The treatment of error in learners of Russian as a foreign language: Visual analytics

Ines A. Gonzalez-Hidalgo
Universidad de Granada

Benami Barros-Garcia
Universidad de Granada

Wenceslao Arroyo-Machado
Universidad de Granada

Received: 30/01/2023 / Accepted: 04/06/2023
DOI: *https://doi.org/10.30827/portalin.viX.27276*
ISSN paper edition: 1697-7467, ISSN digital edition: 2695-8244

ABSTRACT: There are well-known challenges in the assessment of learning in general, and especially in foreign language learning. The treatment of error in the classroom is a recent topic of research and one that has given rise to multiple approaches to pinpoint, identify and classify the errors made by learners of foreign and second languages. This article presents a methodological model based on visual analytics and education data mining to optimise teacher intervention in the face of individual and collective errors in the Russian language classroom. The methodology has been tested on learners of Russian as a foreign language at the University of Granada. It comprised an online questionnaire for skills assessment, with 75 questions that were classified by grammatical category and sub-category. It was filled out by the learners of the 2021/2022 academic year, yielding 31 responses. The responses were then analysed through visual analytics and education data mining techniques. Clustering questions and learners allowed the identification of different error patterns and groups of learners with common errors. This serves to demonstrate the usefulness of these techniques for classroom assessment.
Keywords: visual analytics, education data mining, foreign language, Russian

El tratamiento del error en estudiantes de ruso como lengua extranjera: analítica visual

RESUMEN: Son conocidos los problemas en la evaluación del aprendizaje, en especial en lo referido a los estudios de lengua extranjera. El tratamiento del error en el aula es un tema de investigación reciente y que ha dado lugar a numerosas propuestas para localizar, identificar y clasificar los errores de los estudiantes de lenguas extranjeras y segundas lenguas. En este trabajo se propone un modelo metodológico basado en la Analítica visual y la Minería de datos educativos para la optimización de la intervención docente ante el error individual y colectivo en el aula de ruso. Esta metodología ha sido puesta a prueba en estudiantes de ruso como lengua extranjera en la Universidad de Granada. Se ha elaborado un cuestionario on-line para la evaluación de los conocimientos, con 75 preguntas clasificadas por categoría y subcategoría gramatical. Este fue realizado por los estudiantes del curso 2021/2022, obteniendo un total de 31 respuestas. Mediante las técnicas de analítica visual y minería de datos educativos, las respuestas fueron analizadas. Mediante la clusterización de las preguntas y

los estudiantes se han detectado patrones de errores y grupos de estudiantes con errores comunes. Se evidencia así la utilidad de estas técnicas en la evaluación del aula.
Palabras clave: analítica visual, minería de datos educativos, lengua extranjera, ruso

1. Introduction

One of the main challenges of any foreign language (FL) teacher is the lack of information as to which contents have been comprehended by the learners and whether such comprehension is equitable or, on the contrary, there is disparity among students. Such generalised unawareness or fuzzy knowledge that teachers tend to have poses a significant obstacle for adaptive learning and, as a result, for learners to progress and absorb new contents.

The interest for the treatment of error in the FL classroom is relatively recent. Initially, the error was considered an obstacle to learning, something that should be eradicated and that was mainly caused by L1 interference (Muñoz-Basols & Bailini, 2018). From the second half of the 20th Century, error analysis began to be widely studied as an alternative to contrastive analysis, in order to gain a better understanding of the language learning process (Ellis & Barkhuizen, 2005, p. 52; Khansir, 2012) and to give an explanation to errors that were not related to L1 interference (Darus, 2013). Currently, the error is seen as a necessary element in L2 acquisition, in line with the claims made by Montrul (2014), among others, and anticipated by Corder (1967). As a result, the trend towards learner-centred learning promotes its use as an educational tool (Muñoz-Basols, 2005).

Numerous studies on this topic have allowed for pinpointing and identifying the errors of foreign-language and second-language learners and classify them according to predefined criteria, which vary depending on the author or the reference classification. Alexopoulou (2005) relies on three general criteria: descriptive, linguistic or grammatical, and etiological, emphasising grammatical issues and focusing on the origin or causes of the deviations. Within this classification, the etiological criterion, which strives to understand the causes or the origin of the errors, divides errors into inter-lingual and intra-lingual errors. Vázquez (1992, p. 31, extended in 1999, p. 28), on the other hand, proposes a more thorough classification, to include cultural, pragmatic, and pedagogical criteria that consider extra linguistic factors.

The stages of FL learning also play an important role in the occurrence and explanation of the errors, since the frequency, origin or typology of errors varies according to the language proficiency shown by the learner. Regarding the etiological criterion, Brown (1994) points out that inter-lingual errors are predominant during the early stages of language learning, while intra-lingual errors are more common when learners have a better acquisition of the L2 system. In sum, the numerous research on these language deviations shows the importance of treating the error as an instrument to gain a better command of the foreign language. Nowadays, there seems to be a consensus that making mistakes is an unavoidable and essential part of learning any language (Dulay et al., 1982, p. 138).

While historically Second Language Acquisition (SLA) has shown special interest in identifying universal elements in L2 acquisition, there is some consensus that individual differences, whose variables are growing, have a more substantial impact on this process (Sanz, 2016). Individual differences may be due to multiple factors, such as motivation, previous level of knowledge, own goals and pursuits (Azevedo et al., 2022), sociocultural and situational factors such as gender, educational institution or even academic year (De la Morena, Sanchez & Fernández, 2011), among others. This requires taking into consideration different knowledge levels and structures within the classroom and their influence in the learning process of each learner.

