Article

Perceived Competence and Intrinsic Motivation in Mathematics: Exploring Latent Profiles

Susana Rodríguez [1], Iris Estévez [2,*], Isabel Piñeiro [1], Antonio Valle [1], Tania Vieites [1] and Bibiana Regueiro [3]

[1] Department of Psychology, Faculty of Education, University of A Coruña, 15071 A Coruña, Spain; susana.rodriguez1@udc.es (S.R.); isabel.pineiro.aguin@udc.es (I.P.); antonio.valle@udc.es (A.V.); t.vieites@udc.es (T.V.)

[2] Department of Pedagogy and Didactics, Faculty of Education, University of A Coruña, 15071 A Coruña, Spain

[3] Department of Pedagogy and Didactics, University of Santiago de Compostela, 15782 Santiago de Compostela, Spain; bibiana.regueiro@usc.es

* Correspondence: iris.estevezb@udc.es; Tel.: +34-981-167-000 (ext. 4638)

Abstract: This study aims to use a person-centred approach to identify possible student motivational profiles in mathematics. These profiles are made up of various combinations of two motivational variables: perceived competence and intrinsic motivation. Once the profiles are identified, we examine the differences between them in negative emotions and mathematics performance. Our sample comprised 863 students (50.2% boys, 49.8% girls) aged between 9 and 13 years old. The results indicated three motivational profiles. One group of students with moderately high perceived competence and intrinsic motivation who demonstrated the best performance and the lowest levels of negative feelings about themselves. A second group was defined by moderately low levels of perceived competence and intrinsic motivation. The third group was characterized by very low perceived competence and low intrinsic motivation and demonstrated the worst performance in mathematics and the highest levels of anxiety and negative emotions towards mathematics.

Keywords: perceived competence; intrinsic motivation; mathematics; latent profiles; primary education

1. Introduction

Nowadays, both in the school environment and in society in general, mathematics is seen as the most difficult, most abstract subject [1], featuring many formulas and procedures—which students often fail to see as relevant to their daily lives. The popular belief that mathematics is only for "those who do it well" makes it easy for students to believe that they have poor skills, and to feel negative thoughts and anxiety. In addition, the fact that the results of the Program for International Student Assessment (PISA) 2018 report [2] confirm the idea that mathematics is the area where worst rates of acquisition of basic skills are obtained, increases concern about this issue.

As indicated by the European Commission (2020) [3], insufficient performance in basic mathematical skills means a difficult future to complete schooling. This can lead, in the long term, to greater difficulties for the inclusion of this population into the labor market.

More effort is needed to gain better understanding of this phenomenon and to explore effective ways to alleviate the negative impact it has on students' mathematics learning. Thus, following the Sustainable Development Goal 4, defined as, the attempt to ensure quality education with which young people acquire relevant technical skills and have lifelong learning opportunities [4], is essential to increase knowledge on the acquisition of mathematical skills process; not least students' wellbeing, the quality of their learning, and their educational success. It is for this reason that this study focuses on a series of affective—motivational variables, which have a great impact on the learning process and academic success in mathematics, such as intrinsic motivation, perceived competence and academic emotions [5,6]. By adopting a holistic, well founded and, at the same time,

an innovative approach, the objective is the generation of evidence-based knowledge to promote the effective and sustainable wellbeing of students and the environments in which they live and develop themselves.

1.1. Theoretical Framework: Expectancy-Value Theory

Expectancy-value theory is one of the most deeply-rooted approaches to the study of motivation in the field of educational research (See e.g., [7–9]). This interpretive tradition maintains that students' performance and persistence may be determined according to two main elements, expectations and value. The expectancy component refers to students' beliefs and judgements of their abilities to successfully do a task, the value component addresses students' reasons and motives to involve themselves in a task or not. Considering its impact on student performance and academic achievement in mathematics [8–10], in this study we focus on the analysis of the constructs of expectancy beliefs as perceived mathematics competency and intrinsic motivation towards mathematics as a measure related to intrinsic value [8,9,11,12].

Although the important correlation between the constructs of expectancy and value (e.g., [12,13]) justify the many studies aimed at additive or summative assessment, in this study we propose an interactive, synergetic approach to competency and intrinsic motivation, accepting the suggestion that "the effects of expectation of success will be null or very weak if value is low, even if the expectancies are high (and vice versa)" [12].

In this context, from a person-centred approach, we examine the complex combination of perceived math competence and intrinsic motivation for mathematics in order to differentiate different math motivational profiles between primary school students. As Watt et al. [14] established, up to now few studies have used this approach, synergistically combining expectancies and values to characterize different student motivational profiles in the field of mathematics (See e.g., [14–16]). To the best of our knowledge, there are also few studies using this approach with Spanish primary school children. In order to reduce this gap, and with the premise that the different configurations of expectancies and values will affect students' performance and academic emotions, we use a latent class model in this study.

The person-centred approach focuses on the analysis of possible combinations of variables at the subject-level, producing different intra-individual patterns allowing the identification of profiles, or groups of students with similar characteristics in the variables being studied [17]. The technique of latent class analysis is particularly effective for identifying non-linear qualitative differences between motivational aspects, condensing data into a more manageable, easier-to-interpret form without excluding information which is important about the relationships between variables. In contrast to traditional cluster analyses, LPA uses less arbitrary, more precise criteria to determine how many groups there are in a sample, producing statistical parameters that allow the model that best fits the data to be selected [18].

