Self-regulated learning, motivation and emotions towards university study. A latent class approach

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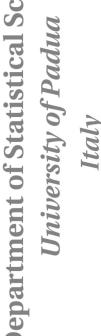Department of Statistical Sciences
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Abstract: Students' attitudes, motivations and emotions towards university study have a great influence on their university careers. In this work, we use a latent class factor analysis approach to reveal the underlying latent factors which summarise a series of items investigating students' positions in three domains: self-regulated learning, motivation, and emotions towards university study. Data come from a CAWI survey conducted in 2012 on a cohort of students enrolled in academic year 2006-07 at University of Padova, a large public university in north-east Italy. Results show that the underlying latent factors are in line with related psychological literature.

Keywords: Self regulated learning, motivation, emotions, Latent Class Models, Psychological item.

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Abstract: Students' attitudes, motivations and emotions towards university study have a great influence on their university careers. In this work, we use a latent class factor analysis approach to reveal the underlying latent factors which summarise a series of items investigating students' positions in three domains: self-regulated learning, motivation, and emotions towards university study. Data come from a CAWI survey conducted in 2012 on a cohort of students enrolled in academic year 2006-07 at University of Padova, a large public university in north-east Italy. Results show that the underlying latent factors are in line with related psychological literature.

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1   Introduction

Recent psychological literature has demonstrated that psychological domains such as self-regulated learning, motivation, and emotions towards university study are closely related (Efklides 2011) and have a great influence on students' university careers (Winne and Nesbit 2010). In this perspective, outcomes such as withdrawals, course changes, delays, and completion of degrees are not only affected by individual characteristics (Arias Ortiz and Dehon 2013; Aina et al. 2011), but also by the psychological aspects of the learning process, all of which are important in explaining successful or unsuccessful careers (Pekrun et al. 2009; Daniels et al. 2009; Pekrun et al. 2011).

In particular, in studying the determinants of students university careers, unobserved factors such as self-regulated learning, motivation, and emotions towards study should be considered as well as participants' observed characteristics. These latent variables may be described by a set of observed indicators (Mega et al. 2014) and analysis of their interrelations can identify the underlying latent variables. This

is the general aim of factor models, used especially when observed items are continuous. Latent class models are preferable when observed indicators are measured on an ordinal scale (McCutcheon 1987). In our case, the items designed to describe several aspects of students attitudes were measured on a discrete ordinal scale, so that latent class analysis could be applied to identify latent underlying factors.

The measurement scale (adapted from Mega et al. 2014) was applied to a sample of students among those enrolled in academic year 2006/07 at the University of Padova, a large public university in north-east Italy. The sample was studied by means of a CAWI (Computer Assisted Web Interview) survey conducted in 2012, with additional information from the University's administrative archives (Clerici et al. 2012). The current study shows that the results of confirmative latent class factor analysis applied to psychological aspects connected with self-regulated learning, motivation and emotions towards university study are in line with theoretical and empirical work in the psychological literature.

The paper is organised as follows; section 2 describes the survey; section 3 introduces the psychological aspects measured in it; section 4 briefly introduces the concepts of latent class analysis and latent class factor models; section 5 summarises the main features of the data, and latent class factor models are applied to identify latent factors. Section 6 concludes, and indicates lines for future research.

2   The University of Padova and the student survey

The University of Padova is among the ten Italian largest public institutions and is one of the oldest and most prestigious university in Europe. It is characterized by a high multidisciplinarity and its courses cover all the main study fields.

In order to study various aspects of students' university careers, a CAWI survey was designed and implemented on a sample of the cohort of 8,473 students enrolled in first-cycle degree courses at the University of Padova in academic year 2006/07. This survey, carried out in early 2012, aimed at a deep understanding of the individual, familiar and psychological determinants of students' university careers. A four-section questionnaire investigating various aspects of their lives was designed for this purpose. The first section aimed at obtaining information on the level of education and work status which students' parents had had. Section 2 studied students' lives during their university careers, taking into account university outcomes, attendance at lessons, temporary work (if any), periods of time spent outside Italy, internships, etc. The third part of the questionnaire is the focus of the current analysis; it explored students' learning processes, grouped into three domains: self-regulated learning, motivation, and emotions towards university study. The fourth section covers the use of student facilities such as tutoring and psychological help provided by the University.