In this sense, ignoring or relativizing the importance of the specificities of the group is one of the biggest problems that any FL teacher may face at the beginning of a course or learning stage. The higher the level, the sharper the gaps seem to be among learners, partly because some of the individual variables are introduced or heightened, such as motivation, self-efficacy, learning strategies (Cancino et al., 2022). Moreover, learners need to become more capable of learning by themselves and of displaying skills such as collaboration, problem-solving, and, in general, self-regulating their learning (Krieger et al., 2022). During such self-regulated learning, cognitive and meta-cognitive strategies rely heavily on teaching methodologies, individual variables and external regulating agents (Azevedo et al., 2022). The growing research on self-regulated learning indicates that the use of this kind of strategies (cognitive, meta-cognitive, behavioural, etc.) is far from uniform, regardless of the model used for analysing or describing such self-regulated learning (Panadero, 2017). The data also shows that in higher levels of teaching there is usually a better understanding of strategies and techniques, but it is not necessarily more widely implemented (Foerst et al., 2017). It seems clear that future research ought to focus on the learner's feelings-thoughts-context interface to move forward to achieve a more beneficial assessment and higher performance (Andrade, 2019), which requires a better understanding of the meaning of assessment, tasks, self-assessment, and self-correction, as well as their interrelations (Yan & Carless, 2022; Falchikov & Boud, 1989).

On the one hand, we must accept that the teacher may easily lose touch with the degree of assimilation of knowledge, or even not be fully aware of the imbalances. On the other hand, we know that this unawareness or partial/biased knowledge jeopardises the possibility of promoting an adaptive and self-regulated learning model, since it requires a good understanding of the classroom (Bienkowski, Feng & Means, 2012).

A better awareness of the group allows to deploy the teaching resources more efficiently in the most relevant aspects (Gómez-Aguilar et al., 2014). Numerous studies prove that feedback is a crucial element in the learning process (Evans 2013, Shute 2008, Black & William 1998) and highly demanded by learners (Misiejuk et al., 2021). From that standpoint, Ferreira (2006) believes that the main purpose of corrective feedback is to provide important information that learners can then actively use in amending their errors. Thus, feedback is of great assistance in learning and acquiring contents because it makes students aware of their difficulties and errors and helps correcting them.

SLA research indicates not only that the teacher's feedback has a direct impact on the learner's self-correction, but also that its absence may cause resentment or frustration on the learners as they receive no advice on their progress (Muñoz-Basols & Bailini, 2018). In fact, when feedback is given in a positive and spirited way, it helps convey positive attitudes and improve motivation (Noels, 2001). Pujolà and Herrera Jiménez (2018) claim that ongoing feedback is registered as an optimal and fundamental experience both in play and in learning in general, especially when it is immediate. Moreover, if students received more immediate recognition for their work, they would most likely make greater efforts

(Kapp, 2012), Likewise, the Instituto Cervantes Curriculum Plan (2012) promotes a model to meet the needs of learners, encourage reflection on the language and offer constructive feedback to give students control of their learning process.

For teachers to have the necessary information to provide precise feedback to learners, first they need to be aware of the difficulties of the group. Understanding this is crucial to produce efficient feedback that helps learners progress and integrate the knowledge. Similarly, having a more realistic knowledge of their own difficulties and strengths helps learners increase their degree of involvement, motivation, and self-efficacy. In the case of Russian as a FL, knowing the classroom level and characteristics is particularly necessary due to the major difficulty that this language usually poses for Spanish speakers. Very uneven language levels and learning difficulties can be found in the same group of learners. Such difficulties may be due to multiple reasons, such as, for example, teaching methods, particularities of the language, immersion programmes or degree of exposition to the language, handbooks used, previous knowledge or any of the many individual variables that mark the development in learning a language from scratch, as is usually the case for Russian.

The main goal of this study is to enhance the teaching intervention in the face of individual and collective errors in the classroom of Russian as a FL through a methodological model based on Visual Analytics (VA) and Education Data Mining (EDM). Therefore, the objective is the optimisation of the teaching intervention against errors by observing how and to what extent the contents of the subjects of Russian as a FL are absorbed in the Degree in Modern Languages and Literatures and in the Degree in Translation and Interpretation at the University of Granada, and which are the most frequent errors, so this information can be used to lay the foundations for a more effective teaching intervention directed towards overcoming common errors that could potentially hinder the following learning stages. Visual analytics and visualisation techniques will be used to pinpoint the errors and systematise and identify clusters of co-errors or networks of shared error based on data collected through questionnaires.

Among the expected benefits are the improvement of teaching and learning based on a better understanding of the classroom (Bienkowski, Feng & Means, 2012), and the optimisation of visual analytics and education data mining techniques in the FL classroom, following previous approaches for other types of subjects and education scenarios (among others, Križanić, 2020; Deng et al., 2019). Likewise, we intend to lay the foundations to enhance the methodology of teaching Russian as a FL based on data, a still unexplored line of research in Spanish scientific literature.

To attain that objective, the work was organised in accordance with the following structure: first, description of error treatment in the Russian teaching classroom and the use of EDM to optimise feedback. Second, description of the data and methods used for the case study.

2. EDM to optimise feedback in the Russian as a FL classroom

Visual analytics is a technique or set of techniques that show great potential for improving the learning process (Gómez-Aguilar, García-Peñalvo & Therón, 2014; Amo & Santiago, 2017), and particularly the pace and degree of acquisition and content-learning, both collectively in a group and individually. Initially, LA (Learning Analytics), VA, and

EDM seemed to have emerged to mitigate the impracticality of face-to-face in online settings (Romero & Ventura, 2005; Mohamad & Tasir, 2013; Romero et al., 2010). However, their contributions to multiple scientific fields (Romero & Ventura, 2020) and to numerous educational contexts (Amo & Santiago, 2017) are indisputable. These tools can shape a valid methodological framework for the decision-making and design of educational programmes, and for the improvement of learning processes.

