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Conceptual learning in pre-service teacher groups through a Text Mining intervention

Aprendizaje conceptual en grupos de profesorado en formación mediante una intervención basada en Minería de Textos

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RESUMEN

Concept acquisition is a critical aspect in the education of teachers yet is especially challenging in group contexts in which traditional teaching strategies often fail to convey complex notions effectively. This study investigates the potential of text mining (TM) based learning analytics as a teaching tool to enhance conceptual learning in pre-service teachers. To do so, it analyses how the learning of complex and abstract educational concepts was affected by a TM-based learning analytics intervention, in comparison with traditional teaching strategies, including the elaboration of an individual project, and the attendance of a master class. Quasi-experimental pre- and post-tests were thus administered to three non-equivalent groups (A, B, and C, respectively) of a total of 81 master's students enrolled in a distance education teacher training programme at a Spanish university, and token corpora were analysed using TM techniques in collected definitions of abstract educational concepts (1017 pre-test and 1133 post-test tokens from Group A; 1127 pre-test and 1111 post-test tokens from Group B; and 1101 pre-test and 1173 post-test tokens from Group C). It was found that the TM-based learning analytics intervention significantly enhanced the students' keyword selection in submitted definitions ($t_{Yuen} = -6.37$, $p < .001$, $\delta_R^{AKP} = -1.03$, $IC_{95\%} = -2.10, -.74$) and the association of relevant terms (with post-test Jaccard values ranging from .217 to .917) compared to the other teaching approaches. This study therefore offers empirical evidence that TM-based learning analytics can be an effective pedagogical tool that promotes an enhanced learning of abstract concepts in the education of teachers. The results underscore the value of TM-based educational technology in optimizing conceptual learning and resource efficiency in higher education settings.

Palabras clave: textual analysis, content analysis, concept formation, social learning, visual learning, educational technology, higher education, teacher education

ABSTRACT

La adquisición de conceptos es un aspecto fundamental en la formación del profesorado, pero sigue siendo un reto, especialmente en contextos grupales en los que las estrategias de enseñanza tradicionales a menudo no logran transmitir las nociones complejas de forma eficaz. En este estudio se examina el potencial de la analítica del aprendizaje basada en minería de textos (MT) como herramienta didáctica para mejorar el aprendizaje conceptual del profesorado en formación. El objetivo fue analizar el efecto de la analítica del aprendizaje basada en MT en la adquisición de conceptos educativos complejos y abstractos, en comparación con otras estrategias de enseñanza tradicionales, como la elaboración de proyectos individuales o asistir a clases magistrales. Se llevó a cabo un estudio cuasiexperimental pre y postest con 81 estudiantes de máster de un programa de formación a distancia en una universidad española. El estudio se centró en analizar los corpus textuales relacionados con la definición de conceptos educativos no tangibles de tres grupos no equivalentes (Grupos A, B y C, respectivamente). Mediante técnicas de MT, se analizaron 1017 tokens pretest y 1133 postest del Grupo A, 1127 tokens pretest y 1111 postest del Grupo B, y 1101 tokens pretest y 1173 postest del Grupo C. Los resultados revelaron que la analítica de aprendizaje basada en MT mejoró significativamente la adquisición de conceptos de los estudiantes en cuanto a la selección de palabras clave ($t_{Yuen} = -6.37$, $p < .001$, $\delta_R^{AKP} = -1.03$, $IC_{95\%} = -2.10, -.74$) y la asociación de términos relevantes (valores de Jaccard postest de .217 a .917) en sus definiciones, comparado con otros enfoques de enseñanza. Este estudio ofrece pruebas empíricas de que la analítica del aprendizaje basada en MT es una herramienta pedagógica eficaz, que contribuye a mejorar el aprendizaje de conceptos abstractos en la formación del profesorado. Los resultados subrayan el valor de la tecnología educativa basada en MT para optimizar el aprendizaje conceptual y la eficiencia de los recursos en entornos grupales de educación superior.

Keywords: análisis de texto, análisis de contenido, formación del concepto, aprendizaje social, aprendizaje visual, tecnología de la educación, enseñanza superior, formación de profesores

INTRODUCTION

Concept acquisition occurs as learners actively categorize and label information, connecting keywords and related ideas in cohesive mental models. Conceptualization exercises, such as sorting tasks and identifying attributes, can reinforce this process by encouraging learners to define and refine their understanding (Bruner et al. 1956) as the basis for developing further knowledge and skills and achieving meaningful learning. Following a long tradition of research on this subject, and particularly in the wake of the COVID-19 pandemic (Gaglo et al., 2022), an increasing number of studies have investigated how applications of educational technology can have a role in enhancing concept acquisition. Indeed, data analytics and artificial intelligence resources such as virtual agents, natural language processing, pattern recognition, data mining and data visualization tools have provided new means and opportunities for technology-enhanced learning in higher education. In particular, text mining (TM) is a data mining technique that leverages quantitative content analysis to help visualize concepts and better understand them (Inada, 2018), and has opened the door to a new research line.

This study evaluates the potential of TM-based learning analytics as a teaching tool to enhance the acquisition of abstract educational concepts, by comparing results of its application with those of other teaching strategies, precisely the elaboration of an individual project, and the attendance of a conventional master class, in three non-equivalents groups of pre-service student teachers. Following a literature review, in order to test the hypothesis that TM-based learning analytics indeed had the potential to be an effective tool, two specific research questions were formulated before applying the strategies and collecting the data. Implications for educational practice were then extrapolated from the findings, and considered in the context of the limitations of the study and emerging research.