During data collection, particular attention was devoted to obtaining a sample representative of the whole population of students enrolled in first-cycle degree courses at Padova in academic year 2006/07 (Clerici and Giraldo 2014). The University's administrative archives provided information allowing us to contact students,

such as official[1] and private email addresses, and telephone (landline) and mobile phone numbers. Having available several types of contact details allowed us to use a mixed-mode type of invitation to participate in the web survey (Porter and Withcomb 2007; Cimini et al. 2011). Contacts with students was organised in four phases, as follows. In phase 1, students were invited to participate in the survey in an email to their official email addresses. Clearly, as students would not normally be at university about six years after their enrolment, due to graduation, withdrawal, or change of university, the official email addresses were sometimes no longer valid. The mixed-mode type of invitation thus avoided the bias which might have arisen due to the use of an official email address as the only source of contact[2]. In phase 2, personal email addresses were used to contact the students, but they were only available for 18% of the cohort. In the next two contact phases, telephone invitations was made, students being chosen in order to obtain a representative sample of the entire cohort. Representativeness was evaluated with respect to the observed distribution of the university outcomes at the third year, as obtained from the administrative archives. This controlled quota sample and the mixed-mode invitations avoided any high level of bias due to self-selection, a common problem in CAWI surveys (Bethlehem 2010).

The final sample consisted of 2,498 students, about 30% of the cohort enrolled in academic year 2006/07 in first-cycle degree courses. An ex-post weighting procedure based on propensity scores (Lee 2006), performed according to the individual data available from administrative archives[3] as well as contact information, compensated for the remaining bias (Clerici and Giraldo 2014; Clerici et al. 2012).

3 Psychological aspects of university study and how they were studied in this survey

The psychological items in the questionnaire refer to three main domains: self-regulated learning, motivation, and emotions towards university study (Mega et al. 2014).

Although the psychological literature proposes various approaches to self-regulated learning (Azevedo et al. 2010; Boekaerts et al. 2000; Muis et al. 2007), all of them follow the basic principle that self-regulated learners actively construct their knowledge by applying diverse cognitive and metacognitive approaches to monitor and organise their academic learning. According to Mega et al. (2014), self-regulated learning may be defined according to five aspects: organisation, personal processing, self-evaluation, strategies for studying for examinations, and metacognition ability. Organisation refers to the ability to plan personal study, allocating different times for different tasks and taking deadlines into due account (Pazzaglia et al. 2002;

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[1] All students are assigned official email addresses on enrolment in the University of Padova.

[2] In that case the sample could present an underestimation of the percentage of students who graduate, withdraw or change university and an overestimation of students still at the university.

[3] In particular, information on some characteristics of students is available (gender, nationality, place of residence), their schooling (type of high school, high school final grades, and age at enrolment at university), and university careers (faculty of enrolment and university outcomes at third year of course).

Pintrich 2004). Personal processing concerns skill in reprocessing contents actively, taking notes, and building conceptual schemes and diagrams (Warr and Downing 2000). Students' self-evaluation involves a high level of awareness of their personal ways of studying and proper assessment of their learning and degree of preparation (Van Etten et al. 1997). Strategies for studying for examinations relate to the ability to monitor and organise what has been learned and understood with respect to the study material (Ruban et al. 2003). Metacognition implies the ability to assess the adequacy of procedures used during study and to identify potential difficulties (Dinsmore et al. 2008).

In this survey, students' level of self-regulated learning was examined with the approach followed in previous studies (see, for example, Mega et al. 2014). In particular, four items, two positive and two negative, were considered for each of the five aspects defining self-regulated learning (20 items in total). Students were asked to indicate on a self-anchoring scale ranging from 1 (never) to 5 (always)[4] how often they enacted each of the twenty behaviours related to self-regulated learning[5].