The use of VA and EDM techniques on data collected through questionnaires and other assessment instruments reveals new information about the classroom and helps understand the particularities and difficulties of the learners in a clear and intuitive manner. In addition, these techniques provide not only for an improved design of the assessment instruments, but also for the tailoring of teaching materials to the needs of the group.

Recent studies show similar proposals aimed at providing the teacher with more information to improve his/her performance. Deng et al. (2019) applied visual analytics to examine student performance in an introductory chemistry course by using the PerformanceVis tool. This analysis was aimed at viewing learner performance not only through the results of several assessment instruments over time, but also through the demographic and academic backgrounds of the students to eventually predict the final score. The results of this study revealed the existence and characteristics of several behaviour patterns among learners. Moreover, it reviewed the difficulty of the questions in the evaluation instruments and the adequacy of their design and found the third exam to be the most difficult one, because questions on the same topic were not closely related to each other. Final score prediction seemed to be more accurate when the number of demographic characteristics was smaller.

Similarly, Križanić (2020) focused on analysing the behaviour of students during a one-semester online course through clustering techniques and decision trees. First, with the aid of the k-means algorithm, learners were grouped by their frequency of access to the available material. This resulted in three different clusters of learners: those with a low frequency of access to the online contents, those with an average frequency of access, and those with a high frequency of access.

Therefore, these behavioural clusters resulted in three decision tree models showing the relationship between the consultation of materials, such as readings, and access to other available contents, such as forums. By adding the variable of the examination scores, the correlation between the frequency of access and the grade obtained was concluded. Hence, learners with a higher frequency of access to the materials obtained the higher scores, those with the lowest frequency were graded the lowest, and in the intermediate group, the majority of learners earned good grades, but there was also a small percentage with low scores.

The approach towards adaptive learning models in which teaching intervention is more personalized and effective is likely to involve optimising the feedback. To that end, this study used information visualization tools. These tools are a real-time assessment instrument and also serve to improve the sometimes insufficient teacher observation. These pedagogical intervention models will result in optimised feedback and an improved control of the learning process in the classroom and will also have a strong impact on learner motivation and the understanding of their perceptions (Misiejuk et al., 2021; Bienkowski, Feng & Means, 2012).

3. Methodology

From a methodological and procedural point of view, we will follow the approach of Barros García & Arroyo-Machado (2020) for the study of Russian FL classroom and the general reviews of Romero & Ventura (2020). The proposal is a methodology based on VA and EDM as an instrument to get to know the classroom and to complement teacher observation in the subjects of Russian as a foreign language of the different degrees taught at the University of Granada. This methodology is aimed at optimising the feedback provided by the teacher and, in doing so, exploring adaptive learning models.

3.1. Data

Russian as a FL is taught at the University of Granada both as part of the degree in Translation and Interpreting and the degree of Modern Languages and Literatures. The latter offers Russian as one of the 4 maior languages. This involves studying the Russian language in 4 modules of 12 ECTS, one per each academic year, from beginner to advanced. The degree in Translation and Interpreting, on the other hand, offers Russian as a second foreign language. The workload of this language consists of 18 ECTS in the first year, 12 ECTS in the second and 12 ECTS in the third. Although the last year does not include any subjects on foreign languages, it does however involve greater contact with the language because of the translation courses.

The student profile is similar in both degrees (Translation and Interpreting, and Modern Languages and Literatures). Most students are of Spanish nationality and with Spanish as their mother tongue. However, there is often a few national and international mobility students and/or students with different mother tongues, but they are usually a minority. Similarly, students of Slavic origin or having Russian as their daily communication language is common. These degrees require no minimum knowledge of Russian for admission. Regarding the materials used for the study of Russian as a FL, both degrees use the handbook series "Поехали!" ("Poekhali!").

Our study begins with the creation of a questionnaire to be filled out by learners of Russian as a FL at the University of Granada. The results will be analysed using VA and EDM tools and methods in search of patterns and co-occurrence of errors, as well as learner behaviour and performance. The co-occurrence of errors will make it possible to group learners into clusters of similar errors and difficulties, which will allow the design of efficient and data-based lines of intervention and resolution of difficulties.

The data used in this research were obtained from a questionnaire. It was designed for this study following the standards of the official Test of Russian as a Foreign Language (TORFL), specifically the proposal of Dubinina et al. (2020) and Maltseva & Kapitonova (2019) at B1 level. While questionnaires were anonymous, learners were given a four-digit number that they could use to retrieve their answers and analyse them in a detailed, individual, and personalised manner. At the beginning of the questionnaire there were several questions relating to the study of Russian and self-assessment. By way of example, there were some questions regarding the place where the learner had studied or was studying Russian (College, Institution, etc.), how many years the student had been learning it, their estimated level according to the Common European Framework of Reference (CEFR), their satisfaction with their level or their enthusiasm for the study of Russian as a FL.

LA is usually based on the Learning Analytics Cycle (Clow, 2013), which represents LA methodology as a feedback cycle between learners, data, analysis, and intervention. Thereby learners generate data that make it possible for us to analyse them to obtain information for the design of efficient interventions on those very same learners. As noticed by Barros García (2021), this cycle is somewhat similar to the essential cycle of VA and, partially, of EDM, whereby data must provide information, and such information must be turned into knowledge. Such knowledge must be then applied back to the data, to once again obtain new information.

The first step in drafting the questionnaires was to choose the relevant grammatical categories in accordance with the language level or the learning stage to be assessed. In our case, in order to identify the difficulties at a near B1 level, the following categories were used: Lexicon, Cases, Aspect, Verbs of motion, and Compound sentences. Although this is not the only possible choice, the above categories are the most frequent and consistent in most tests at this level (Dubinina et al., 2020; Maltseva & Kapitonova, 2019).