1.2. Perceived Competence, Intrinsic Motivation and Academic Performance

An individual's perceived competence is a construct that has received a great deal of educational research attention for many years [19,20]. A person's beliefs about their ability to do certain tasks successfully [21] has a strong, positive, direct relationship with their results in different subjects and domains [22–25]. As Usher and Pajares [26] argued, self-efficacy "predicts students' academic achievement across academic areas and levels". In this way, it would seem to indicate that perceived competence in mathematics exerts a positive motivational influence on performance [27]. Those who have high levels of perceived competence not only set themselves more difficult objectives to achieve, make more effort, and persist in challenges, they may also use better cognitive strategies and be more adept (See e.g., [19,20,22]).

The significant effect of intrinsic motivation on students' academic performance has also been widely documented [28,29]. It is evident that the various reasons behind

students' involvement in a given task will give rise to different motivational orientations, which will in turn lead to different results in terms of learning and achievement. As Ryan & Deci [28,29] suggested, intrinsic (rather than extrinsic) motivation is beneficial to students because it contributes to involvement for reasons linked to enjoyment and satisfaction. Compared to involvement due to reasons linked to winning prizes or external recompense, one would expect students motivated towards mastering mathematics to spend more time on tasks, to be more persistent when solving math problems and to ultimately perform better in the subject at various educational levels [30,31]. Furthermore, a longitudinal study carried out by [32] has shown that a motivational profile characterized by high levels of intrinsic motivation predicts better and more stable academic performance over time, compared to the extrinsically motivated profile.

1.3. Perceived Competence, Intrinsic Motivation and Academic Emotions

Empirical evidence suggests emotions have deep, significant effects on learning and math achievement throughout students' educational careers (e.g., [33–37]). Considering that negative emotions experienced at early ages can affect an individual's construction of their academic identity [36], our study looks at the emotions in students in the final stages of primary education.

Mathematics anxiety, a domain-specific self-belief that refers to the extent to which students feel helpless or stressed when studying mathematics, may be differentiated from other types of academic anxiety, for instance, by the extent to which it can specifically affect visual memory [38]. However, there are many unresolved questions, such as whether the anxiety that students feel about mathematics changes how they approach the subject, and this in turn affects mathematics competence [39]. Whatever the case, what does seem clear is that many students report feeling anxious about and scared of mathematics [40].

Although most research has also found that mathematics anxiety correlates negatively to perceived mathematics competence [34], there is little empirical research to date that has looked at the connection between upper elementary students' emotions and perceived competence in the mathematics context [35]. In this regard, we might assume perceived competence to negatively correlate with negative emotions and positively correlate with positive emotions [37].

Other recent research [5,41] has demonstrated that students' success in mathematics is related to their academic wellbeing, such that levels of anxiety or negative feelings towards mathematics might be less important the more that students believe that understanding mathematics is useful and valuable. Two studies, in particular, have shown that motivation moderates the relationship between mathematics anxiety and mathematics performance, and we can infer that high levels of motivation would mitigate the negative relationship between mathematics anxiety and academic performance (see: [39,42]). Along similar lines, a recent study [43] showed that mathematics anxiety could be a moderator of the effect of perceived competence on students' results.

1.4. Study Aims and Hypotheses

From an interactive perspective for the study of academic motivation with a person-centred approach, the main objective of our study is to identify mathematics motivational profiles in students in the last years of primary education. Assuming, as have Trautwein et al. [12], Watt et al. [14], and Meyer et al. [11], among others, synergistic interaction for the theoretical framework of expectancy-value [7,9], we hypothesize (H1) that there will be student profiles according to different combinations of perceived competence (expectancy element) and intrinsic motivation (value element). Once we have identified these profiles, the second objective is to analyse whether there are statistically significant differences in negative emotions associated with mathematics (anxiety and negative feelings) and in the academic performance in mathematics according to the identified motivational profiles.

Considering previous research, we hypothesize that (H2) profiles characterized by high perceived competence and intrinsic motivation for mathematics to show better achievement (e.g., [22–26,30,31]) and less negative feelings or mathematics anxiety [34,37,42,44] than profiles characterized by low perceived competence and low intrinsic motivation.

In addition, we hypothesize that (H3) in profiles characterized by low confidence in students' own abilities, performance and academic emotions will be more negative if intrinsic motivation is high compared to when it is not high [11,12]. In effect, as Control-Value Theory states [7–9] we expect negative feelings and mathematics anxiety to be associated with a profile of low control and high value placed on success [33,45].

2. Materials and Methods

2.1. Participants

The sample in this study was made up of 863 students from 13 primary schools in the province of A Coruña (Spain). The sample was evenly split between boys (50.2%) and girls (49.8%) aged between 9 and 13 years old (M = 10.77; SD = 0.69). Almost half (419; 48.6%) were in the 5th year of primary education, and just over half (444; 51.4%) were in the 6th year. All the schools were in urban or semi-urban locations.

2.2. Variables and Measures

We used the IAM (Inventory of Attitudes Towards Mathematics) to measure the variables. This instrument is the result of an expansion of the Fennema–Sherman Mathematics Attitudes Scales (FSS) from Fennema and Sherman [46]. We used a Spanish version of the scale that has previously been used in various studies (see e.g., [5,10]) to measure students' attitudes and motivation towards mathematics. We used the following IAM dimensions:

(1) Perceived competence in mathematics ($\alpha = 0.75$): this evaluates the student's level of confidence in themselves for learning mathematics and achieving good results (e.g., "I am very confident in myself about doing mathematics tasks").