As regards motivation, we focused on those aspects which the literature has shown to be important in enhancing students' academic achievement and closely related to self-regulated learning (Pintrich 2003; Cornoldi et al. 2003, Ferla et al. 2008). These were implicit theory of intelligence, self-efficacy, and achievement goals. The implicit theory of intelligence (Dweck 1999) relates to the idea students have about the nature of their intelligence. They may think of it as a malleable, increasable, controllable quality (incremental theory) or as a fixed, uncontrollable trait (entity theory). Depending on which theory they follow, they may actively use various strategies to increase their abilities or reduce their effort if they think it is not worth it (Mega et al. 2014). Academic self-efficacy concerns students' convictions about their success in facing academic study (Bandura 1997; Schunk 1991). These convictions depend to a great extent on past achievements, difficulties and personal history (Lackaye and Margalit 2006). Students with high levels of self-efficacy tend to play a more active role in their learning process and try to plan, monitor, and organise their university study (Linnenbrink and Pintrich 2003; Seifert 2004). Achievement goals pertain to the aims they wish to achieve (Huang 2012), divided into mastery goals and performance goals. In the former, when facing a task, students mainly want to learn; in the latter, they want to demonstrate their skills and abilities (Ames 1992; Dweck and Leggett 1988). Students with mastery-approach goals aim to increase their level of competence by acquiring new knowledge and skills which are developed during the execution of a task. Students focusing on the performance-approach aspire to demonstrate their skills to others through tasks allowing them to exhibit their knowledge (Conley 2012; Muis and Edwards 2009).

The instrument used here to measure these three aspects of motivation was adapted from the approach of Mega et al. (2014). The implicit theory of intelligence was measured by eight items: on a self-anchoring scale ranging from 1 (not at all)

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[4]In the self-anchoring scale (Cantil and Free 1962; Corbetta 2003) only extreme categories in our case 1 (never) and 5 (always) have precise meanings.

[5]Examples of items of behaviours in the self-regulated learning are: "When I'm studying, I sometimes connect new information with old, learned in the past", "When I think my learning strategies are not effective, I change them", "I find it difficult to predict how I'll do in exams".

Table 1: Psychological domains, aspects and number of items considered in the survey

Domain	Aspects	No. of items
Self-regulated learning	Organisation	4
	Personal processing	4
	Self-evaluation	4
	Strategies for studying for an examination	4
	Metacognition ability	4
Motivation	Implicit theory of intelligence	8
	Self-efficacy	4
	Achievement goals	8
Emotions	Positive emotions related to study	10
	Negative emotions related to study	10

to 5 (very much), students were asked to indicate to what extent they thought the eight abilities could be modified[6]. Self-efficacy was composed of four items in which students were asked to indicate, on the same scale as above, to what extent they perceived themselves as capable in four abilities[7]. Achievement goals were studied according to eight items, four positive and four negative. Using the same scale, students were asked to what extent they felt that the eight situations applied to them[8].

The last domain examined here was emotions. The literature shows that students experience a wide range of emotions in various learning contexts (Pekrun et al. 2011). Positive emotions encourage a self-regulated approach to study; negative ones nourish an attitude of dependence (Pekrun et al. 2007). Emotions were measured through 20 items assessing 10 positive and 10 negative feelings relating to study. On a self-anchoring scale ranging from 1 (never) to 5 (always), students were asked how often they experienced all of them. The three domains, their different aspects, and the number of items involved are listed in Table 1.

4   Latent class models

A latent variable is a random variable which, either in principle or in practice, cannot be observed, e.g., phenomena such as emotions or motivation cannot be directly observed and measured. In order to measure latent variables, scholars have proposed batteries of items (sometimes called indicators, or manifest variables) related to latent variables and, according to the empirical relationship found between items, deduce estimates of latent variables. More precisely, it is assumed that the covariation empirically observed between manifest variables is due to the relationship of each manifest variable to a latent variable. If such a variable exists and can be char-

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[6]Examples of abilities were: "Solving mathematical problems", "Learning a foreign language".

[7]Examples of abilities were: "My study skills", "My success in studying".

[8]Examples of situations were: "I can cope with demanding study situations, even though I risk making mistakes", "I like the easy exams".

acterised, then controlling for it will result in a decrease in the covariation among all the manifest variables. It may be said that latent variables are the "true" sources of the originally observed variability (McCutcheon 1987).

