational administration.

> *"Many of the studies (13 studies, 37%) we examined provided no clear definition of dropout from online courses. Furthermore, although some studies did explicitly define the term 'student dropout', their definitions were not consistent with one another, which made it difficult for us to compare dropout factors and retention strategies across universities." (p. 596)*

> *"Future studies, grounded in a clear, standard definition of the term 'dropout', should be conducted to investigate dropout factors which prevail across different online courses." (p. 603)*

In summary, it seems that dropout (both as an "institutional problem" and as an "academic and official definition challenge") has been inherited by distance education from its traditional face-to-face counterpart. On one hand, as an "institutional problem", recent studies indicate that online courses have significantly higher student dropout rates than conventional courses (Herbert, 2006; Smith & Smith, 2010; Tello, 2007). On the other hand, as a "definition challenge", the particular characteristics of adult students, with higher work and family time constraints, would make the dropout decision more complex than merely an "academic" one.

[9] It's interesting to recall here that in the UOC a course lasts one semester.

2.2.4 Existing Definitions of university Dropout

The summary of online dropout studies given in Lee and Choi (2011) literature review, which we see in Table 2.9, shows the heterogeneous nature of several definitions of dropout.[10] For example, as a "formal process not always asked for by students" (Finnegan, Morris, & Lee, 2009), as merely "not starting the course" (Kemp, 2002), as "a voluntary withdrawal entailing financial penalties" (Levy, 2007), or as a combination of the previous or other cases: "formally withdraw, leave without notifying the university, or did not complete a course during a semester" (Castles, 2004).

Author	Year	Dropout definition
Castles	2004	Dropout: students who had formally withdrawn, had left without notifying the university, or did not complete a course during a semester
Cheung and Kan	2002	Dropout: students who were awarded fail or resit
Dupin-Bryant	2004	Dropout: student who did not complete a course during a semester
Finnegan et al.	2009	Withdrawal: (1) withdrawers-had to withdraw from the course officially; (2) successful completers-completed the course receiving a grade of A, B, or C; (3) non-successful completers-received a grade of D or F or an incomplete
Frydenberg	2007	Dropout: students who registered but dropped before class start, before start of instruction, during the orientation week, or after the orientation week
Ivankova and Stick	2007	Dropout: students who withdrew or were terminated from the program
Kemp	2002	Non-completion: students who did not commence work on their course, withdrew from their course, or received an academic failing grade
Levy	2007	Dropout-students are those who voluntarily withdraw from e-learning while acquiring financial penalties
Moore et al.	2003	Non-completion: students who received a grade of F or officially withdrew from the course
Morgan and Tam	1999	Non-completion: students who did not enrol in the following semester
Morris et al.	2005	Withdrawal: students who completed the official withdrawal process. Non-successful completers: students who received a grad of D, F, or an incomplete
Perry	2008	Withdrawal: centre withdrawal (student unable to fulfill the program requirement to complete two courses per year), academic withdrawal (students who fail two courses in the program), and student withdrawal (students who leave for

[10] Despite its age, we'll see at the end of this section that their analysis is still valid nowadays.

		reasons not obviously related to centre or academic requirements)
Pierrakeas et al.	2004	Dropout: including those students who enrolled in at least one module, but failed to deliver one project; who did not complete some or all of their assignment, but indicated they would continue their studies; who would not re-enroll at a future date; who enrolled in multiple courses, who had successfully completed some but not all of their assignments, and had indicated they would not re-enroll at a future date
Pigliapoco and Bogliolo	2008	Dropout: students who did not renew the enrollment at the end of the first year
Shin and Kim	1999	Dropout: students who fail to register after three consecutive terms of non-enrollment
Tello	2007	Non-persistence: students who filed paperwork with the Registrar's office declaring withdrawal from a course before the final grading period
Willging and Johnson	2004	Dropout: students who dropped out of the degree program after starting their first course

Table 2.9: Heterogeneity of Dropout Definitions (extracted from Lee & Choi, 2011).

Besides this heterogeneity, the fact that most of these definitions draw on what happens in a single course makes them unsuitable for the objectives of our research. Literature reviews indicate that the online attrition pattern is not limited to any specific period or level of graduation. Students may withdraw from online classes anytime in the semester and at any level of their learning process (Bawa, 2016).

2.2.5 Continuance intention definition

In the introductory section, we justified the need to adopt a long term perspective that allowed us to consider dropout as a "program phenomena" and not an individual course issue. Additionally, viewing this broader perspective as a starting point, research questions focused our analysis on the students that take a break in the second semester and on "what happens" afterwards in the third semester (a restart of their degree or an eventual dropout).

Our research questions assume that there is a "link" that connects the attitude of students that take a break in the second semester with their final behaviour in the third semester and that this link is based on continuance intention.

Continuance intention in e-learning is defined (Roca, Chiu, & Martínez, 2006; Rodríguez-Ardura & Meseguer-Artola, 2014) as an extension of the Technology Acceptance Model

(Davis, 1989), and "is determined by satisfaction, which in turn is jointly determined by perceived usefulness, information quality, confirmation, service quality, system quality, perceived ease of use and cognitive absorption". One of the most significant results of Davis' study findings is the relative strength of the usefulness-usage relationship compared to the ease of use-usage connection. Usefulness was significantly more strongly linked to usage than was ease of use. Although the difficulty of use can discourage adoption of an otherwise useful system, no amount of ease of use can compensate for a system that does not perform a useful function. The prominence of usefulness over ease of use has important implications for designers, particularly in the human factors tradition, who at the time the study was undergone, had tended to overemphasise ease of use and overlook usefulness.

Continuance intention definition seems more "stable" and univocal than that of dropout, maybe because it is rooted in the concept of Technology Acceptance Model and, probably, admits fewer interpretations. The idea of continuance intention applied to online learning is a construct that has already been analysed by various authors (Cho and Heron 2015; Hachey, Wladis and Conway 2013; M.-C. Lee 2010; Rodríguez-Ardura and Meseguer-Artola 2014). We can build this concept upon different theoretical frameworks like i.e., social-cognitive theory, technology acceptance model, and motivation theory (Ifinedo, 2017). Quality issues, reflected in satisfaction with content and the learning system, also appear to influence continuance intention positively, not only in formal distance learning settings (Dağhan & Akkoyunlu, 2016; Hong, Tai, Hwang, Kuo, & Chen, 2017), but also in new learning contexts such as MOOCs (Yang, Shao, Liu, & Liu, 2017) or mobile learning (Joo, Lim, & Kim, 2013). Other factors that seem to boost continuance intention in online education are usage experience (Zhang, Liu, Yan, & Zhang 2016), the use of social media (Chiu, Hsu, Sun, Lin, & Sun, 2005; Kaewkitipong, Chen, & Ractham, 2016; Lin, 2011) or blogs to enhance the learning experience (Tang, Tang, & Chiang, 2014), and the flow experience (Guo, Xiao, Van Toorn, Lai, & Seo, 2016; Rodríguez-Ardura & Meseguer-Artola, 2014)..

2.3 Continuance intention models

It is interesting to take a more detailed look at the model of continuance intention proposed by Rodríguez-Ardura & Meseguer-Artola (2014), as shown in Figure 2.2, which is based on an investigation carried out also at UOC, integrating various theories. The authors concluded that didactic resources and instructor attitude indirectly impact on user's intention towards continuance.

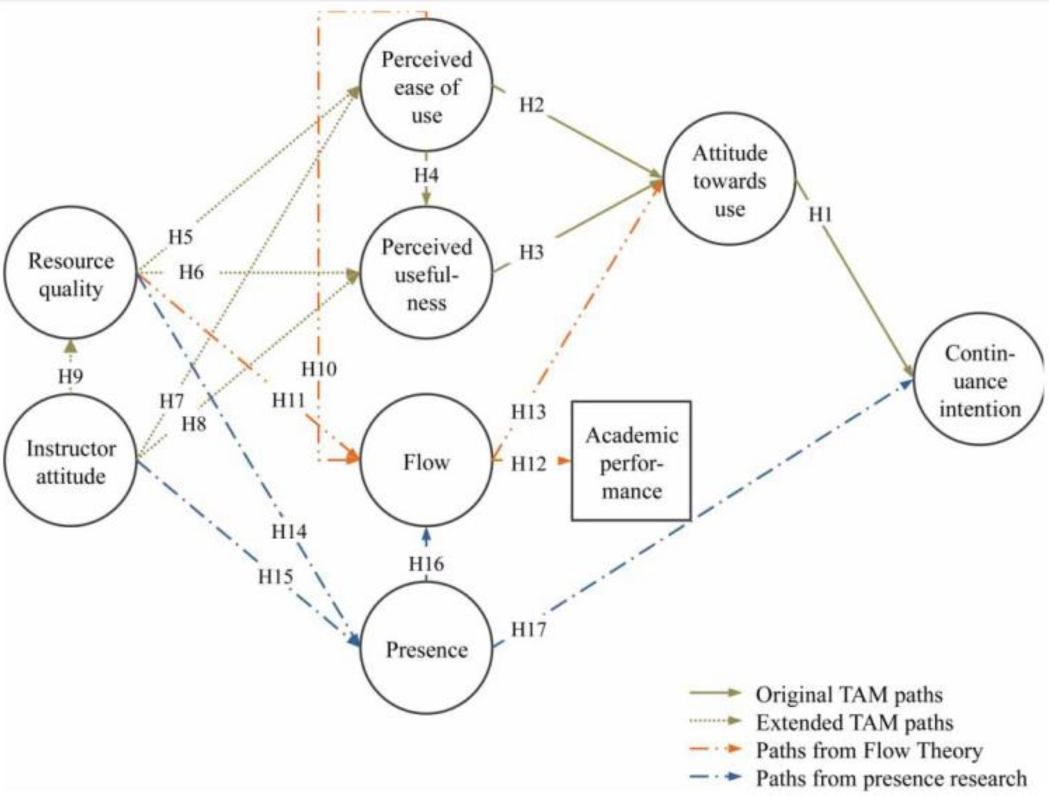


Figure 2.2. Conceptual model of e-learning continuance intention proposed by Rodríguez-Ardura & Meseguer-Artola (2014).

Therefore, attending to Rodríguez-Ardura & Meseguer-Artola analysis, research under the principles of the technology acceptance model (TAM) has shed considerable light on the understanding of learners' perceptions of ease of use and the usefulness of a virtual education environment, and these perceptions link with individuals' behavioural intentions regarding e-learning. Nevertheless, as shown by contributions from the fields of human-computer interaction and consumer behaviour, users' online experiences not only involve their individual beliefs regarding the utility of the online value proposition but also manifest in the form of the psychological phenomena of presence and flow. In the particular context of virtual education environments, users might feel that they are "present" in a real, material space, where they meet their instructors and classmates and have the opportunity of taking part in real debates. And the exploration of didactic resources, together with the cooperative work online, can appear so exciting and captivating that they can generate intense joy and immense satisfaction, characteristic of the states of mind of flow. The effect is that both presence and flow can have an essential role in boosting individuals' behaviour about the continued use of the e-learning environment.

On the other side, Dağhan & Akkoyunlu (2016) proposed an integrated model to understand the determinants of students' continuance intention better. In their model (shown in Figure 2.3), the quality of information, and also that of the system and the service, have a possible effect on satisfaction and confirmation. In addition to these constructs, we consider other four exogenous variables: utilitarian value, outcome expectations, perceived value and perceived usability.

Attending to this model, 58 % of the variance seen in the continuance intention, the target variable of the research model, was predicted by these exogenous variables. It can be also seen that the most potent effect on continuance intention is provided by satisfaction. At the same time, confirmation has the strongest predictor effect on satisfaction, which would confirm the relations between satisfaction, confirmation and continuance intention variables presented in DeLone and McLean's (2003) Information Systems Success Model.

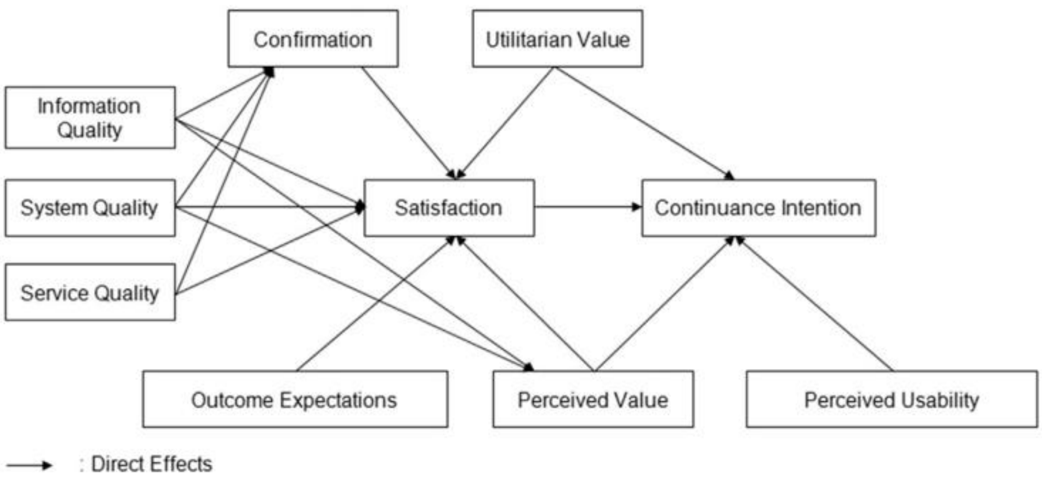


Figure 2.3: Research model used by Dağhan & Akkoyunlu (2016) for continuance intention.

Therefore, continuance intention seems to be mainly influenced by satisfaction with variables related to the learning experience, which can be mediated by student intrinsic motivation, for example in the form of sense of flow (Rodríguez-Ardura & Meseguer-Artola 2014), users' expectations of the information system and the system's, confirmed or not by actual performance (Dağhan & Akkoyunlu 2016), or perceived playfulness (Ifinedo 2017).

More recently, confirming the dominant role of satisfaction as "driver" of continuance intention, Al-Samarraie, Teng, Alzahrani, & Alalwan (2018) have coined the "e-learning continuance satisfaction" expression in a study. Their analysis had as objective to determine the key factors affecting not only students', but also instructors' "continuance satisfaction" with e-learning. To identify the factors that impact e-learning continuation in higher education institutions, the authors conduct a systematic review of the literature. The conclusions of this review reveal that the majority of studies have reported the essential role of satisfaction in mediating the relationship between 11 factors and users' decisions to continue using e-learning systems. The study then proposes that users, both students and instructors, if they are to continue using them, they must continually be satisfied with the e-learning systems. This "constant" satisfaction is named 'e-learning continuance satisfaction.' Moreover, a unified perspective of instructors and students on the core factors that impact e-learning continuance is explored, in addition to the causal relationships between these factors and e-learning continuance satisfaction. The methodology used was The Fuzzy Decision Making Trial and Evaluation Laboratory (DEMATEL) method. Data were collected from 9 instructors, and 38 students via an interview survey and the results yielded five core factors –information quality, task-technology fit, system quality, utility value, and usefulness –that influence users'e-learning continuance satisfaction. Several different causal relationships between the factors identified from both students' and instructors' perspectives were also identified and used to form a single viewpoint.

We can observe these results in Figure 2.4.:

- The results for the instructors demonstrate that they found characteristics related to information quality, task-technology fit, system quality, confirmation, usefulness, attainment value, and utility value to be the core factors for their continued satisfaction with e-learning services. Figure 2.4. (A) shows that confirmation and attainment have a two-way causal relationship. The instructors justified these effects because their confirmation of fulfilling their expectations regarding system usage is usually associated with the personal importance they assign to doing well on tasks.

- Turning to the students, the distribution of factors in Figure 2(B) shows that information quality, task-technology fit, system quality, utility value, and ease of use were the core factors for their continued satisfaction with e-learning services. Additionally, both the task-technology fit and utility value affected the students' attitudes and perceived confirmation, attainment value, and usefulness.
- To unify the instructors' and students' perspectives, they calculated the average of their respective total-relation fuzzy matrices. This helped to articulate a unified understanding of the importance and cause-effect table (Table 5). A threshold value of 0.351 was obtained in order to map the causal relation diagram (Figure 2). The unified view in Figure 2(C) demonstrates that information quality, task-technology fit, system quality, utility value, and usefulness are the core factors that impact both instructors and students for being continually satisfied with e-learning services.

The results reveal that information quality is the most significant effect factor that impacts both instructors' and students' e-learning continuance satisfaction. This factor was found to be associated with their attitude and perceived confirmation, attainment value, utility value, and usefulness. In contrast, ease of use and social influence were the least significant causal factors; they neither affected nor were affected by other factors.

It's important to highlight that information quality, alongside with other factors like task-technology fit and system quality, fall within the scope of the institution, that is, they are directly manageable by academic and educational policies and strategies, what would put satisfaction mainly as an institutional duty. It's also remarkable that other variables more linked to student or instructor subjectivity, like utility value, usefulness, confirmation or utility value, would act as "mediators" between the mentioned institutional factors (information quality, task-technology and so) and final satisfaction, as happened also with Rodríguez-Ardura & Meseguer-Artola's study (2014) with the flow dimension. Last but not least, it is very astonishing that, after almost 30 years after Davis (1989) seminal work on Technology

Acceptance Model, ease of use has “fallen”, again, outside the model in favour of usefulness.

2.4 Dropout in online distance learning models

Once we have found the difficulties of defining dropout in online distance learning univocally and with a "program" perspective, broader than the duration of a single course, the next step of our research will consist of "characterizing" this dropout; that is, describing the principal dimensions and specific variables that are related to it.

The student integration model of Tinto (1975), although being conceived for traditional institutions, already noticed the complexity that lies behind dropout decisions; this model was a reference for later models of online learning dropout. According to Tinto’s perspective, dropout decisions are conditioned mainly by aspects related to student integration at both an academic and social level, as can be seen in Figure 2.5:

In this way, Tinto understands higher education dropout as a process over time, which gathers student's interactions with the institution. More specifically, and despite it was in 1975, Tinto already proposed a wide range of dimensions to explain dropout such as student background, motivation and expectations, financial commitment, and so. This holistic and long-term vision (in terms of Tinto, “longitudinal”) will have a clear continuity in the subsequent analysis of university dropout, as will be seen later.

Additionally, in his literature review, Tinto differentiates persistence from dropout analysis, advancing in the idea that, although being in a certain way two sides of the same coin, it is not a 100% antagonistic relation and they can be analysed separately.

It is interesting to comment on some of the most relevant online distance learning dropout models that try to “capture” the specificity of distance education from its face-to-face counterpart. Most of these models are based on the previously mentioned dropout analysis undertaken by Tinto, adapted to distance-education institutions.

Online distance learning dropout models have already been examined extensively in the literature. Kember (1989), for example, establishes a pattern of dropout at course level that has many similarities with that of Tinto, putting the decision to drop out as a result of academic and social integration, and stressing the importance of goal commitment and motivation (see Figure 2.6).

Kember affirms that “the integration components which test the integration of the student into the academic way of life and the success of the academic intrusion into the student’s family, work, and social life (…) are the ones that make the model a longitudinal one”. Our analysis, even though it centers in the first semesters, will also have this longitudinal perspective since it considers different moments in time.

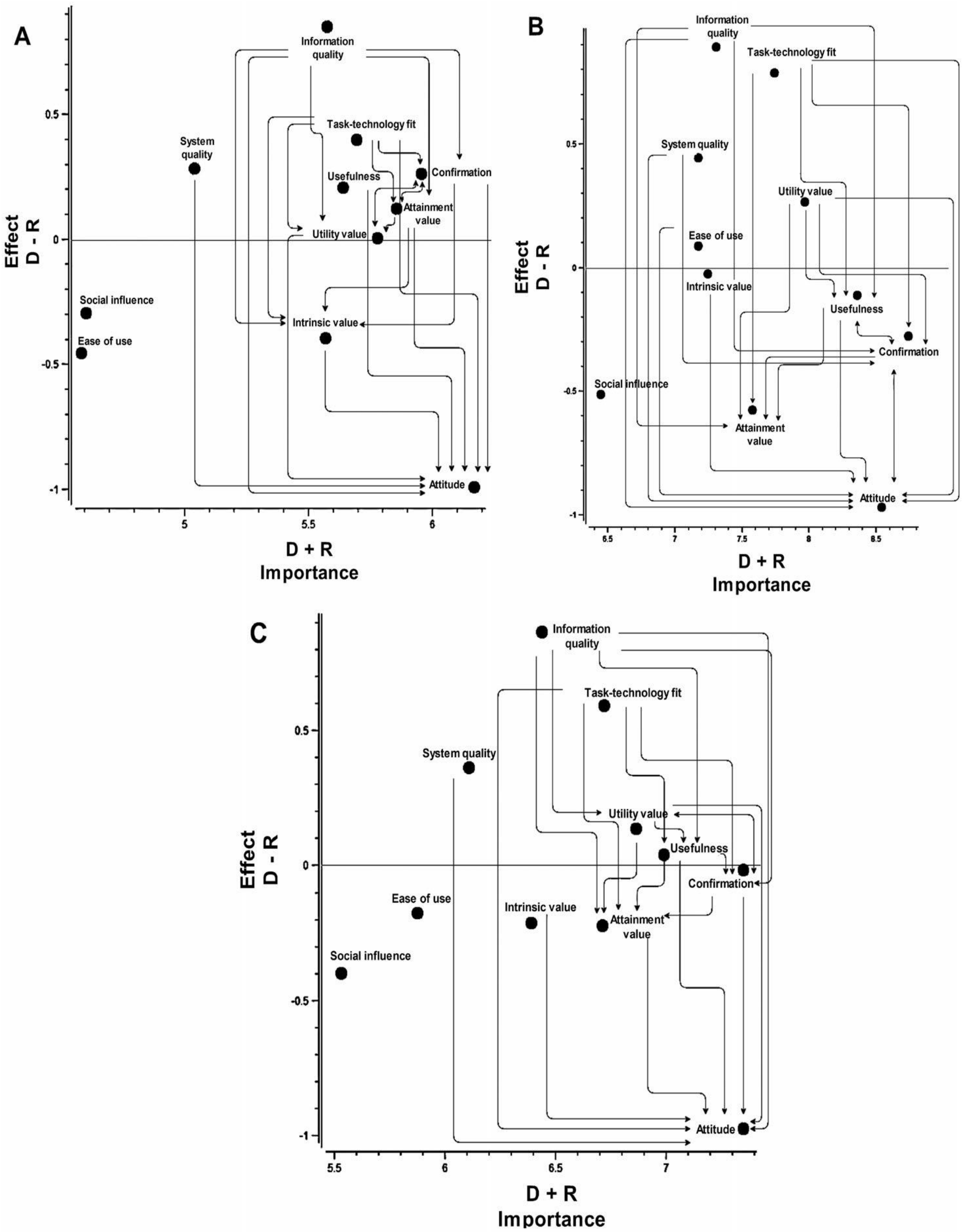


Figure 2.4: Causal relation diagrams. (A) Instructors' views; (B) Students' views; (C) Unified views of instructors and students.

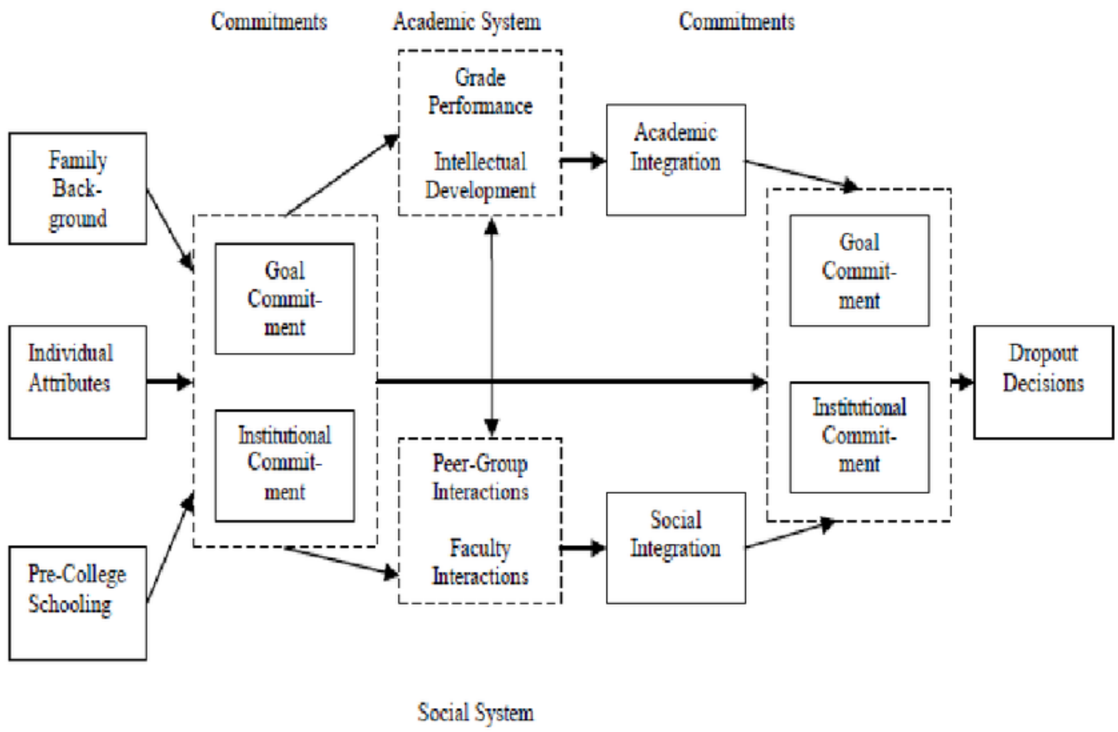


Figure 2.5: Tinto's student integration model (V Tinto, 1975).

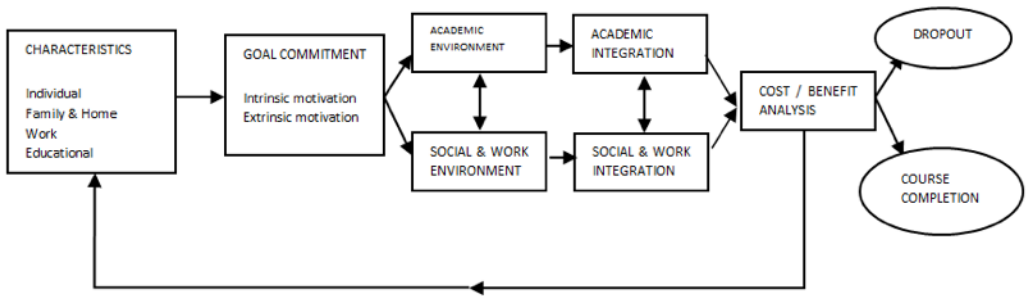


Figure 2.6: Kember's dropout/course completion model, adapted from Kember (1989).