(2) Intrinsic motivation for mathematics ($\alpha = 0.72$): this assesses how motivated the student is to learn and understand mathematics content (e.g., "Mathematics is enjoyable and stimulating for me").

(3) Mathematics anxiety ($\alpha = 0.77$): this assesses the student's anxiety about mathematics (e.g., "Normally I feel nervous and uncomfortable about mathematics").

(4) Negative feelings about mathematics ($\alpha = 0.70$): this assesses the presence and intensity of negative feelings caused by working on mathematics (e.g., "In math class I am sad and unhappy").

Each of the items in each dimension has a Likert-type format with five response options from 1 (completely false) to 5 (completely true).

Academic performance in mathematics was evaluated using the participating students' school grades in the subject. There are 5 grades normally given: unsatisfactory (1), satisfactory (2), good (3), very good (4), and outstanding (5).

2.3. Procedure

The data were collected during normal teaching time by personnel not belonging to the school. We obtained the prior consent of school administrations and the students' teachers, respecting the ethical standards set out in the Declaration of Helsinki. Before collecting the data, which happened at a single time point, we told the participants that it was important for them to respond honestly to the different questions, and reiterated the completely confidential nature of their responses.

2.4. Data Analysis

To produce the motivational profiles, we performed a Latent Profile Analysis–LPA. The best model was selected according to the data from the formal adjusted maximum likelihood ratio test from Lo, Mendell and Rubin [47]–LMRT–, the Akaike information

criterion (AIC), the Schwarz Bayesian information criterion (BIC), and the sample size adjusted BIC (SSA-BIC), as well as the entropy value and the size of each subgroup.

The *p*-value associated with the LMRT test indicates whether the solution with more ($p < 0.05$) or fewer ($p > 0.05$) classes fits the data better. The AIC, BIC, and SSA-BIC are descriptive indices of fit, lower values indicate a better fit for the model. In addition, small classes (those making up less than 5% of the sample) are typically considered spurious classes, indicating the extraction of too many profiles [48].

To determine the selected model's classification accuracy, we considered a posteriori probabilities and the entropy statistic. The value of this statistic ranges from 9 to 1, and the closer it is to 1, the more accurate the classification. Lastly, to evaluate the suitability of the model, we performed a MANOVA, through which we analysed the differences between classes or profiles with respect to the variables used to create them (perceived competence and intrinsic motivation). The between-class differences in the criterion variables are expected to be statistically significant. We used the criteria set by Cohen [49] to interpret effect size, according to which and effect is small when $\eta p2 = 0.01$ (d = 0.20), it is moderate when $\eta p2 = 0.059$ (d = 0.50), and the effect size is large when $\eta p2 = 0.138$ (d = 0.80).

In addition, in response to our second objective, we performed another MANOVA using negative feelings towards mathematics, mathematics anxiety, and mathematics performance as dependent variables, and the different math motivation profiles as the independent variable. As above, we used Cohen's criteria [49] to assess effect size.

3. Results

3.1. Preliminary Analysis

Table 1 gives the descriptive statistics and the correlations between each of the variables. Both the asymmetry and kurtosis for each of the variables met the criteria for normality (see e.g., [50]). The matrix shows that all of the correlations between the variables were statistically significant.

Table 1. Means, standard deviations, asymmetry, kurtosis, and correlation matrix.

	1	2	3	4	5
1. Perceived competence	–				
2. Intrinsic motivation	0.68 *	–			
3. Anxiety	−0.50 *	−0.44 *	–		
4. Negative feelings	−0.43 *	−0.51 *	0.48 *	–	
5. Academic performance	0.29 *	0.19 *	−0.30 *	−0.34 *	–
M	4.05	3.71	1.78	1.78	3.40
SD	0.76	0.86	0.87	0.87	1.26
Asymmetry	−0.88	−0.51	1.26	1.26	−0.42
Kurtosis	0.77	−0.16	1.42	1.42	−0.91

* $p < 0.01$.

3.2. Identification of Motivational Profiles

The latent classes were produced on the basis of two variables, perceived competence and intrinsic motivation. The process of fit was successive with increasing numbers of latent classes, and was stopped on the model that had no substantial improvement over the previous model. In this case, the model with four latent classes, as it did not improve on the previous three-class model. The results of this process are shown in Table 2.

We halted the model fit on four classes because this model produced a class containing less than 5% of the total sample. In addition, in the four-class model, the *p*-value in the LMRT was not statistically significant, indicating that it was no better than the three-class model. Therefore, despite the entropy being higher in the four-class model, and it having slightly lower values for AIC, BIC, and SSA-BIC than the three-class model, because the three-class model had no groups of less than 5% of the total sample, and because the LMRT *p*-value was statistically significant, we considered the three-class model to have a better fit than the four-class model.

Table 2. Results of latent class model fit.