In the sociological and psychological literature, great importance is given to the study of measurement scales to describe theoretical latent constructs (DeVellis 1991). The use of indicators to detect latent constructs is based on appropriate validation of the measurement scale. Although items are measured on nominal or ordinal scales, they are generally considered as continuous according to standard factor analysis (Jöreskog and Sörbom 1979). However, a more appropriate method for dealing with nominal or ordinal level measurement scales is to use latent class models, in which the indicators of latent factors, as well as of the latent variables themselves, may be nominal or ordinal. Advantages derive from the fact that variables are treated in their true nature and - for example, in the ordinal case - no assumption regarding the distance between points on an x-point scale are made. In addition, the normality assumption, frequently violated, is not required.

Latent class models (LCM), first introduced by Lazarsfled (1950) and further developed by Lazarsfled and Henry (1968) and Goodman (1974a, 1974b), apply to nominal or ordinal observed items, the aim being to formulate latent attitudinal variables from them. A fundamental assumption of LCM is local independence: the association between observed variables derives from their relationship with the latent variable. Thus, the latter explains the relationship between manifest variables: the correlation between items disappears once the latent variable is held constant (McCutcheon 1987).

Following Goodman's notation as applied by Hagenaars (1993) and considering for the moment one latent variable X with T classes, indicated by four manifest variables (A to D), the basic structure of an LCM is:

$$\pi_{ijkl}^{ABCD} = \prod_{t=1}^{T} \pi_{ijklt}^{ABCDX} \tag{1}$$

where:

$$\pi_{ijklt}^{ABCDX} = \pi_t^X \pi_{ijklt}^{\overline{ABCD}X} = \pi_t^X \pi_{it}^{\overline{A}X} \pi_{jt}^{\overline{B}X} \pi_{kt}^{\overline{C}X} \pi_{lt}^{\overline{D}X}. \tag{2}$$

π_t^X is the probability of being in latent class t, and gives the size of latent class t; $\pi_t^X \pi_{ijklt}^{\overline{ABCD}X}$ is the conditional probability that a unit belongs to category ($ijkl$) of the joint manifest variable $ABCD$, given $X = t$; $\pi_{it}^{\overline{A}X}$ is the conditional probability that an individual obtains score $A = i$, given that this person belongs to latent class t of X.

Equation (1) states that the population may be divided into T exhaustive and mutually exclusive classes, and that each unit of the population belongs to one and only one latent class. The existence of the latent variable is thus ensured by equation (1). The assumption of local independence allows us to write equation (2) in terms of the products of the conditional probabilities of each manifest variable conditional on the latent variable. This formula clearly shows that the relationship between manifest variables is indirect and passes through X (Hagenaars 1993).

Any LMC is equivalent to a loglinear model with latent variables (Haberman 1979). The model of the four manifest variables may be written in the form:

$$\ln F_{ijklt}^{ABCDX} = \lambda + \lambda_t^X + \lambda_i^A + \lambda_j^B + \lambda_k^C + \lambda_l^D + \lambda_{it}^{AX} + \lambda_{jt}^{BX} + \lambda_{kt}^{CX} + \lambda_{lt}^{DX} \qquad (3)$$

where F_{ijklt}^{ABCDX} is the absolute frequency in the generic cell of a five-way contingency table, and $\lambda_i^A \ldots \lambda_t^X$ are the first-order effects and $\lambda_{it}^{AX} \ldots \lambda_{lt}^{DX}$ the second order effects (Hagenaars 1993).

The local independence assumption results in the absence of any interaction term. The maximum likelihood estimation of the model parameters requires an iterative procedure, since likelihood is not in closed form (see McCutcheon 1987 for details).

When the indicators are ordinal, their relationship with the latent variable may be restricted, for example, by using the adjacent-category ordinal logit model (Goodman 1979), in which the second-order effects in equation (3) become $\lambda_{it}^{AX} = \lambda_t^X \cdot i$, where i is the score assigned to item A.