Berge and Huang (2004), on the other hand, propose a conceptual rather than a causal model (see Figure 2.7), valid to explain dropout at a "course, program, institution or system" level; their model includes as one of its attributes the delivery mode (blended, in-person, or online learning). According to these authors, their model is grounded in previous research and is innovative in at least two ways: 1) it is inclusive and context-sensitive, and 2) it features a dualapproach towards retention enhancement. When a voluntary decision is being made to persist or dropout, it is made by the individual student, influenced by his or her personal circumstances. It draws on the student’s continual cost/benefit analysis of all factors like those resulting from perceived opportunity, relevancy, stress, responsibility and satisfaction within the educational context. Even though the earlier path models are useful when explaining many aspects of the dropout phenomenon, yet another path model would probably not be significantly helpful. A snapshot derived from this model for a particular individual may change rapidly, even from one day to the next in some circumstances. In some way, they propose an “adaptive” model for each context.

As shown in Figure 2.8, Rovai (2003) also refers to the "complexity of the (continuance) decision", stating that “there is no simple formula that ensures student persistence. Adult persistence in an online program is a complicated response to multiple issues. It is not credible to attribute student attrition to any single student, course, or school characteristic”. Rovai comes up with a "composite model" (Figure 2.8) that illustrates the factors involved in the decision to continue at the program level. The main parts that make up the model include Tinto (1975, 1982) as an essential reference and the conceptualisation that Bean and Metzner (1985) made of non-traditional undergraduate student attrition.

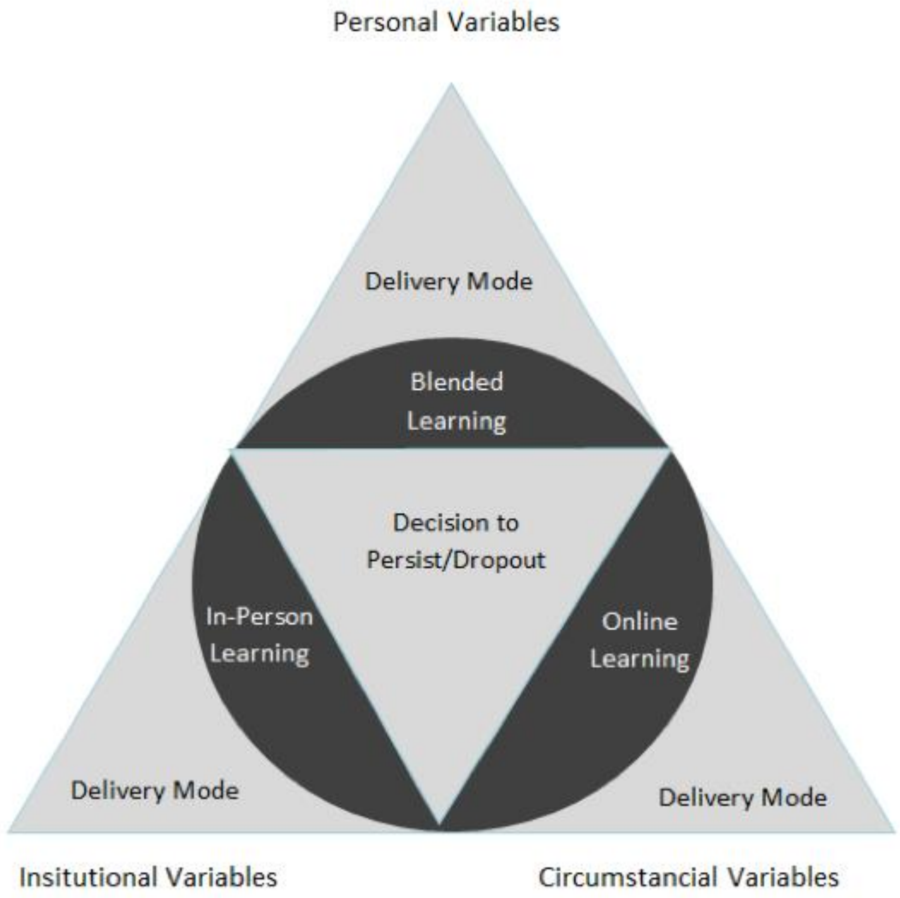


Figure 2.7: Berge and Huang's conceptual dropout model.

Additionally, Rovai's model includes information about the skills required by online students (R. Cole, 2000; Rowntree, 1995), the unique needs of distance education students (Workman & Stenard, 1996), and the requirement to harmonise learning and teaching styles (Grow, 1991). The model has two main parts: on the one side, student characteristics and skills before admission, and on the other, external and internal factors affecting students after admission.

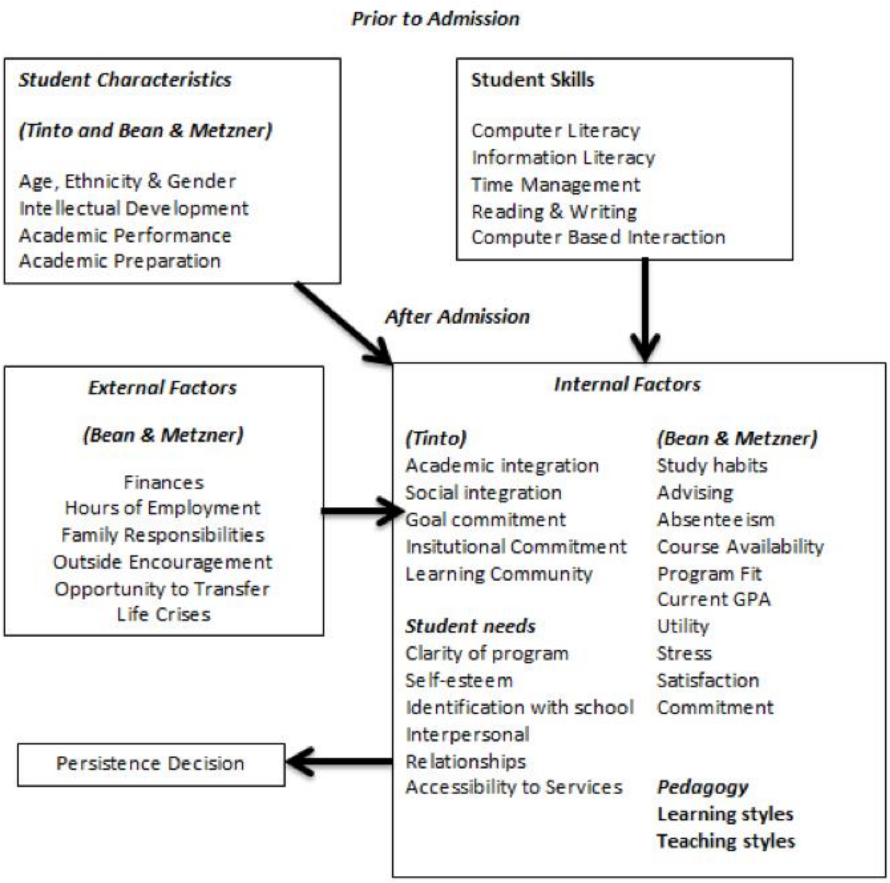


Figure 2.8: Dropout model, figure adapted from Rovai (2003).

More recently, Lee and Choi (2011) analysed and categorised 35 existing studies in online course dropout that reported empirical research findings in peer-reviewed journals from 1999 to 2009, mainly based on a single course analysis. They concluded that "Student factors" are the most widely cited in the bibliography (55% of all papers considered), followed by "Environmental factors" and "Course-program factors (or institutional)" (25% and 20% respectively), as can be seen in Figure 2.9. Later, Hart (2012) and Gazza and Hunker (2014) also used Lee and Choi's (2011) taxonomy to analyse retention in online courses.

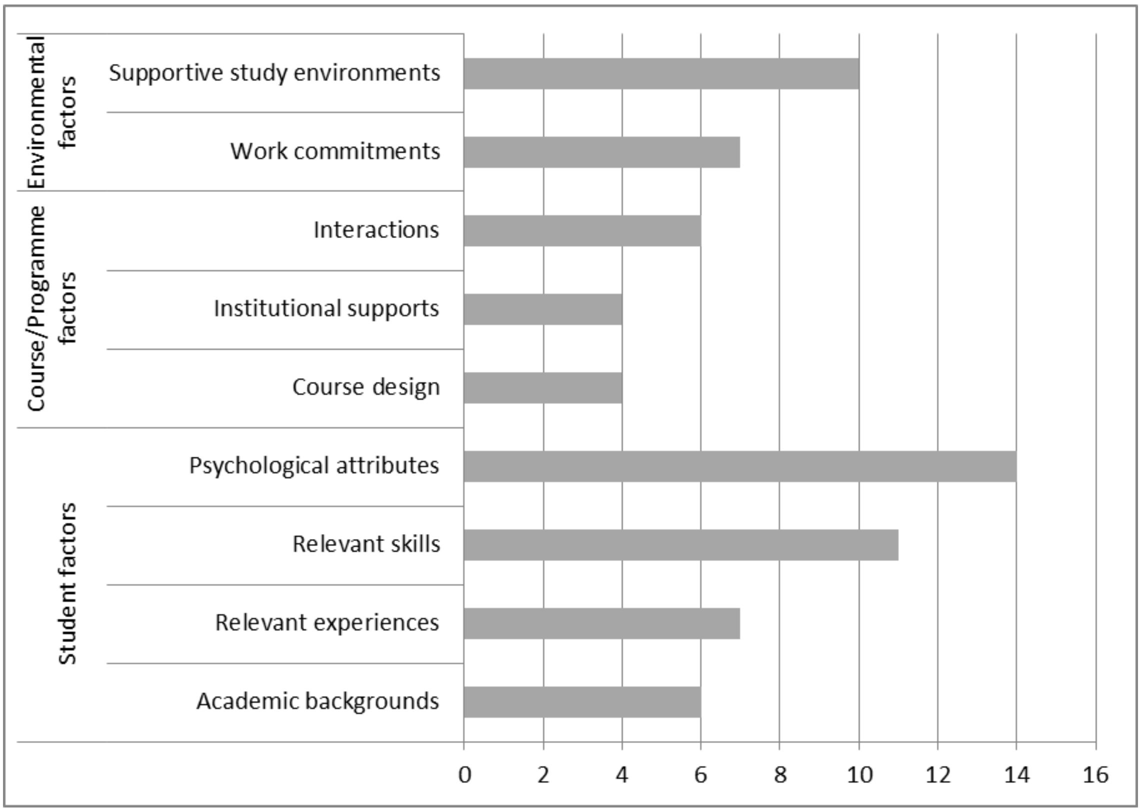


Figure 2.9: Absolute frequency of dropout factors mentioned in previous studies, in Lee and Choi's review (2011).

Later on, in an internal seminar at UOC (Josep Grau-Valldosera, 2017) we ran a bibliographical analysis on the Scopus database of all the articles devoted to online learning dropout that cite Rovai's (2003) article. We should recall that this article builds a "composite/integrative persistence model" of online learning. This analysis pretends to update the results of Lee & Choi's literature review (from 2011, when the review was published, to May 2017, when we held this seminar). Specifically, the 62 references analysed have this "thematic" distribution, attending to Lee & Choi's taxonomy:

- 39 references (63%) put the focus on student factors,
- 28 (45%) on institution or course/program factors,
- Two only (3%) cover the external factors.

We can see that Student factors (self-regulation, self-control, locus of control, motivation, and so on), keep a great importance, like the one they had in Lee & Choi's review, but those related to the Institution (social presence, design features, technology, online too, and so on) seem to gain more relevance, while external factors are a minority.

A word cloud is shown below with the main factors of dropout related to the student (Figure 2.10). These factors are mainly associated with self-regulation, self-control, locus of control and motivation.

Figure 2.10: Word cloud with student-related factors to dropout (own elaboration).

On the other side, Figure 2.11 exposes the main factors related to the institution: online tools, design features, social presence and technology quality.

We do not show “External” factors because of their low presence in the analysis.

Figure 2.11: Word cloud with institutional-related factors to dropout (own elaboration).

Last but not least, is worth to mention some current works that, although that do not deal directly with the phenomenon of dropout in online education, they effectively examine different variables that influence the phenomenon and that in some cases they can be extended to the object of study presented here. For example, Alvarez et al (2014), Bernardo et al (2016), García de Fanelli (2015), Rumberger & Rotermund (2012), Christenson (2012) and Tinto (2001). These works show how the variables relational, engagement (commitment) and academic adaptation to higher education they influence the abandonment of university studies. In addition, some of them include educational policies that could alleviate and prevent the phenomenon of dropout.

2.5 Summary

As a synthesis to this section, considering that there seems not to exist an agreed definition nor a model of dropout, this dissertation wants to make two contributions to the area of dropout in online distance learning. On one side, we propose to arrive at a dropout definition that is empirical and data-driven and, in this way, takes into account the specificities of online distance learning programs, such as the possibility of taking a break. On the other side, considering that a “dominant reason for dropping out cannot be found” (Bawa, 2016; Rovai, 2003; Willging & Johnson, 2009), this dissertation will pursue a longitudinal analysis of early dropout that includes the continuance intention of students that do not re-enrol after the second semester, and their possible return to studies in the third semester.

Next section wants to answer the first of the research questions: a specific definition for online distance learning.

3 A definition of dropout in online distance learning

Although the CRUE definition[11] might be valid for brick-and-mortar (face-to-face) universities, where students consider their courses as their main priority over other professional or family duties, it does not seem to be as valid for online or open universities. In distance education institutions, the majority of students have significant work and family commitments, and where, therefore, they are more likely to skip semesters without enrolment.

As observed in chapter 2, most of the official definitions of dropout, for example, that in Spain, do not reflect the specific characteristics of online higher education. We can summarise our main challenges in essaying a dropout definition in these points:

- Uncertainty: if a given student fails to enrol for several consecutive semesters, it is impossible to be 100% sure that this student has definitively dropped out of their program, as they may merely be taking a more extended break (Astin 1971).
- Sensitivity: the need to “detect” early dropout, that, as has been stated in the previous chapter, is a reality in online distance learning.
- Long perspective: a broad span perspective is needed since although dropout is forged within each semester, it happens at the program level.
- Possibility of generalisation: although bearing in mind the particular characteristics of UOC, the definition should be suitable to other open/online institutions that offer courses of a certain length with non-mandatory enrolment and no (or indulgent) permanence requirements.

[11] We can recall this definition from previous sections: “This definition applies to both brick-and-mortar and online universities (Ministerio de Educación, 2015) as the percentage of students who have not enrolled for either the academic year when they should theoretically finish their course or for the following academic year, with respect to the total number of students who enrolled on this course in the initial semester.”

To overcome these challenges, we will pursue a definition of dropout based on an empirical analysis. This new definition should be able to eliminate or at least reduce the academic/administrative arbitrariness of the official one. Only by way of example, in the case of the Universitat Oberta de Catalunya (UOC), according to the official definition, UOC has a higher dropout rate than brick-and-mortar universities: 39% vs 26%, respectively (CRUE, 2008).

Therefore, attending to the first objective of this dissertation, we want to define and calculate dropout in online higher education at the program level. We will accomplish this objective will following a process based on an in-depth analysis of enrolment data. Recalling the first research question, we want to find "which definition of dropout can take into account evidence of enrolment behaviour and "context" of e-learning students, that is, the need and the right to take rest."

Insisting on the fact that the official dropout definitions do not capture the true nature of dropouts in online (or distance/open) institutions, the consequence is that no comparison between higher education institutions, face-to-face or distance, can be done appropriately. Furthermore, the definition of dropout given in this dissertation can be tailored to each degree, as it captures the differences in the enrolment and break sequences of the students for each one of the programs analysed. This definition, being closer to reality, also allows us to know when dropout really happens, usually before the official definition does. This early detection enables institutions to react to potential dropouts promptly.

To obtain a specific dropout definition, we undertake, as we have already noticed, an empirical (and therefore objective) quantitative analysis of students' enrolment behaviour based on statistical representation. We should stress that this definition of dropout will be established from an institutional perspective, that is, without considering students' perspective. In this way of thinking, students may drop out from the point of view of the university, but they may be fully satisfied with the teaching experience, having achieved their learning objectives, and may not consider themselves to be a dropout case. Therefore, from an institutional point of view, the definition of dropout will always be harsher than reality.

To summarise, this definition would, on the one hand, serve the objective of giving a more precise image of the dropout problem at UOC and, on the other hand, set up a measure that is adaptable to other institutions that have similar enrolment requirements to UOC. Additionally, we should stress that the analysis considers data for the entire student population, not just a sample, which, attending to Lee and Choi (2011), makes it possible to generalise our results.

3.1 Dropout and early dropout at the UOC

The UOC is a fully online university, established in 1994, which offers a wide range of undergraduate and graduate programs. With more than 58,000 active students (60% in Bachelor programs, 27 % in postgraduate programs and the rest in language and open programs) and almost 60,000 alumni, it is the second-largest university in Catalonia, Spain. Regarding the UOC’s student profile, 55.9 % are women, almost 70 % are 25 or over, 81.5% study and work and 72.6% have a prior university education, attending to UOC’s 2016-2017 annual report (2018). New Bachelor students (those that are an object of study of this dissertation) enrol at the UOC biannually, in September and February.

3.1.1 Methodology

This part of the dissertation tries to answer a straightforward question: "What is the real dropout rate for Bachelor students taking a given degree?” putting the emphasis on "real". To do so, we decided to analyse the enrolment patterns of all available data at UOC, to see whether there is a simple way to establish a criterion to differentiate breaks from true dropouts.

The data used in this paper are gathered from UOC academic databases. We have validated data according to UOC internal privacy policies. For the objective of finding a dropout definition, we only need student enrolments. During a period of 26 semesters (from 1994 to 2007, before the establishment of the European Education Area), UOC received 62,450 new students enrolled on officially recognised degrees in Catalan. A total enrolment history was provided for 84,230 students, although we only analysed the mentioned 62,450 (those on the 16 programs with enough available information, out of a total of 19 programs offered during this period). 13.3% of them finished a degree, while 57.6% dropped out of their studies. The rest are considered to be active, although they may not be taking any course in one or more semesters. These figures only include students who have been enrolled in enough semesters to establish a criterion for dropping out.

Figure 3.1 shows the enrolment sequence of new Bachelor students. Students with a question mark will be considered active or dropouts, according to the analysis of each program and the number of consecutive semesters of break that can occur before a given student of a given program is considered to be a dropout. We will explain this procedure of analysis in the rest of this section.

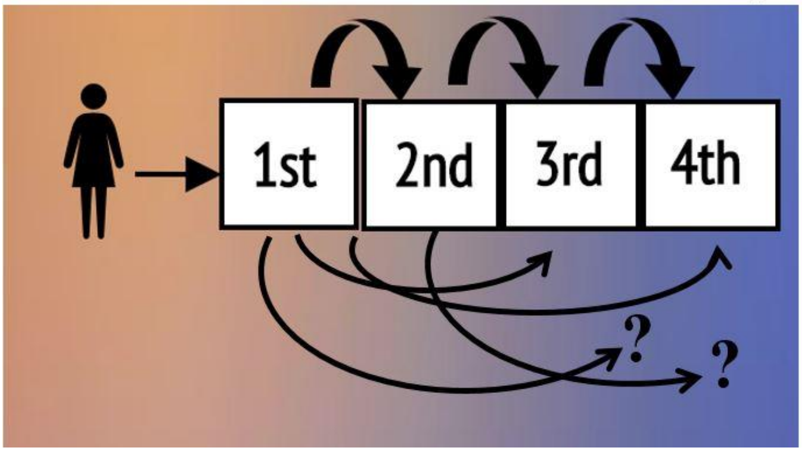


Figure 3.1: Enrolment sequence of new Bachelor students at UOC.

The following data are available: ID, an identification code, unique to each student, which allows individual and at the same time anonymous monitoring; student's gender; student's date of birth; semester of the student's enrolment; codes of the subjects enrolled on by the student; final grades obtained in the subjects; number of credits that the subjects carry; and, finally, the academic program, for example, Law or Computer Engineering. Specifically, there is a record for each subject enrolled on for the officially recognised degrees in Catalan for the period considered (in all 1,169,262 records), recalling that enrolment at UOC opens each semester (twice a year). Only valid enrolments were included, that is, the ones formalised and paid for, thus excluding enrolments that were subsequently cancelled. We have explicitly ignored the pilot cohorts for programs that began at the start of the university that limited student access during the first semester to a closed number and which, for administrative purposes, offered no access to new students during the second semester.

To analyse dropout, we only need to know whether a student is enrolled or not during a specific semester. Therefore, we only considered the "ID", "semester of enrolment", and "academic program" fields. The information from these fields was used to generate 17 files, 16 for each program and a general file for all programs, each of which contains a record for each student. These students are those who enrolled in one or more semesters for the program during the period in question. The records generated have the following coding (as an example, a random record is selected):

<userID>;1;1;1;0;1;0;0;0;0;0;0;0;0;0;0;0;0;0;0;0;0

It's important to notice that userIDs have been anonymised.

Here, the first field is the ID, followed by a binary string for the semester record ("1" = student enrolled at least in one subject, "0" = student not enrolled in any subject). In this case, this student enrolled during her three first semesters; she took a break for one semester, enrolled again for one semester and never enrolled back during the next 16 semesters. The specific nature of this string is that, for analysis purposes, all enrolment sequences have been put in the "same starting position", that is, the first semester when each ID enrols on each degree is considered to be the same for all students. Obviously, the first element after ID is always "1" (the first enrolment of each student). Finally, notice that the sequences "userID_1;1;0;0;0;0;0;0" and "userID_2;1;0;0" are different, as more enrolment history about the first student is available for analysis purposes (specifically, 7 semesters as opposed to 3). Our goal is precisely to determine the length of the trailing zeros that best captures dropout.

Once we generate the enrolment sequences file for each program, it is possible to analyse the frequency of break sequences (i.e., of sequences of one or more zeroes). We perform a pattern information analysis process that computes the most extended break sequence (with "1;0;...;0;1" format) within each enrolment sequence for each individual; this analysis has the feature that if, for example, a student has taken a break once over five semesters and another one over two semesters, they will only compute as having taken a break over five semesters (i.e., the longest one). Note that this process does not consider graduates, as this could have led to consider them as taking a break or abandoning their studies when they have, in fact, obtained their degree. Similarly, from a program performance perspective, we consider students to have dropped out of a particular program even if they move to another one.

	Law degree			MR&T degree		
N	NS	%	Accum. %	NS	%	Accum. %
19	2	0.03	0.03	---	---	---
18	1	0.01	0.04	---	---	---
17	0	0	0.04	---	---	---
16	9	0.11	0.15	---	---	---
15	9	0.11	0.26	---	---	---
14	8	0.11	0.37	---	---	---
13	18	0.23	0.60	---	---	---
12	14	0.18	0.78	---	---	---
11	12	0.15	0.93	---	---	---
10	15	0.19	1.12	---	---	---
9	27	0.34	1.46	---	---	---
8	37	0.47	1.80	5	0.29	0.29
7	29	0.37	2.27	3	0.17	0.46
6	50	0.63	2.90	6	0.35	0.81
5	**69**	**0.87**	**3.77**	7	0.41	1.22
4	107	1.35	5.12	3	0.17	1.39
3	173	2.18	7.30	**30**	**1.75**	**3.14**
2	304	3.83	11.13	40	2.33	5.47
1	815	10.27	21.40	141	8.21	13.68
0	6239	78.60	100	1483	86.32	100

Table 3.1: Analysis of the Break Sequences from Law (left) and Market Research & Techniques Studies (right). N is the number of consecutive semesters of break, while NS is the number of students in such a situation.

For exemplification purposes, Table 3.1 above shows the probability of having a break of N semesters for the Law degree (with 7,938 students and a history of 24 semesters) and the Market Research and Techniques (MR&T) degree (with 1,718 students and a history of 14 semesters). Columns in this table are as follows: The first column gives the number of consecutive semesters of break (namely N); the second column gives the number of students enrolled on the Law degree who take a break of length N; the third and fourth columns give the percentage of such students with respect to the total number of students on the degree and the accumulated percentage, respectively. Columns 5-7 provide the equivalent data for the MR&T degree.

We can see that there are two students on the Law degree who take a break of 19 consecutive semesters, which may be surprising but shows the vast diversity of online students' enrolment behaviour. Nevertheless, to define dropout, we are interested in establishing a threshold for what we consider to be a reasonable period of break time. As shown in bold in this table, only 3.77% of Law students take a break of five or more semesters. In the case of MR&T students, a similar percentage (3.14%) is found corresponding to three semesters or more, showing a relevant difference between academic programs. In short, if we define dropout as taking a break of five or more semesters for the Law degree, we are assuming an error smaller than 5%, which can be considered reasonable. However, we can define dropout for the MR&T degree as having a break of only three semesters to achieve the same error assumption. Note that the fact that a Law student has the "1;0;0;0;0;0" string in their enrolment sequence is not sufficient information to see whether they will drop out, as we need an additional semester as mentioned above. This additional semester at the end of the sequence indicates whether the student has effectively dropped out (1;0;0;0;0;0;0) or not (1;0;0;0;0;0;1). Following this criterion, we are now able to label each student with a sequence of N or more zeroes as a dropout, bounding the classification error.

Therefore, a definition of the dropout rate for a specific program would be reached empirically as being the proportion of students who have taken a break for N or more semesters out of the total number of students enrolled in the program during the period in question. N is determined using the maximum probability of the 5% error rate in classifying the student as a dropout once they have taken a break of N or more semesters for that specific program. As the choice of this threshold of allowed error directly determines the number of consecutive semesters that define dropout, it is interesting to look at the resulting number of semesters for other limits such as 1% and 10%, as shown in Table 3.2.