	Latent Class Model		
	M2	**M3**	**M4**
AIC	3745.919	3549.116	3527.283
BIC	3779.242	3596.720	3589.168
SSA-BIC	3757.012	3564.963	3547.884
LMRT	410.287	193.274	26.525
(LMRT *p*)	(0.000)	(0.000)	(0.069)
Entropy	0.747	0.793	0.815
N° of groups with *n* < 5%	0	0	1

M2 = Model with two latent classes, M3 = Model with two latent classes, M4 = Model with four latent classes; AIC = Akaike's information criterion; BIC = Schwarz Bayesian information criterion; SSA-BIC = BIC adjusted for sample size; LMRT = Lo, Mendel and Rubin formal adjusted maximum likelihood ratio test.

In addition, the values of AIC, BIC, and SSA-BIC were lower in the three-class model than the two-class model. Based on these criteria, the three-class model exhibited better fit than the two-class model. In addition, the three-class model had better entropy than the two-class model, indicating better classification accuracy.

The entropy value for the three-class model is adequate (0.793). Table 3 gives information about the classification accuracy for each class and the numbers of subjects in each class. The coefficients associated with the groups the participants were assigned to are in the main diagonal. Most of the coefficients were close to 100%, indicating high classification accuracy. Analysis of the values outside the diagonal indicates that the classes represent well-differentiated groups.

Table 3. Characterization of latent profiles and accuracy of classifying participants in each profile.

	Model with Three Latent Classes				
	Group 1	**Group 2**	**Group 3**	***n***	**%**
Group 1	0.931	0.000	0.069	64	7.4
Group 2	0.000	0.918	0.082	467	54.1
Group 3	0.025	0.094	0.881	332	38.5

Lastly, we performed a MANOVA with the latent classes as the independent variable and the two variables used to create the classes as dependent variables in order to determine the importance of each of the two variables in the definition of each class. The results indicate that, at the multivariate level, the subjects in the three profiles exhibited statistically significant differences in self-efficacy and intrinsic motivation (λWilks = 0.184; $F(4,1718) = 571.55$; $p < 0.001$; $\eta p2 = 0.571$). The effect size was large. Although the two motivational variables contributed notably in differentiating between the subjects in each of the three groups, perceived competence was dominant. There were statistically significant differences between the three classes in the two criterion variables: perceived competence ($F(2,860) = 1190.04$; $p < 0.001$; $\eta p2 = 0.735$) and intrinsic motivation ($F(2,860) = 730.42$; $p < 0.001$; $\eta p2 = 0.629$). The effect was large in both cases.

Thus, given the statistical data regarding the fit of the models, the results of the ANOVA examining the contribution of each variable making up the profiles to differentiating between classes, and because of its theoretical suitability, we consider the three-class solution to be the most appropriate.

3.3. Description of Motivational Profiles

Table 4 shows the mean scores of the subjects belonging to the three latent classes in the chosen model. In order to most clearly describe the profiles, their similarities, and how they differ, we standardized (in z scores) each of the variables (M = 0; SD = 1). Figure 1 gives a graphical representation of the profiles.

Table 4. Description of the latent profiles (means, standard errors, and confidence intervals).

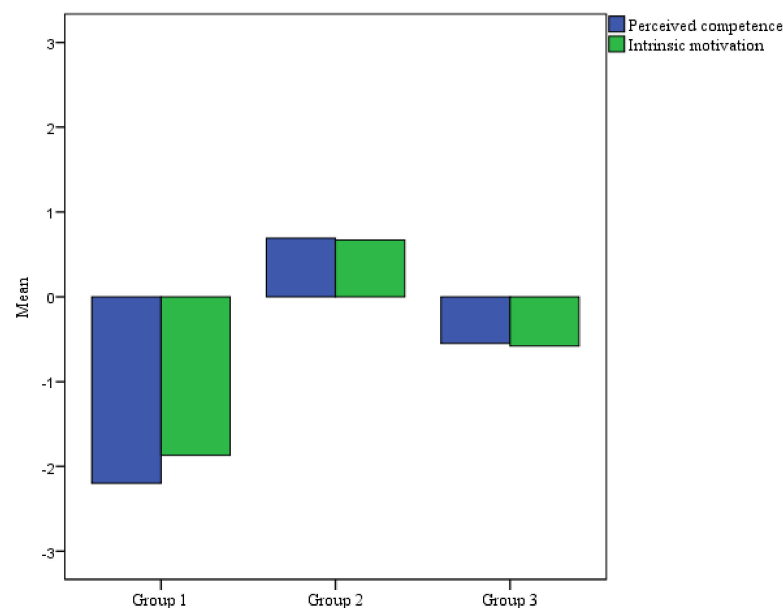|			Confidence Intervals	
	Mean	**Standard Error**	**Lower 5%**	**Upper 5%**
Profile 1 (*n* = 64)				
Perceived competence	2.413	0.098	2.252	2.574
Intrinsic motivation	2.161	0.127	1.952	2.370
Profile 2 (*n* = 467)				
Perceived competence	4.543	0.029	4.496	4.591
Intrinsic motivation	4.275	0.036	4.216	4.335
Profile 3 (*n* = 332)				
Perceived competence	3.666	0.046	3.589	3.742
Intrinsic motivation	3.243	0.052	3.158	3.328

Figure 1. Graphical representation of motivational profiles (z scores). Note. Group 1: very low perceived competence and low intrinsic motivation (*n* = 64); Group 2: moderately high perceived competence and intrinsic motivation (*n* = 467); Group 3: moderately low perceived competence and intrinsic motivation (*n* = 332).