Literature review

Since the last century, the contributions of Bruner et al. (1956) have led to an expansion in the scope of studies of concept acquisition and improvements to their accuracy. Teacher educators have taken interest in this field, with a view to supporting learning processes, enhancing transfer value, and helping pre-service teachers learn about the consistency of educational materials and procedures and how to respond adaptively to different educational scenarios, considering that, without adequate conceptual knowledge, teachers may lack guidance and a clear awareness of what teaching means and involves. Specialized journals have continued to publish studies on the subject (Azadi et al., 2018; Freeman, 2018; Turner, 1975), with a particular focus on abstract educational concepts in teacher education, such as critical thinking, school culture, and curriculum design. Such fundamental yet abstract concepts can be detached from physical reality and are qualitatively different from concrete concepts that are more connected to perceptual and motor experience (Borghi et al., 2019; Gagné, 1985). This means that abstract concepts are particularly difficult to acquire and to relate to practical applications, and their teaching remains a demanding challenge. Although the current study focuses on student teachers in particular, the existing body of knowledge on how concepts are learned in higher education in general is especially relevant, and implications may well extend beyond the immediate context of teacher education.

Concept acquisition in higher education

Engaging students as active participants in their learning process has been shown to stimulate cognitive aspects such as attention, memory, and comprehension (Hernández-de-Menéndez et al., 2019; Nguyen et al., 2021). Furthermore, recent studies have evidenced improvements in the concept acquisition on the integration of active techniques into the learning process, such as flipped classes (Atkinson et al., 2020), asynchronous online discussions (Breivik, 2020), the gamification of lessons (Kortemeyer et al., 2019), and virtual reality simulations (Liao, 2022).

Active learning has been shown to promote concept acquisition if applied as an integral part of the overall strategic planning of teaching activities, and game-based learning has been observed to yield good results (Casanoves et al., 2022), while pre-training videos and real-time cues have, on the other hand, have been shown to have limited effects on conceptual learning (Tsai et al., 2022). Moreover, timed reading, video enactments and writing assignments have been seen to be helpful in certain studies (Guerrettaz et al., 2020; Reynolds et al., 2020), and making students explore, contrast and compare different meanings has appeared to particularly useful in enhancing the potential of writing activities (Wittek, 2018).

Active learning seems to be more effective the more it engages students and is adapted to their specific learning needs, for example, by setting learning goals according to appropriate difficulty levels. Furthermore, the agile creation of reading-only materials such as digital fanzines (Redondo López, 2021) and the provision of specific feedback from lecturers (Gao & Lloyd, 2020) have been observed to contribute to concept acquisition in university courses, especially when tactile and kinesthetics inputs complement visual information in virtual learning environments (Magana et al., 2019).

However, beyond the design of tasks and materials, some research appears to not fully incorporate the theories of comprehensive learning in the vein of Ausubel et al. (1968) and Novak (1977). For instance, student participation in creative exercises and the use of concept maps has been shown to not have a significant impact on students' abilities in explaining concepts (Ye et al., 2020), likely due to a lack of in-depth contextualization around the subject matter, which has been shown to improve the effectiveness of interventions in other studies (Cortes et al., 2019). Contextualization refers to the conditions in which a concept makes sense rather than merely considering its practical function and is particularly relevant for acquiring abstract concepts that entail no physical functionality.

Accordingly, based on previous evidence, concept acquisition seems to be modulated not only by active or passive learning, but also by the arrangement of materials in task designs, the monitoring of student progress, and the contextualization of concepts. In this general context, TM-based learning analytics may have the potential to be a worthy ally in enhancing concept acquisition.

TM-based learning analytics for concept acquisition

Exchanges between peers have been observed on several occasions to facilitate concept acquisition, mostly when students are organized into small groups (Atkinson et al., 2020; Rodriguez & Potvin, 2021). Interactive systems and peer teaching and assessment have also been widely identified as helpful for concept acquisition (Babaahmadi et al., 2021; Koong et al., 2021), particularly in peer-reviewing of writing assignments focused on developing content knowledge (Finkenstaedt-Quinn et al., 2021). This suggests that group discussions can complement individual analytical descriptions of a concept and both can contribute to positive results (Reyes-Santías et al., 2021; Volkwyn et al., 2020).

Thus far, we have considered that elements such as writing and discussion tasks, lecturers' feedback and visual information supplements can all help concept acquisition. These are, in fact, elements that TM-based learning analytics can offer, although evidence of the effectiveness of its application is currently scarce. Papers published on the applications of TM have concerned, for example, the assessment of learning outcomes after a certain educational intervention (Kong et al., 2021), or the automation of the annotation and categorization of exam queries according to concepts to be assessed (Begusic et al., 2018). Furthermore, studies that have directly addressed conceptual learning with the application of TM have looked at concept acquisition in relation to exam repositories (Pintar et al., 2018), semantic relationships between concepts (Shwartz, 2021) and the identification of students' conceptions and misconceptions (De Lin et al., 2021; Taga et al., 2018) by asking students for written definitions and then applying TM to those definitions.