As in factor analysis, in LCM interpreting the connotation of latent variables mainly follows from the relation between latent and manifest variables. In fact, considering the conditional probabilities between latent variables and items, we can name the latent variables according to the characteristics of the manifest variables most closely related to them. In addition, as in factor analysis, we can specify exploratory or confirmative LCM: the former is an attempt to identify latent classes from a set of observed items in the absence of a specific theory; the latter is intended to confirm the adequacy of a theoretical model underlying the data, translated into a hypothesis regarding the characteristics of the conditional or latent class probabilities. In this case, the estimates of conditional probabilities must be restricted (see McCutcheon 1987).

The adequacy of the LCM to observed data is assessed by the likelihood ratio chi-squared statistic L^2, which compares maximum likelihood estimates for expected cell frequencies with the corresponding observed frequencies (Magidson and Vermunt 2004). A model fits the data if the value of L^2 is sufficiently low to be attributable to chance. In the case of sparse data, the chi-squared-based estimation for the p-value associated with L^2 cannot be trusted, since it does not follow a chi-squared distribution. A good alternative is therefore to estimate the p-value by bootstrapping or Monte Carlo simulation[9].

Other alternatives for assessing the model fit, especially helpful when several models are compared, are Akaike's information criterion (AIC) and Bayes' information criterion (BIC). The most frequently used is BIC, defined as: $BIC = L^2 \ln(N) df$, where N is sample size and df the number of degrees of freedom. The model with a lower BIC is preferred (Magidson and Vermunt 2004). To assess the quality of the estimated models, a set of statistics containing information on how

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[9]The bootstrap L^2 procedure consists of generating a certain number of replication samples from the maximum likelihood solution and re-estimating the model with each replication sample. The bootstrap p-value is the proportion of replication samples with a higher L^2 than in the original sample. Bootstrapping can be performed with the Latent Gold package (Vermunt and Magidson 2005b).

well the model can predict class memberships, given the observed variables, is also useful (Vermunt and Magidson 2005b). Classification is based on posterior class membership and the statistics considered here involve pseudo R-squared based on entropy[10] (see Vermunt and Magidson 2005b for details).

The general aim of LCM is to determine the smallest number of latent classes accounting for the association observed among the manifest variables. The analysis starts by estimating a model with only one class, which implies mutual independence between observed variables. If the baseline model does not fit the data adequately, a model with two classes is estimated, and so on. The process of adding a class to the latent variable at each stage continues until the simplest model with the best fit is found. Since the total association in the data may be quantified by L^2, comparing the value of L^2 for the baseline model and for subsequent models is an alternative way of evaluating the power of the models in reducing the correlation between manifest variables (Magidson and Vermunt 2004).

The last step in LCM is classifying cases into appropriate latent classes. The Bayes theorem is applied to estimate posterior membership probabilities, and observations are assigned to the class in which the posterior probability (i.e., the modal class) is highest (see Magidson and Vermunt 2004).

Lack of fit in an LCM means that the basic underlying assumption of the model, i.e., local independency, is not satisfied with T classes. Traditionally, the strategy is to add another latent class to the model, but alternative, more parsimonious solutions may be followed by: (i) adding one or more direct effects; (ii) deleting one or more items; (iii) increasing the number of latent variables (Magidson and Vermunt 2004). A better fit may thus be obtained, given by several latent factors instead of one latent factor with T classes. Bivariate residuals may be used as diagnostic statistics to detect local dependency between items (Vermunt and Magidson 2005b): each pair of items corresponds to a Pearson chi-square statistic (divided by the number of degrees of freedom) in which the observed frequencies in a two-way cross-tabulation of the variables are compared with those expected, according to the corresponding LCM model. A value greater than one indicates that the LCM fails to explain that bivariate relationship. Analysis of bivariate residuals aids the choice among the three alternatives proposed above.

4.1 Latent class factor models

The traditional linear factor analysis model is very common in exploratory data analysis and reduces data dimensionality to a few sets of factors. It is usually applied to continuous indicators and also to nominal and ordinal scales, but it may lead to incorrect results. Magidson and Vermunt (2001) introduced a non-linear factor-analytic model based on latent class analysis, the latent class factor model (LCFM), which is suitable for analysis of both nominal and ordinal manifest variables, since it combines elements from both LCM and traditional factor analysis (Magidson and Vermunt 2005a). Linear approximation of the maximum likelihood estimates of the LCFM are proposed (Vermunt and Magidson 2005a) to provide output measures which are simple to interpret and similar to the standard output of factor analysis

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[10]The closer the values of the statistics to 1, the better the predictions.

