

Table 3. Cont.

Lesson Segment	Description	Resources
<p>Blended Learning Approach: Activity-level Blended Learning—Graduate students have the opportunity to access the online resources which other groups had been working on. They had continued access to the resources that were allocated to the groups prior to class. Key characteristics of Connectivism:</p>		
<p>(i) Diversity—While listening to their peers’ sharing, the Graduate students have the option of looking at the shared screen or they had the option of looking at the actual files via the cloud productivity tool. (ii) Openness—During the course of the sharing, when opportunities were provided, they could unmute themselves and clarify their understanding or they could further probe into a sharing by a group. If they did not feel like verbally sharing, they could post their viewpoints via the feedback from the tutor had created for this purpose. (iii) Connectedness—Even coming together as a whole class, the Graduate students had opportunities to connect via the various platforms—instant messaging, chat feature within the virtual platform, as well as to comment directly on the presentation materials. (iv) Autonomy—Graduate students had choices they could exercise. They could clarify using direct verbal method or they could use chat features. They could provide feedback verbally or through commenting feature in the cloud productivity or via the form created by the tutor.</p>		
<p>Post-class</p>	<p>Focus is on the application of what the Graduate students have learnt during tutorial, and they have the opportunity to design for a possible area of research applying GT design principles. Graduate students work on their own, at their pace. They can access the materials and resources posted by the tutor for the pre-tutorial activity as well.</p>	<p>Learning Management System, instant messaging, cloud productivity tools and online sticky note platform.</p>
<p>Blended Learning Approach: Course Blended Learning—In order to reduce online fatigue, Graduate students now have the opportunity to work on applying the research design to an idea they needed to conceptualize. They could embark on this task on their own time, adopting self-pacing and to contact each other or the tutor if they need guidance. Key characteristics of Connectivism:</p>		
<p>(i) Diversity—Ease of access to various resources available through the Learning Management System. Ease of moving around and self-pacing themselves instead of sitting through a dedicated virtual classroom session. (ii) Openness—Even though the Graduate students were working on their own and self-pacing themselves, the design of the lesson and the availability of resources and channels of communication provided Graduate students with the opportunities to continue to share their learning via the various platforms that have been weaved into the course to support their learning. (iii) Connectedness—While there was no dedicated time set aside for this activity, the availability of the various mediums of communication allowed the Graduate students to be connected to their classmates as well as their tutor. (iv) Autonomy—The Graduate students could exercise choice as to how they wanted to complete the activity. They could complete the task at any time within the deadline set for them. They could get together in groups to discuss and complete their tasks. Due to the online nature of the lesson and the connectivity that was provided, the Graduate students had complete autonomy as to how they wanted to embark on this task.</p>		

Based on these principles, connectivism posits that learning occurs when knowledge is actuated by learners connecting to and participating in a learning community. Defined as ‘the clustering of similar areas of interest that allows for interaction, sharing, dialoguing and thinking together’ [30] (p.3), learners participate in such learning communities and interact among themselves and with others who are more knowledgeable. Such interactions are considered as networks. The key characteristics of such networks, as described by [33], should be given due consideration by educators when designing for learning mediated by technology platforms especially when adopting Blended Learning approach.

(i) Diversity

As described by Downes (2010) [33], the characteristics of ‘diversity’ requires educational resources to be structured to provide maximum diversity for the learners. Educators should then take into consideration, when designing for online synchronous and asynchronous access that the activities and tasks surrounding the learning of the resources allows for learners to experience creativity, ability to hone into their strengths and to learn using multi-modal resources that help them to learn with confidence, in the best possible

manner for them. Educators, in selecting resources, should focus on multi-modal interface and allow for learners to exhibit evidence of learning through the use of creative and alternative assessment.

(ii) Openness

Downes [33] describes participants should be able to navigate freely and to be able to access and share free flow of ideas and artifacts within the system. When designing for learning, educators should provide opportunities for learners to share their ideas and be able to share knowledge. While the educator may be the main source of content knowledge, the learners should also be given opportunities to share their resources. Communication should be seamless and need not be only initiated by the educator but could be championed by the learners. This, thus, brings to attention the selection of technology platforms and tools with affordances that will support ‘Openness’ and for the design of the learning to have tasks and activities that will allow for learners to share freely.

(iii) Connectedness

Connectedness is seen as being able to access and learn from various communities or known as ‘nodes’ in connectivism [31]. As educators design for learning, they need to be aware that learners need to be able to learn not only within the community but also be able to access other communities or resources. These could be experts, industry partners, libraries and other resource portals which will help facilitate learning.

(iv) Autonomy

Autonomy in a connected environment is viewed as the learner having choices or options and having the control to be able to make the choices that best suit their learning [33]. In this regard, educators not only need to ensure that there is a wide array of resources and learning opportunities available to the learner; they must ensure that the learner is not evaluated for making choices that may not seem popular or obvious. Learners need to be empowered to make the choices that best suit their learning needs, especially in a technology-mediated environment where information is readily available at the ‘finger-tips’ and in various modalities.

The re-designed lesson example in Table 3 will discuss how the authors took into consideration the characteristics as advocated by Connectivism and included learning activities, platforms and opportunities to ensure that learning by graduate students was not in any way compromised with a completely online learning environment.

5. Key Design Considerations

The above discussion draws particular attention to the design of learning adopted by educators. Educators need to take into consideration: (i) the profile of their learners; (ii) content being learnt; (iii) pedagogy adopted; (iv) technology tools used; and (v) context where learning is taking place; as well as (vi) assessment. We represent this with a visual representation as depicted in Figure 1.

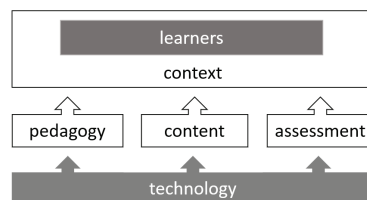


Figure 1. Designing for Blended learning: a revised proposition.

The learners remain at the center of all that we do in IHLs. Hence, when we design for learning, knowing their profiles and needs are of utmost importance. The other key consideration is the context. Given the fact that this Blended Learning approach takes

place in situations where physical interaction is not possible, the context then becomes a significant consideration. With no opportunities to meet physically, educators will have to decide on the repertoire of technology tools that will help provide continued support for their learners. Interactions will have to be mediated through the use of technology tools, thus impacting the decisions educators have to make in relation to the type of pedagogy they are adopting and their choice of modalities, e.g., asynchronous or synchronous. Adopting the relevant pedagogy supported by appropriate technology tools also becomes a key area of focus. Educators need to take into consideration technological affordances that support the pedagogical design of the lesson, the availability of tools as well as connectivity available to the learners. Online modes of lesson delivery also prevent instructors from effectively observing learners' emotions and body language. While assessment still remains an indispensable aspect of teaching and learning, educators will have to make efforts to include creative forms of assessment that will help learners reflect on their own learning and provide information/data to educators about their progress. In this adapted Blended Learning milieu, it is important to note that assessment is influenced by social cognition, multimodal texts and ubiquitous environment [34]. These creative alternatives can go to some extent in reducing the fatigue caused by formal/summative assessment as educators harness the affordance to creatively design for monitoring of learning. It is of paramount importance to note that all of the design considerations have to be dynamically designed with the support of technology tools so as to ensure educators are able to engage students in the learning process.

In summary, Figure 2 below attempts to explicate the contributions made by this concept paper to extend the concept of blended learning. Captured are the adaptations made to the four traditional dimensions in blended learning, i.e., space, time, fidelity, and humanness [20]. We would like to draw attention to Rich* under the virtual column. While fidelity in a physical environment in a blended approach provided for educators to design for a rich learning experience, virtual learning environments used to fall short in this area. Given the rapid advancement in technology and Web 2.0, educators have the opportunity to design for learning virtually with high fidelity, including simulated learning and multi-modal resources. The changes made were necessary in order to respond to the challenges brought about in recent times. The fluid nature of our teaching and learning environments, alongside other key considerations such as learners' online fatigue, shorter attention spans, lack of interactivity, the need for human touch, demanded that we find new ways to approach online/virtual lessons [23].

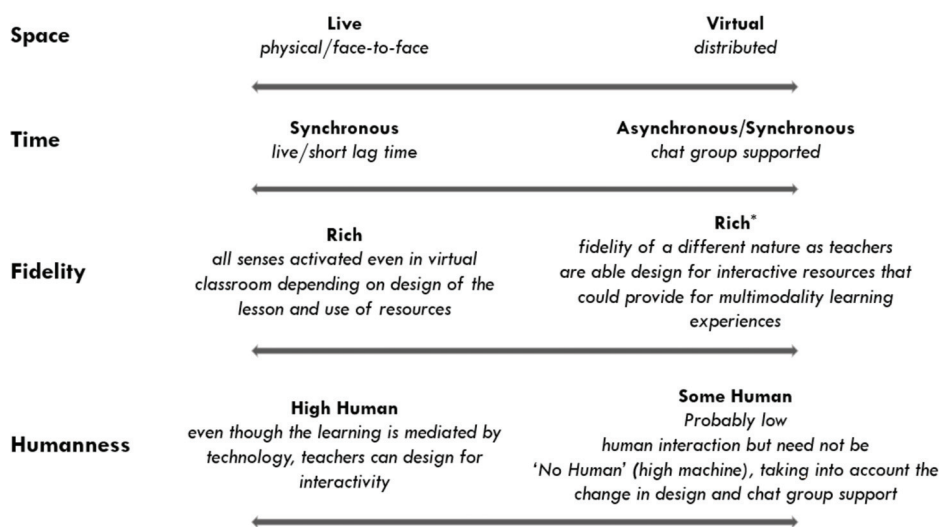


Figure 2. Revised dimensions of interaction in blended learning (adapted from [23]).

6. Conclusions

This conceptual paper started off arguing for a reimagined approach to blended learning in order to maintain continued education for our learners due to the various challenges brought about by the COVID-19 pandemic. It has shown how it is possible to adopt sound pedagogical design principles adapted from the blended learning approach and connectivism to ensure that the business of teaching, learning and assessment can still continue. As explained in the introduction, the intention was not to propose a new theory but rather to connect existing ones in order to shed light on the challenging circumstances that the pandemic has brought about to our institution and other IHLs across the globe. This is performed in the spirit that fellow educators can draw from our experiences and then broaden their scope of thinking when using technology to mediate learning.

What would be useful to support the ideas introduced in this paper would be empirical data about this reimagined approach to blended learning and its impact on learners. The following are some ideas for research: One, more detailed and fine-grained analyses of a wider sample of lessons designs. Two, a study examining instructors' and learners' perceptions of how revised ways of content delivery have impacted their teaching, learning and assessment. Three, a comparative study of how this blended learning approach might differ from subject to subject—starting with the assumption that a one-size-fits-all approach might not to the best way forward.

The COVID-19 pandemic may have abated in many parts of the world but there are still many education jurisdictions that will continue to face challenges—conflicts, disasters, new and old epidemics, etc. In such situations where physical face-to-face interactions are not possible or when physical learning spaces cannot be made available, this proposed approach can become a viable alternative to ensure learning continues. What this approach requires is that educators make the shift in their mindsets about where and how teaching, learning and assessment can take place. The connected environment that technology affords teachers and learners is a powerful one if exploited in the right spirit with the right motives.

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Article

An Exploratory Intervention Program on Chinese Culture among CFL Students at a Vietnamese University

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Abstract: This article reports on a study of an intensive three-week culture intervention program, delivered via VooV Meeting (an online meeting platform) as an additional opportunity for CFL students at a Vietnamese university in December 2021. The primary aim was to explore students' perceptions and experiences of learning about Chinese culture in a non-target language environment since the outbreak of the COVID-19 pandemic. Two hundred and nine mixed-level undergraduate CFL students participated in a survey administered via Google Forms. Overall results indicated that students valued the opportunity offered by this program to learn Chinese culture and acknowledged the importance of cultural study in CFL. There appeared to be different preferences among male and female students and the different year groups in choosing the contents and methods of cultural learning. Additionally, students expressed concerns about using technology in language and culture learning despite its benefits, especially in the absence of real-life human interactions and communications due to travel restrictions. One significant finding was that students recognised teachers' essential role in learning culture. The survey results, in particular the participants' responses to open-ended questions, are discussed in this paper. The understanding gained from this study is expected to provide Chinese language professionals and practitioners with insights and suggestions on how Chinese culture can be better integrated into CFL through appropriate and effective teaching strategies in a post-pandemic era.

Keywords: Chinese as a foreign language (CFL); intervention program; cultural study; Chinese culture; VooV Meeting

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1. Introduction

Vietnam has recently witnessed a rapid shift from a domestic economy to one participating in regional and international markets. In response to keeping pace with regional and international developments, the internationalisation of universities has been positioned as a strategic approach to enhancing the multilingual capabilities of Vietnamese students in a global context [1]. Hence, it poses significant challenges for language educators and learners at Vietnamese universities in improving language proficiency and cultivating cultural competence in an increasingly globalised world.

The framework of the six different language proficiency levels used in the Vietnamese national education system was officially adopted and developed from the Common European Framework of Reference for Languages (CEFR) [2,3]. Foreign language education in Vietnam has embraced opportunities since the Association of Southeast Asian Nations (ASEAN) integration and implementation of political and economic reform [4]. Under the pressure of regional and international economic competition, the Vietnamese Government has firmly committed to improving young Vietnamese graduates' foreign language communicative competence by introducing the National Foreign Languages 2020

Project (NFLP) [5]. According to the goals in the project, Vietnamese students should be able to communicate effectively and appropriately with people from diverse cultural backgrounds. In 2017, the Government of Vietnam approved the revised NFLP for the 2017–2025 period to boost foreign language learning and teaching [6]. As one of the eleven training languages in the Vietnamese higher education system, the Chinese language is represented widely by 76 higher education institutions which train specialists in the Chinese language [7].

2. Context of the Study

This study was conducted in the context of an undergraduate course in Chinese as a foreign language (CFL) at a public university in central Vietnam. Chinese and English are the only two foreign languages offered at this chosen Vietnamese university. The CFL course has become rather popular as there seems to be a high demand of Chinese language speakers given the economic development with Chinese enterprises locally [8]. The university's CFL program was established based on the policies, regulations and standards about national foreign languages education issued by the Ministry of Education and Training (MOET). The four-year period of the undergraduate study consists of three-year of skills and knowledge development before the final year of an internship at local Chinese enterprises. Only one compulsory subject is culture-related and scheduled in the second year of the CFL curriculum. Given the constraints of the curriculum, there are limited resources for CFL students to learn Chinese culture during their study period. With such limitations, an intervention program on Chinese culture was initiated and implemented in December 2021. The program aimed to promote Chinese culture and language learning by encouraging students to reflect on Vietnamese culture through direct engagement with the instructor and tailored learning contents. Simultaneously, students were provided with opportunities to improve their listening and speaking skills required for communication through interactions with one of the researchers, who was the main instructor for the program.

In addition to understanding the foreign language landscape at universities in Vietnam, it is also imperative to know about the connections between China and Vietnam from the perspective of CFL education at Vietnamese universities. For centuries, Vietnam experienced strong cultural influence from China [7]. Based on previous studies [9,10], the Sinosphere (or East Asian Cultural Sphere) contains five entities: China, Japan, North Korea, South Korea, and Vietnam. The creation of ideographic Vietnamese was an adaptation of classical Chinese characters which was used over a period of centuries-long Chinese influence [10]. In addition, Chinese language was used in the educational system of feudal Vietnam until the early 20th century [11]. Clearly, Chinese and Vietnamese cultures are closely associated for historical, social, educational, economic, and political reasons. Schumann (1976) [12] stated that congruence or similarity between the culture of the target language and that of the foreign language can affect social solidarity. If the two cultures are similar, then integration and social distance are reduced. Moreover, similarities and differences can be compared through the observations of students hailing from different cultural backgrounds, thus a deeper understanding of the two cultures can be achieved [13].

Vietnam and China have continuously had cultural exchanges from ancient times to present. The contact between the two countries makes Vietnam much influenced by China, especially in the language aspect. The seemingly identical cultures of Vietnam and China have each developed their unique features over the years [14]. Despite the close relationship between Chinese and Vietnamese cultures, their distinctive characteristics undoubtedly impact Vietnamese CFL students' lives, particularly concerning the socio-cultural influences. In terms of this study, CFL learners study Chinese language in this unique Vietnamese cultural environment, it is important that teachers encourage and help students explore their home culture and language by comparing them to those of the Chinese [15]. This could serve as a point of reference from which CFL students can further their understanding of the concept and nature of Chinese language through comparisons of Chinese culture and their own. It was critical to examine the strong link between these two Eastern

cultures and understand the role of Chinese culture in Chinese language learning. With regard to this, Figure 1 below illustrates the scope of this cultural intervention program, including four conditional key elements (KE). On the one hand, 1 indicates the conditions that are met, that is, KE1 represents the Chinese character culture circle, and KE3 represents the history of using Chinese characters. On the other hand, 0 indicates the conditions that are not met, that is, KE2 represents a non-target language learning environment, and KE4 represents non-native Chinese language learning background.

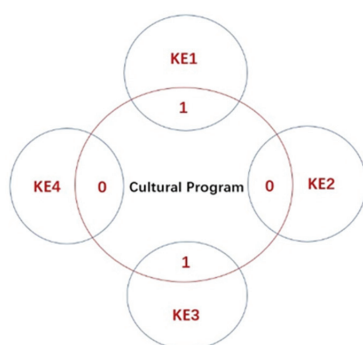


Figure 1. Four key elements constructing the cultural program.

3. Literature Review

3.1. Language and Culture

Language and culture are inseparable, interdependent, and their interrelated relationships benefit each other in language learning and teaching. That is, understanding culture and cultural differences assists learners in achieving language proficiency effectively and vice versa [16]. The most successful language learners learn culture and language simultaneously, therefore teaching language and teaching culture cannot be separated [17,18]. In the same vein, language learning entails linguistic knowledge and awareness of the importance of the context and motives behind communication. There is a large number of published studies that describe the link between culture and language. Research [19] showed that teaching any language involves teaching culture, as culture shapes how language is structured and used. Along the same lines, Stern (1992) [20] argued that cultural teaching often provides context without which the language remains an empty code and lacks credibility from learner's perspective. Researchers [21] also claimed that language and culture interact with each other in a way that connects culture to all levels of language use and structures. Overall, these studies highlight the unique relationship between culture and language.