Surprisingly, although educationalists have applied TM-based learning analytics to understand student concept acquisition, identify learning styles (Aguilar et al., 2022) and analyse outcomes of discussion threads (Hernández-Lara et al., 2021; Pillutla et al., 2020), it has rarely been evaluated as a didactic tool relevant to the design of teaching tasks regarding concept acquisition. Until now, research has mainly been focused on know-how regarding TM as a university teaching evaluation tool. Therefore, in this paper, we aim to present one of the first empirical studies to give evidence on the use of TM-based learning analytics as a teaching tool for promoting the acquisition of abstract educational concepts by student teachers, and applying some of the above discussed learning aspects, including the joint analysis of definitions by peers, and the visual representation of results. The motivation for the research includes a consideration that TM-based learning analytics may potentially offer new mechanisms for providing targeted instruction and data-driven feedback, allowing teachers to more effectively address misconceptions and gaps in concept acquisition. The current study therefore contributes to efforts to optimize classroom management and the use of resources in fostering concept acquisition, through the application of TM-based learning analytics. Overall, this study paves the way for innovative pedagogical strategies that leverage technology to improve teaching and learning outcomes, particularly in teacher education.

Research questions derived from the literature review

Our literature review, as detailed above, led to the hypothesis that TM-based learning analytics can be an effective teaching tool that facilitates the acquisition of abstract concepts. To test this hypothesis in relation to student teachers, we decided to compare TM-based learning analytics to two other teaching strategies, namely asking students to complete individual project work, and to attend a conventional master class. Furthermore, to guide the evaluation of TM-based learning analytics as a teaching tool, we decided to answer two specific research questions (RQs), aimed at collecting evidence on the students' selection of keywords and on associations made between relevant terms in the definition of a concept.

- RQ1: How does TM-based learning analytics promote keyword selection in student teachers compared to other teaching strategies?

- RQ2: How does TM-based learning analytics promote associations between keywords compared to other teaching strategies?

METHODS

This study compares effects on the acquisition of abstract educational concepts relating to the application of three teaching strategies: TM-based learning analytics; the carrying out of individual project work; and the attendance of a conventional master class. The construct of concept acquisition was operationalized using two key indicators relating to the definition of concepts: keyword selection, and the association of relevant terms.

Study design and participants

Quasi-experimental pre- and post-tests were administered to three non-equivalent groups (A, B, and C), composed of a total of 81 students (62.96% female) following a teacher training master's programme at a Spanish university. Group A consisted of 26 students (65.38% female) with a mean age of 32.65 years (standard deviation or SD=5.78), Group B consisted of 28 students (64.29% female) with a mean age of 32.50 years (SD=6.43), and Group C consisted of 27 students (59.26% female) with a mean age of 32.19 years (SD=6.43). All were following the programme through distance education and used the Blackboard platform for online learning.

Learning environment

As a theoretical framework for the online learning interventions, the Data-Driven Decision-Making model (Khong et al., 2023) was selected. This model outlines a cyclical process in which data are systematically collected, analysed, interpreted and thus transformed into information and, ultimately, into actionable knowledge that can be used to guide and inform educational practice and strategy. It can therefore provide valuable insights into the learning strengths and weaknesses of students and offer guidance for structuring more effective teaching strategies.

In the current study, the teaching strategies were administered by the researchers acting as instructors, and were carried out simultaneously for the three separate groups of students. The researchers therefore set up an environment on the Blackboard platform so that students could define concepts with a 280-character limit, considering that the optimal structure for understanding a concept consists of assembling and relating a set of fundamental propositions, in accordance with the learning theories of Bruner et al. (1956) and Greco & Piaget (1959), which agree that students who have a comprehensive overview of a concept are better prepared to understand its details, constituent elements and applications. The definitions allowed us to collect evidence on and analyse the students' overview or general representation of each concept.