The first group of students identified (*n* = 64; 7.4%) was characterized by very low levels of perceived competence and low levels of intrinsic motivation. The second group (*n* = 467; 54.1%) was characterized by moderately high levels of perceived competence and intrinsic motivation. The third group (*n* = 332; 38.5%) was characterized by moderately low levels of perceived competence and intrinsic motivation (see Figure 1).

3.4. Differences between the Motivational Profiles in Anxiety, Negative Feelings, and Performance in Mathematics

The results indicate that there were statistically significant differences in the three variables depending on the profile (λWilks = 0.65; F(81,714) = 51.41; $p < 0.001$; $\eta p2 = 0.194$). The effect size was large. Looking at each variable individually, there were statistically significant differences between the profiles in mathematics anxiety (F(2,860) = 124.88; $p < 0.001$; $\eta p2 = 0.225$), negative feelings caused by mathematics (F(2,860) = 114.99; $p < 0.001$; $\eta p2 = 0.211$) and mathematics performance (F(2,860) = 26.38; $p < 0.001$; $\eta p2 = 0.058$). Table 5 gives the descriptive statistics (means and standard deviations) for each of the variables in each group.

Table 5. Descriptive statistics for anxiety, negative feelings, and academic performance for each of the three profiles.

	Anxiety		Negative Feelings		Academic Performance	
	M	**SD**	**M**	**SD**	**M**	**SD**
Group 1	3.36	1.24	2.91	1.15	2.70	1.16
Group 2	1.69	0.89	1.47	0.71	3.66	1.21
Group 3	2.46	0.96	1.99	0.78	3.17	1.27

The multiple comparisons (Scheffé's test) were statistically significant in all variables and for each group. The variables anxiety and negative feelings use a scale of 1 (completely false) to 5 (completely true). The variable academic performance uses a scale of 1 (fail) to 5 (outstanding).

The results exhibited the same trend in all variables. The students with moderately high perceived competence and intrinsic motivation (Group 2) demonstrated better performance. In addition, this group had the lowest levels of anxiety and negative feelings towards mathematics.

In contrast, students with very low perceived competence and low intrinsic motivation (Group 1) demonstrated the worst performance and the highest levels of anxiety and negative feelings towards mathematics. Moreover, students with moderately low levels of perceived competence and intrinsic motivation (Group 3) demonstrated intermediate levels of negative emotions associated with mathematics—negative feelings and anxiety—and intermediate levels of performance in mathematics.

4. Discussion

The main objective of this study was to identify motivational profiles in students in their last few years of primary education. From an interactive perspective and a person-centred approach, the results support the identification of three math motivational profiles in students in the final years of primary school, so the first hypothesis of this study is confirmed (H1). Starting from the theoretical framework of expectancy-value theory [8,9] and assuming a synergetic interaction between the elements [11,12,14], these three profiles are shaped by combinations of perceived competence (expectancy) and intrinsic motivation (value) for mathematics. A small first group of students in late primary education (7.4%) can be characterized by very low confidence in their ability to tackle mathematics, along with a low interest in the subject. A second, larger group of students is defined by moderately high levels of perceived competence and intrinsic mathematics motivation. Finally, a third group, almost 40% of the sample, can be characterized by moderately low levels of perceived competence and interest in, or value attributed to, mathematics.

The profiles, based on combinations of perceived competence and intrinsic motivation, were not able to differentiate classes with low competence and high intrinsic motivation, or vice versa, as one might assume based on theory (see e.g., [12,14]). Which means that the H3 cannot be confirmed. As Meyer et al. [11] recently suggested, the detection of multiplicative effects may depend on the difficulty of detecting extreme cases that combine low expectations with high task value, and vice versa, variables that are often strongly correlated (r = 0.68 in this study).

After characterizing the motivational profiles, and attempting to respond to the second of our objectives, we found evidence of significant differences in performance and negative emotions associated with mathematics between the three student groups.

In line with previous studies, the worst-performing group of students in mathematics was the group with very low perceived competence and low intrinsic motivation (e.g., [22–26,30,31]), whereas the students who performed best were those who felt themselves to be most competent [19] and found mathematics to be interesting and stimulating [28,29,31,51]. The group with the lowest levels of confidence and intrinsic motivation reported the highest rates of anxiety and negative feelings towards mathematics, whereas the group with moderately perceived competence and intrinsic motivation reported the lowest levels of anxiety and negative feelings (e.g., [34,37,42]). In this sense, the second proposed hypothesis (H2) can be confirmed.

In addition to perceived competence having a critical, powerful influence on academic performance (e.g., [22,25]), because the source of anxiety is not so much the event per se but rather the lack of competence to deal with it [21,52]. It means that self-efficacy functions as an "antidote" to anxiety and negative feelings [5].

4.1. Practical Implications

This study made some significant contributions worth mentioning. Our findings should encourage the promotion of intervention strategies about perceived competence in learning environments in order that students develop better, more adaptive perceptions about their mathematics capabilities (e.g., [26]). It is advisable for mathematics tasks assigned by teachers to be moderately challenging, but potentially doable. This should produce opportunities or conditions necessary for students to be successful, both in their subject grades and in day-to-day classroom tasks [53]. That would mean that they acquire more self-confidence [44] which would potentially have an impact on the levels of anxiety they feel, their academic wellbeing, and ultimately in their future math performance and achievement [5].