The language education issue can be complex and multifaceted [22]. Learning a new language is a complex process, and so is language teaching. With the advancement of technology, the way we learn and communicate has gradually changed [13]. According to the review studies on technology-supported cultural learning conducted by [13], technology plays an essential role in language and culture learning due to the creation of authentic learning experiences. That is, cross-cultural learning based on technological support is especially important, due to the recent pandemic, during which most people have turned to online mediums for human communication [13]. For instance, researchers reported on benefits such as students' positive attitudes towards technology-supported learning activities and that learning activities helped develop language and cross-cultural skills [23]. However, despite the widely recognised advantages created by technologies in formal and/or informal environments, the COVID-19 pandemic has attributed the complexity to new challenges, such as technology accessibility, affordability, and reliability. Hence, it poses significant challenges for language educators to improve language education, par-

ticularly in cultivating learners' cultural competence due to the increasingly global nature of society [24].

As stated earlier, since language reflects speakers' culture, learners should be given insights into the habits, customs, and values and how these are similar to or different from their own. A research study [25] described three reasons for the culture component being so crucial in language learning. The third principal reason for stressing culture in language classes relates to students. On the one hand, students are extremely interested in the people who speak the language they are studying. On the other hand, they probably know very little about the basic aspects of their culture. As Stern (1992) [20] (p. 216) reiterated, "one of the most important aims of culture teaching is to help the learner gain an understanding of the native speaker's perspective". There has been substantial literature on teachers' perspectives toward Western cultures, in which English was the most popular language, and American culture has received more attention than any other culture [24]. However, there is little investigation into examinations on enhancing Chinese cultural learning and teaching in CFL in the Vietnamese university context, from the learners' point of view in particular. The present study attempted to contribute to the literature on this under-researched issue with a clear focus on nation-specific comparisons in culture teaching.

3.2. Cultural Teaching Approaches

Researchers [26] asserted that culture in language learning and teaching needs to be addressed within a comprehensive, dynamic, reflective, critical, and interactional understanding of culture. There is no exception in cultural teaching in CFL, which should assist learners in understanding Chinese culture using appropriate teaching approaches. From the perspective of Chinese language teaching, several key aspects need to be considered when designing cultural learning contents, such as the learner's language background and real-life experience within the East Asian Cultural Sphere, and the learning environment of the target language. These factors may affect the chosen approaches of teaching, the level of student engagement, and the learning experience given the abovementioned scope of the program.

Since the outbreak of the COVID-19, CFL learners have become more reliant on technology to obtain cultural information. However, given that there are many similar cultural characteristics within the Chinese character culture circle, misunderstandings can easily occur with communication. It may pose a potential challenge for CFL learners to establish cultural concepts appropriately and in learning Chinese culture as well as effectively communicating using the Chinese language. Therefore, this study focuses on how CFL learners from another Sinosphere nation, such as Vietnam, can develop their ability to learn Chinese culture, so that they can enhance their Chinese language learning.

While recognising the issues above, the section below section will start with a brief introduction of the four key phrases mentioned in this study, that is, cultural symbols (CS), cultural knowledge (CK), cultural awareness (CA), and cultural competence (CC). What follows is a brief overview of the cultural teaching approaches employed in this cultural program with a reference to the knowledge-based and contrastive approaches suggested by Piatkowska (2015) [27]. A more detailed account of these keywords concerning this study is given in the next section.

Fenner (2000) [28] argued that language learners should be given opportunities to develop CK, CA, and CC in a way that might lead to a better understanding of the target culture, as well as their own culture. Speaking of CS, Peirce [29] believed that the production of meaning was a process of symbolization, and experience was the way to make sense of symbols. In addition, CK, CA and CC were mentioned by several language researchers in describing learner's outcomes of culture learning [30,31]. Nguyen (2017) [32] proposed a three-level framework from CK to CC as a reference for setting pedagogical objectives of teaching culture in language education. The importance of these terms was also illustrated in Byram's model of intercultural communicative competence [33].

Regarding teaching approaches, the main ones are knowledge-based and contrastive approaches. Firstly, according to Nguyen (2017) [32], the knowledge-based approach aims to provide learners with knowledge of facts and information about the target culture, such as Chinese festivals, customs, and arts selected for this program. Byram (2020) [33] stated that cultural knowledge is structured and systematically presented information about culture. For CFL learners in Sinosphere, culture learning can help them raise cultural awareness by acquiring new cultural knowledge and integrating new perceptions and understandings into their personal experience on a daily basis. Additionally, Polanyi (1958) [34] claimed that effective learning needs knowledge classification, that is explicit knowledge and implicit knowledge. Knowledge can better link the learning of explicit and implicit culture [35] because it is the basis of cognitive processes [36]. Knowledge management in this program focused on the connection and coherence between explicit and implicit knowledge. Implicit understanding may result in explicit learning [37]. Secondly, Nguyen (2017) [32] also summarised that the contrastive approach helps learners to be aware of these similarities and differences between their own culture and the target language culture and encourages them to look for a connection between the two cultures. In relation to this program, it is critical that CFL learners can see the relationship between different cultures by contrasting and comparing Chinese and Vietnamese cultures. Generally, the program process and contents described in the following sections were inspired and informed by these theories and approaches to teaching culture with respect to the limitations of both contrastive and knowledge-based approaches pointed out by Piatkowska [27].

4. The Cultural Intervention Program

This cultural intervention program incorporated nine synchronised sessions via VooV Meeting into teaching Chinese culture at a Vietnamese university. This section will provide a comprehensive account of the cultural intervention program, including the program description, the program design and teaching process, and the program contents.

4.1. Program Description

This program was initiated to provide undergraduate CFL students at this Vietnamese university with an opportunity to study Chinese culture via VooV synchronised sessions during the COVID-19 pandemic. Most of the participating students were from years 1, 2 and 3. The students of Year 4 could not participate in the study due to the internships in their final year. The program was conducted from 15 to 31 December 2021, and a total of 9 sessions were delivered to the cohorts of 1st, 2nd and 3rd year CFL students. Each session lasted for 90 min, in alignment with the regular teaching schedules.

Considering different levels of Chinese language proficiency, the same session was offered repeatedly to each year group weekly with the tailored contents suitable for each respective language level. Specifically, all sessions for the Year 1 students were delivered with the support from a local bilingual teacher assistant who explained the contents in a synchronised manner. In addition, interactive learning activities and discussion topics were developed to engage the Year 2 and 3 students considering their relatively higher language levels.

4.2. Program Design and Teaching Process

The program design was guided and informed by several strategic documentations, including policies and standards for Chinese culture and language learning: (1) the three primary dimensions: connecting Chinese and foreign cultures; comparing cultural differences; and cultural interaction in the “Chinese Culture and Society Reference Framework for International Chinese Language Education” [38], which is the first framework of reference used in international Chinese language education; (2) the Vietnamese Government’s National Foreign Language Policies; and (3) the CFL syllabus and curriculums at the university where the study was conducted. Figure 2 below illustrates the cultural program design.

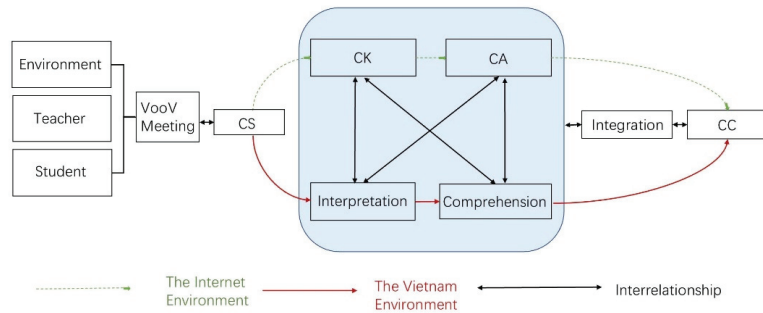


Figure 2. Cultural program design.

The fundamental principle of this program was to use the real cultural environment of Vietnam as an anchor for CFL students to learn Chinese culture naturally and effectively. As shown on the left side of Figure 2, the program consists of three main components: environment, teacher, and student. In terms of learning contexts, the dotted line represents the online environment, and the solid red line represents the Vietnam environment, explicitly referring to cultural learning environment. As indicated in Figure 2, this program was student-centred and teacher-instructed under the interplay of these two learning environments. The central area of Figure 2 displays the gradual and progressive culture teaching process: (1) the acquisition of CK through introducing and explaining CS; (2) the development of CA through understanding cultural concepts; (3) the improvement of CC through integrating CK and CA. It is worth noting that CS is an important medium to connect the two learning environments in the whole process, which enables learners to repeatedly reinforce their learning of CK and CA before they make progress to the next stage CC in cultural learning.

Figure 3 below provides the cultural teaching process at a micro-level. CS, CK, and CA constructed the cultural teaching process with CC situated in the centre. Interpretation, comprehension, and integration are the three-staged teaching objectives in the cultural teaching process. In terms of this study, CS is considered as an important starting point because culture depends on the use of symbols [39] and all human thoughts and experiences are symbolic activities [29]. The next step in this process was to integrate relevant cultural concepts in Chinese language by connecting students' life experience as CK particularly implicit CK is obtained through personal experience, practice, and comprehension [34]. According to the Knowledge Spiral Model by [40], the process of explicit knowledge to implicit knowledge was also an important way from understanding to explanation. The third step was to inquire the meaning of CS and reflect on the differences in similar CS between Vietnamese and Chinese cultures. Researchers [41] stated that cultural learning was a conscious and purposeful process, and cultural learning relies on cultural comparisons, and it is critical to recognise the need for constant repetition between the learner's culture and the culture they are learning from. The final step is CC, which is derived from the ability to integrate CS, CK, and CA in a circular way. Just as Bloom (1956) [36] argued, cognitive learning such as culture, involves knowledge, understanding, application, analysis, and the ability to integrate the elements.

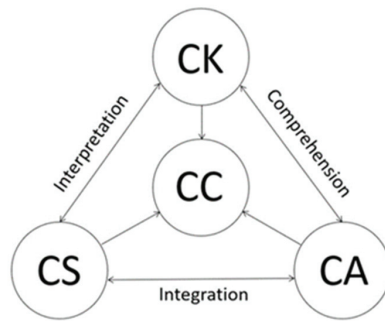


Figure 3. Cultural teaching process.

4.3. Program Contents

It is undeniable that cultural learning is not a simple linear learning process. Teachers should consider local customs, knowledge background, and life experience of CFL learners [41]. Guided by the above-mentioned cultural teaching approaches, this section presents the detailed teaching contents in alignment with the three teaching objectives in Figure 3 above.

All things seen in life are symbols, and the visually visible CS allows CFL students to perceive the cultural topics in the course, and teachers can also clearly explain the relationship between CS and CK, especially in the interpretation of explicit knowledge [39,41]. In this program, the teacher explained the relationships between the five elements and the twelve earthly branches, particularly how the two concepts are reflected in Chinese zodiacs, time calculation, principles of traditional Chinese medicine, and in aspects of architecture. On this basis, it is not only easier for CFL students to connect explicit and implicit knowledge, but they can gain an in-depth understanding of Chinese cultural concepts through contrasts. Specifically, teachers can assist students comprehend meanings behind cultural taboos by introducing several representative Chinese characters, such as blessings (吉、喜、福、壽) and flowers (梅、蓮、菊、蘭). The teacher then demonstrated the relationship between Chinese language and Chinese culture by incorporating several Chinese idiomatic phrases with the aforementioned Chinese characters. For instance, “福” and “壽” contain profound and auspicious meanings in Chinese culture. These two Chinese characters are often combined with other characters, such as “松” and “仙” to form a number of four-word Chinese idioms indicating longevity. Another example is that “菊” (chrysanthemums) is associated with funerals, there it should be avoided when preparing gifts. In addition, the Vietnamese national flower, “蓮花” (lotus flower) is associated and often found at Buddhist temples in both Vietnam and China as a cultural symbol of purity. Thus, the program content enables the teacher to guide the CFL learners to reflect on Vietnamese culture while learning about Chinese culture, and further enhances students’ ability to communicate in the Chinese language in a culturally appropriate way.

5. The Study

The purpose of this study was to find out CFL students’ perceptions of this intervention program based on their true feelings and experiences. It is anticipated that the program will cultivate the ability of CFL students at this university to explore various cultural topics progressively through multiple perspectives, especially in conjunction with their current level and understanding of the Chinese language and culture. The study aimed to address the following research questions:

- What are students’ perceptions of cultural knowledge, cultural awareness, and cultural competence in relation to learning Chinese culture?
- What strategies do students employ to acquire cultural knowledge and develop cultural awareness and competence?

- What are the benefits and challenges of learning Chinese culture using technology from students' perspectives?
- To what extent does this intensive cultural program enhance students' Chinese language learning?

5.1. Research Instrument

Questionnaires are widely employed as devices to gather information about people's opinions [42], and sometimes posing several open-ended questions at the end gives respondents space to formulate their own replies. For this research, the questionnaire was considered an appropriate data collection tool as it enabled data to be gathered from large numbers of participants in a straightforward and time-efficient manner. As investigating CFL students' perceptions was the aim of this study, the advantage of this method is that it allows researchers to make predictions about CFL students' views and experiences on cultural study. The properly constructed and administered questionnaire serves as a most appropriate and valid data gathering tool as it is both resource and time efficient [43].

This study used an online questionnaire created via Google Forms to collect data due to the restrictions imposed by COVID-19 in Vietnam. The procedure involved an invitation email sent out to all the students of the CFL program towards the end of the intensive program. Upon completion of the cultural program, students completed a survey that was used to evaluate the program's effect by measuring their ad hoc perceptions. The study was given institutional ethical approval in December 2021 before commencing the program and students were assured that their participation was voluntary and anonymous. They could withdraw from the study without reason.

The questions and statements in the questionnaire were designed to collect three broad types of information: (1) background information from each student about demographic characteristics; (2) information relating to students' perceptions on CK, CA and CC in general; (3) information relating to students' perceptions on Chinese culture learning in CFL. Keeping this in mind, the survey questionnaire consisted of three sections: demographic questions, rankings on the importance of the three dimensions of culture, CK (Q8–12), CA (Q13–17), and CC (Q18–22), and seven open-ended questions (Q1–7) inquiring about perceptions on the cultural study in Chinese language learning and teaching.

In order to accommodate different levels of Chinese language proficiency among student participants, the survey questionnaire was initially designed in English and then translated into Vietnamese by researchers who are fluent in both languages. The initial questionnaire was refined through iterative consultations with two experienced CFL researchers. Moreover, the questionnaire items were validated after consultation with five participants before the formal investigation. The process enabled the researchers to measure the clarity of the instrument so that adjustments could be made before the final implementation of the online survey. For instance, a few changes were made to the demographic section to ensure data correctness and usefulness.

5.2. Research Participants

As described in Table 1 below, participants (N = 209) were drawn from the body of currently enrolled students in the three levels of the CFL program at a Vietnamese university, including students from the 1st, 2nd, and 3rd year of the program. Eighty-eight per cent (n = 184) were female, 12% (n = 25) being male. Most students (94.7%, n = 198) were between 18–21 years of age. There was an even distribution in terms of the levels of study, respectively, 1st year 36.8% (n = 77), 2nd year 28.2% (n = 59), and 3rd year 34.9% (n = 73). It is expected that the participants' actual proficiency in Chinese ranges from the beginning to intermediate level.

Table 1. Participants' demographic information.

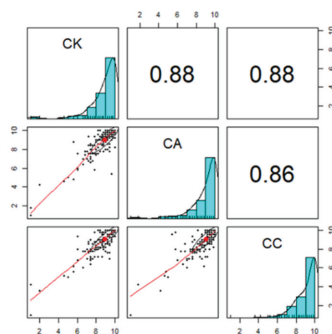
Variable		n	Percent
Gender (N = 209)	Female	184	88.0
	Male	25	12.0
Grade (N = 209)	1st year	77	36.8
	2nd year	59	28.2
	3rd year	73	34.9
Age (N = 209)	18–21 years	198	94.7
	>21 years	11	5.3

5.3. Research Data Analysis

The research data analysis process was twofold, quantitative and qualitative. One researcher in the current study conducted a quantitative analysis to address the research questions. A progressive approach was adopted for the statistical analysis of the collected quantitative data. Specifically, the quantitative analysis of the survey questionnaire was conducted using several statistical techniques with the aid of SPSS and R. Descriptive statistics (Table 2), such as mean standard deviation scores, were used to summarise and present participants' responses in a convenient and informative way [44]. Apart from descriptive statistics, inferential statistics were used to analyse the data and to draw conclusions from the sample populations, that is, Pearson correlations (Figure 4), and regression analysis (Figure 5a,b) among CK, CA, and CC. Statistical tests were chosen for their appropriateness, in particular the BMA method was chosen because it provides simple data visualisation on multiple models generated from the dataset.

Table 2. Descriptive statistics of the three dimensions (CK, CA and CC).