Procedure and teaching strategies

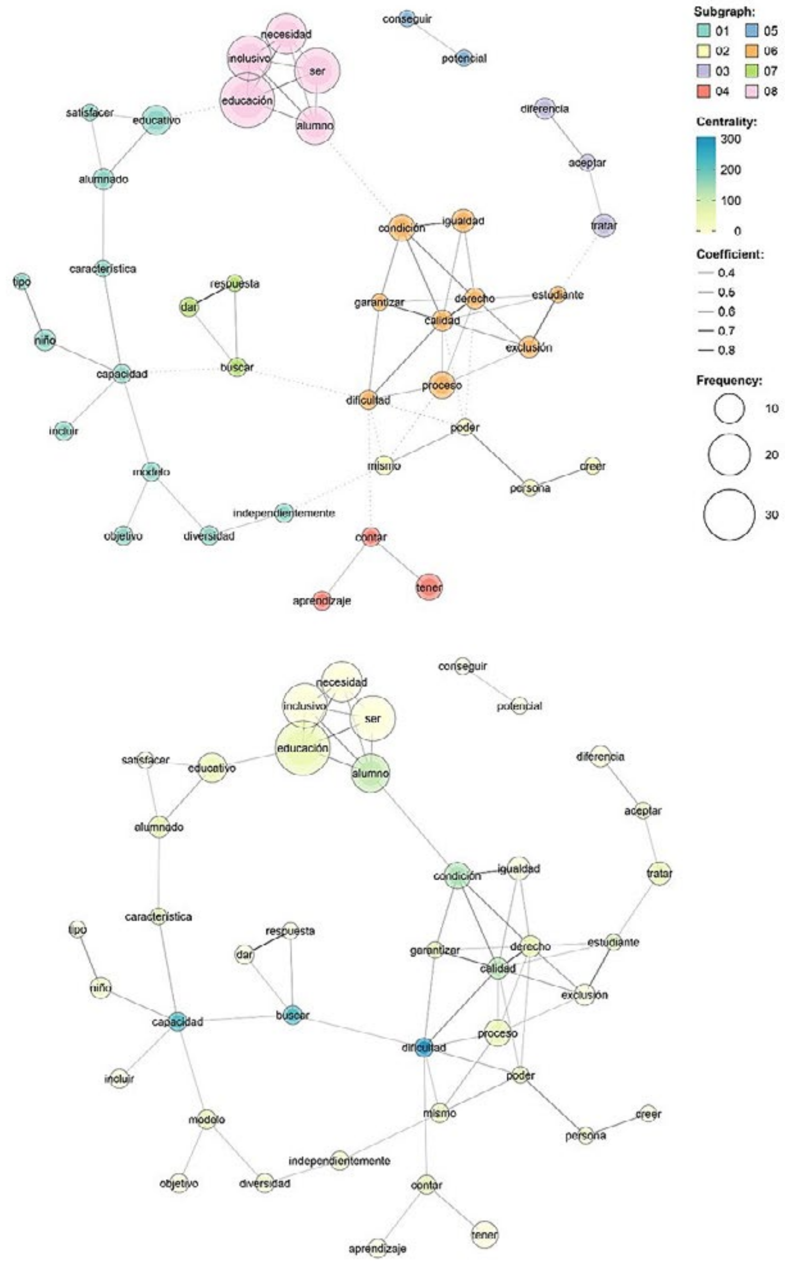
At first, the students of each group had to define a concept and submit their definitions in an individual assignment on the Blackboard platform. They had 15 minutes to complete the task. These first definitions provided the pre-test data. Then, each group carried out the work corresponding to each of the three teaching strategies. Finally, the students submitted a new definition of the concept based on learning derived from the teaching strategies to which they were exposed. These final submissions provided post-test data to compare with the pre-test data, in order to evaluate the effects of the teaching strategies on concept acquisition.

Group A

The students of Group A were asked to define the concept of "inclusive education". Their submissions were collected, pre-processed and analysed using TM in the software KH Coder 3 to obtain term frequency and two co-occurrence networks. The first network included modularity analysis to detect clusters of words, and the second included betweenness centrality to reveal the influence of each word over the flow of information. The network graphs incorporated words with frequencies (f_a) > 4, and the distances between them were measured using the Jaccard coefficient (J_c). Figure 1 illustrates the co-occurrence networks that the students were then shown.

Figure 1

Co-occurrence networks of Group A's pre-test



Based on the networks, students identified which keywords appeared most often in their definitions and which were missing. For example, they had emphasized more the “needs” of “students” in schools than “looking for” their “capabilities” or providing “responses” to their special educational needs. Moreover, although they thought about “capabilities” and “difficulties” and therefore connected many other words to these terms, they did not consider “reducing” difficulties, either as a keyword (e.g., reduce, overcome, eliminate) or in connection with other terms (e.g., capabilities, barriers, needs).

Using TM learning analytics as both a visual and verbal complement, the instructor tried to make students aware of their misconceptions by comparing relevant connections between terms, and incorporating new ideas into the class’s general notion of inclusive education. Subsequently, students had another 15 minutes to reformulate their first definitions and submit them once again to the Blackboard platform.

Group B

The students in Group B were asked to define the concept of an “open and flexible curriculum”. They carried out an individual project in which they examined the curricular documents of a real school, and elaborated proposals to make the school’s curriculum more open and flexible. This exercise took them a couple of weeks, and, afterwards, they briefly discussed their progress with classmates during class time. The instructor then reviewed the projects and gave examples of suggested proposals, and subsequently gave the students 15 more minutes to reformulate their definitions of the concept.

Group C

The students of Group C were asked to define the concept of “meaningful curricular adaptation”. After completing and submitting their definitions, they received an expositive master class on the concept, and, at the end of the lecture, they had 15 minutes to reformulate and resubmit their definitions to the Blackboard platform.

Collecting and processing the analytical sample

All the data was collected during regular class hours. The procedure respected participant rights to informed consent, personal data protection, confidentiality, and non-discrimination, and the participants did not receive any compensation.

The researchers downloaded the concept definitions in text format directly from the Blackboard platform, and performed manual pre-processing of the text. This involved the correction of typos or misspellings, the changing of acronyms to their expanded meanings, and the removal of double spaces, special characters, and inclusive language expressions. The cleaned text constituted the dataset for the analysis without including any stop words. The resulting corpora consisted of an analytical sample for Group A of 1017 pre-test and 1133 post-test tokens, for Group B of 1127 pre-test and 1111 post-test tokens, and for Group C of 1101 pre-test and 1173 post-test tokens.

A set of 10 keywords and 10 associations between terms relevant to each concept were identified as priority elements to be included in the definitions. These keywords supported the evaluation of students' comprehensive understanding of the concepts, while the associations served to compare the relationship patterns of terms with word co-occurrences in the pre- and post-tests regarding each group. Appendices 1 and 2 present the criteria used to evaluate the definitions of the concepts.

The test statistic of Yuen's test of robust paired samples on trimmed means for dependent samples was calculated to obtain an effect size, with associated 95% confidence intervals (CI) around the estimates. Yuen's paired sample trimmed mean test is one of the most robust methods for comparing paired samples with non-normal distributions to obtain more robust results than traditional non-parametric tests. Values of ξ = .10, .30, and .50 were thus taken to correspond respectively to small, medium, and large effect sizes.