As expected, the threshold value used has a significant effect on the value of the number of semesters that define dropout; additionally, it would also affect the percentage of dropout for each semester. It should be noted that a 1% threshold seems to be quite unrealistic, as would imply in many cases waiting for ten consecutive break semesters or more before deciding that a student has dropped out (even worse than with the official definition). On the other hand, a 10% assumed error seems to provide more uniform results, but we consider it to be excessive for our analysis purposes.

Program	Threshold: 1%	Threshold: 5%	Threshold: 10%
Business Sci.	11	5	3
Tech. Eng. in CM	10	5	3
Tech. Eng. in CS	11	5	3
Tourism	6	3	2
Catalan Language	10	4	2
Law	11	5	3
Humanities	10	5	3
Psychology	7	3	2
Business Admin.	9	4	2
Labour Sci.	7	4	2
Political Sci.	7	3	2
Audiovisual Comm.	5	3	2
Documentation	8	4	3
Market Res. & Tec.	6	3	2
Psycho-pedagogy	12	4	3
Computer Engineer.	8	4	3

Table 3.2: Number of consecutive semesters that define dropout for 1%, 5%, and 10% error threshold.

The results of this definition process were published in the 1st International Conference on Learning Analytics and Knowledge 2011 (J. Grau-Valldosera & Minguillón, 2011).

3.1.2 Results using the new dropout definition

Based on the work set out in the previous section, we establish a definition of dropout for each program. Using an error threshold of 5%, the specific program in question is highly relevant. Although logically, the definition of dropout in qualitative terms is the same for all courses, repeating the probability analysis carried out for all programs gives different quantitative results depending on the values of the parameter of this definition -that is different N values for consecutive break semesters-.

Table 3.3 provides a summary of the values associated with the 16 programs analysed. For each program, this table shows the minimum number of consecutive break semesters needed to be considered a case of dropout is N; the maximum error (false dropouts); the number of semesters defined in the curriculum of each program, the number of semesters since the program began and the number of students (NS) with at least N+1 semesters used in the analysis. Finally, the last three columns refer to the percentage of students obtaining the degree (accredited), the total dropout value, and ultimately, the rate of dropout after the 1st semester.

Program	**N**	**Error**	**Length (sems.)**	**Data (sems.)**	**NS**	**Acc. (%)**	**Total dropout**	**1st sem. dropout**
Business Sci.	5	3.78%	6	26	16,818	16.6%	54.3%	24.91%
Tec. Eng. in CM	5	4.11%	6	22	5432	9.8%	66.8%	29.47%
Tec. Eng. in CS	5	4.46%	6	22	7496	8.7%	65.6%	28.44%
Tourism	3	3.38%	6	14	1889	9.6%	49.7%	26.10%
Catalan	4	3.89%	8	22	1194	6.5%	58.9%	25.88%
Law	5	3.78%	8	24	6149	10.2%	54.0%	26.72%
Humanities	5	3.75%	8	24	5396	7.4%	64.3%	28.34%
Psychology	3	4.58%	8	18	7674	3.8%	56.5%	28.81%
Business Adm.	4	3.75%	4	22	3778	38.2%	40.9%	21.33%
Labour Sci.	4	2.82%	4	16	3114	34.5%	44.8%	23.35%
Political Sci.	3	4.27%	4	16	867	21.7%	49.5%	26.53%
AV Comm.	3	2.67%	4	14	1070	21.9%	43.7%	21.12%
Documentation	4	4.48%	4	20	2440	32.3%	50.3%	23.07%
Market R. & Tec.	3	3.14%	4	14	1374	32.4%	38.0%	18.05%
Psychopedagogy	4	4.86%	4	26	4354	25.4%	54.2%	25.01%
Comp. Eng.	4	3.36%	4	16	1541	30.1%	37.3%	15.96%
TOTAL	4	4.35%	---	---	62,450	13.3%	57.6%	24.91%

Table 3.3: Summary of results by program.

As stated previously, official criteria for quantifying dropout are not applicable to have a perception of the whole dropout problem. As an example, we can compare the cohorts of two representative programs according to both dropout definitions: in line with the official definition of dropout, we need to wait until the end of the "official" duration of the program (eighth or tenth semester for Business Science and Humanities, respectively) to measure it. On the other hand, following the definition proposed in this dissertation, the dropout is detected earlier when it really happens (in the fifth semester in both cases, as shown in Table 3.3).

With such a definition, as it was been said before, we can compute the percentage of dropout students for each program. Concerning total dropout, it can be seen that for the group of first-cycle and first-second-cycle programs, Tourism and Computer Engineering seem to have a lower and higher dropout level than the rest of the degrees of this group, respectively. For the group of second-cycle programs, differences are weaker, and only the program of Psychopedagogy would seem to have a significantly higher dropout rate than the rest of the programs in this group.

It is important to notice that dropout in the first semesters seems to follow a similar pattern across all programs, as the probability of dropping out is very high the second semester, and then rapidly decreases until it reaches a relative plateau in approximately the fourth/sixth semester (Minguillón & Grau-Valldosera, 2013), as shown in Figure 3.2. The proportion of first semester dropouts over total dropout follows a quite regular pattern (with values concentrated in an interval between 43% and 52%).

Wrapping up, we can see that, based on the specific dropout definition adopted, total dropout accounted for 57.6% of the student body (Grau-Valldosera and Minguillón, 2011). The first-semester dropout, however, was 25%, almost half of total dropout. Taking a break in the second semester at the UOC is virtually synonymous with dropout. The risk can be quantified (Grau-Valldosera and Minguillón, 2011) at 80% for UOC students, that is, eight out of ten students that take "a break" in the second semester are finally dropping out. Therefore, online learning dropout happens very soon, and our definition captures this fact, providing the institution with early detection of students at risk of dropping out.

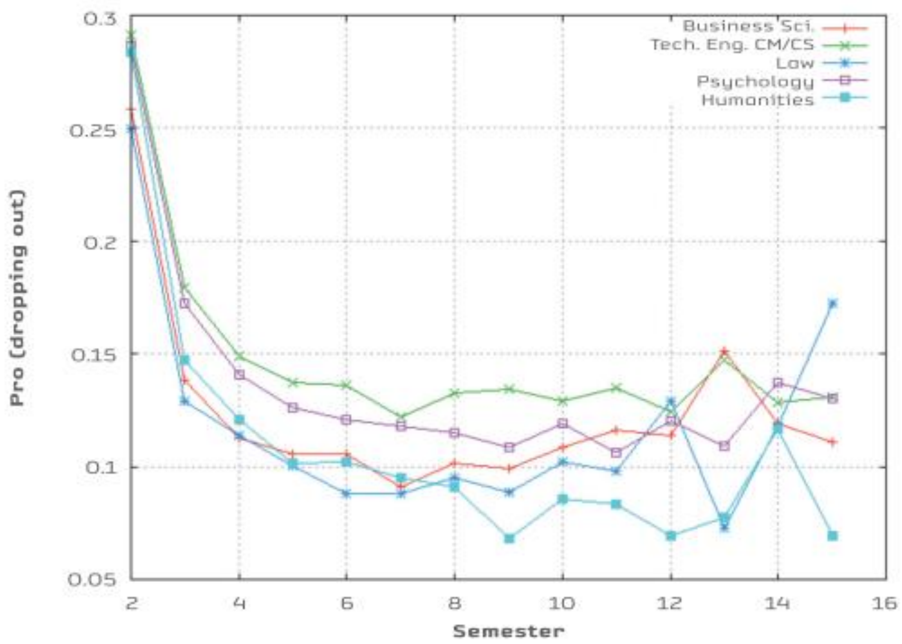


Figure 3.2: Probability of dropping out before starting a new semester.

3.2 Early dropout as a procrastination issue

In Minguillón & Grau-Valldosera (2013), we extended the analysis of the second-semester break or re-enrolment to the duration of the whole program, so to have a broader view of the procrastination behaviour of students. It can be interesting to recall the definition of procrastination given in the literature review as "intentionally deferring or delaying work that must be completed". In this dissertation, the temporal dimension of the course (the semester in the case of UOC), which is the usual time frame in which procrastination is analysed, is widened to that of the degree. That is, we examine "inter-semester" procrastination rather than "intra-semester" one, although both timeframes levels are probably related (Mor, 2009). Then, for a given N and a specific semester (namely S), we can analyse the sequence of semester enrolments for each student, starting from such semester S, as is shown in Table 3.4.

IDP	1st sem	...	(S-1)th sem	Sth sem
idp	1	...	1	X

...	(S+N-1)th sem	...	Last sem
...	Y	...	Z

Table 3.4: Analysis of the sequence of enrolments for each student.

In the Sth semester, students may be enrolled (X=1) or taking a break (X=0). If X=1 we deduce that students are not dropping out in the semester S (maybe they will drop out later but not in that semester). If X=0 we analyse the sequence of N consecutive semesters starting (and including) semester S. As previously defined, if we find N consecutive breaks (that is, Y=0 for all the N semesters starting in semester S), we can conclude that the student drops out. Nevertheless, we will use all available information, to not count students taking a break of length N or higher but continuing later as dropouts (there is at least one Z=1 from the S+N semester until the last semester we have information from such student).

For instance, suppose N=5 and S=2 (the simplest case: dropping out after the first semester or, equivalently, in the second semester).

Table 3.5 describes the different situations we can find when analysing data according to the enrolment pattern. Then, for a given semester S we can classify students according to Table 3.5 and generate a 2x2 contingency table, as shown in Table 3.6:

IDP	Sequence	Situation
IDP1	1;1;X;...;X	This student does not take a break during the 2nd semester. She therefore does not drop out in the 2nd semester.
IDP2	1;0;0;0;0;0;...;0	This student has 5 consecutive zeros starting from the 2nd semester and she never enrols again. We therefore determine that she drops out in the 2nd semester.
IDP3	1;0;0;0;0;0;1;...;1;...;X	This student has 5 consecutive zeros starting from the 2nd semester but she later enrols again. We do not know whether she will be dropping out or not, but we determine that she does not drop out in the 2nd semester.

Table 3.5: Possible situations according to enrolment data.

Break vs dropping out	Does not drop out in S^{th} semester	Drops out in S^{th} semester
Does not take a break during the S^{th} semester	N_{00}	0
Takes a break during the S^{th} semester	N_{10}	N_{11}

Table 3.6: 2x2 contingency table "Break vs dropping out".

Finally, we can estimate the following probabilities:

$$P_{11} = P(\text{dropping out}) = N_{11} / (N_{00} + N_{10} + N_{11})$$

$$P_{10} = P(\text{taking a true break}) = N_{10} / (N_{10} + N_{11})$$

$$P_{1|1} = P(\text{dropping out}|\text{taking a break}) = N_{11} / (N_{10} + N_{11})$$

Here, P_{11} is the estimated probability of dropping out in a given semester. According to our preliminary dropping out analysis, we expect this figure to decrease across the number of semesters and then achieving a "basal" level. On the other hand, P_{10} is the probability of taking a true break (that is, not dropping out after such break). We want to analyse whether this probability varies with time. Finally, $P_{1|1}$ is the conditional probability of dropping out as the result of taking a break. Once again, we assume this probability to be very high in the first semesters and to decrease with P_{11}.

Table 3.7 shows, for the six most populated degrees, their duration in semesters, the number of students enrolled on each degree and the computed N as described in Grau-Valldosera and Minguillón (2011). Taking all this data into consideration, we can extend our analysis, varying S from semester 2 to semester 15. However, as the number of students with available enrolment data decreases with the number of semesters, probabilities computed for large S (12 or more) need to be considered as indecisive for analysis purposes. To exemplify the importance of early dropout, Table 3.8 shows the number of students advancing through the second and third semester. Notice again that we do not use data for all students, but only for those with enough enrolment data (i.e. with at least N+1 semesters) to determine whether they drop out or not according to the definition in (Grau-Valldosera and Minguillón, 2011). This means students with partial records are not included in the analysis. Notice that after the first semester, 13,601 students drop out (27.3%), which is a respectable figure.

Furthermore, after the second semester, accumulated dropping out rises to 18,413 students (13.601+ 4812, 37.0%), which means that one out of three students does not continue after the first year[12]. A 2.010 report from the UNESCO Chair in Higher Education Management and Policy at the Universitat Politécnica de Madrid (UPM, 2010) shows that dropping out rate (according to the official definition) for Catalan universities ranges from 21% up to 33% approximately. This figure is comparable to those for other distance learning providers. For instance, the UK Open University reported a dropout of 45% approximately after the first semester (Ashby, 2004).

Degree	Duration (semesters)	Number of students	N
Business Science	6	18,608	5
Humanities	8	6,582	5
Law	8	5,535	5
Psychology	8	8,407	3
Tecynical Eng. CM/CS	6	12,604	5
Total	---	51,736	---

Table 3.7: Duration, number of students and number of consecutive breaks in order to determine a dropout for each degree.

[12] A 2 010 report from the UNESCO Chair in Higher Education Management and Policy at the Universitat Politécnica de Madrid shows that dropping out (according to the official definition) states that the dropout rate for Catalan universities ranges from 21% up to 33% approximately. Available at http://catedraunesco.es/escuela/Inicio_files/dossier.pdf

Degree	N 2nd sem.	True breaks	Drop-outs	P 1|1	N 3rd sem.	True breaks	Drop-outs	P1|1
Business Science	18,240	1,188 (6.5%)	4,713 (25.8%)	79.9%	11,261	899 (8.0%)	1,560 (13.9%)	63.4%
Humanities	5,396	330 (6.1%)	1,529 (28.3%)	82.2%	3,321	278 (8.4%)	488 (14.7%)	63.7%
Law	5,301	372 (7.0%)	1,324 (25.0%)	78.1%	3,444	227 (6.6%)	445 (12.9%)	66.2%
Psychology	8,401	494 (5.9%)	2,407 (28.7%)	83.0%	5,496	354 (6.4%)	947 (17.2%)	72.8%
Technical Eng. CM/CS	12,459	1088 (8.7%)	3,628 (29.1%)	76.9%	7,649	705 (9.2%)	1,372 (17.9%)	66.1%
Total	49,797	3,472 (7.0%)	13,601 (27.3%)	79.8%	31,171	2,463 (7.9%)	4,812 (15.4%)	66.1%

Table 3.8: Number of students (and percentages) taking a break or dropping out for the second and third semesters.

Figure 3.3 shows the probability of dropping out for a given semester. Notice that we compute this probability assuming that the student enrolled during the previous semester, so we start with S=2 (i.e. the 2nd semester). In other words, S means “student was enrolled in semester S-1 but decided not to take semester S and dropped out”. Notice that, once again, that all degrees seem to follow a typical pattern for dropping out when starting a break, which is very high in the first four semesters and then stabilises. It is also remarkable that for the Psychology degree, the probability of dropping out when starting a break is higher than the likelihood of it being a true break (as it is always higher than 0.5). On the other hand, the other degrees follow almost the same behaviour, except the Humanities degree, where the probability of dropping out continues to reduce with time.

These are “true” dropouts, that is, the student has no further enrolments. Notice that all degrees, even though they have particular features and differences, show similar behaviour, which may reveal underlying institutional circumstances. Data beyond semesters 10^{th} must be cautiously used as the number of students is really small.

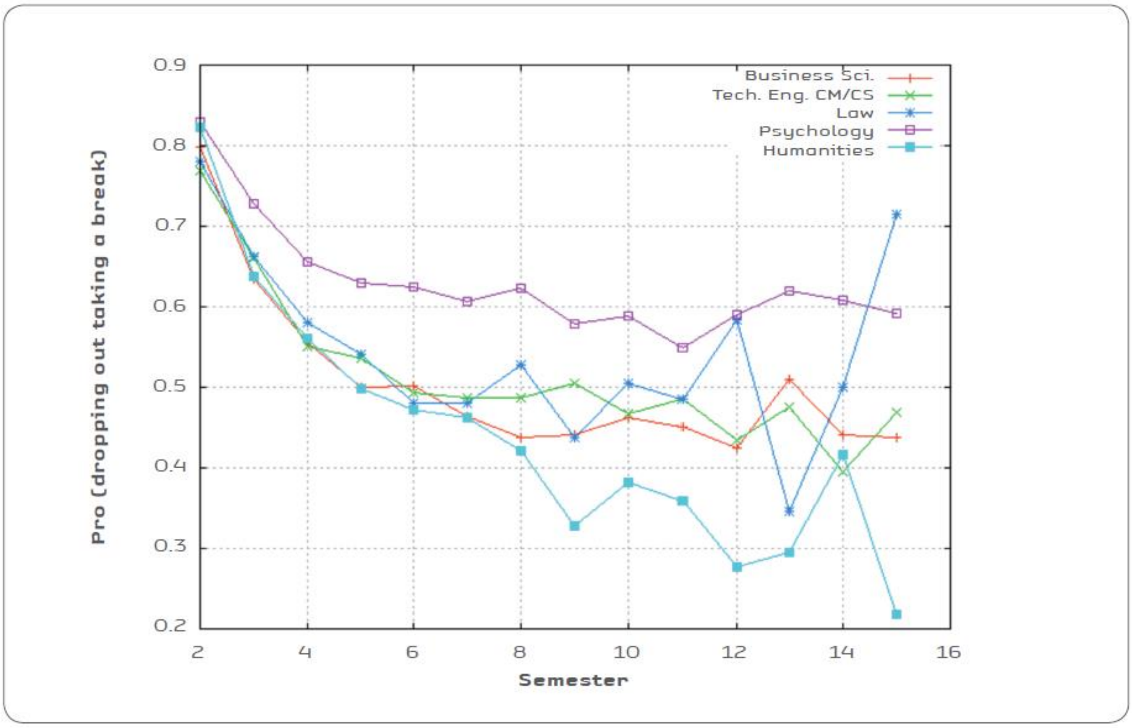


Figure 3.3: Probability of turning a break into a dropout situation.

On the other hand, Figure 3.4 shows the probability of taking a true break, that is, when a student is taking one or more subjects during semester S-1, not taking any during semester S but then enrolling again in semester S+1 or later.

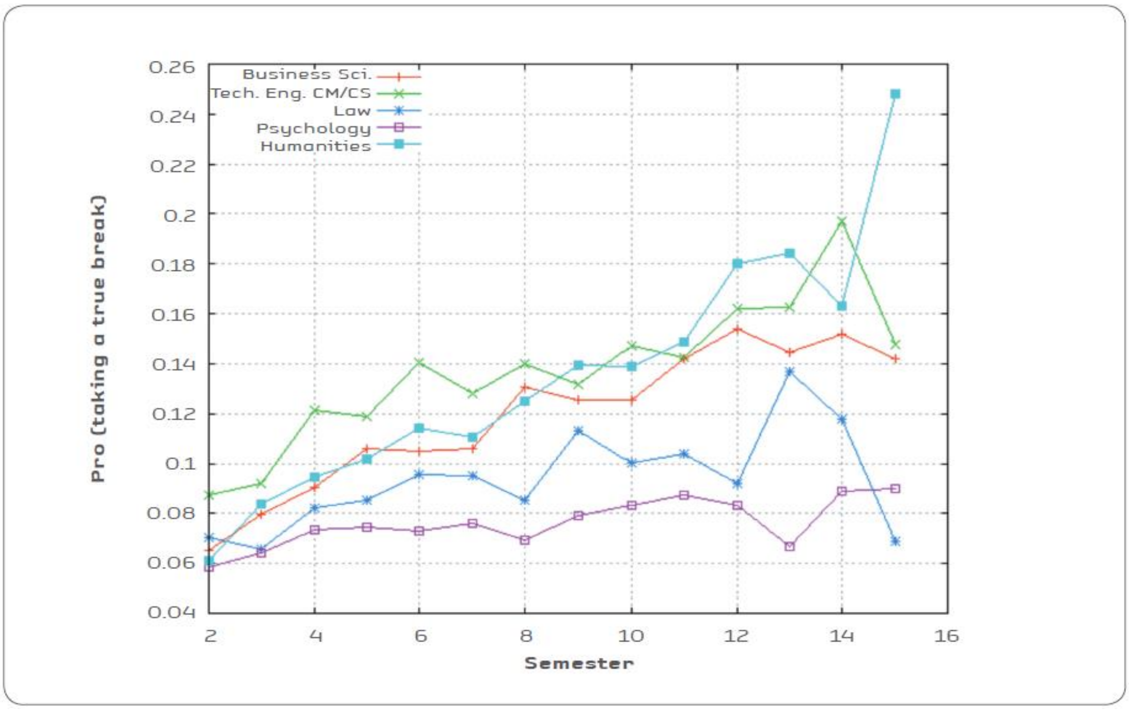


Figure 3.4: Probability of taking a true break (i.e. not dropping out).

In this case, we can see that the probability of taking a true break increases with time, but at a different pace for each degree. However, from a wider perspective, Figure 3.4 shows that this procrastination behaviour seems to have a similar pattern among the various degrees.

3.2.1 Differences between degrees

In light of these results, we can also analyse the differences between degrees. To do this, we build a Generalized Linear Model only for exploratory purposes[13] using the following approach. We generate a dummy variable for each one of the available degrees, which will be 1 for students taking such degrees and 0 for the rest; that is, we convert a categorical variable (degree) with five different values into five different binary variables. We only need four dummy variables as what we do is compare the differences between one degree and the others. We code these dummy variables as BS, HU, LA, PS and TA, following the same order than in Table 3.7.

According to Table 3.8, the Law degree is the one with the lowest dropout rate during the 2nd semester. If we build a generalised linear model using dropout as the dependent variable and BS, TE, PS and HU as the independent variables (that is, removing LA), we obtain the results shown in Figure 3.5.

Notice that HU, PS and CS show substantial differences concerning LA, while BS does not (at a 0.05 significance level). We can repeat this analysis taking one of the degrees at a time, and the results obtained are equivalent: LA and BS degrees have a dropping out behaviour during the 2nd semester which is different to HU, PS and CS degrees. If we repeat the same procedure for the probability of taking a true break during the 2nd semester, using PS as the baseline for building the model, we obtain the results shown in Figure 3.6:

[13] The Generalized Linear Model is only used to spot the differences between degrees. We are not interested in its predictive capacity.

```
Deviance Residuals:
 Min 1Q Median 3Q Max
-0.8297 -0.8217 -0.7732 1.5708 1.6657

Coefficients:
 Estimate Std. Error z value Pr(>|z|)
(Intercept) -1.09987 0.03173 -34.664 < 2e-16
***
BS 0.04551 0.03596 1.266 0.206
HU 0.17201 0.04381 3.926 8.63e-05 ***
PS 0.18749 0.03986 4.703 2.56e-06 ***
CS 0.21028 0.03736 5.629 1.81e-08 ***
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*'
0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family
taken to be 1)

 Null deviance: 58397 on 49796 degrees of
freedom
Residual deviance: 58331 on 49792 degrees of
freedom
AIC: 58341

Number of Fisher Scoring iterations: 4
```

Figure 3.5: Generalized Linear Model using dropout as the dependent variable.

```
Deviance Residuals:
 Min 1Q Median 3Q Max
-0.4275 -0.3815 -0.3670 -0.3553 2.3806

Coefficients:
 Estimate Std. Error z value Pr(>|z|)
(Intercept) -2.77297 0.04638 -59.794 < 2e-16
***
BS 0.10897 0.05524 1.973 0.04852 *
HU 0.04175 0.07334 0.569 0.56912
LA 0.18897 0.07101 2.661 0.00778 **
CS 0.42624 0.05619 7.585 3.32e-14 ***
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*'
0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family
taken to be 1)

 Null deviance: 25,190 on 49,796 degrees of
freedom
Residual deviance: 25,105 on 49,792 degrees
of freedom
AIC: 25,115

Number of Fisher Scoring iterations: 5
```

Figure 3.6: Generalized Linear Model utilizing the probability of taking a true break as the dependent variable.

In this case, we can see that the BS, LA and CS degrees show differences (at a 0.05 level), while HU does not (concerning PS). Therefore, taking into account both behaviours at the same time (dropping out or taking a real break), we obtain three different groups: 1) LA and BS; 2) HU and PS; 3) CS. Notice that this analysis does not say anything about the degrees or the causes that may lead to dropout; it is merely an indication that there is strong evidence that degrees should be analysed separately. Anyway, regardless of the differences between programs in dropout ratios and number of semesters that define dropout, which is already captured by our dropout definition, similar patterns like for example more dropout at the first semesters would justify the aggregated approach of this dissertation (grouping all the programs), at least in a first approach to the problem.

3.3 Summary

As a summary of this section, we have worked on a specific definition of dropout explicitly adapted to the context of UOC and, in general, of online distance learning. This definition is data-driven and based on evidence, in the sense that it takes into account the high diversity of behaviours of enrolment/break /dropout of adult students with family and work responsibilities. Considering this variability, a window of “N” consecutive semesters without enrolment is calculated for each program, resulting in significant differences between programs (lower value for shorter programs). After a Generalized Linear Model is calculated to spot these differences among the most populated degrees, three clusters of programs appear 1) Law and Business, 2) Humanities and Psychology and 3) Computer Sciences, showing the flexibility of our definition, which can be parametrized and eventually tailored to each degree.

From a general perspective, it seems clear that all programs share the same behaviour: there is a clear difference in enrolment and break patterns between the two/three first semesters and the rest of the semester of the program. Related to that fact, we detect a close relationship between early breaks and final dropout (taking a break in the second semester at the UOC is almost synonymous with dropout: this is the case for the 80% of students).

The use of a specific and parametrizable dropout definition for online distance learning based on the abovementioned empirical analysis will allow adapting this definition (which probably would fit better with the term “algorithm”), to different programs and institutions attending to the behaviour of their students. This possibility of generalisation was one of the challenges established at the beginning of this section.

Once we have defined dropout, we will know which students are dropout students, and we can try to explain why they decide not to reenroll (or, the other way around, why they choose to re-start their programs after a break). We will discuss this issue in the next section.

4 Explaining continuance intention and re-enrolment

This section aims to answer the second, third and fourth research questions, namely:

- Which variables or drivers are behind a clear intention to re-enrol in the next term, and on the same degree or program?
- Which variables or drivers are behind the ultimate decision to re-enrol or to extend the break?
- Which differences and similarities between the drivers we detect for continuance intention and effective re-enrolment?

Once dropout is defined based on the analysis of the enrolment behaviour data of new students that we can find in the institution’s databases, the construction of continuance intention and re-enrolment models requires the incorporation of new variables pertaining to the three dimensions pointed out in the literature review section, namely: student, course/program and environmental (Lee & Choi, 2011).