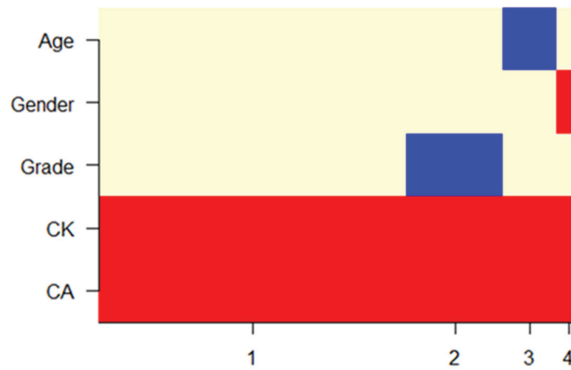
Culture Dimensions	Question	Mean/M	Std. Deviation/SD	Cronbach's Alpha
Cultural Knowledge (CK) (M = 8.93, SD = 1.63, N = 209) CK Cronbach's Alpha = 0.929	Q8	9.14	1.58	0.91
	Q9	8.89	1.58	0.91
	Q10	8.89	1.71	0.92
	Q11	8.88	1.61	0.91
	Q12	8.83	1.66	0.92
Cultural Awareness (CA) (M = 9.04, SD = 1.58, N = 209) CA Cronbach's Alpha = 0.932	Q13	9.15	1.64	0.93
	Q14	9.15	1.44	0.91
	Q15	9.09	1.57	0.90
	Q16	8.85	1.71	0.92
	Q17	8.97	1.53	0.91
Cultural Competence (CC) (M = 9.07, SD = 1.46, N = 209) CC Cronbach's Alpha = 0.937	Q18	8.80	1.78	0.95
	Q19	9.15	1.38	0.91
	Q20	9.03	1.38	0.92
	Q21	9.20	1.40	0.92
	Q22	9.19	1.35	0.92

**Figure 4.** Correlations among CK, CA, and CC.

Call:
 bicreg(x = x, y = y, strict = FALSE, OR = 20)
 4 models were selected
 Best 4 models (cumulative posterior probability = 1):

	p!=0	EV	SD	model 1	model 2	model 3	model 4
Intercept	100	1.476376	0.28796	1.43279	1.58402	1.5893	1.34429
Age	11	-0.00946	0.03422	.	.	-0.08571	.
Gender	4.9	0.002657	0.03017	.	.	.	0.05467
Grade	20.2	-0.01668	0.03942	.	-0.08241	.	.
CK	100	0.482609	0.0604	0.48424	0.4806	0.47712	0.48199
CA	100	0.368831	0.06205	0.36719	0.37211	0.37274	0.36783
nVar				2	3	3	3
r2				0.803	0.806	0.805	0.803
BIC				-328.741	-326.442	-325.23	-323.589
post prob				0.639	0.202	0.11	0.049

(a)



(b)

Figure 5. (a) BMA model analysis results. (b) Models selected by BMA.

Apart from the quantitative analysis, the other two researchers adopted thematic analysis [45] to identify and analyse major themes from a set of responses to the open-ended questions [46,47] using NVivo [48]. Constant comparative method in thematic analysis was utilised in order to make the mass of the collected qualitative data comprehensible. Firstly, responses to the open-ended question in the questionnaire were imported into NVivo. Secondly, the researchers read through the responses thoroughly to identify emerging themes within the texts. Finally, with the aid of several functions in NVivo, such as text search, word frequency search, and querying abilities, the researchers were able to collect and display key words and phrases and similarly coded data for examination [49], ultimately accomplishing a thorough iterative analytic process.

Primary findings from both qualitative data and quantitative data were triangulated. The results section below provides a detailed account of quantitative and qualitative data analysis findings.

6. Results

Survey data for this study were collected from Year 1, 2, and 3 undergraduate CFL students enrolled in a central Vietnamese university. This section reports the results of quantitative and qualitative analyses in response to the four research questions (RQ) and further discussions of the findings with regard to relevant literature is presented in the following section.

6.1. Quantitative Data Result

RQ1: *What are students' perceptions of cultural knowledge, cultural awareness, and cultural competence in relation to learning Chinese culture? (Qs8–22)*

In response to RQ1, most of those surveyed indicated that students perceived that CK, CA, and CC are closely related to learning Chinese culture. First, Table 2 above presents the median values and standard deviation of the participants' responses to each survey item with regard to CK ($M = 8.93$, $SD = 1.63$), CA ($M = 9.04$, $SD = 1.58$), and CC ($M = 9.07$, $SD = 1.46$). The descriptive statistics from the questionnaire indicated that the students perceived that CK, CA, and CC interrelate and interplay in cultural learning. In addition, Cronbach's coefficient alpha was used to determine the internal reliability of the instrument. The result showed that the coefficient alpha was over 0.9, which indicates substantial reliability of the observed variables. Moreover, further statistical tests (independent-samples t -test and ANOVA) were conducted to determine if there were differences in demographical variables (gender, age, grade) for CK, CA, and CC. There was significant difference in CK for male and female ($p = 0.048$). However, there was no difference in the other dimensions for age and grade.

Second, the Pearson correlation test was conducted to see whether students perceive that CK, CA and CC are closely related. The correlation between the two variables is denoted by the letter r and quantified with a number, which varies between -1 and $+1$. For example, correlation coefficient values below 0.3 are considered weak; values between 0.3–0.7 are considered moderate; values above 0.7 are considered strong. Additionally, the p -value helps to assess whether a correlation is statistically significant. To demonstrate the significance of a relationship or association between two variables, a p -value is presented, and it needs to be less than or equal to 0.05 ($p \leq 0.05$) [44,50]. The results of the correlational analysis are summarised in Figure 4 above. The Pearson correlation coefficient determined that there were strong positive correlations that exist between CK and CA ($r = 0.88$, $p < 0.05$); CK and CC ($r = 0.88$, $p < 0.05$); and CA and CC ($r = 0.86$, $p < 0.05$).

Third, the regression analysis was conducted to further examine the relationship between the three independent variables (grade, age, and gender) in relation to the three dimensions (CK, CA, and CC). A multiple linear regression was calculated to predict CC based on CK and CA. A significant regression equation was found ($F(2, 206) = 419.587$, $p < 0.000$), with an R^2 of 0.803. Participants predicted CC was equal to $1.43 + 0.48(CK) + 0.36(CA)$. When CK increased by 0.484 and CA increased by 0.367, then CC increased by 1. Both CK and CA were significant predictors of CC. Importantly, further investigation was conducted to assess multicollinearity in regression analysis. No signs were detected by examining tolerance (T) and variance inflation factor (VIF) for each independent variable: CK ($T = 0.216$, $VIF = 4.639$), CA ($T = 0.217$, $VIF = 4.601$), gender ($T = 0.918$, $VIF = 1.089$), age ($T = 0.701$, $VIF = 1.427$), grade ($T = 0.709$, $VIF = 1.410$).

Therefore, based on the analysis shown in Figure 5a, four models were discovered using BMA method in R for multiple linear regression (Figure 5b). An inspection of the data in Figure 5a revealed that Model 1 (the large red area at the bottom) in Figure 5b was the best one among the four models. The results showed slight differences by adding grade, age and gender as independent variables into Model 2, 3 and 4.

- Model 1: Participants' predicted CC was equal to $1.43 + 0.48(CK) + 0.36(CA)$. $R^2 = 0.803$, post prob = 0.639. When CK increased by 0.48 and CA increased by 0.36, then CC increased by 1. Both CK and CA were significant predictors of CC.
- Model 2: Participants' predicted CC was equal to $1.58 - 0.08(\text{grade}) + 0.48(CK) + 0.37(CA)$. $R^2 = 0.806$, post prob = 0.202. When grade increased by -0.08 , CK increased by 0.48 and CA increased by 0.37, then CC increased by 1. Grade, CK and CA were significant predictors of CC.
- Model 3: Participants' predicted CC was equal to $1.58 - 0.09(\text{age}) + 0.48(CK) + 0.37(CA)$. $R^2 = 0.805$, post prob = 0.110. When age increased by -0.08 , CK increased by 0.48

and CA increased by 0.37, then CC increased by 1. Age, CK and CA were significant predictors of CC.

- Model 4: Participants' predicted CC was equal to $= 1.58 + 0.05(\text{gender}) + 0.48(\text{CK}) + 0.37(\text{CA})$. $R^2 = 0.803$, post prob = 0.049. When male or female increased by -0.08 , CK increased by 0.48 and CA increased by 0.37, then CC increased by 1. Gender (male or female), CK and CA were significant predictors of CC.

6.2. Qualitative Data Result

The qualitative data provided a much richer and more in-depth understanding and exploration of meanings than could be derived from the numerical data collected at the quantitative phase. In this study, apart from the quantitative results reported earlier, the qualitative analysis of the seven open-ended questions revealed several interesting findings detailed in the sections below.

RQ2: *What strategies do students employ to acquire cultural knowledge and develop cultural awareness and competence? (Qs4–6)*

In response to this question, a range of responses from different genders and year groups was elicited. Two recurrent themes, static and dynamic, emerged from the analysis relating to the strategies used to obtain cultural knowledge, cultivate cultural awareness, and develop competence. The static way was mainly through the media materials, such as books, newspapers, and TV programs. In comparison, the dynamic way was via real-life communications and interactions with people from Chinese linguistic and cultural backgrounds.

Firstly, in learning cultural knowledge, apart from acknowledging the values of famous Chinese novels or books, both groups considered that teachers play an essential role in guiding the study of cultural knowledge. Specifically, the male students revealed a keen interest in authentic cultural knowledge, such as history, news, and documentaries, while the female students mainly placed their focuses on Chinese movies and pop culture. A number of students expressed great interests in Chinese history and mentioned that "reading Chinese classical novels and watching dramas and movies" helped them to understand Chinese culture. Interestingly, quite a few students believed that participating in university short-term course was also an effective way to learn about culture. This statement supported students' views on the role of teachers in learning culture.

Secondly, speaking of increasing cultural awareness, the male students tended to delve into historical materials to gain experience and explore Chinese culture, while the female groups were inclined to receive cultural information from multiple perspectives through close observations of people of the target language. As one student pointed out, "I often learn from teachers and friends who understand Chinese culture to improve my cultural awareness." Another student shared this view, who claimed that "the way I understand culture is by going to social networking sites on a regular basis to learn about their customs, behaviours, and the way they interact with each other." Similarly, both groups recognised the important role of teachers in helping them raise cultural awareness. Besides, the 1st and 3rd Year students mentioned that respect was the basic attitude for cultural awareness. One student remarked, "To learn to respect the culture of each country, we must first respect the culture of each place and its language, such as different dialects".

Thirdly, according to language competence and culture, the male students desired dynamic cultural competence, such as cross-cultural communication and social activities, in contrast, the female group preferred to develop cultural competence in a static way, such as books, and multimedia resources. One male student reported, "I often participate in outdoor activities to gain knowledge and improve cultural ability." Additionally, it was evident that the 3rd Year students were eager to enhance their cultural competence through real-life communication. Several third-year students commented that, "After each lesson, we often take part in small discussion groups to share our learning experiences." From the perspective of different year groups, it can be assumed that the 1st Year students were the

most curious group and excited to learn more about Chinese culture. Still, they mentioned that they could not fully understand some of the learning contents due to their limited language abilities.

RQ3: *What are the benefits and challenges of learning Chinese culture using technology from students' perspectives? (Q7)*

When the participants were asked about learning Chinese culture with technology, the majority of those who responded to this item felt that there were benefits and challenges in using technology to learn Chinese culture. Concerning the two aspects of technology use, themes such as accuracy, interest, efficiency, and relevance recurred throughout the dataset. Most of the students mentioned the benefits, such as easy and quick access to information through fast speed internet and its convenience and effectiveness in acquiring materials.

Furthermore, students seemed to agree that technology enhanced language learning performance. As one student remarked, "The use of technology increases motivation and interest in learning Chinese language due to the freshness and richness of the information available." While another student echoed, "Technology stimulates interest in learning and allows students to actively explore and find the right answers."

On the contrary, concerns were expressed about the challenges of using technology in learning Chinese culture. Particularly revealing were how the participants described their experience on Chinese culture learning online relating to degrees of accuracy, reliability and relevance of information, and fear of overuse. It is worth noting that there seemed to be a tendency to rely heavily on technology, resulting in reduced real-life communication and creativity. One individual stated that "using technology to learn Chinese culture could potentially lose the element of direct communication and the pragmatic aspect of language." Moreover, another reported problem was a lack of clear focus and guidance when there was an abundance of opportunities for Chinese culture content to be explored by students. As one student put it, "Learning a lot of information within a short period of time sometimes makes me feel overwhelmed and lost."

RQ4: *To what extent does this intensive cultural program enhance students' Chinese language learning? (Qs1–3)*

The participants on the whole recognised the importance of cultural study in Chinese language learning and valued the opportunity offered by this intervention program. The responses to RQ4 could be grouped into the following three broad themes: (1) benefits for language learning, such as effective communication; and increased learning motivation and curiosity; (2) a new perspective of thinking; and (3) future career enhancement.

Firstly, the themes of close relationship of culture and language, and benefits for language learning recurred throughout the dataset. When considering cultural study in CFL, the more Chinese culture they learned, the more motivated they became while learning Chinese language. A few students stressed this point through these remarks, "a better understanding of Chinese culture makes it more interesting to learn Chinese", "getting to know Chinese culture makes learning Chinese easier and more practical", "a deeper understanding of Chinese culture helps to learn the language more effectively", and "understanding Chinese culture will increase interest in Chinese language learning". In addition, there was a sense of effective communication through learning culture, one student said, "understanding culture is of great help to communicate with people in real life".

Secondly, a new way of thinking could be developed through cultural learning, just as one student said, "learning about culture can broaden one's horizons and give one a new perspective on one's own culture. Because the culture of each country is different, it is beneficial to learn the culture of other countries." Additionally, another student commented on the unique characteristic of Chinese culture, "Chinese culture is one of the oldest and most complex culture in the world, and it has an influence on a vast geographical region of Southeast Asia including Vietnam".

In addition to future career enhancement, many students mentioned the importance of learning Chinese for their future career opportunities. One student mentioned, “Integrating Chinese culture into language learning gives us better job opportunities because there are many Chinese investors building factories in Vietnam”. So they believe that learning Chinese will enhance their opportunities to find a job, thereby, they consider Chinese language to be a useful tool for future employment.

7. Discussion

This study found that CFL students at this subject Vietnamese university acknowledged the significant role of Chinese culture in their language learning. Even though there was a lack of learning about Chinese culture in a target-language environment under the current situation, students were keen to study Chinese culture by engaging in this intervention program at the end of the year 2021. The following section reported on some highlights generated in the findings.

In line with the quantitative findings from the questionnaire, the qualitative results indicated that all the students of the three-year groups believed that visual materials, particularly movies or Chinese TV drama series, were the fastest way to learn cultural knowledge. This is supported by Xing (2006) [51] observation on students spending time watching Chinese movies or reading Chinese books to learn about Chinese culture. “All these visual resources provide ample evidence of the distinctiveness of Chinese culture and its differences from learners’ own cultural life worlds” [51] (p. 151). In particular, for learners who do not have the opportunity to go abroad, using foreign movies has proven helpful in promoting cultural awareness [52]. However, these data must be interpreted with caution because foreign movies may create cross-cultural stereotypes as well [53]. Although all the year groups preferred to explore Chinese culture through online resources, each group seemed to have different preferences. This was in accordance with the review study [13], and researchers argued most people who learn languages and cultures have turned to online media to communicate.

Another important finding is that the 2nd and 3rd Year groups showed great interest in the differences between Chinese and Vietnamese cultures, and they were ready to develop their intercultural communicative competence in learning Chinese, which was echoed by [15,54]. Students believed that comparing the target culture with their own culture helped them to see “real” people speaking the target language and to be aware of how culture affected individuals’ thinking and behaviours. Just as one second-year student said, “Because Chinese and Vietnamese cultures are similar, we can make comparisons to improve our knowledge.” This learning approach also brought about an “enriching appreciation” of their own culture and perception of their cultural identity.

On the question of using technology, many students commented that learning culture with the aid of technology is fast, efficient, and ubiquitous, especially under pandemic conditions. These comments were consistent with the study by [55], which found that foreign language learners can link anywhere and at any time to access appropriate material and learning information. This is because developments in technology have opened up access to cultural resources from all over the world [56]. Furthermore, as witnessed by this present research, cultural learning is closely associated with teachers’ guidance. In the study by [57], they discovered that teacher instructional practices influenced students’ language learning with technology outside the classroom in two cultural contexts: Hong Kong and America. Lyu and Qi (2020) [58] also emphasised the influence of teachers in enhancing students’ self-management and self-monitoring in their language learning when using technology.

8. Conclusions and Limitations

Due to the lack of cultural study in an ideal target language environment, the present study was designed to explore the effects of an intervention program on Chinese culture among CFL students at a Vietnamese university. This study has found that generally CFL

students at this university were highly motivated in learning Chinese language, and they are keen to learn Chinese culture. The analysis of quantitative data suggested that there was no significant difference among the students. Furthermore, the analysis of qualitative data has been synthesised to present overall findings in the interest of cultural study in CFL. Only important themes were reported as a foundation to explore the effects of this cultural intervention program. In general, it was observed that genders and different year groups were the two key factors impacting the students' strategies when acquiring CK and developing CA and CC. Male participants tended to value the opportunity to learn Chinese culture through real-life communication with people who can speak Chinese language, while female ones were interested in exploring Chinese culture using a diverse range of multimedia cultural resources. This is particularly interesting given the common challenges associated with learning culture with modern technology indicated by the qualitative data. In terms of students in different years of study, the current data suggested that the 1st Year students explored Chinese culture mainly out of curiosity; the 2nd Year students were eager to get teachers' guidance in finding out the differences between Chinese and Vietnamese cultures; the 3rd Year students expected to learn more about Chinese culture in order to improve cultural communication skills.

Furthermore, it is worth noting that one of the more significant findings to emerge from this study was that both male and female participants strongly believed that teachers were the key to cultivating Chinese cultural learning. Language teachers need to point out the culturally appropriate way to use language in specific situations and explore culturally based linguistic differences to promote understanding instead of misconceptions or prejudices [59]. However, Luk (2012) [60] mentioned that even though teachers had a positive attitude towards culture in language teaching, they were uncertain about how to incorporate culture in language classes or "hesitate to implement cultural elements into language teaching" [51] (p. 263).

Overall, the findings of this research study underscored the implementation of this plausible cultural intervention program given the fact that culture, especially Chinese culture, is very much "a complex and multifaceted subject for scholars, educators, and students alike to study, teach, and learn" [51] (p. 242). Therefore, Xing (2006) [51] proposes her theory of learnability and argued that "culture proficiency must progress in line with language proficiency" [61] (p. 159) as linguistic knowledge seemed to become an obstacle for teachers and students in addressing culture more systematically and comprehensively [62]. Most importantly, these findings have significant theoretical and practical implications for understanding the nature of Chinese culture in Chinese language learning, as well as "how Chinese culture learning is best integrated into learning to be active and effective communicators in Chinese" [61] (p. 163). However, it is still debatable how to incorporate culture into language teaching regarding objectivity and strategies [63]. Moreover, from an intercultural perspective, learning Chinese language and culture is necessarily intercultural in nature, involving the interaction of two language systems and two cultural codes [61].