All analyses were carried out with "ggstatsplot" package, an extension of the "ggplot2" package, for R.

RESULTS

RQ1: Keyword selection

Table 1 shows the results corresponding to RQ1, while Figure 2 contains box plots representing the pre- and post-tests for each group (A, B and C). The results show that the only significant within-subjects difference was observed in Group A of the students exposed to TM-based learning analytics as the teaching strategy, while a marginal statistical significance was observed in Group B. Group A therefore saw a larger pre- to post-test effect from TM-based learning analytics (t_{Yuen} = -6.37, p < .001, δ_R^{AKP} = -1.03, $IC_{95\%}$ = -2.10, -.74) compared to the effect from the individual project task (t_{Yuen} = -1.78, p = .09, = -.50, $IC_{95\%}$ = -.86, -.10).

Table 1

Results of pre-test and post-test differences in keyword selection for each group

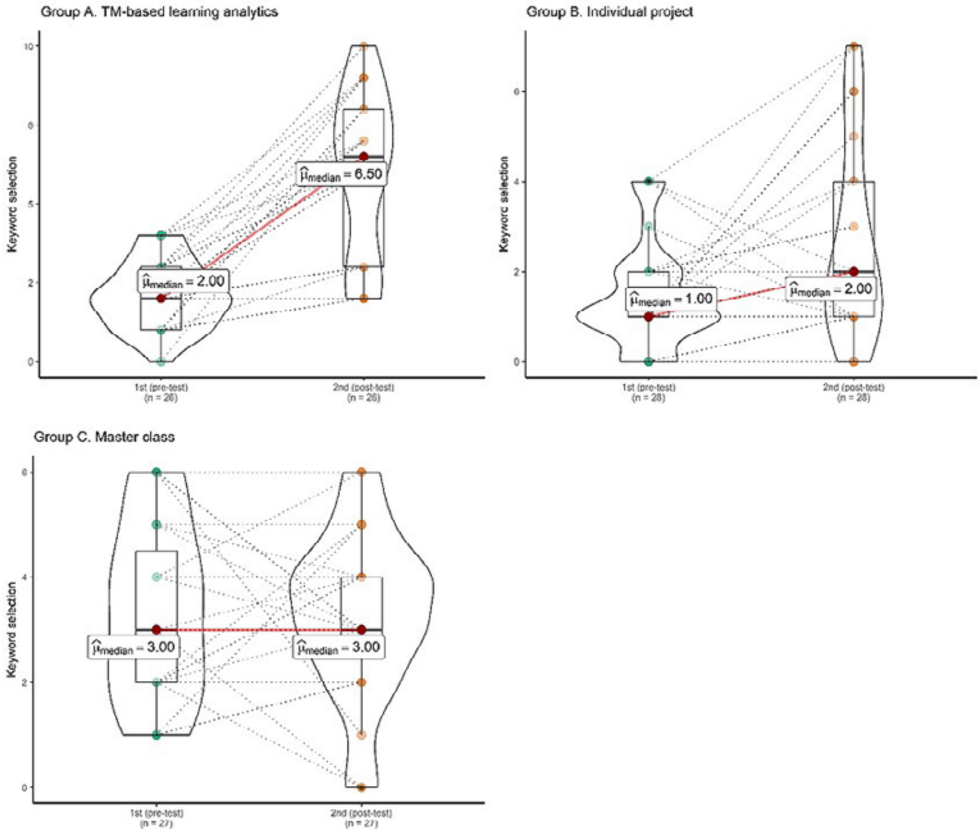
Group	$V_{Wilcoxon}$	*p-value*	$r_{biserial}^{rank}$	$IC_{95\%}$	t_{Yuen}	*p-valor*	δ_R^{AKP}	$IC_{95\%}$
A	NA	NA	NA	NA	-6.37	<.001	-1.03	(-2.10, -.74)
B	.01	.01	-.61	(-.83, -.24)	-1.78	.09	-.50	(-.86, -.10)
C	59.50	.88	.05	(-.37, .45)	-.15	.88	-.03	(-.52, .25)

Note 1. $V_{Wilcoxon}$ = Wilcoxon test statistic; *p*-valor = probability value indicating the significance level; $r_{biserial}^{rank}$ = estimated rank-biserial correlation; $IC_{95\%}$ = 95% confidence interval; t_{Yuen} = Yuen's t-test statistic; δ_R^{AKP} = robust effect size measure; NA = not applicable.

Note 2. For Group A, it was not possible to calculate the Wilcoxon test, since the variables do not meet two of the required basic assumptions: the symmetric distribution of variables with a level of measurement of interval or ratio, and the symmetric distribution of rang differences (Pardo & San Martín, 2010).

Figure 2

Pre- and post-tests box plots for each group



RQ2: Association of terms

For Group A, the Jaccard index for word associations in the pre-test ranged from .000 to .375 (see Table 2). After the session in which students were made aware of their misconceptions using the TM-based visual plot provided by instructor, the post-test Jaccard values increased to a range of .217 to .917, revealing statistically significant differences between the pre-test and the post-test in seven of the top ten words associations (1 to 7 all with p_j and $p_t < .05$) (see Table 2). For certain associations, the Jaccard index increased substantially from pre-test to post-test after applying the TM-based teaching strategy, such as in the case of term associations 2 and 5 (i.e., *accessible – contexts*, and *removing – barriers*, respectively).