In addition, these tasks should be seen by the students as useful, and close to their own interests and preoccupations in order to improve the intrinsic value and utility value of math. In this regard, teacher feedback can be a key factor in encouraging intrinsic motivation from the classroom [53,54]. Providing students with clear information about their progress, from the most individualized perspective possible, and making students understand math tasks as motivating challenges, rather than a threat, will be a core strategy for teaching activity [5,21,44]. Thus, the results of this study call for an improvement in the attention to diversity in schools, in this case in the attention to motivational diversity [55]. In the same way that students are different in their knowledge and skills, they are also different on a motivational level. Recognizing these differences implies that the teacher must start from the student's real motives and interests. In addition, teachers must understand that there are a variety of paths, from a motivational point of view, to achieve learning and academic success. Although some are more desirable than others, not all students necessarily have to follow the same motivational trajectory [55].

4.2. Limitations

One of the main limitations is that the data from this study is cross-sectional in nature and therefore causal relationships between the variables cannot be inferred. Likewise, it would also be interesting for future studies to use longitudinal data to better understand how these profiles progress and develop over time. Despite these limitations, the perspective used to carry out this study (person-centred approach) should be valued, since it focuses on the study of the combination of the two elements that support the basis of academic motivation towards math, and they are not analysed in isolation. This approach portrays reality in a holistic way and allows for generating a better understanding of the phenomenon, as well as the design of improvement proposals more adjusted to the particular needs and interests of the students. Likewise, the fact of having chosen the LCA guarantees the precision in the definition of the profiles, based on statistical and objective criteria. The results of this research begin the path to overcome the gap found in the literature regarding the study of motivation towards mathematics in primary education in the Spanish context through a person-centred approach.

Author Contributions: Conceptualization, I.E. and T.V.; methodology, I.E.; validation, B.R., S.R. and I.E.; formal analysis, I.E., A.V.; investigation, I.P.; data curation, S.R. and B.R.; writing—original draft preparation, I.E. and T.V.; writing—review and editing, A.V.; supervision, I.P., A.V. and S.R.; project administration, I.P., B.R. and A.V. All authors have read and agreed to the published version of the manuscript.

References

1. Wang, C.K.J.; Liu, C.W.; Nie, Y.; Chye, Y.L.S.; Lim, B.S.C.; Liem, G.A.; Tay, E.-G.; Hong, Y.; Chiu, C. Latent profile analysis of students' motivation and outcomes in mathematics: An organismic integration theory perspective. *Heliyon* **2017**, *3*, e00308. [CrossRef]
2. Ministerio de Educación y Formación Profesional (MEFP). Available online: https://www.educacionyfp.gob.es/dam/jcr:e2be368b-f08c-4ab8-8fd9-eb93b76c6bf2/pisa-2018-programa-para-la-evaluaci-n-online.pdf (accessed on 2 February 2020).
3. European Commission. *Sustainable Development in the European Union—Monitoring Report on Progress towards the SDGS in an EU Context*; Publications Office of the European Union: Luxembourg, 2020.
4. United Nations General Assembly. Transforming Our World: The 2030 Agenda for Sustainable Development. Available online: https://www.refworld.org/docid/57b6e3e44.html (accessed on 2 February 2020).
5. Rodríguez, S.; Regueiro, B.; Piñeiro, I.; Valle, A.; Sánchez, B.; Vieites, T.; Rodríguez-Llorente, C. Success in mathematics and academic wellbeing in primary-school students. *Sustainability* **2020**, *12*, 3796. [CrossRef]
6. Walshaw, M.; Brown, T. Affective productions of mathematical experience. *Educ. Stud. Math.* **2012**, *80*, 185–199. [CrossRef]
7. Eccles, J.S.; Wigfield, A. Motivational beliefs, values, and goals. *Annu. Rev. Psychol.* **2002**, *53*, 109–132. [CrossRef] [PubMed]
8. Wigfield, A.; Eccles, J. Expectancy–value theory of achievement motivation. *Contemp. Educ. Psychol.* **2000**, *25*, 68–81. [CrossRef]
9. Wigfield, A.; Eccles, J. The development of competence beliefs, expectancies for success, and achievement values from childhood through adolescence. In *Development of Achievement Motivation*; Wigfield, A., Eccles, J., Eds.; Academic Press: London, UK, 2002; pp. 92–120.
10. Cueli, M.; González-Castro, P.; Álvarez, L.; García, T.; González-Pienda, J.A. Variables afectivo-motivacionales y rendimiento en matemáticas: Un análisis bidireccional. *Rev. Mex. Psicol.* **2014**, *31*, 153–163.
11. Meyer, J.; Fleckenstein, J.; Köller, O. Expectancy value interactions and academic achievement: Differential relationships with achievement measures. *Contemp. Educ. Psychol.* **2019**, *58*, 58–74. [CrossRef]
12. Trautwein, U.; Marsh, H.W.; Nagengast, B.; Lüdtke, O.; Nagy, G.; Jonkmann, K. Probing for the multiplicative term in modern expectancy–value theory: A latent interaction modeling study. *J. Educ. Psychol.* **2012**, *104*, 763. [CrossRef]
13. García, T.; Rodríguez, C.; Betts, L.; Areces, D.; González-Castro, P. How affective-motivational variables and approaches to learning predict mathematics achievement in upper elementary levels. *Learn. Individ. Differ.* **2016**, *49*, 25–31. [CrossRef]
14. Watt, H.M.; Bucich, M.; Dacosta, L. Adolescents' Motivational Profiles in Mathematics and Science: Antecedents and consequences for engagement and wellbeing. *Front. Psychol.* **2019**, *10*, 990. [CrossRef]
15. Lazarides, R.; Dietrich, J.; Taskinen, P.H. Stability and change in students' motivational profiles in mathematics classrooms: The role of perceived teaching. *Teach. Teach. Educ.* **2019**, *79*, 164–175. [CrossRef]
16. Lazarides, R.; Dicke, A.L.; Rubach, C.; Eccles, J.S. Profiles of motivational beliefs in math: Exploring their development, relations to student-perceived classroom characteristics, and impact on future career aspirations and choices. *J. Educ. Psychol.* **2020**, *112*, 70. [CrossRef]
17. Hickendorff, M.; Edelsbrunner, P.A.; McMullen, J.; Schneider, M.; Trezise, K. Informative tools for characterizing individual differences in learning: Latent class, latent profile, and latent transition analysis. *Learn. Individ. Differ.* **2018**, *66*, 4–15. [CrossRef]
18. Pérez, D.O.; Izquierdo, J.M.A. Análisis de clases latentes como técnica de identificación de tipologías. *Int. J. Educ. Dev.* **2019**, *5*, 251–260. [CrossRef]
19. Bandura, A. *Self-Efficacy: The Exercise of Control*; Worth Publishers: London, UK, 1997.
20. Pajares, F.; Schunk, D.H. Self-beliefs and school success: Self-efficacy, selfconcept, and school achievement. In *Perception*; Riding, R., Rayner, S., Eds.; Ablex Publishing: New York, NY, USA, 2001; pp. 239–266.
21. Bandura, A. Self-efficacy conception of anxiety. *Anxiety Stress Coping* **1988**, *1*, 77–98. [CrossRef]
22. Klassen, R.M.; Usher, E.L. Self-efficacy in educational settings: Recent research and emerging directions. In *The Decade Ahead: Theoretical Perspectives on Motivation and Achievement*; Urdan, T.C., Karabenick, S.A., Eds.; Emerald Group Publishing Limited: Bingley, UK, 2010; pp. 1–33.

