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Survive to stay connected: patterns of user experiences in a Life Long Learning digital platform

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Abstract

In an ever-changing world, having the right competences for the job market represents a key challenge for sustained employability. To address this need a growing number of digital platform for life long learning (LLL) has been developed. Anyway, it is less known how users navigate and use these platforms. The present study represents a one of the first attempts to fill this gap, offering a deep analysis for the identification of latent subgroups of learners with similar behaviours on a digital LLL platform. Then, the identified subgroups are described in terms of personal features and survival profiles. Findings reveal three distictive latent classes, with very different survival profiles. The analysis provides interesting insights about how the administators of a digital LLL platform can better personalize their contents according to the type of learner, to support and let them stay on the platform, acquiring the needed skills for the job market.

Keywords: *LifeLongLearning; Survival Analysis; Latent Class Analysis.*

1. Introduction

A better alignment between the skills acquired through education and those required on the job market is becoming of paramount importance today, mainly due to the widespread diffusion of digitalisation, which is deeply transforming all businesses, at an unprecedented speed. Hence, the job market requires a continuous adaptation of people's skills to remain employable in the long term. In line with this perspective, the Digital Agenda for Europe 2020 describes the principles for ensuring the acquisition of digital skills and literacy for all citizens (Levano-Francia et al., 2019). The Future Jobs Report, prepared by the World Economic Forum (2018) predicts that the large number of professions that exist today and in the coming years will require digital skills to be able to perform their work. In this view, educational institutions are called to align their academic offer with the needs of the labor market to increase employability, stay competitive and strenghten the cooperation between university and industry as one of the main drivers of innovation.

The need for a continuous skill alignment and willingness to learn during professional careers has been labelled in the academic literature as Life Long Learning (LLL). It has been firstly defined by Guglielmino (1997) as "self-initiative, independence, and persistence in learning; […]. One who is capable of self-discipline and has a high degree of curiosity." Indeed, LLL requires a stable set of attributes and skills related to self-regulation of continuous learning. The aim of LLL is to offer people the opportunity to acquire, complete or expand their competence and skills to promote their personal or professional development in every moment of their life (Guglielmino, 1997).

Technological advancements have enabled the development of educational digital platforms that can keep the pace of such a fast and evolving need of continuous knowledge update (Perez-Ortiz et al., 2021). However, it is documented that dropout rates of the learners on these platforms are substantially higher than in-presence counterparts (Levy, 2007). In some case, the main predictor of learners' retention in digital LLL platforms is the general level of satisfaction, which represents a proxy of their engagement. Hence, the actual challenge to improve the effectiveness of these platforms is to understand learning paths and learners' behaviours, to identify strategies and tactics that can allow for higher retention and the pursuit of the individual professional and academic goals of the learners.

The present study aims at contributing to the existing academic literature about life-long learners' dropout in digital educational platforms, through the characterization of their behaviour and related survival patterns. The empirical setting for this study is a digital LLL platform developed by the Business School of a leading Italian university, which provides learners with personalised "knowledge nuggets" in line with their career aspirations and their skill gaps. The empirical research is based upon (i) the identification of subgroups of learners with similar behaviours, in terms of engagement and interaction with the platform, and on

(ii) testing whether subgroups differ in their survival curves in the platform. This is done with the purpose of identifying early signals of disengagement before drop-out , that would be relevant to foster the educational potential of LLL digital platforms.

2. The digital LLL platform

The digital platform analysed in this study was developed in 2019 by the Business School of a leading Italian university. The platform, which acts like a "digital mentor", allows learners to settle professional goals along a continuous, personalised learning pathway. The platform is free and open to everyone. Before starting, every learner is asked to fill a short questionnaire about their actual job, role and competences and set the aspirations for future professional career. While the digital, soft and hard skills assessment is optional during the registration phase. According to the settled aspirations, market job requirements, and the skill gaps emerging from the assessments, the digital mentor, using on AI algorithms, provides tailored suggestions and contents to study. The system is able to identify the topics or subjects where the person can bridge the gaps about specific knowledge and skills. The idea is to offer learners a flexible and personalised pathway to support their professional career and improve their employability. The learning experience lasts for six months, after which the learner can set new career aspirations and begins a new learning cycle. Additional features of the platform include challenges, networking with the whole digital community, and job postings from selected companies. The platform proposes three kinds of learning-related activities: daily workout, learning pathway and advanced search. The first relates to short readings or other contents that keep the learner engaged and provide "knowledge nuggets" on a daily basis. The learning pathway has a longer-run perspective, aiming at reinforcing specific compentences and skills of the learner, and lasts until 6 months. Lastly, the search function allows learners to autonomously look for news, courses or other contents they are interested in, by using keywords. The contents indexed and suggested by the platform come from a broad range of sources like MOOC platforms, selected business magazines and blogs. The AI algorithms tailor suggestions also on the basis of the feedback of learners, who may like or dislike proposed contents. The digital mentor allows every learner to reach the settled goals within six months from the registration. This period will be then used as reference to evaluate learner's success (or not).