Despite the findings discussed above, this study is limited by the fact that it only surveyed a limited number of CFL students from one university. The results may not be applicable to other universities in Vietnam. First, the study was only offered for a short period of time during the final exam time at the chosen university. This might have some implications on students' participation given the tight and busy class schedules. Second, only Years 1, 2, and 3 CFL students were given the opportunity to attend the program, while Year 4 students were in their final year of practice. This might have some effects on the findings because of their relatively high level of Chinese language proficiency and long learning experience. Nguyen (2017) [32] stated language education should give learners opportunities to develop CK, CA, and CC of both the target culture and their own culture and suggested that further research is needed to examine learners of different language levels. By comparing the results of different genders and year groups, bearing in mind the possible bias in these responses, the findings may inform CFL practitioners to take effective teaching methods catering for learners with various Chinese language proficiencies.

Third, the reality of gender imbalance in CFL learners at the university may have been a factor in the research findings. Moreover, this research focused on students' perceptions of this intervention, which might miss some critical aspects in CFL teaching and learning. The current investigation was unable to analyse these variables. In spite of its exploratory nature, this study offered valuable insights into pedagogical opportunities which facilitate Chinese culture learning of CFL students in a non-target language environment.

With respect to these limitations, future research needs to include all the year-level CFL students and extend the length of the program in order to get a holistic picture of cultural research in CFL course. In doing so, it enables CFL educators and practitioners to devise credible intervention strategies to promote Chinese cultural study. Student and teacher perceptions, engagement could measure the effectiveness of the intervention, and further backed by the reasonable length of the program. Future studies on the following aspects are therefore recommended: first, more sustainable and systematic planning required to ensure the design of a meaningful cultural invention program that can better support the formal university curriculum; second, taking full advantage of the accessibility and flexibility of abundant cultural information online to enhance CFL learners' motivation to learn culture sustainably; third, optimising CFL learners' learning strategies to warrant a positive bearing on their learning experience. Thus, with systematic and integrated cultural teaching, students' cultural competence can be developed along with their language competence [64]. Likewise, understanding how students perceive the additional learning opportunity may foster lifelong learning as students learn to navigate and comprehend Chinese language and culture through real-world tasks in the online environment [65]. It is envisaged that the present study will shed light on the mechanism underlying cultural learning and teaching in CFL. This may not only help CFL educators to design a nation-specific framework of Chinese cultural teaching, but also for CFL students to construct cultural competence in the target language environment of Sinosphere in the future.

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Article

Providing Institutional Support for Academic Engagement in Online and Blended Learning Programs

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Abstract: In this paper, we examine how universities can evaluate the level of support they provide to help their students with affective, behavioral, and cognitive engagement in their online and blended learning experiences. Additionally, it identifies what types of supports help students engage academically and what barriers hinder their online engagement. Using a survey instrument sent to university students (n = 1295), we conducted a mixed-methods analysis to understand better how students feel the institution supports their online engagement and what barriers they experience. To accomplish this, we addressed the following research questions: (1) How do students feel the institution supports their academic engagement for online and blended learning (including affective, behavioral, and cognitive dimensions)? and (2) What are the barriers to student academic engagement for online and blended learning at the institutional level? We used the Academic Communities of Engagement (ACE) framework as a lens for understanding the types of support institutions should provide in online and blended learning programs. While our descriptive statistics revealed that students might not distinguish the types of support they receive, the qualitative findings suggested they need more behavioral support. Our results also showed that 31% of students reported they experienced three or more barriers to their learning, which should be addressed when considering institutional support elements.

Keywords: learner engagement; online learning; blended learning; institutional support; support for engagement

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1. Introduction

Many researchers focus on student engagement, yet the field has not agreed on precisely what student engagement is. A standard definition that many agree on is that student engagement constitutes three dimensions: *affective* (emotional), *behavioral* (physical), and *cognitive* (mental) [1–3]. Student engagement has also correlated strongly with academic success [4,5], thus requiring that learning environments support student engagement [6,7]. Several studies suggest that interaction, community, and relationships in a learning environment may support and even increase student engagement [8–10]. Because of these findings, many educational programs have tried to implement support structures to aid student engagement [6,7,11,12].

There is usually a wide range of interventions and supports available to help students engage in the learning process and succeed in school in traditional in-person classrooms [13]. Instructors often employ several strategies to increase student interaction with each other, including smaller class sizes, peer tutors, and frequent small group activities [14]. There are also strategies like increasing time on task, fostering positive relationships between teachers and students, reinforcing positive behaviors, giving students more control and autonomy, and ensuring content is appropriate for their abilities [14,15]. The research has demonstrated that these strategies and methods are effective in a traditional classroom. However, research on providing student engagement support in online and blended

learning settings is sparse, even though blended learning is increasingly being promoted for its engagement-enhancing capabilities [7,13,16,17].

The COVID-19 pandemic revealed the necessity of many institutions to adopt an institutional plan to improve their online and blended learning programs and support student engagement in these environments [16,18,19]. The Academic Communities of Engagement (ACE) model [18] provides a framework for supporting student engagement in online and blended learning environments. ACE suggests that providing students with support from their *course* and *personal communities* can increase their ability to engage in online and blended classrooms. Each community consists of *actors* (supportive persons) with varying levels of expertise, experience, and skills to support students' engagement in different modalities. Through the ACE model, institutions can evaluate students' cognitive, behavioral, and affective engagement to uncover what additional supports a student might need to succeed academically and how a student's personal and course communities can provide that support [18]. If both communities provide active support, students are more likely to achieve academic success.

The purpose of this study is twofold: (1) to examine how a university can evaluate the level of support it is providing to help students with affective, behavioral, and cognitive engagement in online and blended courses and (2) to understand what types of things enable students to engage academically and what barriers there are that prevent students from engaging academically. This study also provides a case example of a university assessing institutional support for academic engagement to inform institutional decisions related to reducing barriers to engagement and increasing support for engagement in online and blended coursework.

Research Questions

This study will address the following research questions:

1. How do students feel the institution supports their academic engagement for online and blended learning (including affective, behavioral, and cognitive dimensions)?
2. What are the barriers to student academic engagement for online and blended learning at the institutional level?

2. Literature Review

In this literature review, we first provide context and a summary of student engagement in light of the Academic Communities of Engagement (ACE) framework [18] and justify its use as a model for this study. We also explore existing literature that addresses models for institutional adoption of support to aid students' ability to engage in online and blended learning environments.

2.1. Academic Communities of Engagement (ACE) Framework

Student engagement is a vague term in educational literature with numerous interpretations and definitions [2,7,13]. Despite its nuanced definition, we understand that supporting student engagement is central in online and blended courses, as these environments more easily lend themselves to issues of isolation [20], barriers to technology [21], and the need for greater self-regulation [16,22]. A focus on academic engagement in online and blended learning settings is central to the ACE framework, which intends to clarify many issues associated with defining and measuring student engagement. It also clearly describes the three dimensions of engagement—*affective*, *behavioral*, and *cognitive*—and points out that each type of engagement may also exist independently despite often being associated. The following are definitions of each type of engagement as defined in the ACE (2020) model:

- *Affective Engagement*: “The emotional energy associated with involvement in course learning activities” [18] (p. 813).
- *Behavioral Engagement*: “The physical behaviors (energy) associated with the completing course learning activity requirements” [18] (p. 813).

- Cognitive Engagement: “The mental energy exerted towards productive involvement with course learning activities” [18] (p. 813).

A student’s ability to engage affectively, behaviorally, and cognitively is determined by facilitators (influences) of engagement [12,13]. A learner may possess several facilitators that can contribute to their success, including intrinsic motivation, an interest in the subject matter, or the ability to self-regulate [18]. Additionally, a student’s ability to engage may stem from their course environment where teachers use pedagogical strategies to directly or indirectly affect their ability to engage and their personal community, including family members, friends, and other associates [17,18,23,24]. The ACE framework identifies how students engage and where they receive or lack adequate support from facilitators to cultivate the engagement necessary to achieve academic success.

Communities of Support

The two types of communities identified in the ACE framework as sources of support for student engagement are (a) the personal community and (b) the course community. While the personal community consists of families, friends, and other associates outside of the school environment that exists beyond the timeframe of the course [18,23,25], course communities include actors embedded within a course, including teachers, peers, and administrators [17,18,26]. These course community actors are temporary, existing only during the allotted time of the course. Despite their different actors, timeframes, and characteristics, these communities play a unique role in supporting students [18].

Among the critical aspects of these distinctive communities are how communities can support students, or what are known as the support elements. A support element differs from a facilitator because it refers to the methods communities can employ to assist students instead of the specifics of a supportive environment [18]. While it is essential to understand the definition and purpose of facilitators, support elements lead to actionable strategies that support communities can implement to help students succeed academically.

2.2. Engagement Support Elements

It is important to identify specific support elements appropriate for different types of student engagement so actors in students’ communities can assist their students. The ACE Framework [18] defines support elements that influence engagement differently and provides insight into how these support communities aid their students in engaging in online learning. See Figure 1.

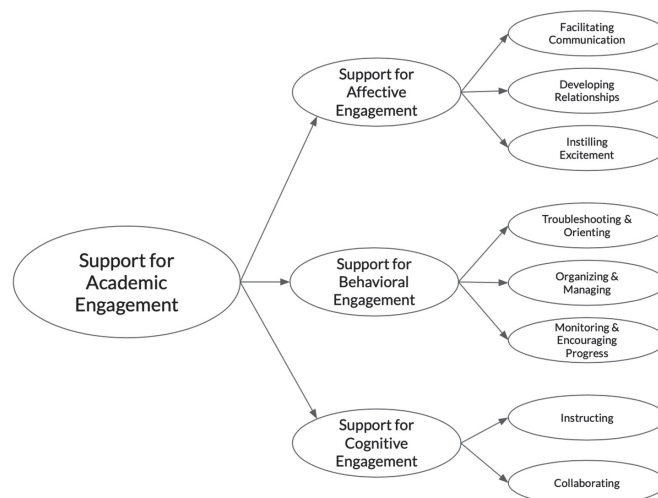


Figure 1. Support Elements in the ACE Framework.

2.2.1. Affective Support Elements

Affective support aligns with actors' abilities to develop relationships and facilitate communication [13,17,18]. Additionally, it considers student self-efficacy, or how well a student expects to do in a course, and how they value the course content [27,28]. The necessary level of affective engagement may be challenging to reach if a student does not appreciate the course content or does not expect to succeed in the course [29]. Online communication requires a different skill set than in-person communication and can seem less personal [20,30]. Thus, students who lack the skills or confidence to communicate and build relationships online must have support. For example, some students may need someone else to initiate conversations or be encouraged [30]. The Community of Inquiry (CoI) framework [31] stresses the importance of having both social and teaching presences online; however, these alone do not foster the relationships necessary for adequate affective engagement [18,19,32]. After establishing a social presence, the group members must become invested and cultivate a community [31]. Organizing students into small groups is one of the most effective ways to create this type of community online [33].

2.2.2. Behavioral Support Elements

Behavioral support elements include troubleshooting, coordinating, and monitoring progress [13,18,21,34]. Borup et al. [18] note that these elements do not directly relate to mastering the content but are often necessary to assist students in fully engaging in the learning process. This support element becomes vital with the added complexity of online and blended courses. de la Varre et al. [21] note that one of the primary reasons students drop out of online classes is a lack of familiarity with the course platforms and technologies. Students may also need support to organize their physical learning spaces, learn self-regulation strategies, and minimize distractions. Students often have greater control of their learning in online and blended learning settings, but this can also mean they are more likely to procrastinate, negatively impacting their performance [22]. The flexibility of online and blended courses makes monitoring progress an integral element for keeping students on track [35].

2.2.3. Cognitive Support Elements

In the ACE framework, instruction and collaboration contribute to cognitive engagement. Instruction occurs when people share knowledge that allows students to acquire new skills and understanding [13,18]. Instruction can include presenting material, summarizing content, eliciting feedback, sharing resources, and clarifying misunderstandings [36]. Individuals with knowledge in specific content areas can offer subject-specific instruction, while those without knowledge can still provide general instruction, such as feedback [18].

Students collaborate when they work together "to co-construct knowledge that neither had previously or to develop a product they could not have created individually" [18] (p. 816). Even though many online courses have emphasized flexibility at the expense of teamwork, students' collaboration is considered a crucial component of good online instruction [33]. While collaboration has been more prevalent in blended or traditional classrooms, many collaboration tools are becoming available and commonplace in online courses, such as social annotation and synchronous and asynchronous video.

2.2.4. Perceptions of Support Elements

According to Conceição & Lehman, online learners perceive self-care, institutional support, friends, family, peers, and instructors as crucial supports to being engaged affectively, behaviorally, and cognitively [37]. Although students emphasized the need for instructors' presence, they also felt that having a network of instructors, family, and friends was equally valuable [37]. In another study, students in an online doctoral program considered faculty, mentors, family members, and coworkers as sources of support, but these support groups also occasionally inhibited their engagement [38]. By examining student perceptions of the support that they receive through the ACE framework, we can identify the best methods

and strategies institutions can adopt to facilitate these support elements to increase student engagement and achievement in online and blended courses.

2.3. Institutional Adoption for Supporting Student Engagement

After identifying these support elements, programs may need to adopt a specific plan at the institutional level to ensure the critical support elements for engagement are in place and accessible to all students [39,40]. Providing support for student engagement at the institutional level can prove critical for the success of online learning programs. Casanovas has argued that when individual instructors implement online or blended learning strategies separate from the institution, there is often a gap in the growth of a program, even if both the institution and the individual instructor favor an online or blended learning approach [41]. Additionally, Casanovas has pointed out that adoption models of online or blended learning programs usually focus on individual adoption without explaining how to accomplish institutional adoption [42]. However, having a well-defined vision and strategy at the institutional level is crucial to adopting a program initiative [39,43]. Embedding academic support within an institution's online or blended learning program can help ensure no disparities between courses and that all students have equal access to the support they need to succeed academically.

3. Methods

In this section, we will discuss this research study's participants and their setting's context. We will discuss our research design, including data collection methods, analysis, limitations, and ethical considerations.

3.1. Participants and Setting

The participants for this study ($n = 1295$) were students at a university in South America in 2021. At the beginning of the Fall 2021 semester, enrolled students at the university were asked to take an optional survey to reflect on their experience in their online and blended courses from the previous semester. The 1295 students that responded to the survey came from various degree programs and specialties and represented 14.2% of the university population.

This South American university is a private, not-for-profit higher education institution with High-Quality Accreditation Status awarded by the Ministry of Education of [location masked for blind review]. It serves the people of [location masked for blind review] and has an academic offer of 109 programs at the undergraduate and graduate levels organized into six colleges: Economics, Administrative and Accounting Sciences; Social Sciences; Humanities and Arts; Legal and Political Sciences; Health Sciences; Engineering; and Technical and Technological Studies. Following the principles of autonomy, harmony, knowledge, and citizenship, this university aims to innovate in educational processes, influenced by creativity, digital transformation, and research, aligned with the United Nations Sustainable Development Goals (SDG). Although it delivers most academic programs in person, the university has an enduring tradition of online programs. It seeks to transform its offer toward blended learning in alignment with Decree 1330 of the Ministry of Education [44].

Due to the COVID-19 pandemic, the university shut down all in-person activity in 2020. Like many other schools and universities across the globe, the university began offering virtual courses. Their goal was to provide learning experiences enhanced by technology and have flexible and adaptable academic environments. By the spring semester of 2021, the university offered courses in various modalities, including blended, live remote delivery and online asynchronous courses. The university became interested in better understanding students' abilities to engage in multiple online modalities to improve and offer classes in each of these modalities even after the pandemic.

3.2. Data Collection

The data in this study were collected via survey to better understand current student needs and university efforts to support student engagement in online and blended teaching modalities (see Appendix A). In this paper, we focus on barriers students experienced in online/blended courses and their perceptions of the university's support to support their engagement. The survey was developed, translated into Spanish, piloted with students, and overseen by university administrative stakeholders. The survey items asked students questions relating to academic success, academic engagement, and academic support for engagement as defined in the ACE framework. It also included a section with questions regarding students' demographic information. It concluded with an open-ended question for students to leave any additional comments they wanted to share on how the university could better support their academic engagement in their online and hybrid courses (See survey items in Appendix A).

To test basic reliability for the overall survey, Cronbach's Alpha was 0.969, which is very high. The survey data set was too large to analyze and report on with one academic paper. Another paper that is in progress contains details of the psychometric properties of the instrument and model using CFA analysis, but that reporting is beyond the scope and purpose of this article. Table 1 shows the specific data we used from the survey to answer our research questions and address the purposes of this study.

Table 1. Data collected from the university survey.

Data Collected	Description
Students' perception of the institutional support they received to help them engage academically in their online and blended learning courses	<p>Questions about the support community at the university (e.g., instructors, advisors, classmates) (See survey items in Appendix A)</p> <ul style="list-style-type: none"> • Affective Engagement Support (9 items) • Behavioral Engagement Support (9 items) • Cognitive Engagement Support (6 items)
Student reporting on external barriers related to demographic conditions	<p>Barriers Data (See survey items in Appendix A)</p> <ul style="list-style-type: none"> • Transportation • Internet access • Computer access • Affordable housing • Technical support • Family environment • Work schedule
Open-Ended Question	<p>Question about how the university can better support students' academic engagement in online/blended environments.</p>

3.3. Data Analysis

To analyze the data, we used descriptive statistics to represent the quantitative findings. We also conducted a qualitative thematic analysis of the open-ended question using Attride-Stirling's approach to organizing findings into thematic networks [45]. See Table 2 for an overview of our data analysis.

Table 2. Research questions, data collected, and data analysis methods.