Although some of these new variables appear in the operational systems (for example, gender and date of birth), most are not or only partially collected for other needs, so they are not enough to have minimum representativeness. For this reason, we designed an "ad-hoc" questionnaire. At this point, we must point out that, although surveys on academic/social adjustment to college do exist, it seems that there does not exist a consensual version fully adapted to the online learning reality. As a matter of fact, we can find questionnaires adapted or specifically designed for online learning, in aspects like motivation (Hartnett St. George, A., Dron,J., 2011) or connectedness (Bolliger & Inan, 2012), but not asking about the motivations behind taking a break (or finally dropping out). Therefore, the three dimensions established by Lee and Choi (Student, Course & Program and Environmental) seem to be a good starting point to build the questionnaire upon.

Given the complexity of the phenomenon analysed, and taking into account that it was a questionnaire tailored to our specific analysis needs, two pilot studies were carried out, the first in February 2014 and the second in February 2015, with students who had not re-enrolled in the second semester (new students that enrolled in the month of September 2013 and September 2014, respectively).

These pilots served to advance in the design of the questionnaire, eliminating questions with little response or with highly correlated results with those of other questions. Likewise, in parallel to the revision of the questionnaire, different methodologies of results analysis were proven (specifically, bivariate analysis and logistic regression). Specifically:

- With the data of the February 2014 survey, bivariate analysis of a descriptive nature was addressed, which was included in a paper published in Arxiv as a preliminary result.
- On the other hand, with the results of the February 2015 survey, an article was written using logistic regression as main methodology and submitted to Interactive Learning Environments, which was accepted for publication (J. Grau-Valldosera et al., 2018).

The rest of this section describes the results that have been achieved using these two surveys.

4.1 1st survey: an exploratory analysis

4.1.1 Methodology

Sample

Taking into account that students can enrol biannually, the sample for our study draws from the population of new students enrolled in September 2013 that did not re-enrol in the following period (February 2014), that is, they were taking a break, or maybe they decided to drop out.

The final sample was reached through an e-mail survey sent to 1,216 non-active second-term students, with 281 responding (response rate = 23.1%, which gives a sample error of +/- 5.1%, with an uncertainty coefficient of 0.5 and a confidence interval of 95%). The survey was active from 1 to 15 April 2014. Figure 4.1 shows the main numbers associated with the fieldwork,

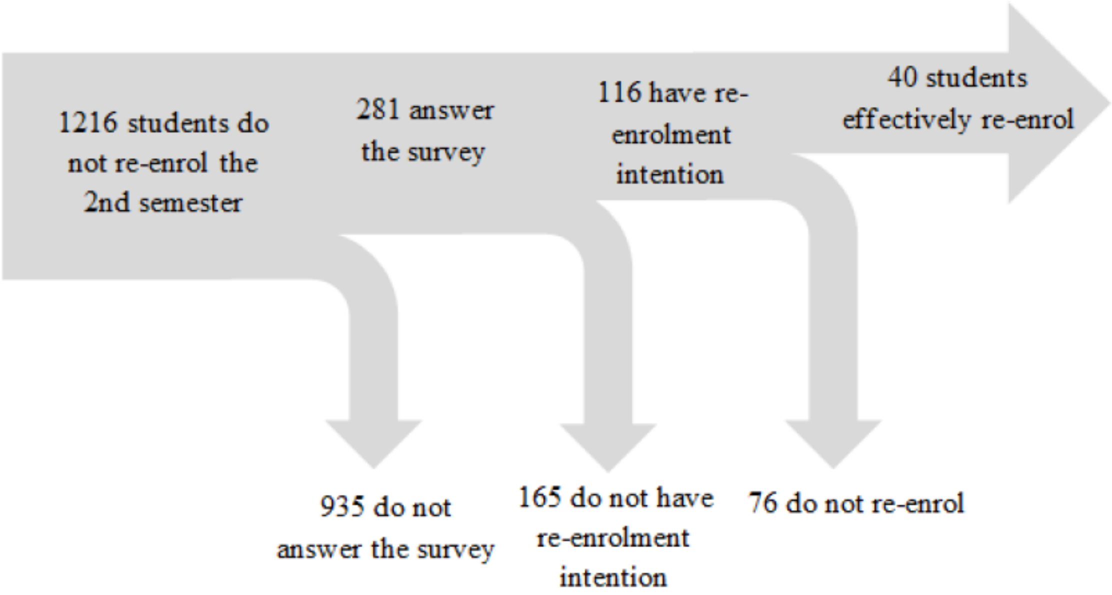


Figure 4.1: Flow of students from the second semester break to re-enrollment or dropping out in the third semester (for the Feb.2014 survey).

Instruments

The email survey used in the fieldwork (a link to the questionnaire is given in Annex 1) consisted of 24 questions that tried to capture variables in each of the three dimensions found in the literature review (Lee & Choi, 2011), specifically: Student, Course/program and Environmental factors. Table 4.1 shows the sections of the survey:

Survey section	Section Title	Section Description	Number of questions	Scale used
1	"Previous experience."	Previous university and online learning experience.	4	Multiple choice
2	"Approach to the UOC"	The motivation for starting university studies and about the program selection process.	4	Multiple choice (2 with an open-ended option)
3	"Your 1st semester at the UOC"	Validation of subjects, opinion about academic information and following the continuous assessment tests.	3	2 multiple-choice 1 Likert with 1-5 range, labelled at the ends
4	"Reasons for not re-enrolling for the 2nd semester."	Which elements of the learning system and process are related to the decision not to re-enrol after the 1st semester	One question with 27 possible reasons	1 Likert with 1-5 range, labelled at the ends

5	"Your experience at the UOC..."	General satisfaction with the semester, level of expectations vs satisfaction with specific attributes, and level of satisfaction with the learning platform (Virtual Campus).	10	General satisfaction (1 Likert with 1-10 points labelled at the ends) Expectations/Satisfaction (7 multiple –choice questions) Virtual Campus (3 Likert with 1-5 range, labelled at the ends)
6	"Dedication to studies."	Time spent on the program	4	3 multiple-choice, 1 with an open-ended option
7	"…and in the future"	Student intention to restart her activity in the program in the upcoming semesters	1	1 single-choice
8	"Professional, family and socioeconomic status"	Sociodemographic data	3	Multiple-choice

Table 4.1: Sections of the Feb. 2014 survey.

We can observe that all three macro-factors defined by Lee and Choi (2011) are widely covered through the survey: the Student dimension is dealt with mainly in the first two sections, while Course-program (or institutional) factors are included in the third, fourth and fifth sections. The Environmental questions form part of the sixth and last section. The items in section seven refer to one of the explained variables of the present study (continuance intention). Information about effective re-enrolment is obtained directly from UOC's data mart, using enrolment patterns. We show the characteristics of sampled students in Table 4.2. We can see that women and people over 40 were overrepresented in the respondent sample.

		Respondents		
Students characteristics	All (n=1216)	Yes (n=281)	No (n=935)	*p*-value*
Gender:				
Female	626 (51,5%)	160 (56.8%)	466 (49.7%)	0.041
Male	590 (48,5%)	121 (43.2%)	469 (50.3%)	
Age:				
[18, 25)	343 (28.0%)	67 (23.8%)	275 (29.3%)	0.007
[25, 40)	673 (55.1%)	150 (53.4%)	523 (55.6%)	
[40, 60]	206 (16.9%)	64 (22.8%)	142 (15.1%)	
Access type:				
Without university studies (no FP/CFGS)[1]	581 (47.8%)	113 (40.0%)	468 (50.0%)	0.17
Without university studies (FP/CFGS)	181 (14.8%)	39 (13.9%)	142 (15.2%)	
University studies not completed	178 (14,6%)	48 (17.4%)	130 (13.9%)	
University studies completed	247 (20.33%)	72 (25.5%)	175 (18.7%)	
Not reported	30 (2.45%)	9 (3.2%)	21 (2.2%)	

*Chi-square test between students' characteristics and Respondent variable
[1]Vocational training/Advanced-level training cycle

Table 4.2 Characteristics of sampled students (n, (%)).

Factor calculation

The question about the reasons for non-re-enrolment (section four of the survey) is essential and points to how the student has experienced the different elements of their studies, and to what extent this experience is related to their decision not to re-enrol. Alternatively, the variables that form part of the learning environment are also included in the analysis, as this is an essential element of the system. For all the variables mentioned above, we obtained factors through principal component analysis. Table 4.3 shows the following for each factor: name, description, variables that it contains -and their mean (M) and standard deviation (SD)-, Cronbach's α, loading of the 1st Eigenvalue, and its variance. Although the Cronbach's α coefficient is relatively low (close to 0.6) for some factors, the high values of the explained variance (0.5 or more) would justify their inclusion in the analysis (Schmitt, 1996).

An explorative factor analysis was conducted in preliminary versions of the survey, showing that almost all items loaded the expected constructs (only in a few cases the same item loaded two different constructs), which served to adjust the final questionnaire.

4.1.2 Results

Once we have the set of variables (and factors that summarise some of these variables), we addressed a bivariate analysis of the relation of these variables and factors with the two explained variables mentioned previously. The first, intention to re-enrol on the same program next semester, and the second, the "materialisation" of this intention, that is, effective re-enrolment for the third semester. The statistic tests used were:

- Chi-square test for the qualitative relations.
- Mann-Whitney-Wilcoxon U-test for quantitative non-normal binary relations.
- Student t-test for quantitative normal binary relations.

Concerning the first explained variable (continuance intention), up to 41.3% of the "resting" students in the 2nd semester (116) expressed their intention to restart their studies the following term; 34.5% (40) of these students effectively re-enrolled (2nd explained variable). Table 4.4 shows the basic descriptive statistics (mean –M-, standard deviation –SD-) and the results of the application of the bivariate analysis.

Factor name	**Factor description: "I did not enrol for the 2nd semester because..."**	**Factor variables: "I did not enrol for the second semester because..."**	**M**	**SD**	**Cron-bach's α**	**PCA 1st Eigenvalue**	
						Ld.	Var.
TIME	"...I have spent a lot of time on my studies."	*I did not have time to keep up with the continuous assessment tests*	3.05	1.56	0.73	1.95	0.65
		The continuous assessment tests did not have flexible dates	2.35	1.46			
		It was hard to keep up with the forums	2.47	1.47			
PERS	"...I did not enjoy the course and could not fit it into my personal life."	*I did not enjoy studying at the UOC*	2.11	1.42	0.64	1.96	0.49
		It's not worth giving up my leisure time for	2.04	1.3			
		I did not have time to meet my family obligations	2.59	1.53			
		I could not fit the UOC in with my personal and professional life	2.79	1.5			
PRICE	"...Economic issues were a problem to continue studying."	*It was too expensive*	3.40	1.58	0.60	1.72	0.57
		Being able to pay in instalments	2.45	1.58			
		I found a more economical option to continue studying	1.43	0.94			
SYST	"...I did not adapt to the UOC's study system."	*I did not have the discipline needed to study alone*	1.89	1.26	0.83	2.64	0.66
		I did not adapt to working online – I prefer face-to-face	1.74	1.18			
		With the virtual system, you do not save so much time	2.10	1.4			
		It has been difficult for me to adapt to the UOC study system	2.21	1.43			
DIF	"...I found the contents and tests too difficult."	*The continuous assessment tests were very difficult*	2.18	1.26	0.81	2.17	0.72
		The subjects were too theoretical	2.07	1.24			
		The subjects were too complicated	1.90	1.18			
SUP	"...I did not receive enough support from the tutor and from the course materials."	*Course materials/class resources were not sufficient*	1.92	1.22	0.89	3.03	0.76
		There was little feedback from course instructors	1.87	1.15			
		The course instructor did not give satisfactory explanations	1.79	1.17			
		The contributions of the course instructors were inadequate	1.86	1.18			
VC_REC	"The learning environment (Virtual Campus, VC) was not a good learning tool for me"	*I have been able to carry out the daily activity on the VC*	3.54	1.22	0.84	2.26	0.75
		I was able to find the spaces and resources on the VC	3.40	1.23			
		I feel the VC is an appropriate platform for supporting my learning process	3.66	1.12			

Table 4.3: Factors calculated from reasons for non-enrolment (n=258) and Virtual Campus (n=232).

Variable	Basic descriptive statistics	Relation w/ re-enrolment intention		Relation w/ effective reenrolment	
		Without intention	With Intention	Non-reenroled	Reenrolled
PREVIOUS EXPERIENCE					
Last university experience has been in the previous 5 years	*<= 5 years* 58.9 %	46.2 %	53.8 %	51.0 %	49.0 %
	> 5 years 41.1 %	60.9 %	39.1 %	88.0 %	12.0 % sr: -2.03
		p = *0.0987*		p = *0.004***	
APPROACH TO THE UOC					
Decision to study at the UOC for its flexibility	*Yes* 56.6 %	40.2 %	59.8 %	62.1 %	37.9 %
	No 43.4 %	62.2 %	37.8 %	67.1 %	32.9 %
		p = *0.0015***		p = *0.7560*	
YOUR 1ST SEMESTER AT UOC					
Satisfaction with the information from the tutor	M = 3.81 SD = 1.23	M = 3.75	M = 3.94	M = 3.79 SD = 1.30	M = 4.22 SD = 1.19
		p = *0.0623*		p = *0.0495**	
Did you follow the continuous assessment tests?	*Yes* 41.8%	42.9 %	57.1 %	61.2 %	38.8 %
	No 58.9%	60.0 %	40.0 %	75.0 %	25.0 %
		p = *0.0163**		p = *0.2186*	
MOTIVES FOR NOT RE-ENROLLING FOR THE 2ND SEMESTER					
"I have spent a lot of time on my studies (TIME factor)"	M = 2.62 SD = 1.20	M = 2.86 SD = 1.24	M = 2.46 SD = 1.14	M = 2.58	M = 2.33
		p = *0.0144**		p = *0.1193*	
"I did not enjoy the course, and could not fit it into my personal life (PERS factor)"	M = 2.37 SD = 0.99	M = 2.76 SD = 1.05	M = 2.06 SD = 0.80	M = 2.14	M = 1.9
		p < *0.001****		p = *0.1040*	
"I did not adapt to the UOC's study system (SYST factor)"	M = 1.98 SD = 1.06	M = 2.31 SD = 1.12	M = 1.64 SD = 0.89	M = 1.73	M = 1.47
		p < *0.001****		p = *0.0970*	
"I found the contents and tests too difficult (DIF factor)"	M = 2.05 SD = 1.05	M = 2.31 SD = 1.10	M = 1.79 SD = 0.93	M = 1.85	M = 1.67
		p < *0.001****		p = *0.2656*	
"I did not receive enough support from the tutor and/or from the course materials (SUP factor)"	M = 1.86 SD = 1.02	M = 2.17 SD = 1.14	M = 1.63 SD = 0.84	M = 1.71	M = 1.48
		p < *0.001****		p = *0.1183*	
"The learning environment was not a good learning tool for me (VC_REC factor) "	M = 2.47 SD = 1.03	M = 2.81 SD = 1.01	M = 2.08 SD = 0.87	M = 2.20	M = 1.85
		p < *0.001****		p = *0.0593*	

YOUR EXPERIENCE AT THE UOC[14]					
Variable (perception about)	**Basic descriptive statistics**	**Relation w/ re-enrolment intention**		**Relation w/ effective re-enrolment**	
		Without intention	With Intention	Non-reenro-lled	Reenro-lled
Price is appropriate for the services offered	1 9.9%	57.1 %	42.9 %	55.5 %	44.5 %
	2 37.5%	63.2 %	36.8 %	59.4 %	40.6 %
	3 47.4%	40.0 %	60.0 %	71.2 %	28.8 %
	4 5.2%	25.0 %	75.0 %	55.5 %	44.5 %
		p = *0.0028***		p = *0.4954*	
Studying at the UOC as an enjoyable experience	1 3.8%	44.5 %	55.5%	60.0 %	40.0 %
	2 20.7%	89.3 % sr: +3.86	10.7 % sr: -3.84	80.0 %	20.0 %
	3 51.3%	45.8 %	54.2 %	68.7 %	31.3 %
	4 24.2%	25.0 % sr: -2.61	75.0 % sr: +2.59	59.5 %	40.5 %
		p < *0.001****		p = *0.7168*	
Adaptation to the UOC study system	1 3.0%	71.4 %	28.6 %	50.0 %	50.0 %
	2 20.7%	72.3 % sr:+2.22	27.7 % sr:-2.20	92.3 %	7.7 %
	3 43.9%	51.5 %	48.5 %	73.5 %	26.5 %
	4 32.4%	30.7 % sr:-2.32	69.3 % sr:-2.30	51.9 %	48.1 %
		p < *0.001****		p = *0.0106**	
You should devote a reasonable amount of time	1 3.4%	62.5 %	37.5 %	66.6 %	33.4 %
	2 33.6%	62.8 %	37.2 %	62.1 %	37.9 %
	3 49.6%	46.0 %	54.0 %	73.8 %	26.2 %
	4 13.4%	25.8 %	74.2 %	47.8 %	52.2 %
		p = *0.0028***		p = *0.1393*	
The subjects would be reasonably difficult	1 7.3%	64.3 %	35.7 %	60.0 %	40.0 %
	2 16.8%	76.9 % sr: +2.43	23.1 % sr: -2.41	77.8 %	22.2 %
	3 60.8%	46.6 %	53.6 %	70.1 %	29.9 %
	4	27.0 %	73.0 %	48.1 %	51.9 %

[14] Concerning the "your experience at the UOC variables", values for experience labels are: 1 (I do not have any experience in this aspect), 2 (My experience was negative), 3 (My experience was average), 4 (My experience was positive).

	15.1%	p < *0.001****		p = *0.1531*	
The course instructors would help me to move forward with the subject	1 9.0%	70.0 %	30.0 %	83.3 %	16.7 %
	2 11.3%	65.4 %	34.6 %	66.6 %	33.7 %
	3 54.3%	47.2 %	52.8 %	71.2 %	28.8 %
	4 25.4%	40.7 %	59.3 %	51.4 %	48.6 %
		p = *0.0442**		p = *0.1916*	
In general, how would you rate your first semester at the UOC? (from 1 = minimum, to 10 = maximum)	M = 5.69 SD = 2.83	M = 4.46 SD = 2.58	M = 6.95 SD = 2.50	M = 6.58 SD=2.62	M = 7.65 SD=2.09
		p < *0.001****		p < *0.034**	
DEDICATION TO STUDIES					
Variable	**Basic descriptive statistics (N=230)**	**Relation w/ re-enrolment intention**		**Relation w/ effective re-enrolment**	
		Without intention	With intention	Non-reenrolled	Reenrolled
How often did you connect to the Virtual Campus? (from 1 to 5)	M = 4.07 SD = 1.21	M = 4.04	M = 4.09	M = 3.9 SD = 1.25	M = 4.4 SD = 1.13
		p = *0.5693*		p = *0.0128**	
Of the hours spent, in your opinion, they ended up being...	*Less than planned* 26.5%	59.0 %	41.0 %	88.0 %	12.0 %
	As planned 27.4%	41.3 %	58.7 %	70.3 %	29.7 %
	More than planned 46.1%	49.1 %	50.9 %	51.9 %	48.1 %
		p = *0.1405*		p = *0.0054***	
PROFESSIONAL, FAMILY AND SOCIOECONOMIC STATUS					
Age	M = 33.38 SD = 9.21	M = 31.74	M = 33.87	M = 36.00 SD = 9.26	M = 29.82 SD = 8.21
		p = 0.3590		*p < 0.001****	

Table 4.4: Results of the bivariate analysis.[15]

[15] Coefficient is significant (2-tailed) at the 0.05 level (*), 0.01 level (**) or 0.001 level (***), only for the variables with a significant statistical relation with the explained variable.

We can summarise the effects of the dependent variables on the two explained variables, for each one of the blocks of the survey, as shown in
Table 4.5.

Block of the survey (N)	**Number of effects (N)**	
	Relation with re-enrollment intention	Relation with effective re-enrollment
Previous experience (N = 183)	0 (N = 155)	1 (N = 116)
Approach to UOC (N = 258)	1 (N = 258)	0 (N = 116)
Your 1st semester at UOC (N = 258)	1 (N = 230)	1 (N = 116)
Motives for not re-enrolling the 2nd semester (N = 258)	6 (N = 230)	0 (N = 116)
Your experience at UOC (N = 232)	7 (N = 230)	2 (N = 116)
Dedication to studies (N = 230)	0 (N = 230)	2 (N = 116)
... Professional, family and socioeconomic status... (N = 258)	0 (N = 258)	1 (N = 116)
Total number of effects	15	7

Table 4.5: Summary of the effects of the dependent variables on the explained variables.

With respect to the explained variable "intention to re-enrol", we can describe the students who intend to continue (versus those that do not intend to) in the following manner: on the one hand, they chose the UOC for its flexibility; on the other hand, they made the most of the continuous assessment tests during the first semester.

Also, they presented significantly lower values (that is, less negative opinions) for the factors of not re-enrolment in the second semester (that is, the TIME, PERS, SYST, DIF, SUP and VC_REC) described in Table 4.3. On the other hand, they were also more satisfied with the different attributes evaluated (study as an enjoyable experience, system of study, time dedicated, difficulty of the subjects, support from tutors and price). Naturally, these differences also related to the higher overall satisfaction of these students with a positive continuance intention.

Furthermore, if we take into account the effective re-enrolment behaviour of the subset of students that expressed their intention to restart studies, we see that, considering into this group the subgroup of the students who eventually re-enrol, they are younger (by more than five years, on average) than the rest. Also related to the age variable is the propensity to re-enrol among students with more recent previous university experience (in less than five years), which is much higher than among those with the more distant university experience.

Moreover, the re-enrolled students give higher value to the information received from the tutor during the enrolment process, and their overall satisfaction with the semester is higher. Likewise, the perception of having adapted to the UOC's study system is proportionally greater; the "re-starter" student is a student who logged on more frequently to the learning environment during the first period at the university. Although they also state that they spent more time than expected to study for the activities, this has not prevented them from re-enrolling.

Interestingly, if we take overall satisfaction for the first-semester variable, we can see, on the one hand, that its value has a mean of almost seven (6.95) for students that intend to continue, compared to a 4.46 value for students without continuance intention. On the other hand, considering only the subset of students that express their intention to restart studies, mean global satisfaction is 7.65 for the students who effectively re-join the UOC in the third semester, compared to a value of 6.58 for non-re-enrolled students. Both mean differences are statistically significant, as can be seen in Table 4.3 (variable "In general, how would you rate your first semester at the UOC", at the end of the "Your experience at the UOC" section of the table).

In summary, we have seen that bivariate analysis (Grau Valldosera & Minguillón Alfonso, 2017) has served to detect trends, while in the next section, a multivariable analysis is undertaken that aims to validate these trends, as well as to reach predictive models for both intention to continue and re-enrollment.

4.2 2nd survey: Continuance intention and re-enrolment models

4.2.1 Methodology

Sample

Taking into account that students can enrol biannually, the sample for our study was taken from the population of new students enrolled in September 2014 that did not re-enrol in the following period (February 2015).

The final sample was reached through an e-mail survey (shown in Annex 1) sent to 1,189 non-active second-term students, with 380 responding (response rate = 31.9%, which gives a sample error of +/- 2.1%, with an uncertainty coefficient of 0.5 and a confidence interval of 95%). The period for response collection was from 1 to 15 April 2015. Only one follow-up email was sent to increase the response rate without inconveniencing the students. Figure 4.2 shows the main numbers associated with the fieldwork.

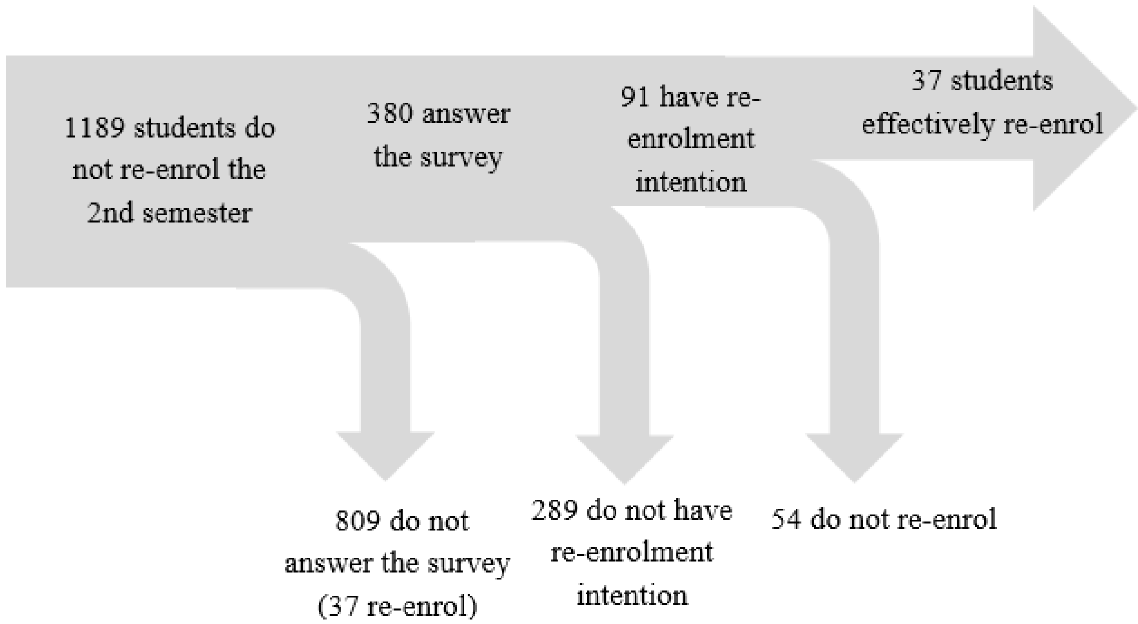


Figure 4.2: Flow of students from the second semester break to re-enrollment or dropping out in the third semester (for the Feb.2015 survey).

We crossed questionnaire information with the student characteristics collected in the registration process. Some registration data was not provided for 16 students (7 responders, and 9 non-responders). As can be seen in Table 4.6, women, people over 40 and with university studies completed were overrepresented in the respondent sample. To correct this bias, we weighted the sample by gender, age, type of access and interaction between gender and age using the inverse probability weighting method (J.M: Chambers, 1992; Lumley, 2004). First, we estimated the sampling probability of respondents using a linear model where gender, age, type of access and interaction between gender and age were the covariates. Later, we used the inverse of this probability to weight the respondent sample.