Table 2
Top 10 term associations by group

Group	Jc tests	Pre-test	f_x	f_y	p_e	p_b	Post-test	f_h	f_z	p_j	p_t	J_c Δ
A	Term association 1	.000	1	4	.473	.645	.609*	23	14	.037	.028	.609
	Term association 2	.000	1	2	.462	.628	.917***	12	11	<.001	<.001	.917
	Term association 3	.111	8	2	.499	.065	.692***	13	9	<.001	<.001	.581
	Term association 4	.187	3	16	.122	.107	.667**	13	17	.002	<.001	.480
	Term association 5	.000[a]	0	1	1.000	1.000	.783**	18	23	.007	.007	.783
	Term association 6	.333	5	3	.028	.078	1.000***	12	12	<.001	<.001	.667
	Term association 7	.333	3	5	.028	.078	.588**	15	12	.007	.007	.255
	Term association 8	.200	5	25	.476	.190	.417	11	23	.746	.806	.217
	Term association 9	.142	1	7	.086	.034	.583	23	15	.337	.401	.441
	Term association 10	.117	3	16	.855	.108	.421	10	17	.179	.200	.304
B	Term association 1	.375*	4	7	.011	.018	.750***	10	11	<.001	<.001	.375
	Term association 2	1.000*	1	1	.005	.012	1.000***	5	5	<.001	<.001	.000
	Term association 3	.555	18	24	.642	.685	.538	21	19	.837	.884	-.017
	Term association 4	.000	8	1	.462	.590	1.000***	5	5	<.001	<.001	1.000
	Term association 5	.055	1	18	.425	.708	.273	7	21	.427	.467	.218
	Term association 6	.250	3	7	.054	.075	.273***	8	11	<.001	<.001	.023
	Term association 7	.000	3	8	.268	.342	.444	8	5	.005	.659	.444
	Term association 8	.000[a]	0	7	1.000	1.000	.000	1	11	.412	.636	.000
	Term association 9	.000[a]	1	0	1.000	1.000	.454**	5	11	.002	.002	.454
	Term association 10	.000[a]	0	1	1.000	1.000	NA	0	0	NA	NA	NA
C	Term association 1	.440	21	15	.543	.595	.565	20	16	.268	.326	.125
	Term association 2	.440	21	15	.543	.585	.480	21	16	.670	.708	.040
	Term association 3	.348	21	10	.825	.842	.348	21	10	.826	.822	.000
	Term association 4	.190	21	4	.142	.263	.227	21	6	.707	.715	.037
	Term association 5	.208	21	8	.233	.240	.261	21	8	.835	.887	.053
	Term association 6	.000[a]	21	0	1.000	1.000	.000[a]	21	0	1.000	1.000	.000
	Term association 7	.136	21	4	.921	.980	.095	21	2	.402	.538	-.041
	Term association 8	.095	21	2	.402	.549	.095	21	2	.402	.526	.000
	Term association 9	.048	21	1	.472	.658	.048	21	1	.473	.650	.000
	Term association 10	.055	15	4	.204	.231	.111	16	4	.678	.735	.056

Note 1. Jc tests = Jaccard tests; *Pre-test* = baseline measurement before application of the teaching strategy; f_x = frequency of the first keyword selection in the pre-test for each association; f_y = frequency of the second keyword selection in the pre-test for each association; f_h = frequency of the first keyword selection in the post-test for each association; f_z = frequency of the second keyword selection in the post-test for each association; p_e = exact p-value (pre-test), p_b: bootstrapped p-value (pretest); p_j = exact p-value (post-test); p_t = p-value with bootstrapping (post-test; * $p < .05$, ** $p < .01$, *** $p < .001$ with bootstrap and exact methods.
Note 2. Appendix 2 shows the term associations for each group.
Note 3. [a] one input vector contained only zeroes.

The students in Group B who carried out individual projects established two significant associations in the pre-test (term associations 1 [attention – individualized] and 2 [equality - opportunities], with p_e and p_b < .05, respectively). After the teacher conceptualized, reviewed the projects and suggested proposals, post-test conceptualization results showed up to five significant associations (term associations 1, 2, 4, 6, and 9, all with p_j and p_t < .05; see Appendix 2 for the term associations). Group B, with the individual project as a teaching strategy, produced pre- to post-test Jaccard coefficient differences less favourable than Group A, but nonetheless produced an evident improvement (t_{Yuen} = -1.78, p = .09, δ_R^{AKP} = -.50, $IC_{95\%}$ = -.86, -.10) (see Table 1 and Figure 2).

Group C, who attended an expositive master class, did not produce significant differences between the pre- and post-tests (t_{Yuen} = -.15, p = .88, δ_R^{AKP} = -.03, $IC_{95\%}$ = -.52, .25). nor did they significantly make relevant associations.

DISCUSSION

The present study provides empirical evidence on the use of TM-based learning analytics as a pedagogical tool, compared to individual project work and attendance of a master class, for facilitating the acquisition of abstract educational concepts, specifically within the university context and in relation to student teachers. Previous research has suggested that active learning involving writing and discussions (Breivik, 2020), detailed feedback (Gao & Lloyd, 2020) and visual information (Magana et al., 2019) can facilitate concept acquisition in university courses, especially when applied in small groups (Atkinson et al., 2020; Rodriguez & Potvin, 2021). Furthermore, it has suggested that the technique of TM can be used to make the assessment of student learning outcomes more efficient (Kong et al., 2021). However, until now, there has been a lack of evidence on the effects of TM techniques used as a teaching strategy for conceptual learning at the higher education level. In this study, TM-based learning analytics supported students in selecting keywords and identifying missing aspects in the definition of an abstract concept, and helped them establish more relevant associations between terms.