The categories were, in turn, divided into more specific sub-categories in order to pinpoint the exact location of potential difficulties. In this way, the category of Compound clause includes the sub-categories of o.com.kotory (relative clauses), o.com.esli/li (conjunction “если”/ particle “ли”), o.com.chtoby (conjunction “чтобы”), o.com.prichina (cause). Each of them evaluates different aspects, such as relative clauses, the difference between the conditional if and the if in reported speech, the difference between что and чтобы, and causal clauses, respectively. The category of Motion verbs, on its part, is divided into two sub-categories: v.mov.asp and v.mov.lex. The former evaluates questions relating to the choice of aspect in motion verbs, and the latter analyses the questions of motion verbs where the key lies in their meaning, usually provided by the prefixes.

As for the duration of the questionnaire, our proposal was to set a time limit of 30 minutes for 75 items, thereby observing the item/time rate used by TORFL at B1 level. All categories were equitably represented in those 75 items: each of the 5 categories was assigned 15 questions in the questionnaire. Likewise, all sub-categories were also represented equitably in the 15 items assigned to each category. Each sub-category of the Compound clause had 4 items, except for the sub-category of cause, which included 3 questions —since it tends to be better acquired by students whose proficiency level is assumed to be close to B1— in order not to exceed the established number of items per category. In the category of Motion verbs, the subcategory v.mov.asp was more strongly represented (9 questions) than the subcategory v.mov.lex. (6 questions). This was since the reference test gave more representation to the subcategory of aspect within Motion Verbs, and we chose to respect that criterion.

The questionnaire was designed in such a way that the questions were representative of one single category, avoiding any ambiguous questions or those that could represent more than one category, in order to make it easier to identify the difficulties. Additionally, when filling out the questionnaire, the questions were randomly displayed, to avoid having the same theme shown consecutively, since learners may recognise it and respond by inertia.

Each question consisted not only of the possible answers, but also included a “Don’t know/no answer” option. Although the official tests of Russian as a FL do not include this “Don’t know/no answer” option, it gave respondents the opportunity to deliberately indicate that they ignored the answer or were unsure of it. In this way, in addition to gaining an interesting variable for the further analysis of self-efficacy, random responses were avoided.

Questionnaires were completed using Google Forms by Russian foreign language (FL) students at the same level (and year) of study. A total of 31 students (N = 31) participated in the survey, which represented 80% of the total number of students at this level. Respondents were asked not to consult reference materials at the beginning of the questionnaire. There was also a notice informing respondents that by completing the questionnaire they were consenting to the use and processing of their data, and that their responses may be used for research purposes.

3.2. Methods

After collecting the responses from the questionnaire, the data were filtered through R (script is accessible at https://zenodo.org/record/7581912#.ZGTmAnbtaX0) in order to extract those relating to the errors made by each learner and by the group as a whole, and VOSviewer in order to display the network of co-errors. Subsequently, the clusters or communities of learners with a similar error behaviour were identified through social network analysis (Louvain algorithm) and unsupervised classification techniques (K-means algorithm). Clustering techniques were implemented following the models of Križanić (2020) and Deng et al. (2019).

Let us remember that the standard educational data clustering process (Dutt, Ismail & Herawan, 2017) involves three stages: data pre-processing, to understand the data set; data standardisation, to prepare and clean the data; and cluster modelling stage, which includes cluster identification, cluster evaluation and validity and, finally, deployment and implementation. While the standard model was followed, we focused on the location of two types of clusters:

1) Clusters of co-errors (social network analysis). This type of networks is made of communities of questions that are failed at the same time, that is to say, they show the specific items that learners typically fail at a time. Pinpointing these clusters is relevant not only to check whether the difficulties in each category are real, but also to differentiate isolated mistakes from systematic errors. Moreover, the data in the occurrence clusters allow to establish possible connections between several categories and, therefore, find out the relationship between them and the difficulties involved for learners.
2) Clusters of error pairing (unsupervised classification). These clusters are pinpointed to identify groups of students with a similar behaviour. In other words, it allows to identify the learners with similar error patterns. It is essential to note that these error patterns are at the same time connected to the error networks identified in the first type of clusters, the clusters of co-errors. Understanding the communities of students with similar error patterns is crucial for the design of teaching interventions that are more efficient and better aligned to the needs of each cluster of learners.

4. Results and discussion

4.1. Learner profile

During the academic year 2021/2022 the questionnaire registered 31 responses, 11 of which were from fourth-year students of the degree in Modern Languages and Literatures and

14 from fourth-year students of the degree in Translation and Interpreting, 5 from students who took the fourth year of the degree in Translation and Interpreting in the 2020/2021 academic year and 1 from a student of the Russian Centre of the University of Granada. Out of the combined 19 students in both groups of the Translation and Interpreting degree program, 6 (31.6%) reported also studying Russian as a FL in parallel at the Russian Centre.

The majority of the respondents (24 persons, 77.4%) reported having studied Russian as a FL for 3-4 years approximately. Figure 1 summarises the self-assessment of their Russian language proficiency level: 16 persons (51.6%) considered their level to be approximately B1; 12 (38.7%) believed that theirs was closer to A2 and 3 (9.7%) judged their level as B2.