Research Question	Data Collected	Data Analysis
RQ #1: How do students feel the institution is supporting their Academic Engagement for online and blended learning (including Affective, Behavioral, and Cognitive dimensions)?	24 statements asking students to rate their agreement with the level of institutional support they received to help them engage academically within each type of engagement: <ul style="list-style-type: none"> • Affective (9 items) • Behavioral (9 items) • Cognitive (6 items) 	Descriptive statistics of averages of each type of support for academic engagement (affective, behavioral, cognitive).
RQ #2: What are the barriers to student academic engagement for online and blended learning at the institutional level?	<p><i>Barriers Data</i></p> <ul style="list-style-type: none"> • Transportation • Internet access • Computer access • Affordable housing • Technical support • Family environment • Work schedule <p><i>Open-Ended Question:</i> Please share any comments or ideas you have about how the university can better support your academic engagement in online/blended environments.</p>	Qualitative thematic analysis using Attridge-Stirling procedure [45].

3.3.1. Descriptive Statistics

In our quantitative analysis, we report means, standard deviations, and some percentages. This basic analysis helped us understand how well students felt the university supported their academic engagement in three dimensions: affective engagement, behavioral engagement, and cognitive engagement [18]. It also helped us understand which barriers students were facing and the relative influence of individual barriers.

3.3.2. Thematic Analysis of Open-Ended Question

Our qualitative thematic analysis helped us better understand the barriers students faced regarding receiving engagement support from the institution. We initially open-coded each response and grouped common codes into organizing themes. We further grouped these organizing themes into global themes according to the various dimensions of academic engagement (affective, behavioral, and cognitive) and any other significant categories that came out in the responses unrelated to the types of engagement. One researcher coded all the answers first and developed a coding structure. A second researcher then independently coded the responses using the same coding structure the first researcher developed. They found that they had a 97% interrater agreement among the global codes. After both researchers independently coded the data, they discussed and agreed on any discrepancies.

3.4. Ethical Considerations

Partners at the university underwent an ethical review process at their institution. Other researchers received archival data to analyze that had no personally identifiable information.

4. Results

We organized the results according to the two research questions we addressed in this study.

4.1. Question #1: How Do Students Feel the Institution Is Supporting Their Academic Engagement for Online and Blended Learning (Including Affective, Behavioral, and Cognitive Dimensions)?

The survey included 12 statements that asked students to rate their agreement with their perceived level of personal academic engagement in their online and blended courses within each type of indicator for engagement: Affective (4 items), Behavioral (4 items),

Cognitive (4 items). Results showed that the average for student engagement was about the same, with affective engagement somewhat lower than behavioral and cognitive engagement (see Table 3).

Table 3. Average of each type of academic engagement (scale: 1 = strongly disagree (not engaged) to 6 = strongly agree (engaged)) (n = 1295).

Engagement Type	Mean	SD
Affective	3.9	1.6
Behavioral	4.2	1.4
Cognitive	4.3	1.4

The survey then included 24 statements asking students to rate their agreement with the level of institutional support they received to help them engage academically within each type of engagement: Affective (9 items), Behavioral (9 items), Cognitive (6 items). The results were consistent with students' perceived engagement levels (See Table 4).

Table 4. Averages of each type of support for academic engagement (scale: 1 = strongly disagree (does not support engagement) to 6 = strongly agree (supports engagement)) (n = 1295).

Support for Engagement Type	Mean	SD
Affective	4.2	1.4
Behavioral	4.3	1.4
Cognitive	4.3	1.4

Students rated their agreement with the level of specific support they received in subcategories within each primary category (affective, behavioral, cognitive). In each subcategory, the mean was about the same (4.3–4.5), possibly indicating that students generally feel well supported across engagement types or do not differentiate between different types of support (see Tables 5–7). Within the affective engagement indicator, students rated their agreement with the level of support they received regarding facilitating communication (3 items), developing relationships (3 items), and instilling excitement for learning (2 items) (see Table 5).

Table 5. Descriptive statistics of affective support elements (scale: 1 = strongly disagree (does not support engagement) to 6 = strongly agree (supports engagement)) (n = 1295).

Affective Support Elements	1	2	3	4	5	6	Mean	SD
Facilitating Communication (3 items)	4%	7%	16%	23%	26%	24%	4.3	1.4
Developing Relationships (3 items)	6%	8%	16%	21%	25%	24%	4.2	1.5
Instilling Excitement for Learning (3 items)	6%	6%	16%	24%	25%	23%	4.2	1.5

For behavioral engagement, students rated their agreement with the level of support they received for troubleshooting and orienting (3 items), organizing and managing their coursework (3 items), and monitoring and encouraging progress (3 items) (see Table 6).

Table 6. Descriptive statistics of behavioral support elements (scale: 1 = strongly disagree (does not support engagement) to 6 = strongly agree (supports engagement)) (n = 1295).

Behavioral Support Elements	1	2	3	4	5	6	Mean	SD
Troubleshooting & Orienting (3 items)	5%	6%	15%	24%	26%	24%	4.3	1.4
Organizing & Managing (3 items)	4%	7%	17%	25%	25%	22%	4.3	1.4
Monitoring & Encouraging Progress (3 items)	4%	5%	14%	22%	26%	29%	4.5	1.4

For cognitive engagement, students rated their agreement with the level of support they received in instruction (3 items) and collaborating (3 items) (see Table 7).

Table 7. Descriptive statistics of cognitive support elements (scale: 1 = strongly disagree (does not support engagement) to 6 = strongly agree (supports engagement)) (n = 1295).

Cognitive Support Elements	1	2	3	4	5	6	Mean	SD
Instructing (3 items)	5%	6%	17%	24%	25%	23%	4.3	1.4
Collaborating (3 items)	5%	7%	15%	24%	25%	24%	4.3	1.4

In Tables 5–7 (above), very few students were extremely unhappy with the support they received in the areas of affective, behavioral, and cognitive support, but about one-quarter of the students scored a three or lower. This number is still too large for university stakeholders to be content with, which provides evidence that we must dig deeper into the barriers students are facing to better understand what causes dissatisfaction among some students.

4.2. Question #2: What Are the Barriers to Student Academic Engagement for Online and Blended Learning at the Institutional Level?

4.2.1. Descriptive Statistics

The survey also asked students to report on the external barriers that they experience as university students in online and blended courses that prevent them from fully engaging academically. Their reported barriers included transportation, Internet access, computer access, affordable housing, technical support, family environment, and work schedule. The primary purpose for asking students about these barriers was to understand how the university can better support students to engage academically in their online and blended courses. Table 8 shows how many students rated each type of barrier and the level of barrier it was for them. Transportation appeared to be the greatest barrier, with 442 (34%) participants rating it between 4–6 on the scale (see Table 8).

Table 8. Descriptive statistics of barriers (scale: 1 = not a barrier to 6 = high barrier) (n = 1295).

Barrier	1	2	3	4	5	6	Mean	SD
Transportation	42%	12%	12%	13%	10%	11%	2.7	1.8
Internet Access/Speed	33%	18%	16%	16%	10%	7%	2.7	1.6
Affordable Housing	53%	9%	11%	9%	7%	11%	2.3	1.8
Technical Support	42%	16%	16%	13%	8%	5%	2.5	1.6
Work Schedule Complications	57%	9%	8%	9%	8%	9%	2.3	1.7
Family Environment	48%	13%	13%	10%	9%	7%	2.4	1.7
Computer Access	52%	14%	10%	9%	8%	7%	2.3	1.6

Overall, the mean for each barrier is fairly low, which may indicate that for the majority of students, these barriers do not inhibit their ability to engage in their learning. However, 66% of all participants experienced at least one barrier as a student. In comparison, almost

half (46%) of participants indicated they experienced more than one barrier as a student, and 31% experienced three or more barriers (See Table 9).

Table 9. Students with multiple barriers (n = 1295).

# of Barriers Reported	# of Students	% of Students
0	436	34%
1	262	20%
2	194	15%
3	129	10%
4	97	8%
5	72	6%
6	49	3%
7	56	4%

4.2.2. Qualitative Findings

The thematic network that we developed through qualitative analysis is presented in Figure 2.

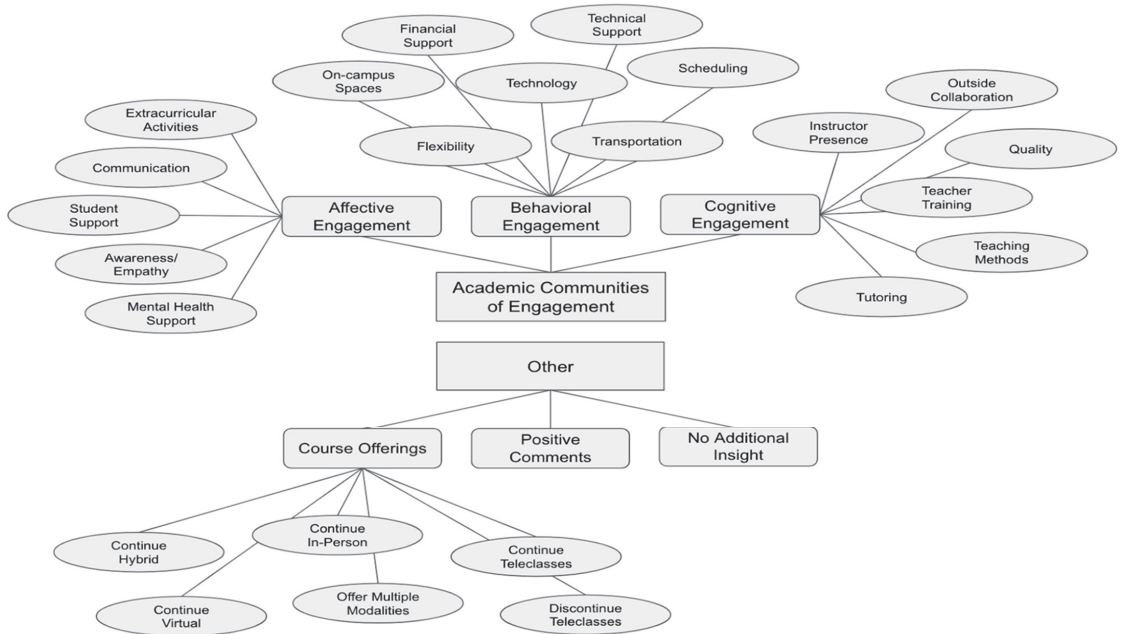


Figure 2. Thematic network.

The findings from the qualitative thematic analysis are presented in Table 10. Participant responses to the open-ended question: “Please share any comments or ideas you have about how the university can better support your academic engagement in online/blended environments” were coded into organizing themes and then grouped into global codes based on the type of support they needed. The global codes included affective engagement, behavioral engagement, cognitive engagement, course offerings, positive comments, and “other.” 291 (22.4%) of the comments indicated a need for greater support for behavioral engagement, and 241 (18.6%) requested greater support for cognitive engagement, while only 161 (12.4%) of codes indicated a need for support for affective engagement (see Table 10).

Table 10. Number and example of each type of global support code.

Global Support Code	Total Codes n = 1295	Organizing Themes	Example Codes
Affective Engagement	161 (12.4%)	Awareness/empathy, communication, extracurricular activities, mental health support, student support	<ul style="list-style-type: none"> • Improve understanding of unexpected events that often occur. All students do not have excellent Internet quality, for example. • Expanding communication with new students so that they feel the confidence to participate in these spaces.
Behavioral Engagement	291 (22.4%)	Financial support, flexibility, on-campus spaces, scheduling, technical support, technology, transportation	<ul style="list-style-type: none"> • Increase the hours in which classes can be accessed. • Provide students with tools to access classes, such as computers or transportation.
Cognitive Engagement	241 (18.6%)	Instructor presence, outside collaboration, quality, teacher training, teaching methods, tutoring	<ul style="list-style-type: none"> • Create and adapt learning strategies and methodology for effectively teaching and learning in the hybrid environment. • Make the classes more dynamic. Since they simply show a few slides, students can easily stop paying attention.
Course Offerings	169 (13.1%)	Continue hybrid, continue in-person, continue teleclasses, continue virtual, discontinue teleclasses, multiple modalities	<ul style="list-style-type: none"> • Continue promoting hybrid environments. • It is better to continue in-person. • I would like the university to continue offering the virtual modality • The teleclass option seems uncomfortable and does not work. It is better if the class is virtual or face-to-face.
Positive Comment	167 (13.0%)		<ul style="list-style-type: none"> • It seems to me that everything is fine.
No Additional Insight	266 (20.5%)	No comment, comment offers no additional insight	<ul style="list-style-type: none"> • I have no suggestions.

Within the category of affective engagement, 74 (46%) of the comments regarded the need for more awareness and empathy for individual student circumstances, and 41 (25%) discussed the need for more general student support that is easily accessible to students. 20 (13%) of respondents also indicated the need for better mental health support in the university community (see Table 11).

The most prominent codes in the behavioral engagement category were technology and flexibility, with 69 (24%) of comments addressing the need for improved technology on campus, and 65 (22%) comments regarding the need for greater flexibility with assignments and due dates in online and blended courses (see Table 12).

Table 11. Organizing themes for affective engagement (n = 161).

Organizing Code	Description	Total Codes	Example Codes
Awareness/empathy	Be more aware and considerate of individual student circumstances	74 (46%)	Kindness and empathy on the part of some teachers in their classes.
Communication	Have more constant communication between university and students; have an easy way for students to communicate with the university	15 (9%)	Create more efficient channels for sending information.
Extracurricular activities	Provide extracurricular activities and opportunities to socialize on campus	11 (7%)	The university can help improve academic engagement in hybrid / virtual environments with recreational activities that help clear the mind during study time because visual and intellectual fatigue are intensified virtually.
Mental health support	Provide student support for issues of mental health that is easily accessible to all students	20 (13%)	Provide more personal psychological assistance to students with constant failure because many times it is due to psychological illnesses such as anxiety or depression.
Student support	Provide general student support at the university-level that is easily accessible to all students	41 (25%)	Monitor situations for students with difficulties

Table 12. Organizing themes for behavioral engagement (n = 291).

Organizing Code	Description	Total Codes	Example Codes
Financial support	Provide financial support in the form of additional scholarships, tuition support, food stamps, etc.	37 (13%)	Provide more financial support for lower-income students
Flexibility	Provide greater flexibility with assignment due dates, assignment types, times class is given etc. for online/blended learning courses	65 (22%)	I think being able to have a little more flexibility in due dates could help since sometimes personal conflicts or losses are happening in these difficult times.
On-campus spaces	Create spaces on-campus to study, login to virtual classes, socialize, etc.	24 (8%)	The university could open study spaces to improve learning.
Scheduling	Improve the scheduling of classes and programs	53 (18%)	Maybe not doing such crazy schedules, because I have class from 6 pm to 9 pm and the truth is, it is a bit much.
Technical support	Provide computers, access to Internet, and troubleshooting for university students	25 (9%)	Provide more support to those people who do not have an Internet service suitable for connection to classes.
Technology	Improve technology functionalities provided by the university	69 (24%)	Improve the computer conditions in the computer classrooms since many students have face-to-face classes and then a virtual class, and the university assigned the computer areas to be able to connect, but neither the camera nor the microphones work.
Transportation	Provide transportation assistance	18 (6%)	Regarding transportation, the university should provide transportation for students that covers more parts of the city to be able to get to school.

Over half of the responses within the cognitive engagement category (66%) addressed the need for different teaching methods in the online and blended course environments. In addition, 41 (17%) of respondents wished they had better-trained teachers to teach in the online and blended settings (See Table 13).

Table 13. Organizing themes for cognitive engagement (n = 241).

Organizing Code	Description	Total Codes	Example Codes
Instructor presence	Have greater instructor presence in the online and blended courses	9 (4%)	The professors' consultation hours should be published, and they should normally be available during that time. Additionally, they should be available for more than just 1 h a week for students to come to receive help.
Outside collaboration	Collaborate with other organizations outside of the university to provide opportunities for the students	3 (1%)	Involve the participation of outside entities that can give us a vision of the issues that are being discussed in our field. Before the pandemic, when there was an opportunity, business visits were made. In the hybrid/virtual environment, videoconferences could be held with companies to discuss these issues in a more practical environment.
Quality	Improve the quality of the online and blended classes	3 (1%)	Improve the quality of virtual classes to match the academic rigor.
Teacher training	Train teachers on how to instruct in online and blended learning settings	41 (17%)	Better train teachers for the hybrid and virtual environments so that learning in virtual classes is not impaired.
Teaching methods	Use teaching methods specific to online and blended learning settings	159 (66%)	Use other models of teaching that not only favor those who are in person so that those remotely do not feel excluded.
Tutoring	Provide tutoring services	26 (11%)	Provide spaces for feedback and tutoring on subjects in addition to the teachers' office hours.

Concerning course offerings, participants had varying opinions regarding which type of course modalities should be offered. However, 101 (60%) of respondents suggested that most courses fully return to the in-person modality (See Table 14).

Both the barrier data and the open-ended responses indicate that the students focused mainly on the need for improvement in support of behavioral engagement. Finding ways to further eliminate each type of barrier and provide increased support within each domain (affective, behavioral, cognitive) should also be considered.

Table 14. Organizing themes for course offerings (n = 169).

Organizing Code	Description	Total Codes	Example Codes
Continue hybrid	Continue offering hybrid classes	13 (7%)	Continue promoting hybrid environments.
Continue in-person	Continue offering in-person classes and move towards making all classes in-person again	101 (60%)	The university should take seriously the option of returning to classrooms in person, thus contributing to learning.
Continue teleclasses	Continue offering teleclasses	5 (3%)	Enable more teleclasses.
Continue virtual	Continue offering virtual classes	23 (14%)	I would like the University to continue offering the virtual modality for future semesters.
Discontinue teleclasses	Discontinue offering teleclasses	5 (3%)	On a personal level, the teleclasses are not good, the sound is bad, the experience is bad, and it is better understood in total virtual or total face-to-face, but teleclass is not understood at all.
Multiple modalities	Continue offering classes in the variety of modalities (in-person, virtual, teleclasses, hybrid)	22 (13%)	Having the option to enroll in a subject in hybrid or virtual seems perfect to me.