		Respondents		
Students characteristics	All (n=1189)	Yes (n=373)	No (n=816)	*p*-value*
Gender:				
Female	598 (50.3%)	219 (58.7%)	379 (46.4%)	< 0.001
Male	591 (49.7%)	154 (41.3%)	437 (53.6%)	
Age:				
[18, 25)	341 (28.7%)	93 (24.9%)	248 (30.4%)	0.005
[25, 40)	651 (54.8%)	200 (53.6%)	451 (55.3%)	
[40, 60]	197 (16.6%)	80 (21.4%)	117 (14.3%)	
Access type:				
PAU[1]	166 (14%)	61 (16.4%)	105 (12.9%)	0.083
FP/CFGS[2]	284 (23.9%)	84 (22.5%)	200 (24.5%)	
Access for >25s or >40s	95 (7.9%)	26 (7%)	69 (8.5%)	
University studies not completed	368 (31%)	102 (27.3%)	266 (32.6%)	
University studies completed	275 (23.1%)	100 (26.8%)	175 (21.4%)	
Not reported	1 (0.1%)	0 (0%)	1 (0.1%)	

*Chi-square test between students' characteristics and Respondent variable
[1]Spanish university entrance exams
[2]Vocational training/Advanced-level training cycle

Table 4.6 Characteristics of sampled students (n, (%)).

Instruments

As stated, the survey used in the fieldwork consisted of 30 questions to capture the variables in each of the three dimensions found in the literature review (Lee & Choi, 2011), specifically student, course-program (or institutional) and environmental factors. The survey had the following sections:

Survey section	Section Title	Section Description	Number of questions	Scale used
1	“Previous experience.”	Previous university and online learning experience.	6	Multiple choice
2	“Approach to the UOC”	The motivation for starting university studies and about the program selection process.	2	Multiple choice (2 with an open-ended option)
3	“Your 1st semester at the UOC.”	Validation of subjects, opinion about academic information and following the continuous assessment tests.	5	1 multiple-choice 1 single choice 1 Likert with 1-5 range labelled at the ends 1 multiple-choice (open-ended) 1 open-text
4	“Reasons for not re-enrolling for the 2nd semester.”	Which elements of the learning system and process are related to the decision not to re-enrol after the 1st semester	One question with 25 possible reasons	1 Likert with 1-5 range, labelled at the ends
5	“Your experience at the UOC...”	General satisfaction with the semester, level of expectations vs satisfaction with specific attributes, and level of satisfaction with the learning platform (Virtual Campus).	2	General satisfaction (1 Likert with 1-10 points labelled at the ends) Virtual Campus (3 Likert with 1-5 range, labelled at the ends)
6	“Dedication to studies.”	Time spent on the program	5	5 single-choice
7	“…and in the future”	Student intention to restart her activity in the program in the upcoming semesters	1	1 single-choice
8	“Professional, family and socioeconomic status”	Sociodemographic data	3	Multiple-choice

Table 4.7: Sections of the Feb. 2015 survey

We can notice that the structure of the survey is basically the same than for the 1st questionnaire, and, therefore, the main dimensions defined by Lee and Choi (2011) are still covered.

New factors

Given the exhaustive survey carried out, and similarly to the exploratory survey data, it was necessary to group the 27 possible reasons related to the question about non-re-enrolment (section 4 of the survey) into different factors. We calculated these factors based on the average of the original items and standardised them to ensure the same scale. Table 4.8 shows the composition of the new factors. Cronbach's α was used to determine the internal consistency of these factors, that is, a measure of how well the total score for the selected items captures the expected score in the entire domain, even if that domain is heterogeneous (Welch & Comer, 1988).

Factor name	**Factor description: "I did not enrol for the second semester because..."**	**Factor variables (Reasons for not having enrolled in the second semester)**	**Mean (SD)**	**Std. Cronbach's α**
Factor Time	"...I have spent a lot of time on my studies."	*I did not have time to keep up with the continuous assessment tests*	2.90 (1.59)	0.8
		The continuous assessment tests did not have flexible delivery dates	2.46 (1.55)	
		It was hard to keep up with the forums	2.48 (1.49)	
Factor Personal	"...I did not enjoy the course, and could not fit it into my personal life."	*I did not enjoy studying at the UOC*	2.14 (1.42)	0.74
		It's not worth giving up my leisure time for	1.90 (1.20)	
		I did not have time to meet my family obligations	2.51 (1.52)	
		I could not fit the UOC in with my personal and professional life	2.75 (1.56)	
Factor Price	"...Economic issues were a problem to continue studying."	*It was too expensive*	3.17 (1.54)	0.61
		Not being able to pay in instalments	2.51 (1.55)	
		I found a more economical option to continue studying	1.47 (1.06)	
Factor System	"...I did not adapt to the UOC's study	*I did not have the discipline needed to study alone*	1.95 (1.29)	

	system."	*I did not adapt to working online – I prefer face-to-face*	1.84 (1.27)	0.83
		With the virtual system, you do not save so much time	2.19 (1.43)	
		It has been difficult for me to adapt to the UOC's study system	2.25 (1.45)	
Factor Difficult	"...I found the contents and tests too difficult."	*The continuous assessment tests were very difficult*	2.12 (1.29)	0.86
		The subjects were too theoretical	2.09 (1.3)	
		The subjects were too complicated	1.84 (1.22)	
Factor Support	"...I did not receive enough support from the tutor and/or from the course materials."	*Course materials/class resources were not sufficient*	1.92 (1.3)	0.90
		I did not have time to assimilate all the materials	2.14 (1.39)	
		There was little feedback from course instructors	1.97 (1.33)	
		The course instructor did not give satisfactory explanations	1.86 (1.22)	
		The contributions of the course instructors were inadequate	1.90 (1.28)	
Factor Degree	"...I decided to change degrees and/, or I lost interest in the degree for which I was studying."	*I lost interest in further study*	1.55 (1.08)	0.55
		The course content was different than expected	2.18 (1.44)	
Factor Sabbatical	"...I decided to take a sabbatical."	*I had to take a rest for personal reasons*	2.78 (1.75)	0.39
		I had to take a rest for professional reasons	2.75 (1.73)	

Table 4.8: Descriptive statistics (mean, SD (standard deviation) and internal consistency (Cronbach's α)) for "Reasons for not re-enrolling in the 2nd semester" grouped into the new factors.

The factors "Degree" and "Sabbatical" were excluded from the analysis because they were related directly to the response (Degree factor) or they were related to educational decisions outside the scope of the study (Sabbatical factor), and therefore high collinearity could exist. Also, as can be seen in the table, both cases had a very low Cronbach's α coefficient.

Data analysis

Several forms of quantitative analysis were carried out. Descriptive statistics, frequencies for qualitative variables and mean and standard deviation for quantitative variables were employed to describe all items of the survey. The appropriate bivariate analysis for each item was used to compare groups defined by each response variable: “Continuance intention” (Continuance) and “Effective re-enrolment” (Re-enrolment). A chi-squared test, Fisher’s exact test or a likelihood ratio test was employed for qualitative items, and ANOVA, the Mann-Whitney-Wilcoxon test or the Kruskal-Wallis test was applied for quantitative items.

Considering the dichotomous nature of the dependent variables, two multivariate logistic models were developed, including socio-demographic, academic and personal information, the new factors and their interactions: one model on continuance intention and another model on effective re-enrolment. First, we developed a basal model with only socio-demographic, academic and personal motivation variables to detect the most significant covariates. Second, a final model, including the new factors and their interactions, was performed.

Stepwise procedures were employed with covariates added to or eliminated from the analysis according to statistical criteria. Only those interactions between factors that could be explained and were meaningful from the research were likely to be included in the analysis. We calculated regression coefficients (*B*), standard errors (*s.e.*) and their corresponding odds ratio (*OR*) with a 95% confidence interval (*95%CI*). To assess the goodness of fit of the models, we calculated the Cox-Snell pseudo R^2 and the overall classification accuracy for each model.

For all statistical tests, we applied a nominal significance level of 5% (p-*value* <0.05). The statistical analysis was performed using R v3.2.3.

4.2.2 Results

Continuance intention response

Descriptive statistics

Continuance intention was higher for women and also for students whose motivation for enrolment related to workplace goals. Having chosen the UOC for its continuous assessment system and prestige was also associated with a higher intention to continue.

Covariate	Continuance intention No (n=212)	Continuance intention Yes (n=89)	*p-value**
Gender (Female):	114 (53.8%)	62 (69.7%)	0.015
Age [18,25)	44 (20.8%)	22 (24.7%)	0.653
[25,40)	117 (55.2%)	49 (55.1%)	
[40,66]	51 (24.1%)	18 (20.2%)	
Previous univ. experience: (Without)	90 (42.5%)	30 (33.7%)	0.161
Experience at the same area	50 (23.6%)	30 (33.7%)	
Experience at other area	72 (34.0%)	29 (32.6%)	
Have children (Yes):	56 (26.4%)	18 (20.5%)	0.346
To be working (Yes):	171 (80.7%)	67 (76.1%)	0.469
Study for work reasons (Yes):	41 (19.3%)	28 (31.5%)	0.033
Study for academic reasons (Yes):	100 (47.2%)	39 (43.8%)	0.685
Study for pleasure. (Yes):	126 (59.4%)	46 (51.7%)	0.266
Previous e-learning experience (Yes):	104 (49.1%)	40 (44.9%)	0.599
Choose the UOC to save time (Yes):	139 (65.6%)	65 (73.0%)	0.258
Choose the UOC for its flexibility (Yes):	112 (52.8%)	58 (65.2%)	0.065
Choose the UOC for price reasons (Yes):	10 (4.72%)	8 (8.99%)	0.246
Choose the UOC to get the degree faster (Yes):	3 (1.42%)	1 (1.12%)	1.000
Choose the UOC to get the degree easier (Yes):	4 (1.89%)	2 (2.25%)	1.000
Choose the UOC for its continuous assessment (Yes):	37 (17.5%)	21 (23.6%)	0.283
Choose the UOC for its tutoring system (Yes):	7 (3.30%)	11 (12.4%)	0.006
Choose the UOC for the quality of its resources (Yes):	10 (4.72%)	5 (5.62%)	0.774
Choose the UOC for the quality of its teaching staff (Yes):	6 (2.83%)	4 (4.49%)	0.489
Choose the UOC for its prestige (Yes):	14 (6.60%)	14 (15.7%)	0.023
Choose the UOC for not needing to move (Yes):	27 (12.7%)	12 (13.5%)	1.000

Table 4.9:.Continuance intention response by socio-demographic, academic and personal motivational variables (n (%)).

Model for continuance intention

First, we estimated the model only with socio-demographic, academic and personal-motivational covariates to detect the most significant ones.

Basal model for re-enrolment intention

Estimated coefficients of the model for re-enrolment intention (CONTSM) appear in Table 4. According to the model, on the one hand, the log of the odds of re-enrolment intention is negatively related to having small children (KIDS) and to having decided to study for enjoyment or to obtain a degree (MOTIVJoy and MOTIVDegree respectively). On the other hand, re-enrolment intention is positively related to being woman, to having previous university experience in the same area (UNIVEXP), and to choosing the UOC for reasons related to not having time, flexibility, continued assistance, price and prestige (MOTIVNoTime, MOTIVFlex, MOTIVContAss, MOTIVPrice and MOTIVPrest respectively). Beginning to study for job reasons (MOTIVJob) also contributes positively to re-enrolment intention.

	Estimate (s.e.)	OR (95%CI)	*P* value
Intercept	-1.93 (0.39)	0.15 (0.07, 0.31)	<0.001 ***
WOMAN, Yes	0.76 (0.16)	2.13 (1.55, 2.93)	<0.001 ***
AGE, [18,25)	-0.06 (0.28)	0.94 (0.55, 1.63)	0.836
AGE, [25,40)	-0.04 (0.22)	0.96 (0.62, 1.50)	0.869
UNIVEXP, Same Area	0.60 (0.20)	1.82 (1.23, 2.69)	0.002 **
UNIVEXP, Other Area	0.29 (0.20)	1.34 (0.90, 1.99)	0.145
KIDS, Yes	-0.44 (0.22)	0.65 (0.42, 0.98)	0.044 *
MOTIVNoTime, Yes	0.75 (0.18)	2.12 (1.49, 3.06)	<0.001 ***
MOTIVFlex, Yes	0.59 (0.17)	1.80 (1.29, 2.54)	<0.001 ***
MOTIVPrice, Yes	0.72 (0.37)	2.06 (1, 4.23)	0.048 *
MOTIVContAss, Yes	0.63 (0.21)	1.88 (1.23, 2.86)	0.003 **
MOTIVPrest, Yes	0.76 (0.27)	2.15 (1.26, 3.65)	0.004 **
MOTIVFar, Yes	0.08 (0.23)	1.08 (0.68, 1.70)	0.731
MOTIVEasy, Yes	0.19 (0.55)	1.21 (0.38, 3.40)	0.723
MOTIVQuality, Yes	-0.73 (0.46)	0.48 (0.19, 1.18)	0.114
MOTIVTeachingQuality, Yes	0.56 (0.51)	1.76 (0.64, 4.76)	0.267
JOB, Yes	-0.24 (0.20)	0.78 (0.53, 1.16)	0.221
MOTIVJob, Yes	0.48 (0.20)	1.61 (1.09, 2.36)	0.016 *
MOTIVDegree, Yes	-0.45 (0.19)	0.64 (0.43, 0.93)	0.021 *
MOTIVJoy, Yes	-0.58 (0.20)	0.56 (0.38, 0.83)	0.003 **
ELEARN, Yes	-0.15 (0.17)	0.86 (0.62, 1.19)	0.356

Table 4.10: Summary of logistic regression analysis for re-enrolment intention (n = 301). We only considered socio-demographic, academic and personal motivation variables.

If we pay attention to odds ratios, the odds of re-enrolment intention for females (WOMANYes) are 2.1 times greater than for males. Choosing the UOC for reasons related to time (MOTIVNoTime), flexibility (MOTIVFlex), price (MOTIVPrice), assistance (MOTIVContAss) or prestige (MOTIVPrest) or having previous university experience in the same area (UNIVEXP, Same Area) also gives a value for the odds of around 2. Professional reasons (MOTIVJob) increase the odds of re-enrollment to 1.61. On the other hand, having young children (KIDS) or studying for enjoyment (MOTIVJoy) or for obtaining a degree (MOTIVDegree) reduces the odds by almost 40% (odds ratio of 0.6 approximately).

Final model for re-enrolment intention

In the final model, we have added the factors of non-enrolment and the interaction between them to the basal model. We have selected only those that were significant. The final model for continuance intention is shown in Figure 4.3 and Annex II - Summary of logistic rogression analysis models.

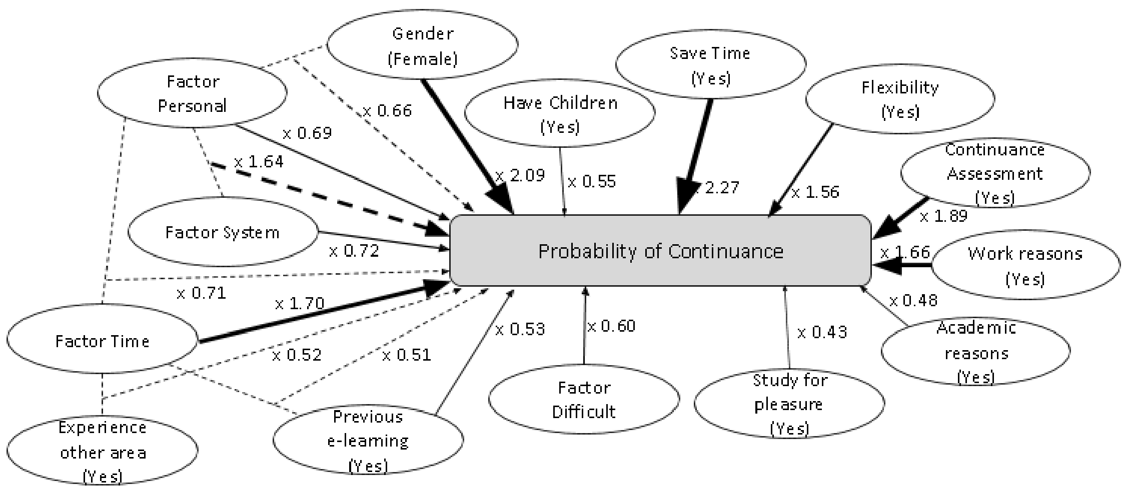


Figure 4.3: Logistic regression model for continuance intention. Only significant covariates are shown. Solid lines indicate the main effects and dashed lines indicate interactions. The multiplier effect corresponds to the value of the odds ratio. Note that a value below 1 implies a lower probability.

According to the model, on the one hand, the log of the odds of continuance intention is negatively related to having small children (OR=0.55, $CI(OR)_{95\%}$=(0.33, 0.89), p=0.017), to having previous e-learning experience (OR=0.53 $CI(OR)_{95\%}$=(0.34, 0.80), p=0.003) and to studying for pleasure (OR=0.43, $CI(OR)_{95\%}$= (0.27, 0.66), p<0.001) or for academic reasons (OR=0.48, $CI(OR)_{95\%}$= (0.31, 0.73), p<0.001). For example, the chances of continuing for students with previous e-learning experience are half those for students with none.

On the other hand, continuance intention relates positively to being a woman; that is, the probability of women having a positive continuance intention is two times that of men (OR=2.09, $CI(OR)_{95\%}$=(1.44, 3.04), p<0.001 (see Table 4.10). Continuance intention is also positively related to choosing the UOC for reasons related to saving time (OR=2.27, $CI(OR)_{95\%}$=(1.50, 3.47), p<0.001), flexibility (OR=1.56, $CI(OR)_{95\%}$=(1.07, 2.29) p=0.023) and continuous assessment (OR=1.89, $CI(OR)_{95\%}$=(1.19, 3), p=0.006).

Regarding the calculated factors, the “Personal” (OR=0.69, $CI(OR)_{95\%}$=(0.49, 0.96), p=0.032), “System” (OR=0.72, $CI(OR)_{95\%}$=(0.55, 0.92), p=0.011) and “Difficulty” (OR=0.60, $CI(OR)_{95\%}$=(0.46, 0.77), p<0.001) factors reduce continuance intention. The probability of having a positive continuance intention decreases by 30% for each increase of one point of the value of the factors. Regarding the interpretation of interactions, we find that combining the factors “Personal” with “System” has a positive effect that counters the main negative ones that both demonstrate separately. All other interactions are negative. The “Personal” factor, concerning the personal cost of studying, interacts negatively with both the “Gender (Female)” and “Time” factors. The last two negative interactions are between previous e-learning experience and the “Time” factor and between previous university experience in other areas and that same factor (Time).

If we look at the odds ratio associated with each variable (see Table 4.10), we can highlight an odds ratio greater than 2 in the case of being female, enrolling due to lack of time (Chose the UOC to save time), or enrolling due to the competitive price of the UOC (Chose the UOC for price). However, with an odds ratio of less than 0.5, and therefore indicating a lower continuance intention, we find the variables of having enrolled for academic reasons or pleasure.

Finally, concerning the goodness of fit of the model, Cox and Snell's R^2 for this model is 0.630, and the classification accuracy is 83.4%. Therefore, it can be considered a good model for explaining continuance intention.

Effective re-enrolment response

Descriptive statistics

No differences in effective re-enrolment were found for any of the socio-demographic, academic and personal motivation covariates (see Table 4.11).

	Effective re-enrolment No (n=54)	Effective re-enrolment Yes (n=37)	p-value*
Gender (Female):	36 (70.6%)	25 (69.4%)	1
Age [18,25)	13 (25.5%)	9 (25.0%)	
[25,40)	29 (56.9%)	19 (52.8%)	
[40,66]	9 (17.6%)	8 (22.2%)	0.864
Previous univ. experience: (Without)	20 (37.0%)	11 (29.7%)	
Experience at the same area	16 (29.6%)	15 (40.5%)	
Experience at other area	18 (33.3%)	11 (29.7%)	0.549
Have children (Yes):	13 (24.5%)	7 (18.9%)	0.710
To be working (Yes):	41 (77.4%)	26 (70.3%)	0.608
Study for work reasons (Yes):	15 (27.8%)	11 (29.7%)	1
Study for academic reasons (Yes):	22 (40.7%)	19 (51.4%)	0.433
Study for pleasure. (Yes):	31 (57.4%)	18 (48.6%)	0.542
Previous e-learning experience (Yes):	21 (38.9%)	20 (54.1%)	0.225
Choose the UOC to save time (Yes):	40 (74.1%)	26 (70.3%)	0.873
Choose the UOC for flexibility (Yes):	35 (64.8%)	25 (67.6%)	0.963
Choose the UOC for price (Yes):	4 (7.41%)	4 (10.8%)	0.711
Choose the UOC to get the degree faster (Yes):	0 (0.00%)	1 (2.70%)	0.407
Choose the UOC to get the degree easier (Yes):	2 (3.70%)	1 (2.70%)	1
Choose the UOC for its continuous assessment (Yes):	9 (16.7%)	13 (35.1%)	0.076
Choose the UOC for its tutoring system (Yes):	6 (11.1%)	6 (16.2%)	0.538
Choose the UOC for the quality of its resources (Yes):	3 (5.56%)	3 (8.11%)	0.684
Choose the UOC for the quality of its teaching staff (Yes):	1 (1.85%)	4 (10.8%)	0.154
Choose the UOC for its prestige (Yes):	7 (13.0%)	7 (18.9%)	0.633
Choose the UOC for not having the need to move (Yes):	5 (9.26%)	7 (18.9%)	0.216

*Chi-square test between socio-demographic, academic and personal motivational covariates and Continuance variable.
Only category "Yes" is shown for dichotomous variables. Category "No" is the complementary.

Table 4.11: Effective re-enrolment response by socio-demographic, academic and personal motivational variables (n (%)).

Basal model for effective re-enrolment

Table 4.12 shows the results of the logistic regression analysis carried out with socio-demographic, academic and personal motivation variables for effective re-enrolment. The factors that related positively with effective re-enrolment are: having previous university experience in the same area (UNIVEXPSameArea) or choosing the UOC for its continuous assessment system (MOTIVContAss) or because of living far away from a face-to-face university (MOTIVFar). Starting university studies for professional reasons (MOTIVJob) or for obtaining a degree (MOTIVDegree), or having prior experience in e-learning (ELEARNYes), also increases the chances of re-enrolment. However, having young children (KIDS), selecting the UOC for its price (MOTIVPrice) or having a job (JOBYes) decreases the probability of effective re-enrolment.

	Estimate (s.e.)	OR (95%CI)	*P* value
(Intercept)	-1.19 (0.76)	0.30 (0.07, 1.33)	0.119
WOMANYes	0.27 (0.36)	1.30 (0.65, 2.65)	0.457
AGE[18,25)	-0.60 (0.59)	0.55 (0.17, 1.71)	0.302
AGE[25,40)	-0.35 (0.46)	0.70 (0.28, 1.75)	0.448
UNIVEXPSameArea	1.48 (0.41)	4.40 (2, 10.08)	<0.001 ***
UNIVEXPOtherArea	0.33 (0.43)	1.39 (0.59, 3.23)	0.448
KIDSYes	-1.22 (0.47)	0.29 (0.11, 0.72)	0.009 **
MOTIVNoTime	-0.38 (0.37)	0.69 (0.33, 1.43)	0.312
MOTIVFlex	-0.07 (0.34)	0.93 (0.47, 1.82)	0.838
MOTIVPrice	-1.71 (0.69)	0.18 (0.04, 0.67)	0.016 *
MOTIVEasy, Yes	0.58 (0.94)	1.79 (0.24, 11.33)	0.535
MOTIVContAss	1.97 (0.46)	7.18 (2.98, 18.37)	<0.001 ***
MOTIVQuality, Yes	-0.15 (0.87)	0.86 (0.13, 4.35)	0.860
MOTIVTeachingQuality, Yes	1.11 (0.89)	3.03 (0.59, 20.85)	0.211
MOTIVPrest	0.46 (0.53)	1.58 (0.56, 4.50)	0.387
MOTIVFar	1.64 (0.48)	5.16 (2.09, 13.76)	<0.001 ***
JOBYes	-0.91 (0.38)	0.40 (0.19, 0.84)	0.017 *
MOTIVJob	0.73 (0.37)	2.08 (1, 4.37)	0.049 *
MOTIVDegree	0.88 (0.39)	2.41 (1.13, 5.18)	0.023 *
MOTIVJoy	-0.18 (0.37)	0.83 (0.40, 1.70)	0.619
ELEARNYes	0.94 (0.33)	2.56 (1.36, 4.93)	0.004 **

Table 4.12: Summary of logistic regression analysis for effective re-enrolment. N = 91 questionnaires. We only considered socio-demographic, academic and personal motivation variables.

The odds ratios for the effective re-enrolment model have been affected by the small sample size (n = 91). In some cases, this increases the variability of the estimation, giving wide-ranging confidence intervals. Therefore, in the following sections, it is preferable to interpret trend instead of the odds ratio.

If we compare these results with the results for the continuance intention model, we can see that some factors have changed their contribution. For re-enrolment intention, a good opinion of the price (MOTIVPrice) is a positive driver to continue but, for effective re-enrolment, it is actually negative. Moreover, studying to obtain a degree (MOTIVDegree) is a negative stimulus in the re-enrolment intention model, but, for effective re-enrolment, the relationship is positive.

Final model for effective re-enrolment

We find the results of the model for effective re-enrolment in Figure 4.4 and supplementary Tabl. As we have seen in the previous section, an initial model only with socio-demographic, academic and personal-motivational covariates was estimated, later adding the new factors.