Consistent with the findings of this study, previous studies at elementary school level have examined the effects of the Sobek topic modelling tool on scientific concept assessments. These studies found that students using TM-based tools performed significantly better on exams (Costa et al., 2017; Reategui et al., 2019). Similarly, research with 54 high school students showed that those using TM-based tools in essay writing incorporated a greater number of relevant concepts into their work (Erkens et al., 2016). These findings are in line with our own, reinforcing the view that TM-based learning analytics can be a valuable tool for enhancing conceptual understanding and retention.

Implications for educational practice

It is no coincidence that TM-based learning analytics can be a powerful ally for university students to acquire abstract concepts, given that the field of neuroscience has evidenced visual attention and its relation to information processing for several decades (Hutmacher, 2019; Kanwisher & Wojciulik, 2000). Indeed, the relevant literature has emphasized that aspects such as colour contrasts and intensity, among others, can stimulate visual attention, and lead to benefits in terms of working memory performance (Itti & Koch, 2001). In fact, in the present study, TM-based visual representations were made to present words in different colours, sizes and contrasts, because we knew that, in the classroom, students tend to have problems maintaining attention, especially when sessions are too long (Ghanizadeh et al., 2024). According the theories of comprehensive learning that are sometimes ignored in research, we know that the quality of the performance of a task, such as defining a concept, depends on a combination of sensory attention and access to prior knowledge records in memory (i.e., executive control) (Nobre & Kastner, 2014).

Although we have seen that TM-based learning analytics help students select keywords and establish relevant associations between terms in an overview of a concept, this does not necessarily guarantee that students will effectively manipulate and handle those conceptions later. It only implies that they acquired the basic notions to the extent of considering their most critical parts, and thus obtaining a general idea of them. We know from seminal works in the literature of the field (Bruner et al., 1956) that having a thorough general idea contributes to successful concept acquisition, but in no case does it guarantee the correct use of concepts in other more complex activities. Some studies have shown how peer review, for instance, did not always promote improvements in higher-order reasoning skills following concept acquisition (Turner et al., 2018).

Just as other tasks are deliberately aimed at developing higher-order thinking (e.g., asynchronous online discussions) (Jeong & Chiu, 2020), there is currently a lack of evidence of any effects of the use of TM-based learning analytics on the this type of learning. Therefore, we cannot yet design reliable tasks incorporating TM-based learning analytics for purposes such as longer-term assessments taking a concept as a criterion or comparing it with other concepts. For now, we know that TM-based learning analytics can certainly be used as a teaching resource at the beginning of a course to help students acquire fundamental abstract concepts. Subsequently, it would be necessary to design other different assignments to learn how to develop these concepts in certain given contexts (Cortes et al., 2019). For example, in the case of Group A in our study, we would need to teach the students to practically assess whether a certain school or teaching strategy was inclusive through other activities such assembling a rubric.

One of the benefits of TM as a tool is that it generates a detailed description of a group's level of acquisition of a given concept, and presents a more precise and generalized explanation for the whole class, detailing missing aspects and misconceptions in definitions of the concept. With the use of TM, lecturers can save time and avoid a situation in which students arrive one by one at resolving doubts about the concept, or, worse, have unresolved doubts and do not achieve desired learning outcomes regarding a subject due to a lack of understanding of fundamental notions.

Nevertheless, TM-based learning analytics involves procedures that certainly not all university instructors will be familiar with, and therefore adequate training programmes will need to be developed presenting TM as a teaching tool, for lecturers to conduct those procedures successfully. Moreover, such training is relevant at this time in which higher education institutions are increasingly investing in educational technology, and their teaching staff need to know how to get the most out of it in order to make investments profitable. All in all, our findings support the investment of resources in TM-based learning analytics as a tool for university teaching and not just for assessment, as has been more common according to the studies we have reviewed (e.g., Begusic et al., 2018; Hernández-Lara et al., 2021).

Limitations and emerging research

Although the present study provides evidence of the potential of TM-based learning analytics as a teaching tool for concept acquisition at the university level, the design of the study has limitations that impact both the internal and external validity of the results. One specific limitation is the lack of a formal validation process in the design and implementation of the teaching strategy before its execution. A formal validation process should consider aspects such as feasibility, acceptability, and validity, and potentially provide preliminary evidence of the teaching strategy's impact. An expert panel might have further contributed by discussing aspects such as the content being studied, various teaching strategies, the intervention duration and frequency, and administrator criteria, among others. Future studies should include a teaching strategy protocol and prior validation process to ensure the consistency of the findings. Additionally, they should also consider experimental designs with a TM-based intervention control and homogeneous measures between groups (e.g., by analysing the same concept).

Another limitation of the study is its limited statistical power to detect significant differences between conditions, due to the small sample sizes. Additionally, these limited sample sizes may have introduced bias, restricting the generalizability of our results. Therefore, future studies with larger sample trials are needed to confirm these preliminary findings.