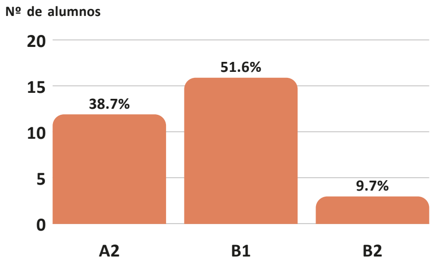

Figure 1. *Self-assessment of Russian language level*

However, respondents were given the following options: A2, A2+, B1, B1+, B2 or B2+. The (+) distinction allowed students to specify whether their language proficiency corresponded to the standard level or was closer to the following one. 8 persons (67%) believed that their level was A2+, 9 students (56.25%) considered their level of Russian to be closer to B1+ and, lastly, 1 person (33%) reported that their level approached B2+. As can be observed, most A2 students believed that their level was close to B1. As for B1 themselves, the results were similar, since more than half of respondents considered that their level was approaching B2. This can be due, for starters, to the ambiguity of the + option, since the limits between A2 and A2+ are not usually well defined and establishing one's own proficiency level is often confusing. Another explanation could have to do with the fear or insecurity of identifying one's level with a higher one, that is, the student may feel more comfortable claiming that their level is A2+ instead of B1.

4.2. Error detection

Figure 2 shows the distribution of errors by category for each different item in the questionnaire. As can be noted, there seems to be no clear common pattern of behaviour among the students. However, in some categories, such as Lexicon or Compound clause, the range of error percentage is wider (within the same category we can find cases with a low error percentage and other cases with a high one) that in categories such as Aspect or Case, where the range is narrower. It is also noticeable that the students who made a higher number of errors spread them proportionally across all categories, while those with a lower error rate tend to concentrate them in one or a few categories.

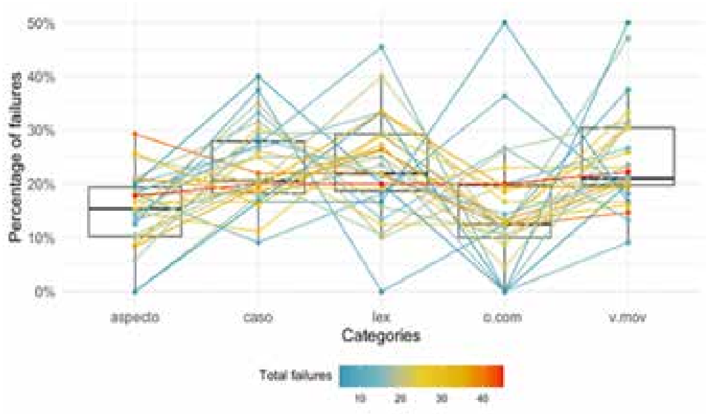

Figure 2. *Percentage and distribution of student errors by categories and total number of failed questions per student*

The network of co-errors shows clusters of questions based on the error patterns of the students and is filtered to display relationships of at least 2 co-errors, that is, questions that were failed by at least 2 different students (Figure 3). This trimming helps to exclude unwanted relationships created by students with a high error rate who, therefore, generate a large number of co-errors. 5 clusters of questions were identified in total.

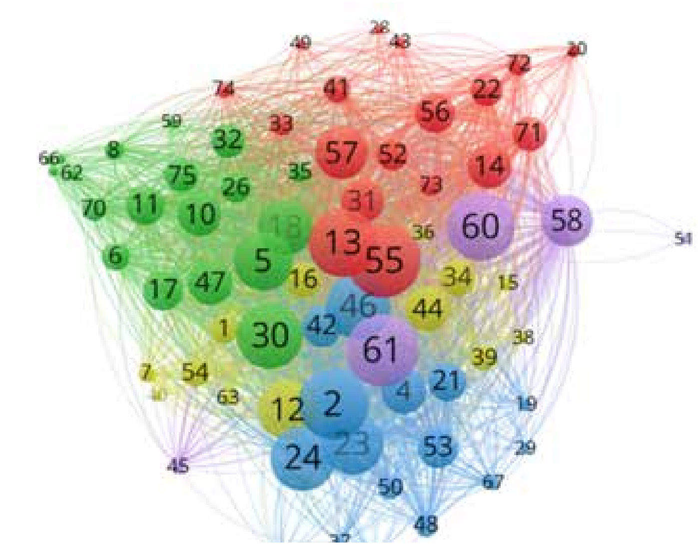

Figure 3. *Network of co-errors filtered to display questions with a relationship of at least 2 co-errors. The thickness in the edges reflects the total number of co-errors between questions, the node size reflects the total number of co-errors of each question and the colour is the cluster. An interactive version can be accessed at: https://tinyurl.com/2pssea67*

Absolute values of errors do not inform on clusters of students with a similar error pattern, because the groupings obtained using these data were built from the number of errors and not from their behaviour pattern. Figure 4 below is the result of the same process, but with percentage values, and the percentile was calculated to better differentiate the clusters. Using the k-means method required establishing the number of clusters to be identified. After several trials, it was decided that the most appropriate value was 4.

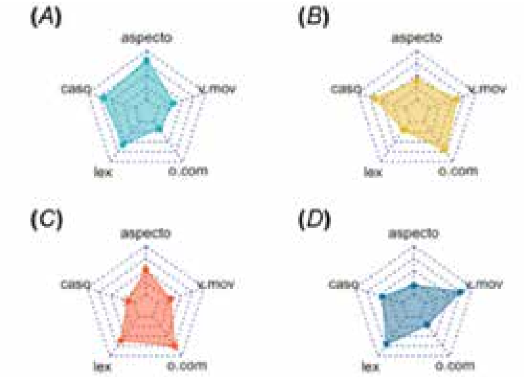

Figure 4. *Error profiles of students of Russian based on common error patterns*

Among the respondents, 4 different behaviour patterns can be extracted. The first (Figure 4A) involves 8 students, showing difficulties mainly in the categories of Aspect, Case and Lexicon. The second (Figure 4B) includes 10 students, for the categories of Case, Motion verbs and Compound clause. Third-year students (Figure 4C) contains 7 students, failing more often in Lexicon and Compound clause. The last error pattern (Figure 4D) encloses 6 students, showing difficulties mainly in the categories of Lexicon, Motion verbs and, to a lesser extent, Case.