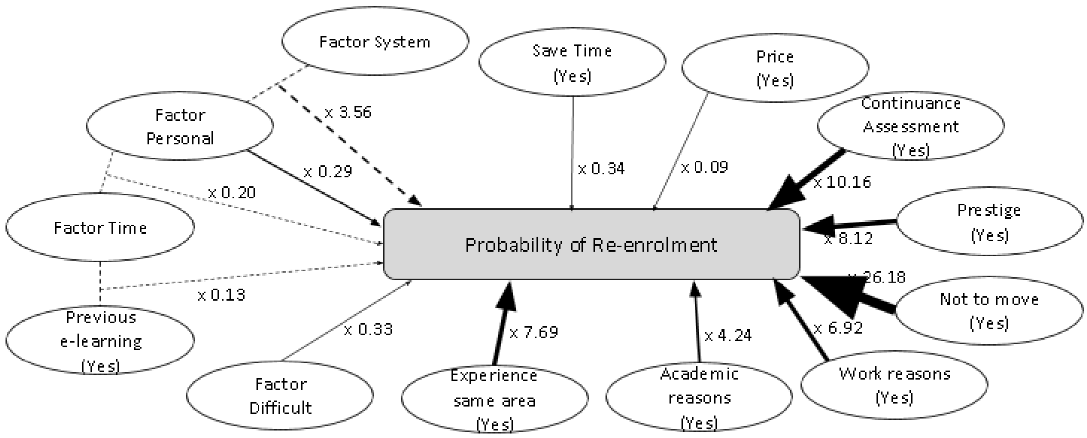


Figure 4.4: Logistic regression model for effective re-enrolment. Only significant covariates are shown. Solid lines indicate the main effects and dashed lines indicate interactions. The multiplier effect corresponds to the value of the odds ratio. Note that a value below 1 implies a lower probability.

The odds ratios for the effective re-enrolment model have been affected by small sample size (n = 91). In some cases, this increases the variability of the estimation, giving wide-ranging confidence intervals. Therefore, it is preferable to interpret trends instead of odds ratios.

The features that are related positively with effective re-enrolment are: having previous university experience in the same knowledge area, choosing the UOC for its continuous assessment, for its prestige or due to living far away from a face-to-face university, to improve their work situation and for academic reasons (obtain a degree).

If we analyse the interactions with a positive sign, the only interaction found is between personal reasons and system reasons (Personal factor * System factor). In this case, this interaction partially offsets the effect that personal reasons (Personal factor) have.

In contrast, the features that characterise the individual with less chance of effectively re-enrolling are: to be employed full-time (OR=0.40, $CI(OR)_{95\%}$=(0.15, 1.01), p-value=0.057, Tabl), having enrolled in the UOC to save time or for reasons related to affordable prices. Although getting a degree can improve his or her work situation, at the same time, being employed full-time could make it difficult to achieve that goal. Furthermore, reasons of personal costs (Personal factor) or the difficulty of the learning experience (Difficulty factor) also influenced the decision not to effectively re-enrol in the second semester.

In regard to the analysis of the negative interactions, we observe that the combination of reasons related to time and personal costs (Time factor * Personal factor) implies a decrease of about 80% (OR=0.20, $CI(OR)_{95\%}$=(0.07, 0.47)) in terms of effective re-enrolment, which is clearly higher than the 30% that this same interaction had in the continuance intention model (OR=0.71, $CI(OR)_{95\%}$=(0.56, 0.89)). Moreover, having previous experience in e-learning in combination with time reasons also discourages effective re-enrolment; the same occurs with the interaction between “Gender (Female)” and “Personal factor”.

The Cox and Snell's R^2 for this model is 0.779, and the classification accuracy is 87.3%. Therefore, we can consider that the model provides valuable insights into effective re-enrolment.

If we compare both models, as can be seen in Table 4.13, we can observe that reasons like not having time for on-site class attendance (Chose the UOC to save time) or being affordable (Chose the UOC for price) change their contribution. For continuance intention, these factors provide positive encouragement to continue, but for effective re-enrolment, the effect is negative. Meanwhile, studying for academic reasons, though positive for continuance intention, has a negative impact on the effective re-enrolment model.

Furthermore, we can observe that the contribution made by personal, system and difficulty factors does not change. Therefore, factors related to reasons for not continuing one’s studies have proven to be consistent regarding the explained variables for continuance intention and effective re-enrolment. Finally, there are many covariates that lose their statistical significance when comparing the effective re-enrolment model to the continuance intention model: covariates “Gender (Female)”, “Have children”, “Chose the UOC for flexibility”, “Study for pleasure", "Previous e-learning experience", and the factors "Time" and "System" in no way contribute. There are new reasons that are statistically significant only in the effective re-enrolment model: to be employed full-time, having previous experience in the same area and having enrolled at the UOC due to living far away from a university or for its prestige.

	Change between models		
	Continuance Intention	→	Effective re-enrolment
Intercept	-	=	-
Gender (Female):	+	→	n.s.
Previous univ. experience: (Without)			
Univ. experience at the same area	n.s.	→	+
Univ. experience at other area	n.s.	=	n.s.
Children (Yes):	-	→	n.s.
Working (Yes):	n.s.	=	n.s.
Choose the UOC to save time (Yes):	+	→	-
Choose the UOC for flexibility (Yes):	+	→	n.s.
Choose the UOC for price (Yes):	+ (n.s.)	→	-
Choose the UOC for its continuance assessment (Yes):	+	=	+
Choose the UOC for its prestige (Yes):	n.s.	→	+
Choose the UOC for not to have to move (Yes):	n.s.	→	+
E-learning experience (Yes):	-	→	n.s.
Job motivation (Yes):	+	=	+
Academic motivation (Yes):	-	→	+
Study to enjoy (Yes):	-	→	n.s.
Factor Time	+	→	n.s.
Factor Personal	-	=	-
Factor System	-	→	n.s.
Factor Difficult	-	=	-
Gender * Factor Personal	-	=	-
Factor Time * Factor Personal	-	=	-
Factor Personal * Factor System	+	=	+
E-learning * Factor Time	-	=	-
Univ. experience at the same area * Factor Time	n.s.	=	n.s.
Univ. experience at other area * Factor Time	-	→	n.s.

Table 4.13: Comparison between the model for continuance intention and the model for effective re-enrolment. + / - / n.s. denotes positive / negative / non-significant coefficient = denotes no change.

As a summary of this section, we have approached the analysis of drivers of continuance intention and re-enrolment through two methodologies of analysis with complementary objectives, specifically: bivariate analysis and multivariate logistic regression. Both analyses were applied to two consecutive surveys, the first in February 2014 and the second in February 2015.

On the one side, the results obtained with the bivariate analysis describe a student progressively more involved and satisfied with the learning experience as she progresses through the stages of "interested in continuing" and "definitively re-enrolled". Additionally, students that finally re-enrol tend to be younger and therefore with a more recent university experience. This behaviour would not be, in principle, a factor of surprise, except for the fact that usually excessive emphasis is placed on factors external to the university in the processes of retention or abandonment.

On the other side, if we consider results obtained with the multivariate logistic analysis, we would have the same “overall picture” (mainly the negative contribution to continuance intention made by personal, system and difficulty factors), with more detailed aspects derived from the usage of a more robust analysis methodology and also a higher response base. For example, on the one hand, women tend to have a higher continuance intention, while having kids has a negative relation; on the other hand, having university experience in the same knowledge area and being employed full-time are related to having more or less chance of effectively re-enrolling, respectively.

We can affirm that, albeit some small differences, there seems to exist a basic coincidence between both methodologies, which we will analyse more thoroughly analysed in the next section.

A sunmary of the logistic regression models can be seen in Annex 2.

5 Discussion

After having answered the research questions raised in the introductory section, we should contrast the results with the theoretical framework based on the literature review in Section 2. Consequently, this section aims to assess how much we have learned from the analysis of results in the context of such a theoretical framework. The ultimate objective of the discussion would be to apply this learning to the increase of re-enrolment intention and eventual re-enrolment of students who have taken a break in the second semester.

5.1 A new dropout definition

In Section 3, we have defined dropout as a prerequisite to measuring it (establish a ratio for each program) and to analyse it (explore the drivers that describe and predict this dropout). The definition achieved has tried to overcome these four challenges: uncertainty (we never know 100% whether a student is dropping out, or she is taking an extended break), sensitivity (a need to detect early dropout), long perspective (at program level, longer than the single course one) and possibility of parameterization to other online distance learning institutions.

The fact that the definition has been built, rather than as a static statement, as a dynamic algorithm based on empirical and data-driven analysis, has helped to overcome those challenges and, subsequently, to adapt the results to each of the programs of the UOC and, potentially, to those of other institutions. Our dropout definition is dynamic in the sense that establishes, for each program, a different value for the “N” consecutive semesters needed to differentiate a student that is taking a break from a dropout student. Therefore, any institution that has an academic system with non-compulsory enrolment and lax or non-existent completion deadlines, which seems to be the case of most distance learning institutions, could potentially apply our definition to its idiosyncrasy.

As long as in 1975, one of the authors who has put great emphasis on creating a university dropout framework for higher education expressed the need to move forward on "definition issues" (V Tinto, 1975). Thirty-five years later, in their literature review for online distance learning dropout, Lee & Choi (Lee & Choi, 2011) reported “a high heterogeneity of dropout definitions”. Last but not least, from a governmental point of view, a European Union report

(Vossensteyn et al., 2015) denounces that there is also “a lack of systematic knowledge, data and indicators on study success in Europe”, which could be reduced using a dropout definition that, albeit being “unique”, is sensitive to the specificities of each institution.

On the other side, the flexibility of completion deadlines also increases for face-to-face education, as a response to the needs of students. For example, in the US, the percentage of undergraduates who manage to earn a bachelor’s degree within six years is only 59 % nationwide; for low-income and first-generation college students, the rate is even lower (Boucher, 2016). Therefore, it seems that the parametrizable definition established in this dissertation could also apply to virtually all institutions in higher education systems, allowing for stimulating comparisons between countries and delivery modes. As a matter of fact, the possibility of taking breaks has never been exclusive of distance learning: for example Astin (1971) affirmed, in a context of face-to-face education, that it was impossible to find a perfect classification of dropouts versus non-dropouts any time while students are still alive, as there was always the possibility that they may return to college. Only a good approximation would be possible:

> *(...)” the term ‘dropout’ is imperfectly defined: the so-called dropouts may ultimately become non-dropouts and vice versa... But there seems to be no practical way out of the dilemma: A “perfect” classification of drop-outs versus non-dropouts could only be achieved when all the students had either died without ever finishing college or had finished college. (p. 15)”*

Table 3.3, which we show in a simplified version in Table 3.3, illustrates the adaptability of the definition, described in Grau-Valldosera and Minguillón (2014), showing that the number of semesters that define dropout in each program has a particularly relevant variability. This figure varies between three and five semesters assuming an error smaller than 5%.

Initial analysis of these results shows that there appears to be no relationship between the type of program content, that is technical or humanistic, and the number of semesters that determines dropout. For example, in the case of Computer Engineering (Tec. Eng. in CS), the value is high (5 semesters), but it is the same as in the case of Humanities. On the other hand, it does seem that in programs where students have prior higher education experience related to the curriculum they are studying (in Spain known as "second cycle" degrees), students decide to drop out within fewer semesters than on programs where this experience is not required (known as "first cycle" or "first and second cycle"). Specifically, for first-cycle or first-and-second-cycle programs, up to five degrees have an N = 5 semesters value, Catalan Language has a value of N = 4 and Psychology has a value of N = 3. For second-cycle programs, there are no degrees with an N = 5 semesters value, and the majority of bachelors have a value of N = 4. From a complementary perspective that would in some way confirm our results, other research at the UOC (Carnoy, Rabling, Castano-Munoz, Duart Montoliu, & Sancho-Vinuesa, 2011) shows that students taking shorter degree courses at UOC are much more likely to complete their degrees. Therefore, students enrolled in shorter programs decide before if they drop out and, in the end, finish their programs with a lower dropout level. We must notice at this point that we made our analysis for bachelors before the European Higher Education Area (EHEA), which was established in Spain in 2006. Before EHEA, “first and second-cycle” programmes could last up to five years. Nowadays, the maximum duration of EHEA programs is four years.

Program	**Length (semesters)**	**N**	**Total dropout**	**1st sem. Dropout**
Business Sci.	6	5	54.3%	24.91%
Tec. Eng. in CM	6	5	66.8%	29.47%
Tec. Eng. in CS	6	5	65.6%	28.44%
Tourism	6	3	49.7%	26.10%
Catalan	8	4	58.9%	25.88%
Law	8	5	54.0%	26.72%
Humanities	8	5	64.3%	28.34%
Psychology	8	3	56.5%	28.81%
Business Adm.	4	4	40.9%	21.33%
Labour Sci.	4	4	44.8%	23.35%
Political Sci.	4	3	49.5%	26.53%
AV Comm.	4	3	43.7%	21.12%
Documentation	4	4	50.3%	23.07%
Market R. & Tec.	4	3	38.0%	18.05%
Psychopedagogy	4	4	54.2%	25.01%
Comp. Eng.	4	4	37.3%	15.96%
TOTAL	---	4	57.6%	24.91%

Table 5.1: Summary of Results of applying an evidence-based dropout definition at UOC (data from 1994 to 2007)

The higher level of completion of students enrolled in shorter programs (Carnoy et al., 2011) could be related, among other things, to a higher “finishing intention”, which student report in a survey just after enrolment. We can see that the question: “Do you plan to finish the program you have just started”? gets a positive response from the majority of students, but with an essential difference between Bachelor and Master programs (the proportion of Bachelor students that has clear finishing intention is almost 8 points lower than that of the Master students). We can see the ratios for 2016-17 and 2017-18 courses in Figure 5.1, with a little increase of finishing intention for Master Programs and a slight decrease for Bachelor Programs.

Nevertheless, it is essential to recall that the focus of analysis of this dissertation are Bachelor programs, as they are the most important concerning the number of students. In chapter 3 we have seen that dropout in the first semesters seems to follow a similar pattern across all programs, as the probability of dropping out is very high the second semester, and then rapidly decreases until it reaches a relative plateau in approximately the fourth semester. This similar behaviour shows that some reasons for dropping out are out of the scope of a single program, and that there must be “transversal/general” reasons related to the institution considered globally and/or the inherent characteristics of the learner (level of motivation, e-learning readiness, etc.), which encourage a “general” study.

Although early dropout is, as we have seen, very important, it is interesting to give a brief look at the dropout phenomena at the middle-end of the program duration, even that dropout analysis at these stages of the program is not the objective of this dissertation. For example, in Minguillón & Grau (2013) the total duration of the program is considered. After the high initial dropout in the first semesters, it is not surprising that figures stabilise around the 6th / 8th semester, as this number coincides with the expected duration of the degree (3 or 4 years, depending on the case).

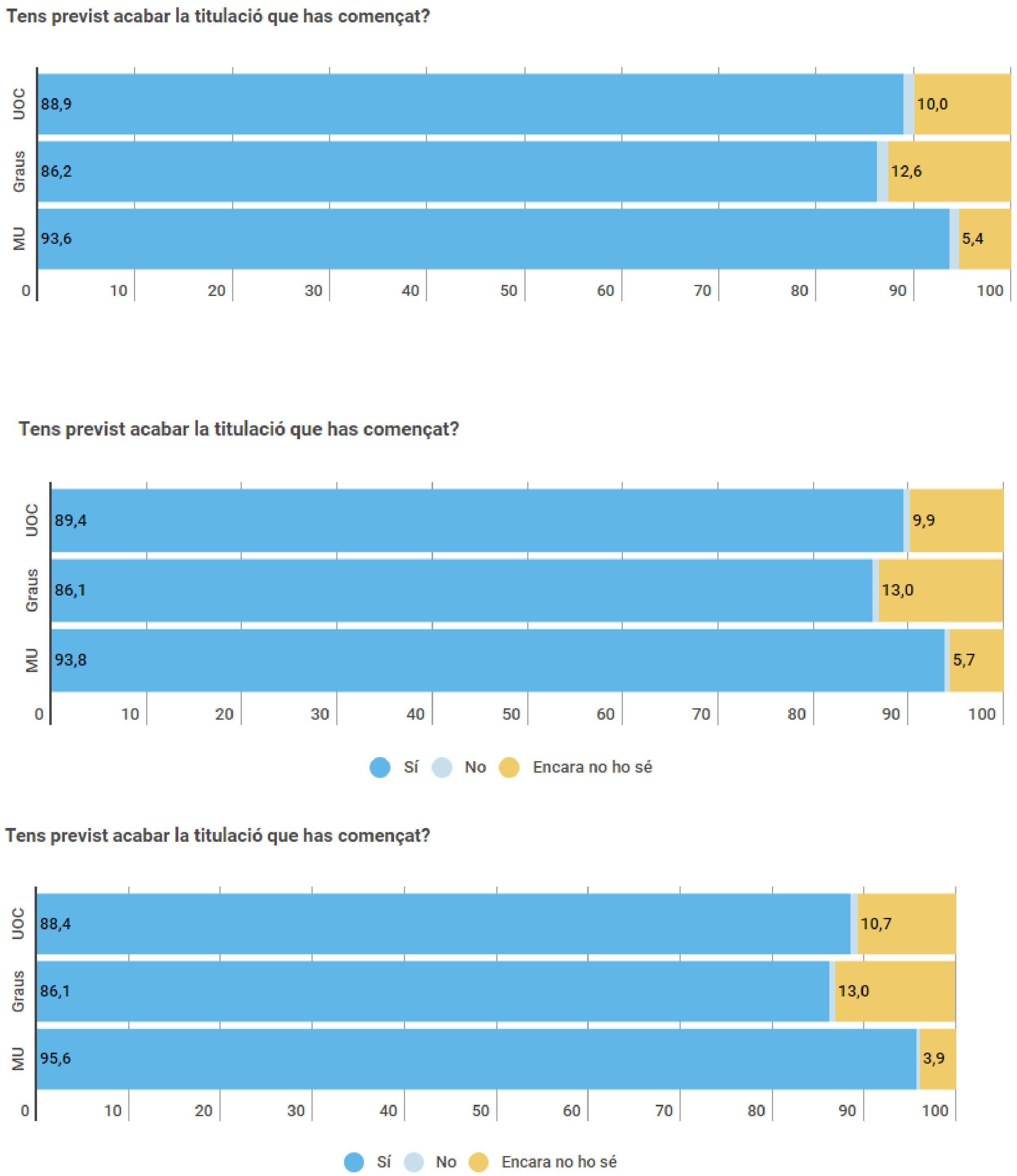


Figure 5.1: Finishing intention of first-year students: global, Bachelor and Master students. 2016-17, 2017-18 and 2018-19 courses (source: internal report at UOC)

Preliminary experiments show that students at UOC usually enrol in half the number of subjects each semester, so, on average, they double the expected degree duration. It is reasonable to think that students reaching the 6th / 8th semester with half a degree ”in the bag” have a different mindset than students in their first semesters. This fact may be used to explain dropping out using two different approaches: during the first semesters, dropping out may be caused by the clash between the student (becoming a student again for adult learners with different expectations and personal situations) and the institution (methodology, support, etc.). On the other hand, after the 4th / 6th semester, dropping out may be caused by attrition, that is, students that foresee that they will take too long to finish their degree and become disappointed (Kizilcec & Halawa, 2015; Reed et al., 2013; Ryan & Greig, 2017; Stiller & Köster, 2016). This group of students undoubtedly deserves the attention of the institutions in general, and UOC in particular, since they have invested a significant amount of time and money in their degree and could see their expectations frustrated in a big way in the middle of their programs.

Concerning the focus of the present dissertation on early dropout (in the second semester), it is crucial in online distance learning (Asdi, 2015; J. Grau-Valldosera & Minguillón, 2014; Nistor & Neubauer, 2010; Tyler-Smith, 2006). Once we have defined dropout and calculate it based on an empirical definition, the objective is to arrive at some results that allow us to answer research questions 2, 3 and 4, specifically:

- RQ2: Which variables or drivers are behind a clear intention to re-enrol in the next term, and on the same degree or program?
- RQ3: Which variables or drivers are behind the ultimate decision to re-enrol or to extend the break?
- RQ4: Which differences and similarities between the drivers we detect for continuance intention and effective re-enrolment?

Consequently, in chapter 4 we have incorporated in the analysis the relation of continuance intention of non-enrolled 2nd-semester students with their eventual re-enrolment in the 3rd semester. That long-span analysis is one of the main contributions of our research: although is frequent the literature on continuance intention in e-learning settings (Lin, Chen, & Fang, 2011; Rodríguez-Ardura & Meseguer-Artola, 2014; Zhang, Liu, Yan, & Zhang, 2016) and on re-enrolment or retention (Bawa, 2016; Boston, Ice, & Gibson, 2011; Cochran, Campbell, Baker, & Leeds, 2014; Herbert, 2006), our main contribution would be to combine the analysis of both continuance intention and re-enrollment for the same cohort of students in different points of time.

5.2 Discussing the 1st survey exploratory analysis

After having defined dropout in an online learning context in the 1st question, to characterise dropout at UOC and answer the 2nd to 4th research questions, a specific questionnaire was designed to determine the main drivers of continuance intention and re-enrollment at UOC. As was explained at the beginning of Section 4, we carried out two pilot studies, the first in February 2014 and the second in February 2015, with students who had not re-enrolled in the second semester (new students that enrolled in September of the previous year for each survey). These pilots served to advance in the design of the questionnaire. With the data of the February 2014 survey, bivariate analysis of a descriptive nature was addressed, which is published in Arxiv as a preliminary result.

In light of the results achieved with the 1st survey described in Section 4.1, we can affirm that 2nd semester break students with a positive continuance intention are not significantly different from those without this intention in terms of the socio-demographic and academic variables considered in our study ("student" or "environment" variables in Lee and Choi's terminology). It is remarkable that continuance intention models do not usually consider this typology of variables, except some recent exceptions like Ifinedo (2017) or Rodríguez-Ardura and Meseguer-Artola (2014), which include variables related to intrinsic motivation. In contrast, dropout models (Berge & Huang, 2004; Kember, 1989; Rovai, 2003) do tend to include these variables out of the learning experience itself. They effectively appear as significative in our results, specifically age and recency of previous college experience.

On the other side, we found that there exists a relation between the perceptions associated with the learning experience during the first semester and both continuance intention and effective re-enrolment. The positive attitude of students not enrolled in the second semester that declare their intention to continue in the next semester is based mainly on lower values for the motives for not re-enrolling in the 2nd semester (variables TIME, PERS, SYST, etc.). These motives lead to higher satisfaction with the main elements that constitute their educational experience: instructors, study system, joy of learning, etc. (Dağhan & Akkoyunlu, 2016; Rodríguez-Ardura & Meseguer-Artola, 2014). Additionally, these course-program factors that constitute the learning experience also appear to be related to effective re-enrolment (or dropout), although for a lower number of variables than continuance intention: satisfaction in global terms and adaptation to UOC study system. Both variables were relevant in the main dropout models presented in this dissertation.

Therefore, from the results of the exploratory analysis it can be affirmed that continuance intention is somewhat more rational, mainly related to the satisfaction with course-program variables, while the eventual re-enrolment is more pragmatic and would arise from a more complex decision process, in which other context variables related to the student and the environment would influence the final decision.

5.3 Discussing 2nd survey continuance intention and re-enrolment models

The results of the February 2015 survey were submitted and published (J. Grau-Valldosera et al., 2018). It's interesting to notice the few differences between the first and the second survey, concerning the number of questions suppressed, modified and added. Table 5.2 shows a summary of these changes:

	# total questions	# questions suppressed	# questions added	# questions modified
February 2014 survey	33	5	2	2
February 2015 survey	30	-	-	-

Table 5.2: Changes in the questionnaire between February 2014 survey and February 2015 survey

The improvement of the questionnaire served mainly to the objective of supporting a more sophisticated analysis, and, therefore, to the construction of more explicative models both for continuance intention and re-enrollment. As a "collateral benefit", cross-validation of the results obtained for similar questionnaires but using different methodologies (the first more exploratory, the second more predictive) could be undergone.

Applying logistical regression, we compared the effects of the variables considered on both the continuance intention and useful re-enrolment models. These effects can be classified based on the taxonomy proposed by Lee and Choi (2011), namely student, environmental and course-program variables, which has also been used similarly, more recently, by other authors like Bawa (2016).

Firstly, it is worth noting that both models have negative intercepts: we can affirm that, in general, students that take a break in the second semester do not have an intention to re-enrol in the next semester and the same degree, with even fewer eventually re-enrolling in the third semester. Figure 4.3 and Figures 4.4 provide a graphic representation of the flow of students from the break during the second semester to eventual re-enrolment in the third semester. Looking at these figures, we can affirm that the intention to continue of students who are taking a break from their studies is a necessary although the not sole condition of them effectively restarting their learning activity in the next semester, as almost all re-enrolled students have previously expressed their prior intention to continue.

Concerning to the interaction between student and environmental variables, being a woman seems to be related to having a higher intention to continue, but this intention is affected negatively when “personal costs” appear as one of the reasons for not having enrolled in the second semester (Kim, Sung-Wan. Park, 2015; Müller, 2008). To be employed full-time decreases the chances of re-enrollment in the third semester (Park, Perry, & Edwards, 2011; Tello, 2007), which is somewhat paradoxical given that online distance learning programs aim mainly at active professionals. However, it seems that students tend to adopt a pragmatic and “realistic” position when it comes to deciding re-enrolment.

Regarding the student factor variables, having university experience in the same knowledge area acts as a positive driver of effective re-enrolment, which is logical, since, in this case, students would be trying to finish an already-started program. This result is related to the negative impact that the interaction between having a university experience in a knowledge area different from the one they study at the UOC and the perception of too much time devoted to studying has on the intention to continue. Also worthy of comment are the results for the previous e-learning experience variable. The fact that they act as a negative driver of re-enrolment (both in terms of intention and effective re-enrolment, especially when there is the perception of a great deal of time invested in the program) is quite surprising if we consider previous research which has stated just the opposite (Hachey, Wladis, & Conway, 2012; Shea & Bidjerano, 2014). One possible interpretation would be that the previous e-learning experience was in easier or shorter courses than the ones taken at the UOC, but the survey did not gather enough information to attest this. Nevertheless, higher education institutions should try to state this difference clearly, as some students might have a wrong idea about online degrees.