(factor loadings, factor correlation, communalities)[11]. The advantages over traditional factor analysis are:

- the factors do not need to be rotated to be interpretable;

- ML estimates for factor scores are obtained directly from the model, without the need to impose additional assumptions, such as normality;

- variables may be continuous, categorical (nominal or ordinal), or counts, or any combination of these;

- extended factor models which include covariates and correlated residuals can be estimated (Magidson and Vermunt 2002).

The basic R-factor LCM may be defined as a restricted LCM (Magidson and Vermunt 2001) which contains R mutually independent latent variables, containing parameters (factor loadings) which measure the association of each latent variable on each indicator. In particular, a two-factor LCM is a restricted form of the four-class LCM, but is more parsimonious and parameterised for easier interpretation of results (Magdison and Vermunt 2001). LC factor models were initially proposed by Goodman (1974b) in the context of confirmatory latent class analysis.

5   Results

Analyses were conducted on data from the CAWI questionnaire on the sample of 2,498 students. Data were weighted (see section 2) in order to be representative of the entire cohort of students enrolled in academic year 2006-07; 53% of the respondents were women and 82% were resident in the Veneto region; 3% were foreign students. As regards university outcomes, 8% of the students changed university, 28% graduated, 13% withdrew, and 19% were still at university 6 years after enrolment (for more information on sample characteristics, see Giraldo 2014).

In this work, we used a latent class factor model to summarise in a few latent factors the items on the three domains of psychological aspects of university study described in section 3. We followed a confirmative approach. In particular, to confirm the existence of five latent variables for the domain of self-regulated learning (organisation, personal processing, self-evaluation, strategies to prepare for examinations, and metacognition ability), three latent variables for motivation (implicit theories of intelligence, self-efficacy, and achievement goals) and two latent variables for emotions (positive and negative emotions), we carried out confirmative latent class factor analysis separately for each domain. For example, in the domain of motivation, the confirmative model was estimated under the hypothesis of three latent variables and setting different to zero only the conditional probabilities of the items related to the specific latent construct. We thus restricted the items to refer only to the specific latent variable indicated in the literature.

We estimated various LCFM, varying the number of classes for each latent variable in each domain, and evaluating the plausibility of the theoretical model, testing

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[11]LCFM are implemented in Latent Gold software (Vermunt and Magidson 2005b).

Table 2: Model selection for Self-regulated learning

Model	No. of items	L^2	df	BIC	No. of direct effects
null model	20	95544.2	2398	76784.1	0
(3,3,3,3,3)	20	90018.9	2388	71337.0	0
(3,3,3,3,3)	20	89328.1	2384	70677.5	4
(3,3,3,3,3)	15	55536.6	2409	36690.4	4

Table 3: Model selection for Motivation

Model	No. of items	L^2	df	BIC	No. of direct effects
null model	20	98458.8	2398	79698.6	0
(2,2,2)	20	89757.6	2395	71020.9	0
(3,3,3)	20	87364.1	2392	68650.9	0
(4,4,4)	20	86478.8	2389	67789.1	0
(4,4,4)	13	42901.4	2424	23937.9	0
(4,4,4)	13	42734.2	2418	23817.6	6

the validity of the restrictions on the conditional probabilities. The results of the different models are listed in Tables 2-4. The choice of the best model in terms of the optimum number of classes was evaluated by examining the BIC statistics. The bivariate residuals (BVR) are examined in oder to test the hypthesis of local independence. High values of BVR are found between items related to the same latent factor. These items are been removed from the models with the idea that they were measuring the same concept. The overall fit of the models was evaluated with pseudo R-squared, since L^2 might be misleading due to the sparseness of the contingency tables.