As for subcategories, Figure 5 shows that the distribution of errors by subcategory was highly imbalanced, since most errors concentrate in 3 subcategories only: Aspect, Lexicon and Case. So much so that, apparently, there are not several error patterns in this case, but one single general pattern. It must be pointed out that barely any errors were found in the Cause subcategory, suggesting that this content was assimilated evenly by learners.

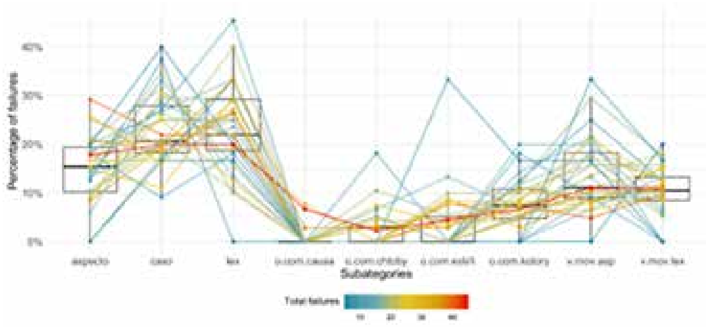

Figure 5. *Percentage of errors by subcategory*

In general, the Lexicon category poses great difficulty for learners, since it stands out in three out of four error patterns, and it is also the most failed category. These results seem to reveal the need for harder student work, but also for more specific activities for the assimilation of vocabulary.

If the categories in the questionnaire are analysed individually, it becomes evident that certain relationships can be found. In this case, there seems to be a correlation between the variables of Lexicon and the Motion verbs. The lack of lexical knowledge often makes it impossible to choose the right motion verb. Surely, this hypothesis could be applied to every other variable, but it is even more relevant in this case, because Russian motion verbs express particularly precise and detailed nuances, which hinder their learning (Gagarina, 2009; Hasko, 2009; Launer, 1987; Nesset, 2000).

On the other hand, there seems to be a correlation between self-assessment of Russian language proficiency and the results obtained in the questionnaire, since the students who estimated their own level at B2 obtained lower error percentages (Figure 6). Nevertheless, there are some cases where students self-evaluated their level at A2 or B1 and obtained better results than those who thought their level was A2+ or B1+. This would reinforce the idea that learner insecurity about their Russian language proficiency (expressed using +) can make them believe their level is lower than it is.

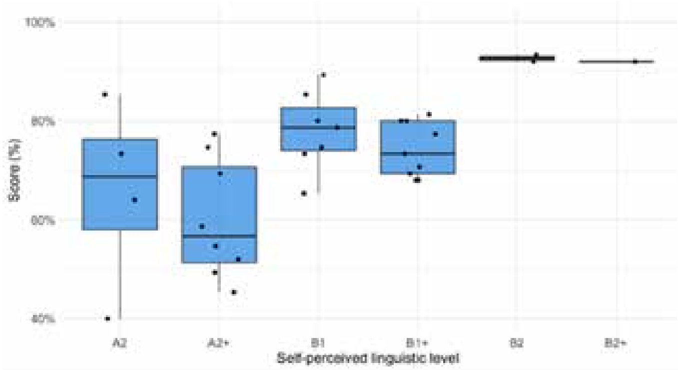

Figure 6. *Box-and-whisker plot of students' scores according to self-perceived language proficiency level*

5. DISCUSSION

In this paper, we have presented a proposal to identify shared and individual errors in the classroom using VA and EDM. Our methodology has been implemented by analysing the errors of students of Russian at the University of Granada. An automated form run an analysis, and then the responses were processed and used to generate communities and display errors broken down by students and questions.

This work is not without its faults. We have not been able to analyse learner behaviour concerning the "Don't know/no answer" option, which is a relevant field when studying self-efficacy. Similarly, the data collected through the questions relating to self-assessment and self-efficacy were not exploited in this piece of work, nor were they cross-checked with the results obtained from the questionnaire. The sample has not allowed us to compare the results of the students who only learn Russian at the University with those who also attend the Russian Centre of the University of Granada. Moreover, it must be pointed out that our questionnaire consisted of 75 items, whereas most language proficiency tests of Russian as a FL for this level range from 120 to 160 items. A smaller number of items makes it more difficult to find clusters of learners with similar error behaviours and to detect significant networks of students. However, it also makes it easier to collect the data: the participation rate in this study (that is, the percentage difference between potential and actual respondents) was 70.5%.

A broad horizon of analysis lies ahead in terms of the correlation between respondent perception and performance. The questionnaire that we used was aimed at B1 level learners in accordance with the TORFL standards. Therefore, there is the possibility of extended it to other language levels and analysing the difficulties of different profiles of learners. Furthermore, the questionnaire could be extended to groups of learners that have learned Russian as a FL using other handbooks, to analyse the effectiveness of those handbooks and their potential impact on comprehension and learning. We limited our study to groups working with the same handbooks so we could establish more precisely their learning stages and the contents completed.

These tools are increasingly used in educational contexts due to their enormous potential. Nonetheless, for classroom knowledge, these techniques are more useful in larger groups, since that is when teachers encounter the greatest difficulty in pinpointing patterns of error from observation.

6. Conclusion

Our proposal has revealed that a methodology based on VA and EDM can contribute to a better understanding of the difficulties and particularities of the classroom, which can in turn help the teacher provide more precise feedback and enhance the teaching intervention in the face of individual and collective errors.