5. Discussion

The central purpose of this study was to better understand how institutions support university students' academic engagement in online and blended courses, identify barriers that exist for university students in online and blended courses, and what institutional support can be provided to mitigate these barriers for students. The study results reveal that most students experience barriers, and many experience more than one barrier. Following the guidelines provided by the ACE framework, institutions can potentially alleviate many of these barriers by implementing specific support systems for their students in online and blended courses. Significant takeaways from the findings of this study include:

- Transportation and Internet access were the most common barriers that students experience. Universities with similar barriers may want to first focus on behavioral engagement support and ensure all students have the access they need to have the ability to engage academically in online and blended courses.
- The greatest need for affective support is more empathy and understanding from instructors and faculty.
- Proper teaching methods for online and blended learning settings are vital to helping students be able to engage cognitively in online and blended learning courses.

One observation from these findings is that while this study focused on the university as a whole, it may be essential for universities and learning programs to look at different types of learners within a student population to develop adequate learning support. For example, while there was no significant difference between the students' perceptions of the different types of support (affective, behavioral, cognitive) they receive from the institution, the standard deviations in each area seem large. This result could indicate that there is a wide variance in what students are experiencing at the university. Rather than focus on the entire student population, it may be more beneficial to understand specific types of students or learning contexts that are less academically engaged than the university as a whole. The findings also revealed that many students experience multiple barriers to fully engaging in online and blended learning courses. A large portion of students experience multiple barriers, while others experience only one or no barrier to their learning. Understanding

the specific situations of students experiencing these different levels of barriers is crucial. It may be one way practitioners can work towards providing institutional support that fits the needs of the different groups, rather than aiming for a “one-size fits all” approach.

Institutions may consider looking at the average scores of students experiencing two or more barriers to understand their situation better. Understanding this information would help a university or learning program know how to focus their energy on improving the institutional support for academic engagement for more specific demographics rather than focusing everywhere at once [39,40,43,46]. Understanding these barriers through the lens of the ACE framework can also help practitioners determine concrete solutions to eliminate many of these barriers and enable students to become more fully engaged in the online and blended course modalities [18].

A second observation from these findings is that behavioral engagement support seems to be the most needed type of support to help students overcome the most prevalent barriers of this study. The need for behavioral engagement support was the most extensive global code in our thematic network—many student responses corresponded with the types of barriers they experienced. Student responses indicated a need for greater financial support, greater flexibility in scheduling, technical assistance, and transportation assistance. These suggestions from students align with many of the barriers they were experiencing, such as difficulty finding affordable housing, difficulty getting transportation to school, challenges with the Internet, and lack of technology and resources. Students need to be behaviorally engaged before they can engage cognitively and affectively. Behavioral engagement gives students the skills to access an online course and know how to navigate it [18,21]. As such, an institution’s top priority for providing academic engagement support to students could first be to ensure that all students are behaviorally engaged. The ACE framework gives practical suggestions for supporting this type of engagement, including troubleshooting, monitoring progress, organizing physical learning spaces, learning self-regulation strategies, and minimizing distractions [18,22,47,48].

An additional observation the thematic analysis revealed is that students not only lack support for behavioral engagement, but cognitive and affective engagement as well. As noted in the findings, 74% of the responses regarding affective support indicated a greater need for more awareness and empathy regarding student circumstances. Research on affective engagement shows that this is a critical component of fully engaging academically [18,27–29]. Universities can primarily support this by facilitating effective online communication [18], which often requires a different skill set than in-person communication [20,30]. Additionally, students indicated a need for easier access to general student support services and mental health resources. As Garrison et al. note, cultivating a community online is key to providing this affective support [31].

Regarding cognitive engagement, participants’ most prominent need was teaching methods specific to online and blended learning, as well as instructors who are better trained in online and blended learning modalities to teach these classes. We know from online and blended learning research that proper teaching methods and techniques are critical for the success of this type of learning. Improving the quality of online and blended courses and ensuring instructors are properly trained to teach these types of classes could significantly influence the ability of students to engage cognitively with the material [33,49]. Last, participants’ suggestion for courses to return face-to-face most likely supports the previous findings that there is not currently adequate support for these types of classes. While there may be specific courses better suited for the traditional face-to-face teaching model, implementing the proper support at the institutional level for online and blended courses could mitigate many of the issues and barriers students are experiencing in these classes.

Limitations

This study includes some limitations. First, because the survey instrument was voluntary, we only received responses from a portion of the university’s student population. The results may not be fully representative of the entire study body. Likewise, the results

may also not be representative of other universities. Because each university has unique needs, it may be difficult to generalize these specific results and suggestions and apply them to different settings. For example, the barriers students reported on are particular to the needs of students in this region and may not directly apply to all other areas of the world. Instead, this study can serve as a model for other universities to follow to find the unique needs of their students. An additional limitation may be the lack of in-depth qualitative data. Because this study focused on covering breadth instead of depth, we may need more qualitative data to understand better the barriers students face in their online and blended courses and how institutions can provide adequate support.

6. Conclusions

The main objective of this study was to understand how institutions support university students' academic engagement in online and blended courses (RQ1) and identify the barriers that may exist for university students in online and blended courses (RQ2) in order to better understand how institutional support may alleviate these barriers. Our findings revealed that students generally feel adequately supported by their institution; however, there are still several students that lack the necessary support they need to succeed academically in their online and blended courses. To understand how to support these students, we must first understand the barriers they are experiencing that inhibit them from fully engaging academically. Our data have shown that students are experiencing barriers to their learning, with many experiencing more than one obstacle. There is insufficient institutional support for many to overcome these barriers and engage fully in online and blended learning.

6.1. Implications for Practitioners

Following the guidelines provided by the ACE framework [18] institutions can alleviate many of these barriers by implementing specific support systems for their students' online and blended courses. While the findings may not apply directly to other universities whose students experience different barriers, this study can serve as a model for administrators and institutions to use to learn how to better support students in online and blended courses at the institutional level.

6.2. Implications for Future Research

To better understand how institutions can support students in online and blended learning environments, future research should look more in-depth at learners with specific barriers. This could help institutions know exactly what causes certain barriers in different types of learners and uncover more specific solutions for mitigating those barriers for particular populations. Other groups of students that researchers may want to investigate include students' areas of study, school level, gender, age, and social class. Understanding each of these different groups and how they experience barriers may also reveal insights that could help institutions know how to support all types of learners. Additional qualitative studies would also be beneficial to better understand students' experiences and specific needs of different types of students with varying levels of barriers.

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Institutional Review Board Statement: We hereby certify that the study entitled Institutional ACE Survey 1.0: University Support for Academic Engagement, developed during the second semester of 2021 was conducted under institutional guidelines of data protection and confidentiality, reviewed by the General Secretary Office at UNAB and duly considered in the MOU signed by UNAB and

BYU on 10 August 2021 and registered with the code 150826 at Alfanet, the university's information system, on 7 September 2021. Please note that UNAB encourages institutional studies for strategic purposes that will benefit our student services. As such, this study was conducted by the Direction of Academic Affairs, a unit supervised by the Academic Vice president, with the approval of the President's Office. These institutional studies have a different process than the ones implemented by faculty and researchers affiliated to the Direction of Research. Therefore, the review of ethical use of information and anonymity of the students who responded to the survey, was carefully taken into consideration and approved by the Academic Vice president, General Secretary and Director of Academic Affairs. If you need further information, you can contact us at viceacademic@unab.edu.co. BYU researchers worked with UNAB to help analyze the anonymized existing data set.

Informed Consent Statement: In compliance with the provisions on Personal Data Protection, the Autonomous University of Bucaramanga NIT 890.200.499-9 requires your free, prior, express, unequivocal, and duly informed authorization to carry out the collection, registration, storage, use, circulation and anonymity of the students who responded to the survey, was carefully taken into consideration and approved by the Academic Vice president, General Secretary and Director of Academic Affairs. If you need further information, you can contact us at viceacademic@unab.edu.co. BYU researchers worked with UNAB to help analyze the anonymized existing data set.

Informed Consent Statement: In compliance with the provisions on Personal Data Protection, the Autonomous University of Bucaramanga NIT 890.200.499-9 requires your free, prior, express, unequivocal, and duly informed authorization to carry out the collection, registration, storage, use, circulation, deletion, processing, compilation, exchange, updating, and in general the treatment of all the data that will be requested in this survey. The purposes of the survey are (i) to measure the experience of the students under the concept of Academic Communities of Engagement in hybrid/virtual environments, (ii) its use for the creation of reports and statistical reports within the institution, and (iii) circulation of anonymous reports to allied institutions; as well as the use for presentation to national and international entities, private and public on the issues that are related to this survey. Some of the data requested here correspond to sensitive data, such as gender and socioeconomic status. You are not obliged to provide such information. Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Archival data for the research was provided by Universidad Autónoma de Bucaramanga (UNAB) and are not publicly available.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A.

Appendix A.1. Survey Instrument

Questions about Support Community at the University (e.g., Instructors, Advisors, Classmates)

STEM: I have a support community at the university (e.g., instructors, advisors, classmates) that can help me to ... (1 = strongly disagree to 6 = strongly agree).

Affective Support Elements	Survey Items
Facilitating Communication	<ul style="list-style-type: none"> feel comfortable communicating with others (e.g., instructors, advisors, classmates) online. have opportunities to communicate with others online. use a variety of online technologies to communicate with others (i.e., synchronously and asynchronously).
Developing Relationships	<ul style="list-style-type: none"> feel accepted by others while learning online. feel like an important part of the online learning community. develop relationships with others (e.g., instructors, advisors, classmates) online.
Instilling Excitement for Learning	<ul style="list-style-type: none"> enjoy online learning activities. get excited to learn new things in my online learning experiences. increase my interests in the subjects/topics I am learning online.

STEM: Rate your agreement with the following statements about your online learning experience this past academic year (1 = strongly disagree to 6 = strongly agree).

Behavioral Support Elements	Survey Items
Troubleshooting & Orienting	<ul style="list-style-type: none"> troubleshoot technological issues related to my online learning. learn the digital platforms I need to be successful in my online learning experience. know what it takes to be successful in online learning experiences.
Organizing & Managing	<ul style="list-style-type: none"> develop time-management skills for online learning. use online technologies to track projects and due dates. learn how to keep my online environment organized.
Monitoring & Encouraging Progress	<ul style="list-style-type: none"> keep working on my online assignments even when it's difficult. meet online assignment deadlines. recover following academic setbacks such as missing assignments or getting a poor grade.

STEM: Rate your agreement with the following statements about your online learning experience this past academic year (1 = strongly disagree to 6 = strongly agree).

Cognitive Support Elements	Survey Items
Instructing	<ul style="list-style-type: none"> learn new concepts online in a way that I can understand. find answers to difficult concepts when I have questions related to online learning activities. get useful feedback on my online assignments.
Collaborating	<ul style="list-style-type: none"> work with others to understand online course material. collaborate with others to complete a course assignment online. learn from online interactions with others.

Appendix A.2. Barriers Data

STEM: Identify how much of a barrier each of the following are to your participation in your online learning. (Scale: 0 = no barrier to 6 = very large barrier)

- Transportation difficulties (cost, access, travel time, etc.)
- Internet access/speed in my home
- Access to a good computer
- Access to affordable housing in the metropolitan area
- Access to technical support
- Family environment (childcare, care for parents, etc.)
- Work schedule complications

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Article

The Effects of Blended Learning on the Performance of Engineering Students in Mathematical Modeling

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Abstract: This paper presents the implementation of an active learning methodology known as blended learning in an ordinary differential equations (ODE) course for engineering students. Our purpose was to evaluate the effect of b-learning on students' mathematical modeling performance. To this end, synchronous and asynchronous activities were made available to the students as face-to-face and remote learning sessions, in which the experience acquired by students during the sanitary isolation due to COVID-19 was crucial. Benjamin Bloom's cognitive domain taxonomy was used to design the present didactic proposal. Results show that the students moved upward from the lower knowledge and understanding taxonomical levels, to the upper analysis and application levels, as they learned systems modeling using ODEs.

Keywords: blended learning; mathematical modeling; mathematics education; differential equations; STEM; engineering education

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1. Introduction

Training university students is the main responsibility of higher education institutions in any country and it is, at the same time, a valuable opportunity to contribute to the development of better human beings. Our current 21st-century society needs young students in science, technology, engineering, and mathematics (STEM) to acquire specific knowledge and skills or abilities that commit them to social and economic progress. To achieve a defined university profile, didactic research in the engineering field uses several active learning approaches supported by existing digital technologies to study the fundamentals of a discipline from different perspectives and strengthen the students' theoretical and practical understanding of the field.

Collaborative, problem-based, project-oriented, and competency-based learning, as well as the flipped classroom and gamification techniques, among others, are some of the most commonly used active learning approaches in mathematics education and engineering training [1–8]. Each approach or methodology has particular characteristics, but all share the notion that the student is at the center of the learning process. For example, the problem-based and collaborative approaches encourage teamwork among members with different skills and share responsibility for achieving a goal [9].

The interactions among these different personal perspectives can be enabled using a combination of electronic media (online tools operating synchronously or asynchronously) and face-to-face interaction, which gives rise to an educational practice known as blended learning or b-learning. B-learning requires the student to use learning styles other than their preferred one and to adapt to the different activities and materials available for the subject under study [10].

Currently, most STEM programs are designed to work best in the classroom, where discussing analytical methods and laboratory practices are some of the learning activities. During the partial lockdown due to the COVID-19 pandemic, the performance of these activities was limited; however, digital technologies, such as online software platforms and

virtual laboratories, played a very important role as mediators for students to adapt more quickly to these circumstances [11–18].

1.1. The B-Learning Approach

B-learning is a pedagogical approach to teaching and learning that can potentially harmonize the best practices normally conducted in the classroom with different technological applications [19,20]. This procedure requires an adequate interaction environment involving direct or remote communication for students to use different learning styles [21]. In b-learning, different virtual media are used to present interactive content that favors interaction and enhances the STEM student's learning experience, for example, images or diagrams (infographics or graphic organizers), animations, videos, software, online platforms to promote collaborative learning [9], and virtual laboratories [22].

This approach can have multiple benefits for student performance, even more than a completely face-to-face learning environment because the course contents and activities are not restricted to the classroom, and students can study these contents and carry out the practical tasks in their schedule. On the other hand, as [23] has been pointed out, diagnostic conversations or personal feedback in face-to-face environments are impractical and comments received within an online environment are found to be more pleasant for students; therefore, b-learning increases the interest of students in participating in learning activities.

The relevance and pertinence of adopting a b-learning approach became evident during the COVID-19 lockdown, and most college students are already using their cell phones, tablets, or computers to carry out almost all of their academic activities. Unfortunately, the adjustments made to bring teaching to the virtual environment had to be made in haste to mitigate the negative effects of the lockdown on the educational process. Now that the health emergency has subdued, the empirical learning of the experience must be used to implement b-learning systematically with planned and significant activities to provide the student with the experience of true active learning. Consequently, the teaching and learning processes currently used in mathematics training within university-level engineering programs must be rethought.

According to [24], the promise of better learning methods is possible if the teachers' resistance to the use of digital technology is overcome, as well as their inertia to value face-to-face interaction over the potential benefits of online learning or a combination of both. Therefore, teachers should enthusiastically assume the responsibility and commitment to redesign courses to incorporate content and activities with a b-learning approach and provide students with an increased and more varied learning experience than that available only online or only in the classroom.

1.2. Taxonomy of the Cognitive Domain

Engineers use their skills, competencies, knowledge, and techniques in their professional practice to solve problems specific to their discipline. One way to measure and assess how these skills, competencies, knowledge, and techniques are acquired, developed, or strengthened through the teaching and learning process carried out in college uses the taxonomy proposed by Bloom [25], which classifies the achievement of educational objectives at six different levels: knowledge, understanding, application, analysis, synthesis, and evaluation (see Figure 1).

According to Bloom, knowledge is the most basic achievement level, which includes behaviors and situations where ideas, content, or phenomena are recognized or recalled. At this level, a student's response to a test situation should be similar to what it was during the original learning situation. At the understanding level, if students are confronted with oral, written, verbal, or symbolic communication, they are expected to know what is being communicated and to use the concepts or ideas contained in the information. At the application level, in a situation where no solution is specified, students are expected to correctly use the appropriate abstraction to solve a given problem.

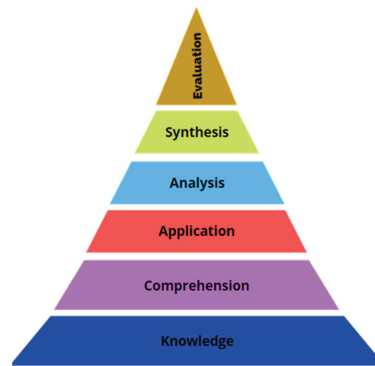


Figure 1. Cognitive domain levels for the achievement of educational objectives. Elaborated by the authors based on [25].

At the analysis level, the student separates the information into its constituent parts, identifying the relationships, interactions, or connections between them and recognizing their structure. At the synthesis level, the student activates their most creative part, refers to many different sources, and builds a scheme or pattern that was not clear before to solve a problem within some theoretical or methodological framework. Finally, at the highest cognitive domain level, evaluation, the student is expected to make quantitative or qualitative value judgments using specific criteria and parameters to measure the accuracy or effectiveness of information, methods, or solutions.

Bloom's taxonomy is idoneous for the design of mathematics learning activities aimed at engineering students. For example, to analyze a system's dynamics or phenomenon using first-order ordinary differential equations (ODEs), the student requires knowledge and understanding of the characteristics and other important aspects of ODEs. For this purpose, a b-learning environment is favorable for combining both remote and classroom-based activities. The challenge is to identify the most adequate and compatible strategies and activities to meet the goals of each educational situation.

1.3. Application of ODEs to Mathematical Modeling

In a mathematical modeling process, students move higher through the different cognitive domain levels. In the case of ODEs, this means knowing the relevant parameters and variables and their dimensional analysis [26], understanding the meaning of each term in the ODE [27], applying methods to obtain the analytical solution and its corresponding error analysis [28], and interpreting the solution [29]. Implementing approaches, such as b-learning, can support students as they experience these complex cognitive processes [30] and improve the comprehension and use of mathematical concepts [31].