3. Data and Methods

3.1. The dataset

Data are extracted from the platform and, after the cleaning processing, the number of observations (learners) is 2403. Variables can be categorised into three groups: (i) platform-learner interaction, (ii) learners' characteristics and (iii) learner survival time within the platform (time between learner registration and final action within six months). The first cluster of variables, described in Table 1, concerns the type of activity the learner carried out in the platform (daily workout, learning pathway or search) and the number and length of sessions (on a daily, weekly or monthly basis). These variables are used to detect latent classes and describe different patterns of learners' interaction with the platform. Then, descriptive information are used to describe the subgroups identified. These variables related to learners' age, citizenship and education. The last set of variables describes the learning path in the platform: the status defines whether the learner completed the learning pathway after six months from the registration and, if he/she dropped out before, when the event occurs. This information is essential to study the survival function of latent classes, in linea with the second research objective.

Table 1. Variables used in the first step of LCA: description and mean.

Variable Name	Description	Mean
avgDailySessions	Num sessions / num active days	1.214
avgMonthlySessionsTotal	Num sessions / total months on Flexa	1.804
avgSessionsDuration	Total duration of sessions	1029.7
percentWeekendSessions	Num weekend sessions / num sessions	0.182
percentSessionsDailyworkout	Num dailyworkout sessions / num sessions	0.276
percentSessionsLearningPathway	Num learning pathway sessions / num sessions	0.15
percentSessionsSearch	Num search sessions / num sessions	0.16
percentOpenContents	# contents opened / # of recommended contents	0.103
percentLikeContents	# contents with like / # of recommended contents	0.049
percentOpenSearchedContents	# open searched content / # searched content	0.081
percentLikeSearchedContents	# content searched with like / # content searched	0.012

3.2. Methodology

Two different methodologies are adopted along the study. First, a Latent Class Analysis (LCA) is used with the aim of detecting hidden patterns in leaerners' interaction with the platform and classify them into latent subgroups (Muthén & Muthén, 2000). By latent subgroups, we mean clusters of observations (in this case, learners), who share underlying common features in terms of important dimensions (in our case, the level of interaction and the type of activity in the platform). Firstly, the latent classes are defined based on 11 indicators described in Table 1, and dichotomised, meaning that a value equal to 1 is assigned when the observed value is above the mean, 0 otherwise. As a result of step 1, each observation is assigned to the group for which the probability of class membership is the highest. The number of classes is selected assessing the goodness of fit of the model through the Bayesian Information Criterion (BIC) and the Lo-Mendell-Rubin (LMR) test (Lo et al., 2001). In step 2, multinomial regressions are run to characterise the latent classes by means of personal information on the learners.

The second methodology is the survival analysis (Ameri et al. 2016), employed with the aim of studying the survival curves of the identified latent subgroups. The Kaplan-Meyer functions, $S(t_i)$, are estimated to visualise the probability of "surviving" on the platform with time-dynamics. This is a step-function, a non parametric estimation characterised by discontinuities at points given by time events: $S(t_i) = S(t_{i-1}) * (1 - \frac{d_i}{n_i})$. $S(t_{i-1})$ is the probability of being alive at t_{i-1}, n_i is the number of active learners just before t_i and di is the number of events at t_i. The event is defined when at least one learner drops-out (not survive). The underlying assumption is that the drop-out events are uncorrelated.

4. Results

Three is the number of latent classes that proxies data at best, as indicated by the lowest value of the BIC, and the platform-learner interaction profile of each class is presented in Figure 1. The first class is composed by a low share of learners (6.0%) and characterised by a high profile of activity. Their activities mainly relate to daily workout sessions, thus they are often logged in as confirmed by the high number of sessions with a relatively short duration. Also, they open and like contents proposed by the digital mentor, and for this reason are labelled *Platform-engaged learners*. The second class, represented by the 20.5% of learners, report an high number of sessions, but their activity is mainly characterised by searching contents by themselves. For this reason, the can be labelled *Self-engaged learners*. Lastly, 73.5% of learners interact very poorly with the platform. They are the least active and log in few times for long time, thus they can be labelled *Disengaged learners*. To characterise the identified classes, the multinomial regression in Table 2 provides a picture about some of their characteristics. The probability of being a *Self-engaged learner* is higher for young learners, compared to the other groups of learners. For all the other characteristics, *Self-engaged* and *Platform-engaged* learners are rather similar, while *Self-engaged* and *Disengaged learners* differ in terms of citizenship and assessment status – *Disangaged learners* are more likely to have not even started or completed the initial skill assessment. In this respect, *Disengaged learners* tend to be so since their enrolment in the platform. Finally, having followed one or more courses at the Business School does not affect the probability of belonging to a specific class of learners.