23. Recber, S.; Isiksal, M.; Koç, Y. Investigating self-efficacy, anxiety, attitudes and mathematics achievement regarding gender and school type. *Ann. Psychol.* **2018**, *34*, 41–51. [CrossRef]

24. Rosário, P.; Lourenço, A.; Paiva, O.; Rodrigues, A.; Valle, A.; TueroHerrero, E. Prediction of mathematics achievement: Effect of personal, socioeducational and contextual variables. *Psicothema* **2012**, *24*, 289–295. [PubMed]

25. Talsma, K.; Schüz, B.; Schwarzer, R.; Norris, K. I believe, therefore I achieve (and vice versa): A meta-analytic cross-lagged panel analysis of self-efficacy and academic performance. *Learn. Individ. Differ.* **2018**, *61*, 136–150. [CrossRef]

26. Usher, E.; Pajares, F. Sources of self-efficacy in school: Critical review of the literature and future directions. *Rev. Educ. Res.* **2008**, *78*, 751–796. [CrossRef]

27. Honicke, T.; Broadbent, J. The influence of academic self-efficacy on academic performance: A systematic review. *Educ. Res. Rev.* **2016**, *17*, 63–84. [CrossRef]

28. Ryan, R.M.; Deci, E.L. Intrinsic and extrinsic motivations: Classic definitions and new directions. *Contemp. Educ. Psychol.* **2000**, *25*, 54–67. [CrossRef] [PubMed]

29. Ryan, R.M.; Deci, E.L. Intrinsic and extrinsic motivation from a self-determination theory perspective: Definitions, theory, practices, and future directions. *Contemp. Educ. Psychol.* **2020**, 101860. [CrossRef]

30. Denissen, J.J.; Zarrett, N.R.; Eccles, J.S. I like to do it, I'm able, and I know I am: Longitudinal couplings between domain-specific achievement, self-concept, and interest. *Child Dev.* **2007**, *78*, 430–447. [CrossRef] [PubMed]

31. Nicolaidou, M.; Philippou, G. Attitudes towards mathematics, self-efficacy and achievement in problem solving. *Eur. Res. Math. Educ. III Pisa Univ. Pisa* **2003**, *1*, 1–11.

32. Henderlong, J.; Wormington, S.V. Profiles of intrinsic and extrinsic motivations in elementary school: A longitudinal analysis. *Int. J. Exp. Educ.* **2014**, *82*, 480–501. [CrossRef]

33. Frenzel, A.C.; Pekrun, R.; Goetz, T. Girls and mathematics. A "hopeless" issue? A control-value approach to gender differences in emotions towards mathematics. *Eur. J. Psychol. Educ.* **2007**, *22*, 497–514. [CrossRef]

34. Goetz, T.; Cronjaeger, H.; Frenzel, A.C.; Ludtke, O.; Hall, L.C. Academic self-concept and emotion relations: Domain specificity and age effects. *Contemp. Educ. Psychol.* **2010**, *35*, 44–58. [CrossRef]