When engineering students take on the challenge of modeling actual systems based on ordinary life or related to their professional field, they become immersed in a truly significant learning process [32] in which mediators are essential for generating an environment conducive to the formation and discussion of new concepts [33,34]. In such an environment, students regulate their learning themselves while they also spend time on teacher–student interaction during face-to-face activities, for example, counseling using the board and support for carrying out projects, both of which are indispensable in engineering contexts [23].

1.4. Theoretical Basis

The design and implementation of this study were based on Vygotsky's sociocultural theory of cognitive development, whose fundamental hypothesis states that higher mental functions, such as application and analysis, are socially constructed and culturally trans-

mitted. In an educational context, changing the thinking tools available to the student promotes the emergence of a radically different mental structure [35,36].

The concept of the zone of proximal development (ZPD) is one of the most important contributions of Vygotsky's theory to education. This concept stems from the discussion about the relationship between development and learning. Vygotsky recognizes the existence of a relationship between the maturity of an individual's organism and their ability to learn certain subjects. However, he adds that two levels of development must be considered in said relationship between maturity and learning skills: current development and potential development. Current development is determined by the individual's ability to solve problems independently. Potential development is determined by their ability to solve problems in collaboration with a more capable partner or under the guidance of an adult.

Vygotsky defines ZPD as the distance between an individual's current developmental level, as determined by the ability to independently solve a problem, and the potential developmental level, as determined by their ability to solve problems under the guidance of an adult or in collaboration with other, more capable companions. The author also considers that an essential aspect of learning is that it creates the ZPD; that is, learning awakens a variety of developmental processes capable of operating only when the individual interacts with other people in their environment and collaborates with their peers. This notion highlights, on the one hand, the importance of studying the individual when immersed in their social environment and interacting with it and, on the other hand, the interdependence between the individual's development process and the resources that the social environment provides for such development.

Although Vygotsky's ZPD theory emphasizes the support of a more capable person, there are more and more researchers who consider that there may also be other factors as efficient as ZPD that facilitate the appropriation of knowledge by the student. For example, a structured environment can guide the student toward the use of elements that are new to them but accessible in their ZPD. Similarly, it has been stated that, within the ZPD, impersonal feedback from the material with which the individual interacts can be as effective in promoting development as interpersonal support.

This emphasis on the role of the ZPD environment is particularly promising when considering school instruction where, due to the large number of students that often make up classes, it is not always easy for the teacher to establish an interpersonal relationship with each person and provide each one with the necessary feedback. Therefore, the idea of investigating the possibility of structuring the school environment in a way that helps the student to increase their understanding potential within their ZPD for specific topics, particularly mathematical ideas, is very attractive. Recent studies have investigated this possibility, obtaining encouraging results. However, it was observed that, although structuring the environment and the activities was crucial to optimize the ZPD's potential, working in dyads or in groups, as well as teacher interventions to provide support and guidance, continued to be essential elements of the learning process.

2. Methodology

This study aimed to evaluate the effect of b-learning on student performance in constructing and resolving a mathematical model using first-order differential equations. For this purpose, we recruited a small group of students enrolled in an ODE course in a university-level engineering program ($n = 19$). The teacher was not involved in the sample selection; therefore, since the desired randomness failed to be achieved, a pre-experimental design including pre-test and post-test was implemented. The sample was considered time-dependent in the experimental design, and its members could easily work in a digital technology environment.

This research was carried out at the beginning of 2022, during the transition from virtual to face-to-face activities at an institution with different venues and 62 ODE courses. For practical reasons, the study focused on a single campus with nine ODE groups and

191 registered students (the population under study). In addition, the group of students (sample) was assigned to the teacher, and its size agreed with the literature, which indicated that the b-learning approach worked better with small groups [23,31]. The results of this pilot study will allow for obtaining information to implement it with more students from the study's population.

2.1. Research Question

Does the use of b-learning improve student performance in mathematical modeling?

2.2. Hypothesis

To answer the research question, this paper proposes the following hypotheses.

H₀. *The use of b-learning does not affect student performance in mathematical modeling.*

H_A. *The use of b-learning affects student performance in mathematical modeling.*

2.3. Goal

The purpose of the present study was to evaluate the effect of b-learning on the performance of engineering students in constructing and resolving a mathematical model using first-order differential equations. To this end, we designed remote and face-to-face learning activities to analyze a system or phenomenon. Bloom's taxonomy of cognitive domain levels was used in the design of these activities.

2.4. Implementation of the Didactic Proposal

According to the b-learning approach, the learning activities were designed to be carried out in two ways: online (synchronous or asynchronous) and face-to-face. The asynchronous activities were carried out via Google Classroom, where educational content such as reading materials, exercises, videos, and tutorials was available. The synchronous activities consisted of Google Meet videoconferences supported by a virtual whiteboard where the procedures of different methods to obtain analytical solutions to ODEs were presented; in addition, tutorials on Matlab's online platform taught students how to obtain the symbolic and numerical solutions of an ODE. On the other hand, the face-to-face activities focused on highlighting important aspects of the subject, such as the qualitative aspects of mathematical modeling, and clarifying doubts related to the analytical solution or software use.

The content of all the activities was designed to favor interaction among the students and with the teacher. At the same time, they moved upward through the cognitive domain levels [25]; that is, from the most basic levels, where the student must know and understand the definitions, classification, terminology, and symbology of first-order ODEs, to activities focused on the modeling itself, where the analysis, argumentation, relationship, debate, and discussion of the subject were carried out in a collaborative environment [37]. Finally, we considered different situations where a simple mathematical model using first-order ODEs can be built for the central activity, such as exponential growth, the mixing of substances, temperature changes, and electrical circuits.

The set of didactic activities, see Table 1, carried out remotely and in person, were organized in different sessions as follows:

Table 1. Organization of learning activities in different remote and face-to-face sessions.

Session	Type	Learning Activities
1	Synchronous remote	Presentation of subject, purpose, and support materials. Diagnostic evaluation. Formation of work teams.
2	Asynchronous remote	Readings, videos, and activities focused on the principles of ODEs. Matlab R2022a tutorials (algebra, graphs, calculus, and ODEs). Readings, videos, and exercises to solve ODEs analytically.
3	Synchronous remote	Advice regarding analytical method procedures to solve ODEs.
4	Asynchronous remote	Administration of Questionnaire 1. Readings and videos of exponential growth systems modeling.
5	Synchronous remote	Development of a mathematical model for a system and its analytical solution. Numerical solution of a system's mathematical model on the online software platform.
6	Face-to-face	Analytical and numerical comparison of solutions to the system's dynamics. Random assignment of exercises from different situations to build a mathematical model using first-order ODEs.
7	Asynchronous remote	Construction of a mathematical model and an analytical solution. Obtention of the numerical solution.
8	Face-to-face	Drafting of a written report. Presentation and discussion of results. Administration of the rubric.
9	Asynchronous remote	Administration of Questionnaire 2. Administration of the survey.

During the asynchronous remote sessions, the students worked independently and in teams, and the instructor guided the synchronous remote sessions through videoconferences. Following the ZPD approach, face-to-face sessions were also held [35,36]. It is worth mentioning that, to motivate students' interest in modeling, activities 5 and 6 considered the current context and focused on the evolution of the number of people infected by SARS-CoV-2 in the city where their university is located. Therefore, the task assigned to the teams consisted of systems of interest to engineering students, such as growth and decay, carbon dating, Newton's law (cooling/warming), and series circuits.

Questionnaires were included as part of the observation and measurement instruments to assess the effect of the learning activities; these instruments are essential in asynchronous online activities because they can make a difference in student learning. It has been reported that online questionnaires, together with support material, can homogenize or level the knowledge acquired by students during their first engineering cycles [23]. Other data necessary for the present study were obtained using a rubric and a survey (see Table 2). The rubric has five criteria: (1) the mathematical model, (2) the analytical solution, (3) the numerical solution, (4) the written report of the work completed, and (5) the verbal presentation of the work. The answers have four levels on the Likert scale (null, regular, well, and excellent). The first three criteria evaluate the development of hard skills, while the last two evaluate the development of soft skills.

Regarding Questionnaire 1, five questions and five exercises were integrated into the pre-test. (1) What is a differential equation (DE)? (2) What types of differential equations exist? (3) What does the order of a DE mean? (4) What is a condition of a non-linear DE? (5) What type of solution can a DE have? In addition, three exercises were given to check the solutions of DE and two to obtain the general or particular solution of DE. The pre-test content was designed to measure the student's knowledge and understanding of the basics of a DE. The five questions measure knowledge of a DE's concept, classification, and type of solution. In contrast, the five exercises measure understanding the structure and the method to solve a DE. The pre-test is located at levels 1 and 2 of Bloom's taxonomy.

Table 2. Observation and measurement instruments designed for the study.

Instrument	Contents	Purpose
Diagnostic Evaluation	Items/questions regarding the definition, domain, differentiation, and integration of one-variable functions.	Verify the homogeneity of prior knowledge possessed by the sample using converging questions (multiple choice).
Questionnaire 1 (Pre-test)	Items related to ODE definitions, symbols, classification, use, structure, and solution methods.	Measuring the extent of ODE knowledge and understanding (cognitive domain levels 1 and 2).
Questionnaire 2 (Post-test)	Items related to the meaning of ODE terms, rules, and procedures for a mathematical model.	Measuring how effectively ODEs are applied and used to analyze a system (cognitive domain levels 3 and 4).
Rubric	Five criteria with four levels.	Qualitative evaluation of hard and soft skills development.
Survey	Items with responses on a six-point Likert scale.	Qualitative evaluation of student satisfaction with the b-learning approach adopted in the activities.

Regarding Questionnaire 2, six questions were integrated into the post-test. (1) How can a DE be applied? (2) What methods do you know to solve a DE? (3) Did you understand the meaning of each term that appears in the DE? (4) What do you understand by mathematical model? (5) How useful is a mathematical model? (6) What tools do you know to analyze a mathematical model? The post-test content was designed to measure the student's ability to apply the DE in a basic mathematical model and to apply solution techniques for a DE; likewise, for the analysis of the meaning of the terms of a DE and the response or behavior of the modeled system. The post-test is located at levels 3 and 4 of Bloom's taxonomy.

The data and information obtained by the research instruments were processed and analyzed by quantitative and qualitative methods [38]. The quantitative analysis was performed during the diagnostic evaluation using a normality test, and during the pre-test and post-test using descriptive statistics. A hypothesis test compared the means of paired samples using Student's *t*-test in OriginPro 2022 software (The University of Guadalajara, Guadalajara, Mexico). The qualitative analysis consisted of a rubric evaluating student performance in the application of ODEs to the modeling and analysis of a system's response. In terms of soft skills, the achievement was assessed based on student reports, teamwork, communication, and a survey to evaluate the students' activities.

3. Results

The purpose of the diagnostic evaluation was to measure the homogeneity of the sample in the recall (cognitive level 1) of previous topics, such as the definition, domain, differentiation, and integration of one-variable functions. For this purpose, the Shapiro–Wilk normality test was applied to the diagnostic evaluation results, and a *p*-value > 0.05 (see Table 3) was obtained, indicating that the sample comes from a normally-distributed population. This means that, at the beginning of the study, the students had a homogeneous degree of prior knowledge.

Table 3. Shapiro–Wilk normality test on the results of a diagnostic evaluation.

Shapiro–Wilk Test for a Sample			
DF	Statistic	<i>p</i> -value	Decision at level (5%)
19	0.91865	0.10684	Normality cannot be rejected

The student sample carried out the learning activities in three synchronous and asynchronous remote sessions; after that, Questionnaire 1 (pre-test) was used to measure knowledge and understanding (cognitive levels 1 and 2, respectively) of ODE fundamentals, such

as definitions, symbols, classification, use, structure, and solution methods. Quantitative analysis with descriptive statistics of the pre-test results (see Table 4) showed a mean of 6.15 with a variability of 2.33, which indicates that, at the end of the three sessions, the group of students knew or understood basic ODE concepts. This can be explained because the topics were addressed abstractly, without the reference context in which the ODEs are applied; therefore, the students' interest in understanding these topics was not yet generated.

Table 4. Statistical results of the pre-test and post-test.

	Descriptive Statistics						
	N	Mean	Standard Deviation	Variance	Minimum	Median	Maximum
Pre-test	19	6.15789	2.33959	5.47368	2	7	10
Post-test	19	8.84211	1.70825	2.91813	4	9	10

Team-based activities were carried out during five synchronous and asynchronous face-to-face or remote sessions. Questionnaire 2 (post-test) was then applied to assess how ODEs were applied to the construction of a mathematical model and how the response of the modeled system was analyzed (cognitive levels 3 and 4, respectively). Quantitative analysis with descriptive statistics of the post-test results (see Table 4) showed an increase in the mean and a lower dispersion than the pre-test results. This indicates that the learning activities had a positive effect on student learning.

However, for greater formality, a paired sample Student's t -test was applied to pre-test and post-test results to test the hypothesis (see Table 5). The null hypothesis H_0 was established as $H_0: \mu_1 - \mu_2 = 0$ and an alternative hypothesis as $H_A: \mu_1 - \mu_2 < 0$, taking $\alpha = 0.05$ as a significance level. The result shows that H_0 should be rejected because, on the one hand, in the test statistic method, $t_0 = -3.69885$ is lower than the critical value of the test, in which 18 degrees of freedom corresponds to $t_{0.05,18} = -1.73406$ and, on the other hand, with the p -value method, it was observed that the result was $8.21435 \times 10^{-4} < \alpha$, confirming the rejection of H_0 . Consequently, the H_A was accepted, which means that there is a statistically significant difference between the two means in favor of μ_2 and, with a confidence level of 95%, it was concluded that the delivery of activities based on the b-learning approach (treatment) had a significant effect on student learning concerning the application of ODEs and the analysis of the modeled system's response.

Table 5. Hypothesis test of the pre-test and post-test.

Paired Sample Student's t -Test			
t_0 statistic	DF	$t_{0.05,18}$	p -value
-3.69885	18	-1.73406	8.21435×10^{-4}

Concerning the qualitative evaluation, the results of the rubric showed that the design of the activities favored interaction among the students and allowed them to apply the ODEs to model the system assigned to each team. Similarly, the analysis of the system's response; that is, obtaining the analytical and numerical solutions, was adequately achieved. As for soft skills, we observed remarkable progress in areas such as teamwork, report drafting, organization skills, and verbal communication used to convey information to the group.

Regarding the feedback for this work, the survey responses revealed that the group of students felt comfortable with the activities and work dynamics proposed. Table 6 shows some answers provided by the students, which are considered as feedback to improve the design of this didactic proposal for future applications.

Table 6. Survey responses.

Item	Sample Responses
Describe the interaction or collaboration in your team when carrying out these activities.	<p>Collaboration was very good, each person did what they had to do, and there was a lot of chemistry since my partner and I have known each other for a long time; that is why I feel that everything went just fine.</p> <p>There was adequate cooperation and collaboration when we carried out the tasks; we agreed on ideas and made everybody's work easier.</p> <p>The communication with my partner was very good; we both contributed equally to the task.</p>
What do you think about the material (text, software, etc.) you used to solve your task?	<p>Very useful to solve the problem and acquire the right solution with the right tools to better understand the subject.</p> <p>After researching different sources, we could completely satisfy our doubts and clear up any issues that came our way.</p> <p>As far as the problem was concerned, it was very clear, we also relied on the book, and we had all of Matlab's support materials.</p>
Describe the difficulties you had during this activity.	<p>In my opinion, the most difficult thing was that I could not fully understand the difference between the numerical and the analytical solution.</p> <p>Better understand the relationship between the variables.</p> <p>Implementing the script in Matlab for it to provide a numerical solution.</p>

Finally, this research work has the following limitations. (i) The students' sample was only from an educational program; therefore, a broader sample is necessary to include students from other educational programs and generalize the conclusions. (ii) It is necessary to validate the observation and measurement instruments in order to strengthen their internal consistency and the evaluation of the results. In future implementations, it is essential to consider the participation of other teachers or other institutions and the use of the statistical technique of analysis of factors to understand better the information provided by the measuring instruments.

4. Conclusions

In the present study, we implemented a didactic proposal for mathematical learning based on the b-learning approach, which led to the following observations.

The results from Questionnaire 1 indicate that it is necessary to diversify the activities, enriching the learning environment from the beginning with possible applications of ODEs; this can generate greater interest in students in understanding the basic concepts of ODEs. The descriptive statistics and the hypothesis test of Questionnaire 2 results allow us to conclude that the delivery of activities based on the b-learning approach (treatment) had a significant effect on student learning concerning the application of ODEs and the analysis of the modeled system's response. However, during the qualitative evaluation, it was possible to detect the need to add new dimensions to the rubric and questions in the survey, and to have more elements to improve the evaluation of the development of soft skills.

The use of b-learning had a positive effect on student performance in a task that consisted of using ODEs for mathematical modeling and systems analysis.

Active methodologies, such as blended learning and ICTs, are powerful resources to advance the research in mathematics education, contribute to improving educational processes, and significantly enhance knowledge acquisition by engineering students. To study this process, it is necessary to enable an adequate experimental design to formalize the analysis and observation of interactions in the classroom and in virtual environments that facilitate learning.

The use of Bloom's cognitive domain levels in the design of the learning activities was found to be adequate to organize the content and degrees of difficulty in the learning activities.

Students' and teachers' experiences during the lockdown due to the COVID-19 pandemic were a facilitating antecedent for the proper development of synchronous and asynchronous remote activities. As educational institutions return to regular activity within their facilities, such experience should be taken into account. Teachers can enrich their

courses with the advantages of b-learning; their challenge is to design adequate activities and materials and to find a balance between online and face-to-face interaction. Students can activate different learning styles by taking advantage of the potential offered by the different multimedia tools and digital technologies available in blended courses.

Educational institutions should continue analyzing and appraising the extent to which integrating technology into educational processes enhances active learning.