Furthermore, while we know that acquiring a concept overview facilitates the meaningful learning of that concept by promoting fundamental inclusiveness in Ausubel's terms, our study does not provide information about the further development of the concept that the students defined. It is likely that TM facilitates only the acquisition of a general overview of an abstract concept, and other teaching strategies are necessary to learn how to develop its contents and apply it successfully in professional practice. More research is needed to further explore how the benefits of TM extend to the acquisition of abstract concepts in groups of undergraduate students, particularly in teacher education.

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APPENDICES

The token words in Appendices 1 and 2 came from student data contained in the submitted definitions. The researchers examined the texts considering multiple synonyms and word combinations to obtain the following tables that made it possible to evaluate the data. The parts of speech identified are indicated at the end of both appendices.

Appendix 1

The top 10 keywords for each group

Group A's keywords	Group B's keywords	Group C's keywords
"Participación" [N,V]	"Individual" or "Personal" [AQ,AV,N,V]	"Necesidad" or "Limitación" [N]
"Accesibilidad" [AQ]	"Equidad" [N]	"Objetivo" [N]
"Equidad" [N]	"Adaptación" [N,V]	"Contenido" [N]
"Aceptación" [V]	"Ordinario" or "Común" [AQ]	"Competencia" [N]
"Barrera" or "Dificultad" [N]	"General" or "Básico" [AQ]	"Evaluación" [N, V]
"Derecho" [N]	"Autonomía" [AQ,N]	"Tiempo" [N]
"Capacidad" or "Potencial" [N]	"Docente" or "Profesor" [AQ,N]	"Centro" or "Aula" [N]
"Sociedad" [AQ, N]	"Formación" or "Cualificación" [AQ,N]	"Material" or "Recurso" [N]
"Aprendizaje" [N,V]	"Equipo" or "Grupo" [N]	"Mínimo" [AQ]
"Necesidad" or "Limitación" [N,V]	"Material" or "Recurso" [N]	"Individual" [AQ,AV,N]

Note. AQ = adjective, AV = adverb, N = noun, V = verb.

Appendix 2a

Associations between blocks of terms in Group A

Jc tests	Block of terms #1	Block of terms #2
Term association 1	“Barrera” or “Dificultad” [N]	“Participación” [N,V]
Term association 2	“Accesibilidad” [AQ]	“Contexto” [N]
Term association 3	“Igualdad” [AQ,N]	“Oportunidad” [N]
Term association 4	“Aceptación” [V]	“Necesidad” or “Limitación” [N,V]
Term association 5	“Suprimir” or “Eliminar” [N,V]	“Barrera” or “Dificultad” [N]
Term association 6	“Derecho” [N]	“Garantizar” or “Asegurar” [V]
Term association 7	“Desarrollar” [N,V]	“Capacidad” or “Potencial” [N]
Term association 8	“Sociedad” [AQ, N]	“Educación” [AQ,N]
Term association 9	“Barrera” or “Dificultad” [N]	“Aprendizaje” [N.V]
Term association 10	“Atender” or “Superar” [N,V]	“Necesidad” or “Limitación” [N,V]

Note. AQ = adjective, AV = adverb, N = noun, V = verb.

Appendix 2b

Associations between blocks of terms in Group B

Jc tests	Block of terms #1	Block of terms #2
Term association 1	"Atención" or "Enseñanza" [N]	"Individual" or "Personal" [AQ,N]
Term association 2	"Igualdad" [N]	"Oportunidad" [N]
Term association 3	"Concretar" or "Adaptar" [AQ,N,V]	"Currículum" or "Métodos" [AQ,N]
Term association 4	"Centro" or "Escuela" [N]	"Ordinario" or "Común" [AQ]
Term association 5	"General" or "Básico" [AQ]	"Concretar" or "Adaptar" [AQ,N,V]
Term association 6	"Autonomía" [AQ,N]	"Docente" or "Profesor" [AQ,N]
Term association 7	"Autonomía" [AQ,N]	"Centro" or "Escuela" [N]
Term association 8	"Formación" or "Cualificación" [AQ,N]	"Docente" or "Profesor" [AQ,N]
Term association 9	"Equipo" or "Grupo" [N]	"Docente" or "Profesor" [AQ,N]
Term association 10	"Disponibilidad" [N]	"Material" or "Recurso" [N]

Note. AQ = adjective, AV = adverb, N = noun, V = verb.

Appendix 2c

Asociaciones entre bloques de términos para el Grupo C

Jc tests	Block of terms #1	Block of terms #2
Term association 1	"Necesidad" or "Limitación" [N]	"Individual" [AQ,AV,V]
Term association 2	"Adaptar" or "Ajustar" [N,V]	"Objetivo" [N]
Term association 3	"Adaptar" or "Ajustar" [N,V]	"Contenido" [N]
Term association 4	"Adaptar" or "Ajustar" [N,V]	"Competencia" [N]
Term association 5	"Adaptar" or "Ajustar" [N,V]	"Evaluación" [N,V]
Term association 6	"Adaptar" or "Ajustar" [N,V]	"Tiempo" [N]
Term association 7	"Adaptar" or "Ajustar" [N,V]	"Centro, Aula" [N]
Term association 8	"Adaptar" or "Ajustar" [N,V]	"Material" or "Recurso" [N]
Term association 9	"Adaptar" or "Ajustar" [N,V]	"Mínimo" [AQ]
Term association 10	"Individual" [AQ,AV,V]	"Aprendizaje" [N,V]

Note. AQ = adjective, AV = adverb, N = noun, V = verb.