In regard to the motivations for choosing the UOC, the intention continuance model harks back to an important part of the motives that existed at the time of first enrolment: those related to the learning methodology (specifically: flexibility, continuous assessment and saving time) as well as having a good opinion of the price paid. Some notable differences occur in comparison to the effective re-enrolment model: saving time helps ideally to build a positive continuance intention, due to the convenience of online distance learning. Anyway, at the moment of truth, when it comes to re-enrol in the third semester, it is a handicap, probably because the student really does not have so much spare time when this is one of the main drivers of continuance intention. The same happens with having a good opinion of the price: this contributes to a positive intention to continue, but in the end, it is not enough. The mere fact of getting a good deal will not motivate students to continue if they lack the time that needs to be invested to pursue the course successfully, as time would be a more scarce resource than money. An extreme example of this case is that of MOOCs, which are free, although it can be debated that the main motivation for taking these courses is not so much completing them but getting to try out new content (Bakki, Oubahssi, Cherkaoui, & George, 2015). Finally, the fact that motivators such as living far from a traditional university or the prestige of the online distance learning institution are significant only in that the re-enrolment model confirms the more pragmatic tone for the re-enrolment decision we detected in the exploratory analysis.

Apart from the motivations for having chosen a specific institution, the motives for having restarted university studies in the first semester are also different between continuance intention and re-enrolment models. Furthering one’s career is a positive stimulus for continuance intention while obtaining a certain degree (“academic reasons”) or simply enjoying the study experience (study for pleasure) act as a deterrent. In a realistic approach to effective re-enrolment, we can see that extrinsic motivational issues (studying to further one’s career or to obtain a certain degree) are re-enrolment factors in line with the findings of Johnson, Stewart, and Bachman (2015) or Hartnett, St. George, and Dron (2011). Thus, there seems to be some contradiction, since furthering one's career acts as a positive driver of re-enrolment while being currently working acts as a negative one, as we have seen earlier in the discussion on the effects of environmental factors. There is probably a tension between both variables that is decided for the second when the hours dedicated to work are excessive. As a matter of fact, only one out of five graduates at UOC apply directly to their job the competencies acquired in their degree (Agència per a la Qualitat del Sistema Universitari de Catalunya, 2011) which would indicate that, when we are talking about careers, we should probably take into account other dimensions out of the professional one.

The variables related to motives for not re-enrolling in the second semester deserve thorough analysis (shown in Table 5.3), as they point directly to dissatisfaction with course-program factors. Apart from small differences, almost all of them are significant in both models and have a negative relation with continuance intention and effective re-enrolment. Bawa (2016) is one of the authors that stresses the importance of institutional factors, especially the "lack of instructor understanding of online learners", or "faculty limitations of using technology" and, last but not least, "institution limitations to training faculty".

	Change between models		
	Continuance Intention	→	Effective re-enrolment
Factor Time	+	→	n.s.
Factor Personal	-	=	-
Factor System	-	→	n.s.
Factor Difficult	-	=	-
Gender * Factor Personal	-	=	-
Factor Time * Factor Personal	-	=	-
Factor Personal * Factor System	+	=	+
E-learning * Factor Time	-	=	-
Univ. experience at the same area * Factor Time	n.s.	=	n.s.
Univ. experience at other area * Factor Time	-	→	n.s.

Table 5.3: Factors of continuance intention / effective re-enrolment

Commenting on the specificities of the two models:

For the continuance intention model, paradoxically, perceiving the time devoted to the program in the first semester as excessive has a positive impact on continuance, which we can interpret as more significant implication with the program on the part of the student (Kahu, Nelson, & Picton, 2017). However, when the "Time" factor interacts with the "Personal" factor, the effect is negative and, eventually, the impact on the decision to finally enrol will be negative. The reason is that the student perceives that additional time will have to be dedicated to studying, detracting from personal time and resulting in having to make a more significant effort to balance one's personal life with academic duties. The positive result for "Factor Personal * Factor System" interaction would counter the main negative effects that both show as separate variables, one possible interpretation being that UOC's study system requires a high degree of personal implication and motivation, and when this implication exists a positive result is shown on continuance intention (Deimann & Bastiaens, 2010; Holder, 2007; Johnson et al., 2015; Kim & Frick, 2011).

For the effective re-enrolment model, evidence would indicate that the key element at the time of re-enrolment is not how the study experience has been perceived in objective terms, such as time invested or e-learning system assessment. The main issue would be how this experience has finally affected the students' day-to-day life (their feeling that it was difficult or that they had to sacrifice personal time). The last sentences would be the interpretation of the third first row of Table 5.3. The explanation for the interaction between the "Personal" and "System" factors would be the same as that given in the continuance intention model.

It is important to note that basal models hardly change when course-program factors are added from basal models (which consider only socio-demographic, academic and personal motivation variables) to the complete models, which would indicate that both environmental and student variables have a continuous effect, from intention to final re-enrolment. However, the effects of adding items for the course-program factors are much higher in the continuance intention model than the re-enrolment one, as is shown in Table 5.4 and Table 5.5.

Continuance intention model		
	Basal model	*Final model*
Cox-Snell pseudo R-squared	0.3288	0.6303

Table 5.4: Change of goodness of fit from basal to final continuance intention model

Final re-enrolment model		
	Basal model	*Final model*
Cox-Snell pseudo R-squared	0.555	0.779

Table 5.5: Change of goodness of fit from basal to final re-enrolment model

The reasonably positive values of the goodness of fit of the calculated models would support the decision of having used a questionnaire adapted to the specific characteristics of the UOC. Even this specificity, as mentioned on Section 4.1.1, the structure of the survey draws from the theoretical framework, trying to capture variables in each of the three dimensions found in the literature review (Lee & Choi, 2011). The design of the questionnaire, therefore, would facilitate its adaptation to other institutions, starting from a shared general structure and adapting the questions to the specific characteristics of each university.

Therefore, from the results of the exploratory analysis it can be affirmed that, on the one hand, continuance intention is more rational, even logical, and is based on the level of satisfaction or dissatisfaction with the factors that comprise the educational experience, such as the perceived difficulty of the learning materials or the opinion of the learning system. Moreover, the continuance intention model accounts for how these elements have impacted the day-to-day life of the students, in terms of the time invested or personal costs incurred. On the other hand, the effective re-enrolment model is more practical or pragmatic, placing more importance on the effects of the variables of the student dimension, such as motivations related to studies and previous university experience, or environmental variables such as having a job (Choi, Lee, Jung, & Latchem, 2013; Rodríguez-Gómez, Meneses, Gairín, Feixas, & Muñoz, 2016).

5.4 Comparative of results between exploratory and predictive analysis

The main statement that can be made based on the comparison of both models is that the outputs from applying both methodologies with the results of the two surveys are very similar, which would implicate a reciprocal validation of results. As explained in sections 4.1 and 4.2, the factors related to online learning dropout detected by Lee and Choi (2011) were used to elaborate a questionnaire adapted to the specific characteristics of UOC students and methodology. Some later contributions have been included in the analysis to validate the questionnaire (Bawa, 2016; Grau-Valldosera & Minguillon, 2017) so we can have a reasonable grade of certainty that the survey has captured the main aspects of the reality. The last thing is assured by the R^2 indexes for both the continuance intention and the re-enrolment model, shown in Table 5.4 and Table 5.5.

5.5 Some considerations about considering the positive path in our analysis

From the figures that represent the flow of students from second semester break to re-enrolment or dropping out in the third semester (Figure 4.4), we can observe that the ratio of re-enrollment in the third semester, obtained with the division of the number of students re-enrolled over the total number of students in a break situation, is of 6.2%. Independently of the fact that we need to include this small subset of students to answer our research questions, these poor ratios would not seem, at first sight, to justify the effort invested in the analysis of the positive flow of break students from continuance intention to re-enrolment. Anyway, it is noticeable that completion ratios –above dropout ones- are the most common perspective in official Higher Education statistics like OECD (2014).

If we consider the most usual analysis of the negative flow, that is, the focus on students that finally drop out, we see that this has been one of the prominent research subjects in higher education, including distance education and, more recently, online learning. Paradoxically, this effort has obtained very few fruits in the form of reduction of dropout ratios. For example, we presented in Table 2.4 increasing dropout ratios for the 1st year Bachelor students in Spain from 2010-11 to 2011-12 course (from 21.2 % to 22.9 %[16]), or, in Australia, Beer & Lawson (2017) stresses the importance of distance learning dropout:

> *"A more recent example can be found in the report of Garret (2018) about higher education and inequality in the US, in which is affirmed that we are in front of a "conundrum" in which fully online delivery widens access, but lowers odds of completion."*

So, it seems that looking at the positive path would seem that it deserves an opportunity. One doubt that naturally appears at this point is what part of information are we losing if we focus only on the analysis of surviving students (or, the other way around, only on dropout ones). Another way of seeing this is reasoning if the drivers that explain retention are the same drivers that would explain dropout (obviously, with an opposite sign). An elegant analysis undergone by Wald (Wald & Ellenberg, 2016) would add some light on the matter. Wald was a

[16] There is no more recent data available.

mathematician that was asked to analyse the American planes that came back from engagements over Europe during the Second World War, and which were covered in bullet holes.[17] But the damage was not uniformly distributed across the aircraft. There were more bullet holes in the fuselage, not so many in the engines. The immediate reaction would be to beef up the fuselage, but Wald's insight was simply to ask: "where are the missing holes? The ones that would have been all over the engine casing, if the damage had been spread equally all over the plane?" Wald was pretty sure he knew. The missing bullet holes were on the missing planes. The reason planes were coming back with fewer hits in the engine is that planes that got hit in the engine were not coming back.

If we try to make the analogy of the survival analysis unerdrgone by Wald with dropout analysis, probably some attributes do not appear in continuing students that have been one of the causes of dropout for students that eventually take a break in the 2nd semester and therefore do not show up in the 3rd. Alternatively, students that eventually decide to re-enrol in the third semester may incorporate new information into the model that we could not anticipate before. In short, the last image of students is not enough to have the whole picture, and we need information both from students that drop out (aeroplanes that do not come back) and from students who re-enrol (aeroplanes that return). This dissertation analyses both moments: the one "just after the battle", when students are taking a break after the first semester, and when they come back at the beginning of the third semester.

5.6 Stability or change? Dropout as a "wicked problem."

Facing the two models for continuance intention and re-enrolment, both capturing the most of the variability of the objective variables, a question arises around the stability of the models built in this dissertation. We can question this stability from two these two dimensions, and how they can change over time:

- The variables of the models: do the models gather all the relevant variables to explain continuance intention and re-enrolment?
- The models themselves: the relations between and weights of the variables that contain the model are fixed or variable?

[17] The full story can be read in Annex 3.

Concerning the two previous questions, new perspectives have arisen that take into account the complexity and variability of the higher education context (and specifically the online learning one). Beer and Lawson (2017) introduced the concept of “wicked problem” to explain attrition in higher education. Wicked problems cannot be strategically addressed using traditional approaches to problem-solving (that is, building models). The practical implications of this approach reinforce that current approaches to attrition are likely to fail. The authors affirm that the increased flexibility of study options and delivery models has led to complex and often controversial definitions of student attrition. Attrition can refer to a student withdrawing from a course, cancelling their programme, failing to re-enrol in the next term, accepting their offer but not completing their enrolment, accepting their offer, enrolling but failing to attend classes and so on. Aso Rovai (2003), as we have seen in Section 2, stated that “there is no simple formula that ensures student persistence”. This dissertation would have solved this dilemma opting for a definition based on empirical analysis at a program (Bachelor) level. Apart from the difficulty of definition, it is important to consider that student attrition is an extraordinary complex and multifaceted problem, which is challenging to address. The multiplicity of variables that make us categorise us the dropout issue as a “wicked problem” would add to the justification of having used a questionnaire adapted to the UOC.

Additionally, an important variable that would highlight the importance of student motivations to study and put in question the consideration of dropout as a failure (at least from the point of view of the institution) is the possibility of not finishing, that is, partial completion (Luckman & Harvey, 2019; Ryan & Greig, 2017). Partial completion would be a planned strategy of students just at the beginning of their programs. In the case of UOC Bachelors, we have seen previously that this value was around 14 %[18]. Considering dropout also from the initial motivations of new students would offer with no doubt new insights to the problem and even question the validity of the models reached so far.

On the other side, in the era of “Big Data”, new information technologies, especially learning

[18] Including students that did not have a clear finishing intention

analytics, cannot be underestimated. The philosophy behind the resolution of wicked problems would require the collection of instant information from various sources of the institution in order to enable collaboration and rapid response through predictive analysis and statistics simulation ("agile modelling") between the different stakeholders of the university involved with the attrition problem, from teaching methodologies to academic processes (Forsman, Linder, Moll, Fraser, & Andersson, 2012). Learning analytics can be used to help personalise and adapt learning and academic processes to different student typologies, and also to the evolving context of academic periods. This new approach would situate the dropout problem each time not only in the student sphere but also in the institutional arena.

5.7 Dropout as a loyalty issue

Keeping in mind the positive path that has guided research all through this dissertation, another way of approaching the dropout issue would be incorporating the concept of loyalty, mainly from the business/management discipline.

Continuance intention in online learning is a construct that has already been analysed by various authors (Cho & Heron, 2015; M.-C. Lee, 2010; Rodríguez-Ardura & Meseguer-Artola, 2014), but the analysis of the concretion or materialisation of this intention in effective re-enrollment has not received much attention in the literature. We find this gap in attention quite surprising, given the widespread existence of breaks in an adult distance learner context (Hachey, Wladis & Conway, 2011; Nora & Snyder, 2009). It is worthy to note that here we are adopting a long-term definition (J. Grau-Valldosera & Minguillón, 2014) of the concept of dropout for its analysis, approaching it from a programme perspective and taking into account the continuance of students after one or more periods of non-enrolment. This completely differs from the single course perspective taken in the majority of the literature on online learning dropout mentioned previously, in which the continuance perspective does not exist.

Additionally, we think that interesting parallelism can be drawn between the concepts of continuance intention, followed or not by effective re-enrolment, and that of loyalty. Loyalty, from a management perspective, can be understood as a favourable attitude to repurchase or an effective repurchase behaviour. The relation between very high levels of satisfaction and loyalty is relevant in most sectors (Bowen & Chen, 2013; D. Lee, Moon, Kim & Yi, 2014).

This analysis of continuance as loyalty can undoubtedly enrich the current vision of the enrolment/break behaviour of online learning students. Nevertheless, more recent viewpoints have considered a composite measurement of both dimensions (Frisou, 2005; Lichtlé, 2008). Some references exist about the relationship between satisfaction and loyalty in the educational arena, both in face-to-face higher education institutions (Serenko, 2011; Temizer & Turkyilmaz, 2012) and in an online learning context. There it can be noted that a favourable attitude has been measured much more than behaviour as a dimension of loyalty, as can be seen in Chiu et al. (2005), Lin, Chen & Fang (2011) or Wang & Chiu (2011).

Looking at Lichtlé (2008), in a general analysis of consumer loyalty, satisfaction does not influence repurchase behaviour, although it is a "necessary but insufficient condition of loyalty":

> *"However, while this link is considered obvious in managerial literature, it is currently debated in academic circles. Certainly, relations can easily be established between satisfaction and loyalty intentions (Ngobo and Gharsallah, 2004), or satisfaction and attitude (toward loyalty behaviour) (Frisou, 2005), but the link between satisfaction and actual loyalty behaviour is less obvious."*

Concerning the previous affirmation, Oliver (1997) states that "satisfaction does not influence repurchase behaviour; it only affects the emotional phase of loyalty. It is, therefore, a necessary, but insufficient, condition of loyalty."

Interestingly, we can derive very similar conclusions from our research if we establish a parallelism between "loyalty intention" or "repurchase behaviour" in consumer loyalty terms and continuance intention and effective re-enrolment. Although online learning dropout or continuance is multidimensional both from an intention and an effective re-enrollment behaviour perspective (Gazza & Hunker, 2014), satisfaction with the product (in our terms, course-programme variables) would play a more determinant role in continuance intention ("loyalty intention") than in the final re-enrolment ("repurchase behaviour") decision, which would have more influence than the student and environment dimensions.

6 Conclusions

A general overview of HE dropout

Dropout in higher education is not a new problem, and in the present context of the expansion of access and scarcity of public budgets, it has acquired renewed relevance. Official HE statistics put the focus on completion as one of the main priorities (OECD, 2018; Vossensteyn et al., 2015). We have to notice that financial costs of dropout are only part of the total costs: non-pecuniary (or affective) costs –more challenging to measure –are also crucial for dropout students (Beer & Lawson, 2017; Johnes, 1990), along with the loss on institutional reputation.

Far from being less critical, the dropout issue has also an important presence in the field of distance and online distance learning. In fact, in parallel with the advantages that online distance learning can offer to institutions and also to students, it has to be considered that one of the most significant minuses attributed to distance education is the burden that comes with high dropout rates (Cho & Heron, 2015), especially at the first stages of programs, named *early dropout* (De Santiago Alba, 2011). Not surprisingly, desertion has been one of the most researched problems in higher education[19]. Even that enrolment patterns are different between distance and face-to-face learning (distance students drop out more, earlier and take twice as long to graduate), both modes of delivery share dropout as a burning issue and a research objective. Unfortunately, despite the considerable effort invested in its analysis, dropout ratios seem to be immune to reduction: taking, for example, the case of Spain (Ministerio de Educación, 2016), we see that dropout rate for distance learning is quite higher than that for face-to-face learning: 60.5 % vs 24%, respectively.

Defining dropout

Considering the importance of dropout from institutional and personal levels, it is remarkable, and somewhat surprising, that international comparative data on this issue is only partial and not updated.

[19] A simple search returns 8476 results in ISI WoS (considering a search by subject) or 9022 in Scopus (considering a search by Title, Abstract o Keyword), using "(dropout OR retention) AND higher education", as search query as of 10th May 2019.

This gap of information is mainly due to the lack of periodical data in some countries and also, when data exists, to the differences that generally appear in dropout definitions among higher education systems. Related to the shortage of data on higher education dropout in the European Union report (Vossensteyn et al., 2015), there is also a lack of systematic knowledge, data and indicators on study success in Europe. This dissertation concludes that a clear definition of study success (and, reciprocally, dropout) is the first step towards a more effective policy design.

From an academic perspective, one of the authors who has put great emphasis on creating a university dropout framework is Vincent Tinto (19º). Tinto stressed the importance of reaching a good definition of university dropout, which he saw as essential as detecting the causes of this dropout. For the specific case of online distance learning, the summary of online dropout studies given in Lee and Choi (2011) literature review shows the heterogeneous nature of several definitions of dropout. There does not seem to exist a consensus on which is the dropout definition, as sometimes this is based on a formal declaration of students, or a consequence of not-enrolling in the next academic term, or even as an opposite to what is considered to be retention in each institution. It is remarkable that in many cases, most research goes forward without an agreed definition of dropout.

Consequently, this dissertation wants to make an effort to find a suitable dropout definition adapted to UOC students. The best way to overcome the mentioned complexity of dropout is basing its definition on evidence, specifically, on an objective analysis of the enrolment and break behaviour of students. This analysis focuses on bachelor programs held in Catalan from 1994 to 2007, before the establishment of the European Higher Education Area, which introduced changes significant enough to make advisable a focus on pre-Bologna programs (and at the same time allowed to have an extensive set of historic enrolment data). The objective underpinning the search of a specific definition was to see whether there is a simple way to establish a criterion to differentiate breaks from true dropouts. We have made a probabilistic analysis of each program, specifically of the number of consecutive semesters of break (N) that trigger that a given student of a given program is considered to be a dropout (with a probability lower than 5% of returning).

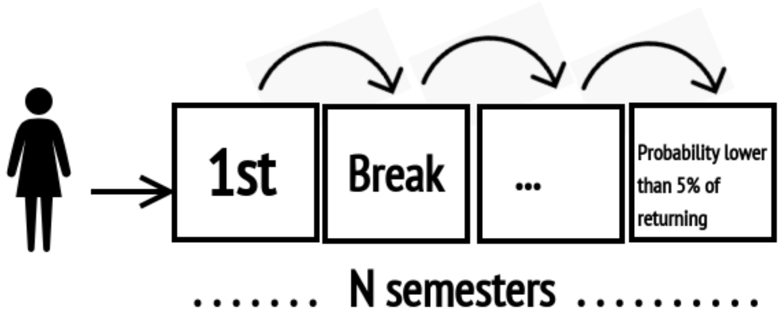


Figure 6.1: Graphical representation of our dropout definition.

Measuring dropout

Empirical analysis has brought us to consider a broader perspective than the predominant in the literature review, which is the course perspective; even that dropout appears in each course and each semester, the real path of student academic life –and therefore also of dropout- takes place at a more long-term length: that of the program. More than a static definition, we can affirm that such empirical analysis has led us to a flexible definition -that takes the form of an algorithm- which has as a result a different value of N for each program. This flexibility would also allow us to apply this definition to varying programs at UOC or even at other institutions. It is also noticeable that this method of calculation is especially valid for distance-online learning institutions, where students have higher work and family time constraints and therefore a more generative enrolment behaviour with a higher probability of taking a break.

Another consequence of building this definition over objective analysis is that in most cases, we do not consider students' subjectivity: some students do not think themselves to be dropouts, even that the institution labels them as being so. They may be just waiting for a better moment to come back, or, on the other hand, they may consider that they have obtained what they needed from a partial study of the contents, without having the intention to finish the program. Therefore, from an institutional point of view, the definition of dropout will always be harsher than reality.

With such definition, we can calculate the different values of N for each program, ranging from 3 to 5; additionally, we can compute the percentage of dropout students, which goes from 37% to 67 %

for total dropout, and 16 % to 29% for the first-semester dropout.

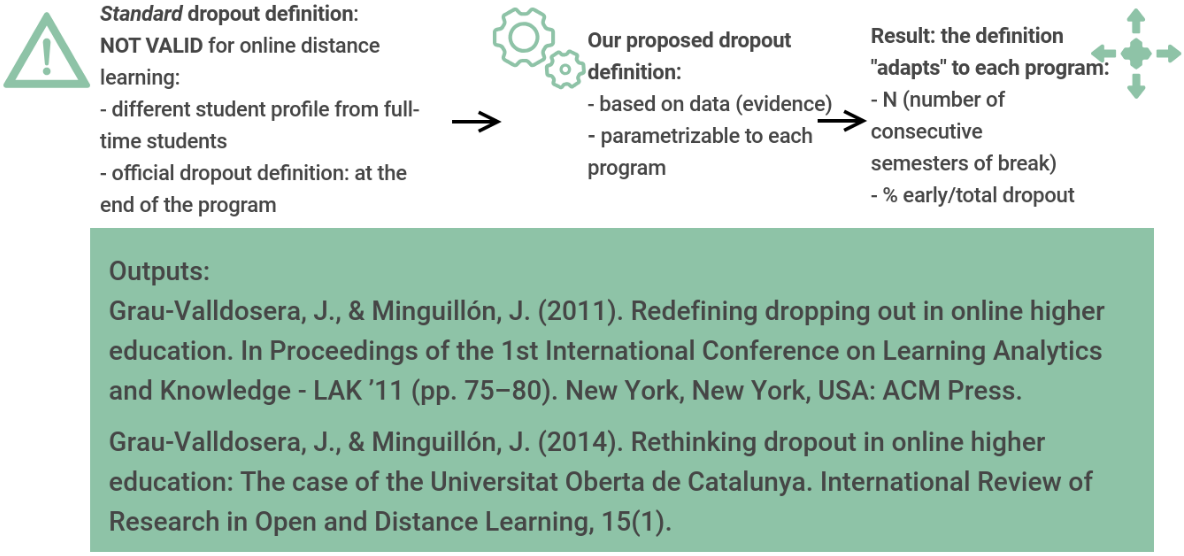


Figure 6.2; Synthesis of the dropout definition process

Initial analysis of these results shows that there appears to be no relationship between the type of program content, that is technical or humanistic, but it is the number of semesters that determines dropout: shorter degrees have lower dropout ratios. From a complementary perspective that would in some way confirm our results, other research at the UOC shows that students taking shorter degree courses at UOC are much more likely to complete their degrees (Castaño-Muñoz, Carnoy, & Duart, 2015). Therefore, students enrolled in shorter programs decide earlier if they drop out and, in the end, finish their programs with a lower dropout level. This higher rate of completion of students enrolled in shorter programs could be related, among other things, to a higher finishing intention, which is one of the results of an internal survey received by students just after enrolment (in this case, for Bologna programs).

Importance of early dropout

Even though differences exist between the N value for each program, and the % value for total and early dropout, all programs keep something in common: the high probability of dropout after a break (especially when this break is in the second or third semester), as shown in Figure 3.3:

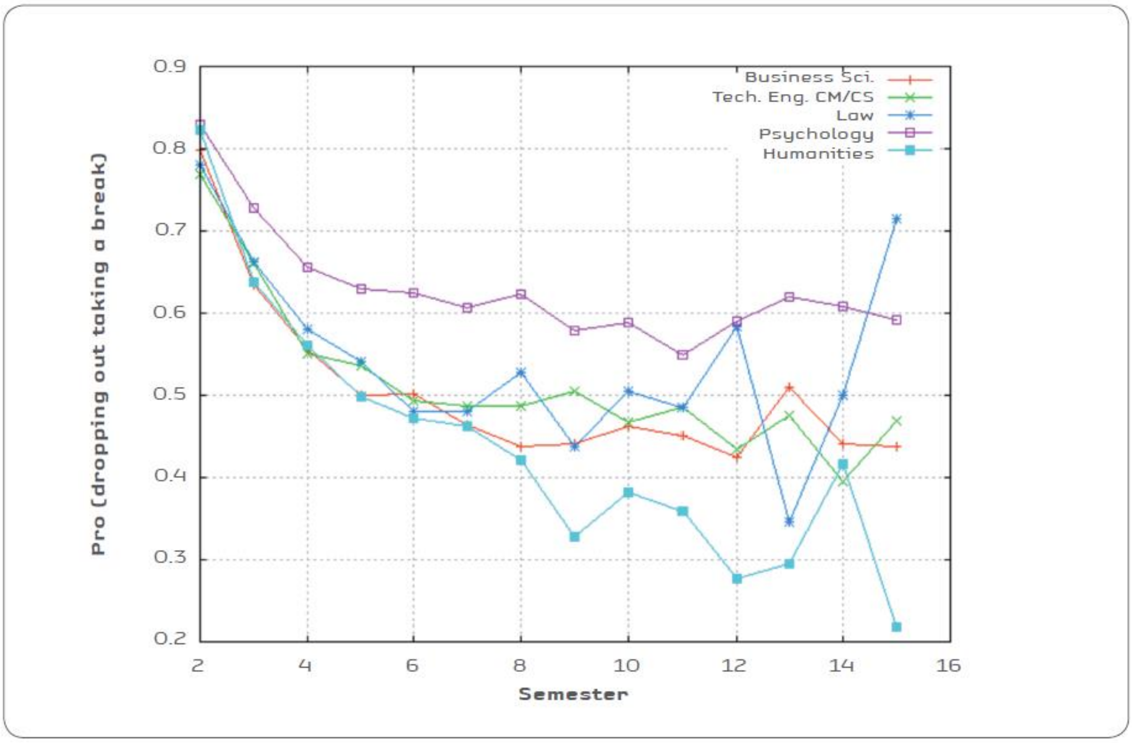


Figure 6.3: Probability of turning a break into a dropout situation.