The data collected through the questionnaires were subjected to techniques of filtering, social network analysis, unsupervised classification, and clustering. This has made it possible to obtain communities of questions that tend to be failed at the same time (which allows to verify the validity of the categories used when creating the tests), as well as to observe whether a certain error was isolated or indicative of a shared pattern. Additionally, we have identified communities of learners with similar error patterns and knowing them is crucial to enhance the feedback and to design a truly effective teaching intervention.

The results allow us to better understand not only the particularities of the classroom of Russian as a FL at the University of Granada, but also the content acquisition and the learning process of the targeted groups.

7. Acknowledgement

El presente artículo es resultado del Proyecto de investigación “Visualización analítica para la optimización del feedback y la evaluación en el aula de Traducción e Interpretación y Enseñanza de lenguas extranjeras" (PPJIA2021.40) del Plan Propio de Investigación de la Universidad de Granada.

8. References

Alexopoulou, A. (2005). Aproximación al tratamiento del error en la clase de E/LE desde la perspectiva del análisis de errores. *Estudios de Lingüística Aplicada*, *23*(41), 101-125.

Amo, D. y Santiago, R. (2017). *Learning Analytics. La narración del aprendizaje a través de los datos*. UOC.

Andrade, H. L. (2019). A Critical Review of Research on Student Self-Assessment. *Frontiers in Education*, *4*(87). doi.org/10.3389/feduc.2019.00087

Azevedo, R., Bouchet, F., Duffy, M., Harley, J., Taub, M., Trevors, G., Cloude, E., Dever, D., Wiedbusch, M., Wortha, F. and Cerezo, R. (2022). Lessons Learned and Future Directions of MetaTutor: Leveraging Multichannel Data to Scaffold Self-Regulated Learning with an Intelligent Tutoring System. *Frontiers in Psychology*, *13*. doi.org/10.3389/fpsyg.2022.813632

Barros García, B. (2021). La representación visual de los resultados de investigación. En M. Cruz Piñol (Ed.), *e-Research y español LE/L2. Investigar en la era de las tecnologías* (pp. 228-247). Routledge.

Barros García, B. & W. Arroyo-Machado (2020). El examen como punto de partida: técnicas de visualización y análisis de redes para optimizar el feedback en el aula de ruso como L2. doi.org/10.5281/zenodo.4472655

Black, P. & Wiliam, D. (1998). *Inside the black box: Raising standards through classroom Assessment*. Phi Delta Kappan, *80*(2), 139-144.

Bienkowski, M., Feng, M., y Means, B. (2012). *Enhancing Teaching and Learning Through Educational Data Mining and Learning Analytics: An Issue Brief.* eric.ed.gov/?id=ED611199

Brown, H. D. (1994). *Principles of Language Learning and Teaching*. Prentice Hall.

Cancino, M., Arenas, R., & Herrera, C. (2022). Exploring the Relationship between L2 Language Proficiency, Language Learning Strategies, and Self-Efficacy: Evidence from Chilean Classrooms. *Revista de Lingüística y Lenguas Aplicadas, 17*, 1-9. doi.org/10.4995/rlyla.2022.16122

Clow, D. (2013). An overview of learning analytics. *Teaching in Higher Education*, *18*(6), 683-695. doi.org/10.1080/13562517.2013.827653

Corder, P. (1967). The significance of learner's errors. *International Review of Applied Linguistics*, *5*, 167-170.

Darus, S. (2013). Error analysis. En P. Robinson (Ed.), *Second Language Acquisition*, (pp. 213-215). Routledge.

De la Morena, M., Sánchez, A. y Fernández, M. P. (2011). Diferencias en los niveles de motivación por sexo, curso y tipo de centro educativo en el aprendizaje estratégico de la lengua extranjera. *ARBOR Ciencia, Pensamiento y Cultura*, *187* (Extra 3), 225-230.

Deng, H., Wang, X., Guo, Z., Decker, A., Duan, X., Wang, C., Ambrose, G., y Abbott, K. (2019). Visual analytics of student performance data from an introductory chemistry course. *Visual Informatics*, *3*(4), 166-176. doi.org/10.1016/j.visinf.2019.10.004

Dubinina, N. A. et al. (2020). *ТРКИ - на 100%: Тесты по русскому языку. Открытые экзаменационные материалы СПбГУ. Первый уровень (B1)*. Златоуст. [TRKI - na 100%: Testy po russkomu âzyku. Otkrytye èkzamenacionnye materialy SPbGU. Pervyj uroven' (B1). Zlatoust].

Dulay, H., M. Burt & S. Krashen. (1982). Language Two. Oxford University Press.

Dutt, A., Ismail, M. A. y Herawan, T. (2017). A Systematic Review on Educational Data Mining. *IEEE Access*, *5*, 15991-16005. doi.org/10.1109/ACCESS.2017.2654247

Ellis, R. y Barkhuizen, G. (2005). *Analysing Learner Language*. Oxford University Press.

Evans, C. (2013). Making sense of assessment feedback in higher education. *Review of Educational Research*, *83*(1), 70-120. doi.org/10.3102/0034654312474350

Falchikov, N., & Boud, D. (1989). Student Self-Assessment in Higher Education: A Meta-Analysis, *Review of Educational Research, 59*(4), 395-430. doi.org/10.3102/00346543059004395

Ferreira, A. (2006). Estrategias efectivas de feedback positivo y correctivo en el español como lengua extranjera. *Signos*, *39*(62). doi.org/10.4067/s0718-09342006000300003

Foerst, N. M., Klug, J., Jöstl, G., Spiel, C., & Schober, B. (2017). Knowledge vs. Action: Discrepancies in University Students' Knowledge about and Self-Reported Use of Self-Regulated Learning Strategies, *Frontiers in Psychology, 8*, 1288. doi.org/10.3389/fpsyg.2017.01288

Gagarina, N. (2009). Verbs of motion in Russian: an acquisitional perspective. *The Slavic and East European Journal, 53*(3), 451-470. http://www.jstor.org/stable/40651166

Gómez-Aguilar, D.-A., García-Peñalvo, F.-J., y Therón, R. (2014). Analítica visual en e-learning. *El profesional de la Información*, *23*(3), 236-245.