35. Hanin, V.; Van Nieuwenhoven, C. Developing an expert and reflexive approach to problemsolving: The place of emotional knowledge and skills. *Psychology* **2018**, *9*, 280–309. [CrossRef]

36. Hanin, V.; Van Nieuwenhoven, C. Emotional and motivational relationship of elementary students to mathematical problem-solving: A person-centered approach. *Eur. J. Psychol. Educ.* **2019**, *34*, 705–730. [CrossRef]

37. Peixoto, F.; Sanches, C.; Mata, L.; Monteiro, V. "How do you feel about math?": Relationships between competence and value appraisals, achievement emotions and academic achievement. *Eur. J. Psychol. Educ.* **2017**, *32*, 385–405. [CrossRef]

38. Stankov, L.; Morony, S.; Lee, Y.P. Confidence: The best non-cognitive predictor of academic achievement? *J. Exp. Educ.* **2014**, *34*, 9–28. [CrossRef]

39. Lyons, I.M.; Beilock, S.L. Mathematics anxiety: Separating the math from the anxiety. *Cereb. Cortex* **2012**, *22*, 2102–2110. [CrossRef] [PubMed]

40. Morony, S.; Kleitman, S.; Lee, Y.P.; Stankov, L. Predicting achievement: Confidence vs self-efficacy, anxiety, and self-concept in Confucian and European countries. *Int. J. Educ. Res.* **2013**, *58*, 79–96. [CrossRef]

41. Yi, H.; Tian, L.; Huebner, E.S. Mastery goal orientations and subjective well-being in school among elementary school students: The mediating role of school engagement. *Eur. J. Psychol. Educ.* **2019**, *35*, 429–450. [CrossRef]

42. Monteiro, V.; Peixoto, F.; Mata, L.; Sanches, C. Mathematics: I don't like it! I like it! Very much, a little, not at all . . . Social support and emotions in students from 2nd and 3rd cycles of education. *Anal. Psicol.* **2017**, *35*, 281–296. [CrossRef]

43. Wang, Z.; Lukowski, S.L.; Hart, S.A.; Lyons, I.M.; Thompson, L.A.; Kovas, Y.; Michèle, M.M.; Mazzocco, R.; Stephen, A.; Petrill, S.A. Is math anxiety always bad for math learning? The role of math motivation. *Psychol. Sci.* **2015**, *26*, 1863–1876. [CrossRef]

44. Pérez-Fuentes, M.D.C.; Núñez, A.; Molero, M.D.M.; Gázquez, J.J.; Rosário, P.; Núñez, J.C. The Role of Anxiety in the Relationship between Self-efficacy and Math Achievement. *Psicol. Educ.* **2020**, *26*, 137–143. [CrossRef]

45. Frenzel, A.C.; Goetz, T.; Pekrun, R.; Watt, H.M. Development of mathematics interest in adolescence: Influences of gender, family, and school context. *J. Res. Adolesc.* **2010**, *20*, 507–537. [CrossRef]

46. Fennema, E.; Sherman, J.A. Fennema-Sherman Mathematics Attitudes Scales: Instruments designed to measure attitudes toward the learning of mathematics by females and males. *Math. Educ. Res. J.* **1976**, *7*, 324–326. [CrossRef]

47. Lo, Y.; Mendell, N.R.; Rubin, D.B. Testing the number of components in a normal mixture. *Biometrika* **2001**, *88*, 767–778. [CrossRef]

48. Hipp, J.R.; Bauer, D.J. Local solutions in the estimation of growth mixture models. *Psychol. Methods* **2006**, *11*, 36–53. [CrossRef] [PubMed]

49. Cohen, J. *Statistical Power Analysis for the Behavioral Sciences*; Lawrence Erlbaum: London, UK, 1988.

50. Finney, S.J.; DiStefano, C. Non-normal and categorical data in structural equation modeling. In *Structural Equation Modeling. A Second Course*; Hancock, G.R., Mueller, R.O., Eds.; Information Age Publishing: Charlotte, NC, USA, 2006; pp. 269–314.

51. Jansen, M.; Lüdtke, O.; Schroeders, U. Evidence for a positive relation between interest and achievement: Examining between-person and within-person variation in five domains. *Contemp. Educ. Psychol.* **2016**, *46*, 116–127. [CrossRef]

52. Nie, Y.; Lau, S.; Liau, A.K. Role of academic self-efficacy in moderating the relation between task importance and test anxiety. *Learn. Individ. Differ.* **2011**, *21*, 736–741. [CrossRef]

53. Olivier, E.; Archambault, I.; De Clercq, M.; Galand, B. Student self-efficacy, classroom engagement, and academic achievement: Comparing three theoretical frameworks. *J. Youth Adolesc.* **2019**, *48*, 326–340. [CrossRef] [PubMed]

54. Schunk, D.H.; Pajares, F. Self-efficacy theory. In *Handbook of Motivation at School*; Wentzel, K.R., Wigfield, A., Eds.; Routledge: London, UK, 2009; pp. 35–54.

55. Núñez, J.C.; Cabanach, R.G.; Rodríguez, S.; González-Pienda, J.A.; Rosário, P. Perfiles motivacionales en estudiantes de secundaria: Análisis diferencial en estrategias cognitivas, estrategias de autorregulación y rendimiento académico. *Rev. Mex. Psicol.* **2014**, *26*, 113–124.