In Tables 5-7 are reported the factor loadings of the latent variables separately for the three domains. As an example, Table 7 lists the two latent factors identified for the domain Emotions. The first refers to positive feelings such as hope and enthusiasm; the second describes negative emotions such as worry and embarrassment. These results and those for the other two domains are in line with the psychological literature (Mega et al. 2014).

Table 4: Model selection for Emotions

Model	No. of items	L^2	df	BIC	No. of direct effects
null model	20	101606.6	2398	140955.8	0
(2,2)	20	91043.3	2401	130369.0	0
(3,3)	20	88341.5	2399	127682.9	0
(3,3)	12	38935.9	2434	19894.1	0
(3,3)	12	38347.6	2429	19344.9	4

Table 5: Factors loadings for the domain Self-regulated learning

Items	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Item1	-0.5862	-0.0000	-0.0980	-0.0000	0.0000
Item2	0.7153	0.0000	0.0000	0.0000	-0.0000
Item3	-0.4966	0.1171	-0.0000	-0.0000	-0.0771
Item4	0.7085	0.0000	0.0000	0.0000	-0.0000
Item5	0.0000	0.8386	-0.0000	-0.0000	0.0000
Item6	-0.0863	0.5933	-0.0000	-0.0000	-0.0134
Item7	0.0000	-0.0000	0.5751	-0.0000	0.0000
Item8	-0.0000	0.0000	-0.4627	0.0000	-0.0000
Item9	0.0000	-0.0000	0.4975	-0.0000	0.0000
Item10	-0.1494	0.0000	-0.4572	0.0000	-0.0000
Item11	-0.0000	0.0000	0.0000	-0.4081	0.1338
Item12	0.0000	-0.0000	-0.0000	0.4919	0.0000
Item13	-0.0000	0.0000	0.0000	0.0000	0.6296
Item14	-0.0000	0.0000	0.0000	-0.0827	0.5649
Item15	-0.1054	0.0249	-0.0000	-0.0000	-0.4107
Entropy R-squared	0.6736	0.6835	0.5541	0.3191	0.6289

Table 6: Factors loadings for the domain Motivation

Items	Factor 1	Factor 2	Factor 3
Item1	-0.7635	0.0262	-0.0415
Item2	-0.8433	-0.0012	-0.0301
Item3	-0.7210	0.0567	-0.0000
Item4	-0.0000	0.3912	0.0000
Item5	-0.0000	0.5672	0.0000
Item6	-0.0590	0.4099	0.0000
Item7	-0.0542	0.6346	0.0000
Item8	0.0080	0.3886	0.0522
Item9	-0.0732	0.4905	-0.0040
Item10	0.0469	-0.0016	0.7366
Item11	0.0923	0.0248	0.6067
Item12	0.0000	0.0000	0.7955
Item13	0.0000	0.0000	0.7480
Entropy R-squared	0.7670	0.5321	0.7039

Table 7: Factors loadings for the domain Emotions

Items	Factor 1	Factor 2
Loneliness	-0.0002	0.5444
Resignation	0.0854	0.6335
Anger	-0.0001	0.6141
Worry	-0.1172	0.6316
Embarrassment	-0.0003	0.6539
Inferiority	0.0501	0.6320
Pride	-0.6011	-0.0016
Enthusiasm	-0.7301	-0.0012
Hope	-0.5220	0.0883
Interest	-0.6497	0.0508
Confidence	-0.5683	-0.1613
Challenge	-0.5625	-0.0020
Entropy R-squared	0.7174	0.7210

6 Conclusions and future research

This paper describes the use of latent class factor models to summarise in a few latent constructs three psychological domains: self-regulated learning, motivation, and emotions. Latent class factor models instead of traditional factor analysis were used because of the ordinal nature of the items measuring the latent variables making up the three domains. The results show the success of the proposed approach in summarising latent variables and also the ability of these factors to characterise fully students with various university outcomes according to the latent constructs. Latent factors may be fruitfully introduced into regression models, for better understanding of the effect of students characteristics (personal, familiar, previous education, psychological) on university outcomes. Further research will consider this as a starting point to assess the effects of these constructs on students' outcomes at university in a competing risk model, updating the work of Clerici et al. (2014).

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