Hasko, V. (2009). The locus of difficulties in the acquisition of Russian verbs of motion by highly proficient learners, *The Slavic and East European Journal, 53*(3), 360-385. http://www.jstor.org/stable/40651162

Instituto Cervantes. (2012). *Las competencias clave del profesorado de lenguas segundas y extranjeras.* http://cvc.cervantes.es/Ensenanza/biblioteca_ele/competencias/default.htm

Kapp, K. M. (2012). *The Gamification of Learning and Instruction: Game-Based Methods and Strategies for Training and Education*. Pfeiffer.

Khansir, A. A. (2012). Error Analysis and Second Language Acquisition. *Theory and Practice in Language Studies*, *2*(5), 1027-1032.

Krieger, F., Azevedo, R., Graesser, A. C. & Greiff, S. (2022). Introduction to the Special Issue: The Role of Metacognition in Complex Skills - Spotlights on Problem Solving, Collaboration, and Self-Regulated Learning. *Metacognition Learning*, *17*, 683-690. doi.org/10.1007/s11409-022-09327-6

Križanić, S. (2020). Educational data mining using cluster analysis and decision tree technique: A case study. *International Journal of Engineering Business Management*, *12*. doi.org/10.1177/1847979020908675

Launer, M. K. (1987). The semantic structure of verbs of motion in Russian. *Russian Language Journal / Русский Язык*, *41*(140), 77-105. http://www.jstor.org/stable/43676558

Maltseva, M. y Kapitonova, T. (2019). *Тесты, тесты, тесты. Элементарный уровень. Базовый уровень. I сертификационный уровень*. Златоуст. [Testy, testy, testy. Èlementarnyj uroven'. Bazovyj uroven'. I sertifikacionnyj uroven'. Zlatoust].

Misiejuk, K., Wasson, B., y Egelandsdal, K. (2021). Using learning analytics to understand student perceptions of peer feedback. *Computers in Human Behavior, 117*. doi.org/10.1016/j.chb.2020.106658

Mohamad, S. K., y Tasir, Z. (2013). Educational data mining: A review. *Procedia - Social and Behavioral Sciences*, *97*, 320-324.

Montrul, S. A. (2014). Interlanguage, Transfer and Fossilization. Beyond Second Language Acquisition. En Z. Han y E. Tarone (Ed.), *Interlanguage: Forty Years Later* (pp. 75-104). John Benjamins.

Muñoz-Basols, J. y Bailini, S. (2018). Análisis y corrección de errores. En J. Muñoz-Basols, E. Gironzetti y M. Lacorte (Ed.), *Spanish Language Teaching. Metodologías, contextos y recursos para la enseñanza del español L2* (pp. 94-108). Routledge.

Muñoz-Basols, J. (2005). 'Aprendiendo de los errores con la abuela Dolores': el error como herramienta didáctica en el aula de ELE. En *Actas del Primer Congreso Internacional de FIAPE*. RedELE. 20-23 marzo 2005.

Nesset, T. (2000). Iconicity and prototypes: A new perspective on Russian verbs of motion. *Scando-Slavica*, 46, 105-119. doi.org/10.1080/00806760008601154

Noels, K. (2001). Learning Spanish as a Second Language: Learners' Orientations and Perceptions of their Teachers' Communication Style. *Language Learning*, *51*(1), 107-144.

Panadero, E. (2017). A Review of Self-regulated Learning: Six Models and Four Directions for Research. *Frontiers in Psychology*, *8*(422). doi.org/10.3389/fpsyg.2017.00422

Pujolà, J.-T. y Herrera F. J. (2018). Gamificación. En J. Muñoz-Basols, E. Gironzetti y M. Lacorte (Ed.), *Spanish Language Teaching. Metodologías, contextos y recursos para la enseñanza del español L2* (pp. 583-595). Routledge.

Romero, C. y Ventura, S. (2007). Educational Data Mining: A Survey from 1995 to 2005. *Expert Systems with Applications*, *33*, 135-146. doi.org/10.1016/j.eswa.2006.04.005

Romero, C. y Ventura, S. (2020). Educational data mining and learning analytics: An updated survey. *WIREs Data Mining and Knowledge Discovery*, *10*(3). doi.org/10.1002/widm.1355

Romero, C., Ventura, S., Pechenizkiy, M., y Baker, R.S.J.D. (Eds.). (2010). *Handbook of Educational Data Mining* (1st ed.). CRC Press. doi.org/10.1201/b10274

Sanz, C. (2016). Adquisición del Español Como Segunda Lengua: Investigación. En J. Gutiérrez-Rexach (Ed.), *Enciclopedia de Lingüística Hispánica* (pp. 242-252). Routledge.

Shute, V. J. (2008). Focus on formative feedback. *Review of Educational Research*, *78*(1), 153-189.

Vázquez, G. (1992). *Análisis de errores y aprendizaje de español/lengua extranjera*. Peter Lang.

Vázquez, G. (1999). *¿Errores? ¡Sin falta!* Edelsa.

Yan, Z. & Carless, D. (2022). Self-assessment is about more than self: the enabling role of feedback literacy, *Assessment & Evaluation in Higher Education*, *47*(7), 1116-1128, doi.org/10.1080/02602938.2021.2001431