This high probability of dropout after a break goes hand in hand with an average proportion of almost 25% dropout for all programs analysed: dropout at UOC happens mostly in the second semester.

Output:
Grau, Josep; Julià Minguillon. "When procrastination leads to dropping out: analysing students at risk." eLearn Center Research Paper Series [en línia], 2013, , p. 63-74.

We related the early dropout phenomena with the procrastination concept. Academic procrastination is defined "as intentionally deferring or delaying work that must be completed" (Schraw, Wadkins, & Olafson, 2007). Understanding procrastination in the sense of taking a break of one or more semesters, it can be observed that this is not uncommon at distance universities (due to their relaxed enrolment requirements), as students have more opportunities to decide how many subjects they take each semester and their pace.

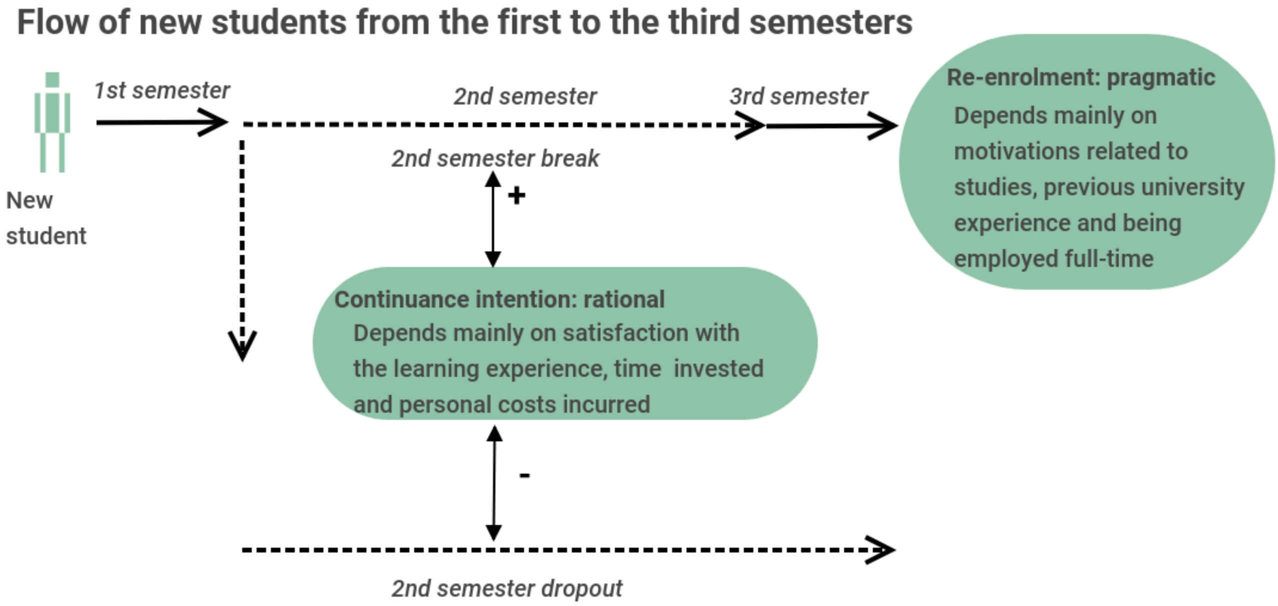
Characterising dropout

With a focus on early dropout, fruit of a long-term perspective in our analysis (Mor, 2009), we have formulated research questions that try to characterise not only dropout but also a previous state of mind: continuance intention (level of motivation to continue) of students that take a break in the 2nd semester and their eventual retention in the 3rd semester. Taking into account that the dropout phenomena goes in parallel to that of retention, we have undergone a longitudinal analysis that puts the focus on the *positive path* of students through their programs, from their continuance intention in the 2nd semester to the further validation of this intention as re-enrollment in the 3rd.

Literature review confirms what would be a previous assumption: that online learning dropout, as well as continuance intention, is a multifaceted problem, where various dimensions play their game. Firstly, the student dimension with their academic background, motivations, attitudes, skills and so on; secondly, the course/programme factors which include course design, institutional supports and interactions; thirdly, environmental factors like supportive study environments and work commitments. We designed a questionnaire based in the three mentioned dimensions adapted to the UOC context to gather more relevant information.

The analysis of the survey results can be briefly summarized as follows: on the one hand, continuance intention is more rational, even logical, and depends on the level of satisfaction or dissatisfaction with the factors that comprise the educational experience, such as the perceived difficulty of the learning materials or the opinion of the learning system. Moreover, the continuance intention model accounts for how these elements have impacted the day-to-day life of the students, in terms of the time invested or personal costs incurred. On the other hand, the effective re-enrolment model is more practical or pragmatic, placing more importance on the effects of the variables of the student dimension, such as motivations related to studies and previous university experience, or environmental variables such as having a job.

Arrived at this point, we have to highlight an essential fact: a positive continuance intention is a necessary (although insufficient) condition for future re-enrollment, as the variables that are related to continuance intention are, fundamentally, different from those that are related to re-enrolment.



Outputs:

Grau-Valldosera, J., Minguillón, J., & Blasco-Moreno, A. (2018). Returning after taking a break in online distance higher education: from intention to effective re-enrollment. Interactive Learning Environments. https://doi.org/10.1080/10494820.2018.1470986

Grau Valldosera, J. (2017). Returning after taking a break in online higher education: from intention to effective re-enrolment. Retrieved from http://hdl.handle.net/10609/94446

Exploring the positive trail

From the data analysis, we know that break prolongation in the 3rd semester is almost synonymous with dropout, which we also see in Figure 6.4: only 6.2 % (74 over 1,189) of non-enrolled students in the 2nd semester re-start their studies in the 3rd. Interestingly, if we make this proportion only for the students that answer the survey (37/380), it goes up to almost 10%. It might seem that answering the survey is an element that anchors the students to the program, contributing to their re-enrollment in the third semester, although it is probably just another trigger for self-selection bias.

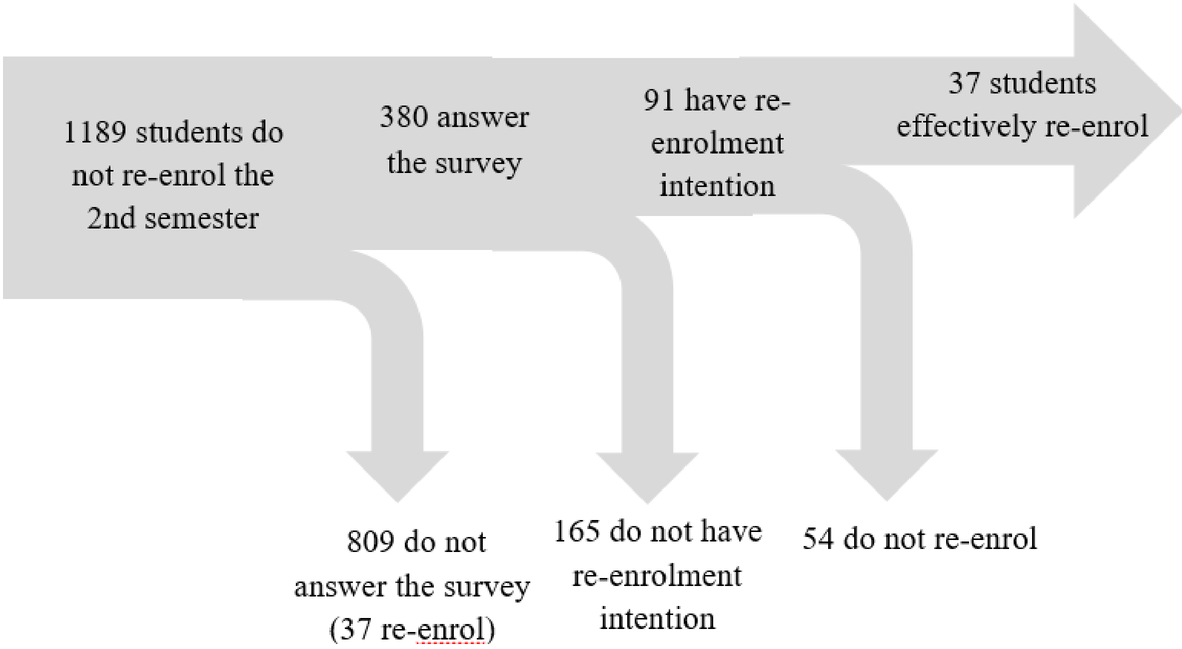


Figure 6.4: Flow of students from 2nd-semester break to eventual 3rd-semester re-enrolment.

This longitudinal analysis is, as has been stated previously, one of the main contributions of this dissertation, along with the dropout definition explained already. From another point of view, one of the main contributions of this dissertation would be not studying dropout and retention as two parallel realities, even not as two sides of the same coin. Dropout and retention are two different but interrelated problems, both of high complexity, being –at UOC- the first (dropout) more based on a passive attitude, and the second (retention) grounded in a more active decision.

Another practical learning from this dissertation would help to break another stereotype: that of the specific characteristics of distance education students (adult people with work and family obligations), which are not behind the 99% of dropout decision. This way, these unique characteristics are no more a big excuse for not taking action in dropout reduction policies. Therefore, higher education institutions have an essential part of responsibility and action margin, through the introduction of changes in their academic and teaching processes, and, concerning the variables over which they do not have influence (student and environmental ones), increasing their knowledge of the relation of these variables with continuance intention. A positive continuance intention is essential for driving the students to a final re-enrolment or dropout decision.

This responsibility is not exempt of difficulty: recent approaches to the attrition issue (Beer & Lawson, 2017) have classified it as a “wicked problem”, that is, problems that cannot be strategically addressed using traditional approaches to problem-solving (that is, building models). The practical implications of this approach reinforce that current approaches to attrition are likely to fail. The philosophy behind the resolution of wicked problems would require the collection of instant information from various sources of the institution to enable collaboration between the different actors involved in the fight against dropout.

In summary, dropout and retention are organisational challenges of the first order and increasing complexity, but at the same time there exist a growing set of analytic tools and base of knowledge that, along with increasing levels of collaboration between the organisation stakeholders, can provide decisive tools to solve these challenges.

Potential impact of this dissertation

The last paragraph sketched out some of the clues of the internal impact of the results of this dissertation at UOC. One of the more immediate applications of results would be to test the use of the dropout definition, the survey and the models for continuance intention and effective re-enrolment to other programs at UOC (especially master programs). The exploration of specific programs, those with more students and therefore, more available data, would permit to design specific actions for each program. Additionally, also putting the focus of research in later semesters would help to obtain a complementary vision to that of early dropout, which has been the focus of this dissertation.

The external impact would depend on the exportability of the definition and the continuance intention and re-enrolment models to the idiosyncrasy of other institutions. This would also be an exciting area of validation and would allow comparing total dropout ratios, differences in classification accuracy of continuance intention and re-enrolment models and, possibly, to assess the need for new variables. Concerning the definition, even though we have designed it as an algorithm easily instantiable to diverse contexts, it is interesting to consider the commonalities and differences between some of the leading online distance learning providers, as we can see in Table 2.7 of Section 2. These differences and, above all, the common points are those that would condition the applicability of the results obtained in the UOC to other institutions, as all these specificities shape enrolment patterns and should be taken into account when analysing dropout.

Concerning to the models of continuance intention and re-enrolment, the external impact seems to be less direct than it was for the definition algorithm, but, anyway, the main dropout dimensions detected by Lee & Choi (Lee & Choi, 2011) and Bawa (2016) seem an excellent basis on which to build models adapted to each institution.

Future research

The consideration made in the discussion section of dropout as a wicked problem (Beer & Lawson, 2017), that is, a complex, non-linear problem, makes us think more in a constant revision of models than in their rigid application. Attending to the nature of wicked problems, we see that the interconnected networks of factors that contribute to attrition are contextually dependent on specific student context, and this makes it a challenging issue for universities to address. As stated in Beer & Lawson (2017), the culminating influence of a range of factors that are interconnected between the micro, meso and macro levels can cause a student to drop out of their studies. This complexity makes it difficult for a university to map the causes of attrition to develop or target support interventions. The development of a single vector linear solution will fail to address the interconnectivity of factors that contribute to the student's decision to leave. Knowing that the factors that lead to student attrition are related and changing also creates uncertainty amongst decision makers about the path forward. The uncertainty associated with wicked problems engenders a high degree of conflict, as there can be little consensus on its resolution. A new line of research from a "wicked approach" would undoubtedly offer unique opportunities for analysis.

Without little doubt, the consolidation of technologies like learning analytics can help to address research back to the student (the individual student) dimension, along with the institutional one we have emphasised in this dissertation. For example, in the mentioned work of Bawa (2016), the author points to the solutions the institutions can provide, for example in the form of orientation programs and also of better preparation of faculty. From the student perspective, Tinto advocates seeing the problem of dropout literally "through the eyes of students" (Vincent Tinto, 2017). Related to this, it seems interesting to consider further research with the alleged anchoring power that appears to have the questionnaire sent to students in a break situation.

One of the variables that belong to this student dimension and will introduce a factor of disruption to the present models is the non-existence, from the very beginning, of an intention to finish the program on the part of the students. This non-finishing intention would be related to the objective of students of acquiring knowledge, or only certain skills, more specific than the contained in the whole program. A fact associated with the non-finishing intention is the enrolment to other programs different than the one started at UOC[20]: from the 1,189 students non-enrolled in the second semester, 111 re-enrolled in the third: 74 in the same program, but the other 37 in different programs. Very likely, these 37 students should not be classified strictly as dropout students, and deserve more thorough research.

The possibility of translating loyalty models from the marketing arena to higher education also appears as a new ground of research, even more, when we put the student at the centre of the research. Another area of possible exploration also pointed by Bawa (2016) would be the analysis of the relation that instructors have with the higher education institution and how this relation and their level of fulfilment has an influence over the satisfaction and, eventually, enrolment behaviour of students.

The confluence of dropout theories and the progressive blurring out of the differences between online learning and traditional face-to-face learning in the form of blended systems or, more generally, ICT facilitated teaching methods would also open new possibilities of study through mutual enrichment of variables and models between both modes of delivery.

Last but not least, the calculation of the economic cost of dropout is a challenge that would permit to justify –if that was needed at this point- the efforts invested in dropout analysis and reduction.

Recommendations

Besides exploring into one or several of the future research opportunities abovementioned, the more immediate actions seem to point to the application of the results of this dissertation, including the systematisation of the questionnaire to 2nd-semester students in a break situation. Additionally, it

[20] And the possibility of enrolment at other institutions, which is an information we do not have access to.

seems interesting to contrast these results with the ones of the specific projects that the UOC has undertaken around the dropout issue in academic and teaching areas. Some of these actions incorporate the results obtained in this dissertation. At the end of 2018, UOC projects around dropout analysis and reduction were:

- ESPRIA
- UOC Training Camp
- Tutorial actions
- Possibility of “de-enrolling” one subject with economic reimbursement

Regarding the first project (ESPRIA), this is an institutional project centred in an intervention to improve support to first-year students and so increase retention. Results of this project show a significant improvement in academic performance and retention for students who followed recommendations regarding enrolment in specific learning itineraries. The design, implementation and evaluation of the ESPRIA intervention served as an excellent opportunity to deploy learning analytics strategies. These strategies will form the basis for a new institutional research office that will nurture similar projects shortly while taking into account the value of developing a strong relationship between organisational policy formation, intervention design and planning and evidence-based evaluation.

We have also to consider the potential use of the enrolment data for different objectives, as for example that of visualisation (Blasco-Soplón et al., 2015).

For dropout/retention research having an impact we need to take into account the context: this affirmation, taken from the evaluation of the social impact of research, can also be applied to the internal impact, which should be inter-departmental (*interdisciplinary*) to cover all the dimensions that intervene in these issues. In short, the collaboration between academia, teaching and management is essential to give context to the research and obtain results with real impact.

In the same line of collaborative strategies needed to solve wicked problems, the mentioned analysis of higher education dropout in the EU (Vossensteyn et al., 2015) bets for “a mix of policy instruments each addressing different aspects of study success. A policy mix that includes strengthening students’ choices, promoting their social integration in the program, monitoring and counselling, and rewarding successful completion – is more likely to be successful". The same report highlights the importance of prompt action on early dropout.

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Annexes

Annex I - Questionnaires used

Questionnaire for the Feb. 14 study

Link to the 2014 survey (PDF).

Questionnaire for the Feb. 15 study

Link to the 2015 survey (PDF).

Annex II - Summary of logistic rogression analysis models

Summary of logistic regression analysis for continuance intention

	B (s.e.)	OR (95%CI)	*p*-value
Intercept	-1.75 (0.44)	0.17 (0.07, 0.41)	<0.001
Gender (Female):	0.74 (0.19)	2.09 (1.44, 3.04)	<0.001
Age [18,25):	-0.30 (0.32)	0.74 (0.39, 1.39)	0.346
Age [25,40):	-0.09 (0.25)	0.91 (0.56, 1.51)	0.723
Univ. experience in the same area:	0.21 (0.23)	1.24 (0.78, 1.95)	0.361
Univ. experience in another area:	-0.10 (0.24)	0.91 (0.56, 1.46)	0.693
Have children (Yes):	-0.60 (0.25)	0.55 (0.33, 0.89)	0.017
To be employed full-time (Yes):	0.13 (0.23)	1.14 (0.73, 1.80)	0.561
Chose the UOC to save time (Yes):	0.82 (0.21)	2.27 (1.50, 3.47)	<0.001
Chose the UOC for flexibility (Yes):	0.44 (0.19)	1.56 (1.07, 2.29)	0.023
Chose the UOC for price (Yes):	0.81 (0.42)	2.26 (0.99, 5.12)	0.051
Chose the UOC for its continuous assessment (Yes):	0.64 (0.23)	1.89 (1.19, 3)	0.006
Chose the UOC for its prestige (Yes):	0.51 (0.31)	1.67 (0.90, 3.10)	0.102
Chose the UOC for not having the need to move (Yes):	0.34 (0.27)	1.40 (0.82, 2.39)	0.211
Previous e-learning experience (Yes):	-0.64 (0.22)	0.53 (0.34, 0.80)	0.003
Study for work reasons (Yes):	0.51 (0.22)	1.66 (1.07, 2.56)	0.022
Study for academic reasons (Yes):	-0.73 (0.22)	0.48 (0.31, 0.73)	<0.001
Study for pleasure (Yes):	-0.85 (0.22)	0.43 (0.27, 0.66)	<0.001
Time factor	0.53 (0.18)	1.70 (1.20, 2.42)	0.003
Personal factor	-0.37 (0.17)	0.69 (0.49, 0.96)	0.032
System factor	-0.33 (0.13)	0.72 (0.55, 0.92)	0.011
Difficulty factor	-0.52 (0.13)	0.60 (0.46, 0.77)	<0.001
Gender * Personal factor	-0.41 (0.21)	0.66 (0.44, 0.99)	0.046
Time factor * Personal factor	-0.34 (0.12)	0.71 (0.56, 0.89)	0.004
Personal factor * System factor	0.49 (0.12)	1.64 (1.28, 2.09)	<0.001
E-learning * Time factor	-0.67 (0.19)	0.51 (0.35, 0.74)	<0.001
Univ. experience in the same area * Time factor	-0.31 (0.20)	0.73 (0.49, 1.08)	0.115
Univ. experience in another area * Time factor	-0.65 (0.21)	0.52 (0.34, 0.79)	0.002
Goodness-of-fit			
Cox and Snell R^2	0.630		
Classification accuracy (%)	83.4		

Table II.1: Summary of logistic regression analysis for continuance intention (n = 301). All factors have been introduced (socio-demographic, academic, personal motivation and new factors).

Summary of logistic regression analysis for effective re-enrolment

	B (s.e.)	OR (95%CI)	*p*-value
Intercept	-2.94 (1.29)	0.05 (0.003, 0.54)	0.022
Gender (Female):	-0.54 (0.64)	0.58 (0.16, 2.03)	0.400
Age [18,25):	-0.84 (0.82)	0.43 (0.08, 2.16)	0.308
Age [25,40):	0.06 (0.62)	1.06 (0.31, 3.66)	0.924
Univ. experience in the same area:	2.04 (0.70)	7.69 (2.13, 34.28)	0.004
Univ. experience in another area:	-0.70 (0.70)	0.50 (0.12, 1.98)	0.318
Have children (Yes):	-0.32 (0.71)	0.72 (0.17, 2.89)	0.647
To be employed full-time (Yes):	-0.93 (0.49)	0.40 (0.15, 1.01)	0.057
Chose the UOC to save time (Yes):	-1.09 (0.53)	0.34 (0.12, 0.94)	0.040
Chose the UOC for flexibility (Yes):	-0.38 (0.42)	0.68 (0.30, 1.53)	0.358
Chose the UOC for price (Yes):	-2.38 (0.75)	0.09 (0.02, 0.38)	0.002
Chose the UOC for its continuous assessment (Yes):	2.32 (0.63)	10.16 (3.11, 38.13)	0.001
Chose the UOC for its prestige (Yes):	2.09 (0.72)	8.12 (2.14, 36.35)	0.003
Chose the UOC for not having the need to move (Yes):	3.27 (0.75)	26.18 (6.55, 130.17)	<0.001
Previous e-learning experience (Yes):	0.05 (0.56)	1.05 (0.35, 3.20)	0.933
Study for work reasons (Yes):	1.93 (0.61)	6.92 (2.28, 25.28)	0.001
Study for academic reasons (Yes):	1.44 (0.48)	4.24 (1.68, 11.31)	0.003
Study for pleasure (Yes):	0.58 (0.55)	1.79 (0.63, 5.46)	0.286
Time factor	0.62 (0.68)	1.86 (0.49, 7.35)	0.360
Personal factor	-1.25 (0.63)	0.29 (0.08, 0.91)	0.046
System factor	0.69 (0.48)	2 (0.80, 5.36)	0.150
Difficulty factor	-1.11 (0.50)	0.33 (0.12, 0.86)	0.028
Gender * Personal factor	-1.21 (0.65)	0.30 (0.08, 1.06)	0.065
Time factor * Personal factor	-1.62 (0.48)	0.20 (0.07, 0.47)	<0.001
Personal factor * System factor	1.27 (0.57)	3.56 (1.33, 12.08)	0.025
E-learning * Time factor	-2.06 (0.63)	0.13 (0.03, 0.42)	0.001
Univ. experience in the same area * Time factor	0.81 (0.54)	2.24 (0.81, 6.78)	0.133
Univ. experience in another area * Time factor	-0.75 (0.58)	0.47 (0.15, 1.47)	0.197
Goodness-of-fit			
Cox and Snell R^2	0.779		
Classification accuracy (%)	87.3		

Reference categories: “Male”, “Age [40, 66]”, “Without univ. experience” and “No” for all dichotomous variables.

Table II.2: Summary of logistic regression analysis for effective re-enrollment (n = 91). All factors were introduced (socio-demographic, academic, personal motivation and calculated factors).

Annex III – Wald's story

The following text has been extracted literally from the site "Medium.com" (Wald & Ellenberg, 2016):

"The military came to the SRG with some data they thought might be useful. When American planes came back from engagements over Europe, they were covered in bullet holes. But the damage was not uniformly distributed across the aircraft. There were more bullet holes in the fuselage, not so many in the engines.

Section of plane	Bullet holes per square foot
Engine	1.11
Fuselage	1.73
Fuel system	1.55
Rest of the plane	1.8

Table III.1:: Bullet holes per square foot for the different sections of plane

The officers saw an opportunity for efficiency; you can get the same protection with less armour if you concentrate the armor on the places with the greatest need, where the planes are getting hit the most. But exactly how much more armor belonged on those parts of the plane? That was the answer they came to Wald for. It was not the answer they got.

The armour, said Wald, does not go where the bullet holes are. It goes where the bullet holes are not: on the engines.

Wald's insight was simply to ask: where are the missing holes? The ones that would have been all over the engine casing, if the damage had been spread equally all over the plane? Wald was pretty sure he knew. The missing bullet holes were on the missing planes. The reason planes were coming back with fewer hits to the engine is that planes that got hit in the engine were not coming back. Whereas the large number of planes returning to base with a thoroughly Swiss-cheesed fuselage is pretty strong evidence that hits to the fuselage can (and therefore should) be tolerated. If you go to the recovery room at the hospital, you'll see a lot more people with bullet holes in their legs than people with bullet holes in their chests. But that's not because people do not get shot in the chest; it's because the people who get shot in the chest do not recover.

Here's an old mathematician's trick that makes the picture perfectly clear: set some variables to zero. In this case, the variable to tweak is the probability that a plane that takes a hit to the engine manages to stay in the air. Setting that probability to zero means a single shot to the engine is guaranteed to bring the plane down. What would the data look like then? You'd have planes coming back with bullet holes all over the wings, the fuselage, the nose—but none at all on the engine. The military analyst has two options for explaining this: either the German bullets just happen to hit every part of the plane, but one, or the engine is a point of total vulnerability. Both stories explain the data, but the latter makes a lot more sense. The armour goes where the bullet holes are not.

Wald's recommendations were quickly put into effect and were still being used by the navy and the air force through the wars in Korea and Vietnam. I can not tell you exactly how many American planes they saved, though the data-slinging descendants of the SRG inside today's military no doubt have a pretty good idea. One thing the American defence establishment has traditionally understood very well is that countries do not win wars just by being braver than the other side, or freer, or slightly preferred by God. The winners are usually the guys who get 5% fewer of their planes shot down, or use 5% less fuel, or get 5% more nutrition into their infantry at 95% of the cost. That's not the stuff war movies are made of, but it's the stuff wars are made of. And there's math every step of the way.

The armour, said Wald, does not go where the bullet holes are. It goes where the bullet holes are not: on the engines."