To address the second research objective, the Kaplan Mayer curves, in Figure 2, give a visual estimate of how fast the survival probability of each latent class decreases over time. Results suggest that *Disengaged learners* have a completely different survival function compared to the other two classes. The curve registers an initial drop at time 0, meaning that many learners log in the platform one time to never come back. The other two curves are very similar, even though *Platform-engaged learners* show an initial drop, too. Interestingly, the survival probability of *Self-engaged learners* is higher than that of *Platform-engaged* learners until the 140th day, when the curves overlap and then switch. The probability of surviving until the end of the learning path (after six months) is pretty low (<25%) for all the three classes.

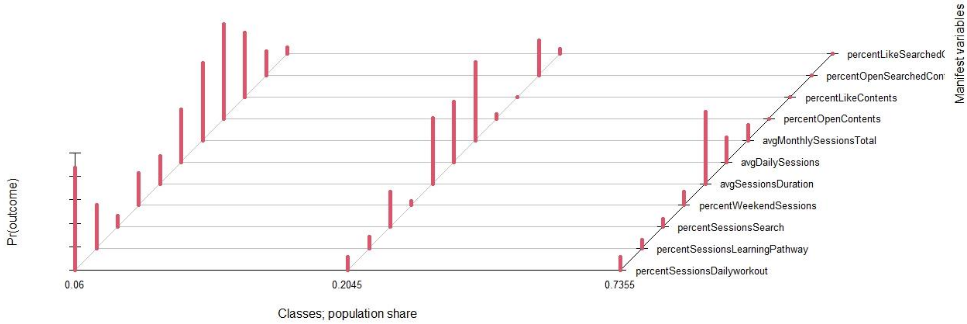

Figure 1: Latent Classes' profiles

Table 2. Multinomial regression to characterise latent classes

	Dependent variable (ref.: Disengaged learners)	
	Platform-engaged learners	Self-engaged learners
age	-0.027*** (0.007)	0.003 (0.011)
Italian	0.304** (0.149)	0.495* (0.257)
learnerTypeStudent	0.748*** (0.136)	0.974*** (0.227)
assessmentStatus: not completed	-0.589*** (0.198)	-1.313*** (0.429)
assessmentStatus: not started	-1.502*** (0.176)	-2.068*** (0.350)
mipEducations_dummy	-0.242 (0.592)	0.029 (1.061)
Constant	-0.779 (0.656)	-3.358*** (1.151)
Akaike Inf. Crit.	2,903.671	2,903.671

Note: *p<0.1; **p<0.05; ***p<0.01.

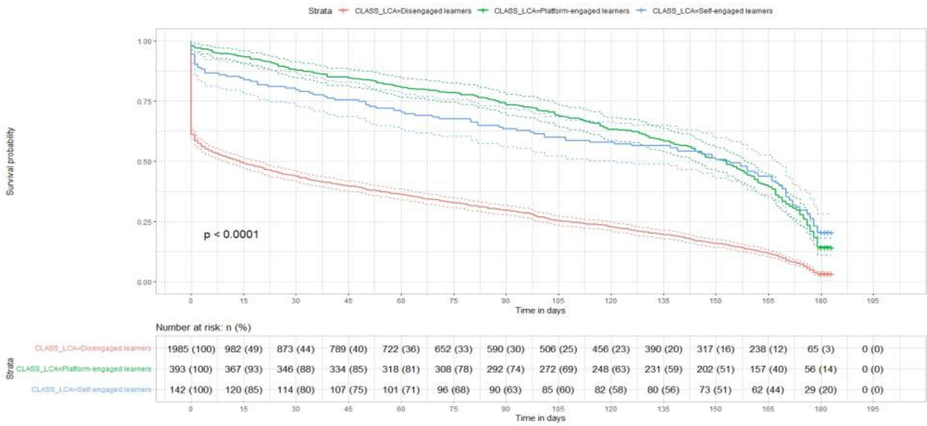

Figure 2: Kaplan-Meyer curves of identified Latent Classes.

5. Conclusions

The paper explores data derived from a digital LLL platform based on AI algorithms to explore the patterns of platform-learner interaction and observe the probability to persist on the platform until the end of the learning pathway. The high drop-out rate and risk of disengagement is a critical issue in digital education (Levy, 2007; Bañeres Besora & Conesa Caralt, 2017), which may undermine the effectiveness even of highly personalised learning experiences (Moreno-Marcos et al. 2020). The investigation of data generated by the interaction of learners on the platform provides relevant insights and contributes to understanding how Life Long Learners – typically professionals for whom bite-sized learning (e.g., Koh et al., 2018) could be highly beneficial, interact with a personalised platform.

Findings suggest that the majority of learners (73.6%) do not even take a step further after registering, a behaviour observed also among MOOC learners (Agasisti et al., 2021). The paper contributes to the academic debate on the identification of digital Life Long Learners' profiles (Binali et al. 2021), showing that despite the high personalisation of contents, it is registered high levels of disengagement, as observed in other digital formats (Korableva et al., 2019). In terms of practioners' implications, findings suggest possible early warning signals that may help prevent learners' dropout, as disengaged students tend to show their attitude since the very beginning. Also, a personalized learning journey can be designed following users' profiles from the LCA and survival patterns. As seen, this research may provide a set of interesting and valuable insights for improving the effectiveness of the platform.

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