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Article

Predicting Student Performance Using Clickstream Data and Machine Learning

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Abstract: Student performance predictive analysis has played a vital role in education in recent years. It allows for the understanding students' learning behaviours, the identification of at-risk students, and the development of insights into teaching and learning improvement. Recently, many researchers have used data collected from Learning Management Systems to predict student performance. This study investigates the potential of clickstream data for this purpose. A total of 5341 sample students and their click behaviour data from the OULAD (Open University Learning Analytics Dataset) are used. The raw clickstream data are transformed, integrating the time and activity dimensions of students' click actions. Two feature sets are extracted, indicating the number of clicks on 12 learning sites based on weekly and monthly time intervals. For both feature sets, the experiments are performed to compare deep learning algorithms (including LSTM and 1D-CNN) with traditional machine learning approaches. It is found that the LSTM algorithm outperformed other approaches on a range of evaluation metrics, with up to 90.25% accuracy. Four out of twelve learning sites (content, subpage, homepage, quiz) are identified as critical in influencing student performance in the course. The insights from these critical learning sites can inform the design of future courses and teaching interventions to support at-risk students.

Keywords: Learning Analytics; Educational Data Mining; student performance prediction; clickstream data

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1. Introduction

Learning Analytics (LA) is a rapidly growing research field. The most widely used definition for LA is “the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs” (p. iii) [1]. As the definition implies, LA is connected to computer-supported learning environments and educational data that are collected from Virtual Learning Environments (VLEs), such as Learning Management Systems (LMSs) [2]. The past two decades have seen an increased adoption of LMSs, leading to the availability of large educational data sets. With appropriate LA and data mining techniques, analysis of these data sets can provide a better understanding and insights into learners' learning processes and experiences.

Current research in LA has explored various methodologies, including descriptive, diagnostic, predictive and prescriptive analytics [3]. Predictive analytics in education involves inferring uncertain future events or outcomes related to learning or teaching [3]. Some tasks predict an aspect of teaching, such as course registration, student retention, or the impact of a given instructional strategy on learners [3]. Other tasks focus on learning and learners' perspectives, such as predicting academic success, course grades or skill acquisition [3]. Student performance prediction is one of the significant areas because

it can be used to enhance student academic performance and reduce student attrition, for example, by using early warning systems to support at-risk students [4]. This research is an exploration of LA for the purpose of student performance prediction.

The data used in student performance prediction tasks rely on the course design and the data generated from LMSs. Commonly used data include demographics, academic background, and learning behaviour data [5–7]. Some studies only focus on behaviour data (e.g., video-viewing data) to perform these tasks [8]. Others use mixed-category data (e.g., both demographics and behaviour data) to predict student performance [9]. However, due to a variety of course design, models built for specific courses using specific course-related data can be difficult to reuse in other courses. As a category of data reflecting student behaviour, clickstream data indicates the path a student takes in navigating one or more learning sites in LMSs. The strengths of using clickstream data include its ease of access, regardless of course conditions, such as course structure, assessments or learning activities. One limitation of this data category is its less explicit connections with students' learning behaviours compared to other data, such as discussion board data. This may explain why it has received insufficient attention from educators and researchers to date. Despite this limitation, studies have used clickstream data and observed connections between click actions and students' learning behaviours [10], confirming its value and potential in student performance prediction tasks. In addition to the introduction (Section 1), Section 2 of this paper presents a literature review on Learning Analytics and Educational Data Mining, student performance prediction, and clickstream data. The research methods, including the research aim and objectives, data sets, and experiments, are discussed in Section 3. The implementation and results of the experiments are presented in Section 4. The findings are discussed in Section 5, and the conclusion is provided in Section 6.

2. Literature Review

2.1. Learning Analytics and Educational Data Mining

This research concerns two closely related research fields, Learning Analytics (LA) and Education Data Mining (EDM). LA is an increasingly explored area in education [11]. The data used in LA are considerably diverse, from log and survey data to eye tracking, automated online dialogue and “Internet-of-Things” data [2]. Generally, LA aims to generate insights from educational data to improve learning and teaching [12,13]. These insights help educational institutions to enhance education-related policies, management strategies, and learning systems or environments [14]. Educational Data Mining (EDM) is a closely related field to LA [15]. EDM “is an emerging multidisciplinary research area, in which methods and techniques for exploring data originating from various educational information systems have been developed” (p. 3) [16]. EDM has a stronger emphasis on the technical element of data mining and analysis, but shares the overarching goal with LA of generating insights to support learning and teaching improvement.

LA and EDM can be used to support students, teachers, researchers, and educational institutions in a number of ways. LA and EDM can provide insights into students' learning experiences, processes and performance [17]. For teachers, it can lead to enhanced course planning and material evaluation tools [18]. For students, it allows those who encountered learning difficulties to acquire timely interventions from their instructors [19]. For educational researchers, it enables them to better understand learners' behaviours and the impact of the learning environment on student learning [17]. For institutions, it can help improve student engagement and potentially achieve higher retention rates [19]. Predictive analysis is a key focus in LA and EDM research. A systematic review identified four main areas of focus in LA and EDM: (a) computer-supported prediction analytics, (b) computer-supported behaviours analytics, (c) computer-supported learning analytics, and (d) learning visualisation analytics [20]. Ref. [21] pointed out that for the studies they investigated from 2000 to 2017, the biggest proportion of research was in the area of computer-supported prediction analytics (63.25%). Classification and regression are popular prediction methods in EDM, involving using variables to predict students' academic performance or success

(e.g., whether drop-out students or academic grades). Early warning systems are one type of such applications [4,22]. Another method, called Knowledge Inference or Latent Knowledge Estimation, is associated with using EDM techniques to “assess the skills of students based on their responses to a problem-solving exercise” (p. 184) [21]. For example, natural language processing technologies (e.g., Transformers) have the potential to be used to measure human language knowledge acquisition [23]. This research sits the classification method, one of the commonly seen methods in predictive analysis [20].

2.2. Student Performance Prediction

With the rapid expansion in the volume of educational data, methodological approaches in LA and EDM research have continued to grow and mature, along with sophisticated data analysis techniques [17,24]. Today, LA and EDM drive an advanced method of prediction that enhances traditional techniques in student performance prediction. The term ‘student performance’ is used differently across different studies. There are generally two types: performance at the program level [25–27] and at the course level [28]. For the program level, prediction tasks can be related to identify the probability of student dropouts or graduates from a degree program (e.g., a bachelor’s degree). For the course level, student performance is defined as students’ learning outcomes such as assignments or assessments in their courses after a study period [29]. Its prediction tasks can focus on predicting students’ final scores or grades, or their pass or fail status at the end of the course [4,7]. At-risk students are those who are more likely to fail the course [4]. The aim of this type of prediction task is to identify at-risk students and help them achieve their academic goals. This research focuses on the course-level performance prediction, and investigates student learning behaviours on various learning tasks.

Predictive analysis at the course level can provide valuable insights for enhancing teaching and learning. It can help instructors understand student behaviour (e.g., the total time in learning content viewing) [12] and design instruction accordingly [17]. It can also give students who encounter learning difficulties the opportunities to receive timely interventions from their instructors [19] and adjust their learning strategies. Furthermore, the integration of predictive analysis has been shown to enhance educational strategies from an institution perspective. For example, [30] investigated the adoption levels of blended learning systems using online behaviour data found that the use of predictive analysis can support the strategic developments of LMS. Previous research has employed feature importance analysis in performance prediction tasks to determine the influence of student-related features on academic performance [31,32]. Identifying these important features can provide valuable insights for improving teaching and learning [33].

A number of approaches and techniques are adopted in student performance prediction tasks. From the data usage perspective, comparative analysis of the trained datasets (e.g., generating multiple feature sets through feature extraction) to validate predictive models has less attention. A systematic literature review reported that nearly 92% of studies used only one dataset in model training, while 8% used multiple datasets to search for optimal predictive models [34]. Moreover, in classification tasks for predicting student performance, several data mining algorithms have proven particularly popular, including Decision Tree, K-Nearest Neighbor, Support Vector Machines, Naïve Bayes, Random Forest, Boosted Trees, Adaptive Boosting and Gradient Boosting [34,35]. In addition to achieving high performance in predictive modeling tasks, the popularity of certain algorithms may also be related to their ability to generate explainable output. This means that these algorithms are able to provide clear and intuitive explanations of their predictions, which can be useful for interpreting the results of the model. Explainable models are significant in solving problems in education, including predicting student performance [36]. Explainable models such as tree-based algorithms (53%) and rule-based algorithms (33%) are more commonly used than deep learning algorithms (6%) [36]. Deep learning models are instances of “black-box” models, meaning that the way models work cannot be explained or understood by human. However, recent studies have revealed a shift in focus from explainable models

or “white-box” models to more complex “black-box” models that are capable of solving challenging problems [37].

2.3. Clickstream Data

Researchers devote themselves to investigating student performance prediction using features extracted from the LMS usage data. LMSs produce various data based on their functionalities and the course design. Some researchers use data regarding students’ personal and social background, previous academic achievements (e.g., transcripts, admission data), or student self-reporting (e.g., interview or survey data) [38–40]. These data indicate individuals’ information or learning environments, which could impact students’ academic performance. Other data categories, such as event-stream data, are also popular due to their direct link to students’ learning behaviours in activities or tasks, such as discussions/forums, quizzes, learning material access, video viewing, and assignments/homework.

Recent literature shows the usage of clickstream data in predictive analysis. For instance, in business analysis, clickstream data are analysed to inform webpage design and evaluate the effectiveness of marketing programs [41]. In education, clickstream indicates the path(s) a student takes through one or more learning sites. Clickstream data have been used in research to understand student learning behaviours in online courses [42], and how their learning behaviours impact their academic performance [7]. For example, visitation of some pages or sites may be consistent with students’ navigation habits in learning [43]. Therefore, those pages can be used to display the most important materials or notifications when considering course presentation design.

Clickstream data in educational research has value in understanding the teaching and learning process. However, like any other data, clickstream data have limitations. It shows non-continuous events in behaviour patterns, resulting in sparse data. Each click action could be the start point or endpoint of each fragment in learning, so the mid-process could be missed. For example, a click on a URL indicates that a student has requested the URL directory path (e.g., a sample URL <https://xxxxxx/homepage>) but the request itself is not semantically meaningful in educational contexts [42]. Therefore, the link between a click action on a particular site or page (e.g., homepage in the case of the sample URL) and the corresponding learning behaviour is implicit.

Despite the limitations, research has confirmed that clickstream data are reliable and offer valid and nuanced information about students’ actual learning processes [42]. For example, clickstream data contain subtle information with time-stamped “footprints” on individual learning behavioural pathways [42,44]. In prediction tasks, these “footprints” can indicate learning efforts, and are more reliable measures compared to conventional methods of self-reporting [42,45]. For instance, recent research has used clickstream data to examine student engagement with videos in learning (by clicking on pausing or changing playback speed on videos) [46], as well as students’ effort regulation and time management behaviours [42]. In recognition of its strengths and potential in student performance prediction tasks, clickstream data are chosen for the purpose of this research.

3. Methods

3.1. Research Aim and Objectives

In this research, we aim to examine how machine learning and clickstream data can be used to predict student performance in online learning and teaching. This aim will be achieved by addressing the following Research Objectives (RO):

- RO1: Feature extraction: to extract feature sets from the original datasets, that can be effectively used for student performance prediction
- RO2: Feature selection: to investigate the impact of different features on prediction outcomes with the aim to identify the important features
- RO3: Model evaluation: to compare the performance of different models when using different feature sets, with and without a feature selection method, as well as multiple

machine learning (including deep learning) algorithms, to find the most optimal model for predicting student performance.

To achieve these objectives, this research adopted a commonly used prediction method in data science, including data preparation, feature extraction (RO1), and model training with/without a feature selection method (RO2) and model evaluation (RO3).

3.2. Data Sets

This research utilised open-source clickstream data OULAD (Open University Learning Analytics Dataset) from a distance-learning university—Open University [47]. According to the description of OULAD, the data adhered to the Data Protection Policy and Policy on Ethical Use of Student Data for Learning Analytics [47]. The data were collected anonymously, and all the students consented to their data being used for academic research. The Open University courses were represented in a VLE with typical online course structures [47]. Each course (called a Module) has multiple module presentations. Each module presentation consists of a few formative assessments and a final exam. The original data reflected four aspects of students: registrations, assessments, VLE interactions, and demographics [47]. Only two of these aspects were used due to their alignment with the aim of this research. One is demographics, containing the classification label (the final result of the course); its dataset named studentInfo [47]. Another is VLE interactions, containing students' clickstream data; its dataset named studentVLE [47]. Details of studentVLE are shown in Table 1.

After assessing the OULAD data, it was determined that a single course's data was used for this research to gain deep insights into teaching and learning for that specific course. To select a course with the largest dataset, the number of non-withdrawn students was compared among seven courses from the raw datasets. As a result, the course *BBB* was selected as it had the most number of non-withdrawn students. This was a course in the Science, Technology, Engineering and Mathematics (STEM) discipline [47].

Table 1. Details of the studentVLE dataset [47].

#	Columns	Description	Data Type
1	code_module	the module identification code	nominal
2	code_presentation	the presentation identification code	nominal
3	id_site	the VLE material identification number	numerical
4	id_student	the unique student identification number	numerical
5	date	the day of student's interaction with the material	numerical
6	sum_click	the number of times the student interacted with the material	numerical

3.3. Experiments

This session covered data preparation, followed by feature extraction (RO1), model training (RO2), and model evaluation (RO3) methods. A feature is a measurable piece of data that can be used for analysis or prediction.

Data preparation. For the purpose of simplicity, the original labels in the studentVLE dataset with three classes *pass*, *fail* and *distinction* were simplified to two classes *pass* and *fail*. Specifically, the label *distinction* was merged with *pass*. As a result, for the total sample of 5521 students, 68% (3754) were labelled as *pass*, and 32% (1767) students were labelled as *fail*. The course *BBB* had 12 activity categories (denoted by Act in this research), including: *forum* (Act1), *content* (Act2), *subpage* (Act3), *homepage* (Act4), *quiz* (Act5), *resource* (Act6), *url* (Act7), *collaborate* (Act8), *questionnaire* (Act9), *onlineclass* (Act10), *glossary* (Act11), and *sharedsubpage* (Act12) (According to OULAD, *id_site* are categorised into 12 activities, named *forumng* (Act1), *oucontent* (Act2), *subpage* (Act3), *homepage* (Act4), *quiz* (Act5), *resource* (Act6), *url* (Act7), *oucollaborate* (Act8), *questionnaire* (Act9), *ouilluminate* (Act10), *glossary* (Act11) and *sharedsubpage* (Act12). The activity category *ouilluminate* (Act10) indicates an online classroom for live lecture broadcasting or real-time tutorials).

Before extracting feature sets, the data were cleaned. When merging studentInfo and studentVLE, it was found that 180 students had no recorded click behaviours in studentVLE. These 180 samples were discarded, leaving 5341 students' data for the research.

Feature extraction. Two feature sets representing click counts for activity categories were extracted from OULAD. These feature sets were extracted by (1) aggregating time-based click count and (2) transforming the data structure. As the first step of the feature extraction, the click counts were summed with two levels of granularity sizes - week and month, indicating the click count every week and month. To do this, the whole course period (T) was divided into two parts. The first course period was T0 (e.g., *week0* or *month0*), indicating the time period before the course officially commences. The aggregation method was to sum up all the click counts in T0. The second course period started from the date when the course officially commences to the end of the course (T1, . . . , Tn) (e.g. from *week1* to *week39*, from *month1* to *month9*). As the second step of the feature extraction, the pieces of data were further transformed into the structure of balanced panel data. A balanced panel data refers to a structure where each panel member (i.e., student) is observed in regular time intervals. As a result, two feature sets, named WEEK and MONTH, were generated as the structure of Figure 1. The columns indicate activity categories, the rows indicate time-based observations of students' click counts. The total of 5341 sample students was extended to 213,640 observations in WEEK, and 53,410 observations in MONTH. The rationale of the strategy is to avoid high-dimensional feature sets while keeping both the time and activity dimensions.

student 5341		week	activity1	activity2	activity12	label
.....	week0						pass

student 2		week	activity1	activity2	activity12	label
.....	week0						pass
.....	week1						fail
.....						pass
.....	week39						fail

student 5341		month	activity1	activity2	activity12	label
.....	month0						pass

student 2		month	activity1	activity2	activity12	label
.....	month0						pass
.....	month1						fail
.....						pass
.....	month9						fail

Figure 1. Generated two feature sets WEEK (left) and MONTH (right) for training models. WEEK contains 213,640 rows (that is 5341 students \times 40 weeks) \times 13 columns (that is 12 features + 1 label). MONTH contains 53,410 rows (that is 5341 students \times 10 months) \times 13 columns (that is 12 features + 1 label).

Model training methods. In this research, machine learning, including traditional machine learning (LR, k-NN, RF, GBT) and deep learning (1D-CNN, LSTM) methods, were used for model training. For traditional machine learning, LR (Logistic Regression) was selected as the baseline algorithm because of its effectiveness with clickstream data in previous research [14]. LR is a transformation of linear regression that can be seen as a simple version of the regression model for binary classification [48]. It is based on the estimation mechanism of probability with the 0 or 1 output of the model [48]. k-NN (k-Nearest Neighbors) is another traditional machine learning method used for classification. It is a simple, similarity-based algorithm that classifies by comparing the similarities between testing and training samples [49]. The choices of RF (Random Forest) and GBT (Gradient Boosting Trees) [5], were motivated by their boosted capacities. RF is an ensemble classifier that improves the performance of classic tree-based algorithms using the Bagging method [50]. It creates an uncorrelated forest of trees and combine them in parallel [51]. The prediction by the committee of RF is more accurate than that of any single tree [51]. GBT, or GBDT (Gradient Boosting Decision Trees), uses the Boosting method to sequentially combine weak learners (typically shallow decision trees) to allow each new tree to correct the previous errors [52]. This method reduces Bias, which is one of the

components of accuracy. Some recent studies have found GBT to perform better than RF in clickstream data classification tasks [5,53].

For deep learning methods, CNN (Convolutional Neural Network) is designed for image-related tasks. An innovative study used an enhanced 2D-CNN (Two-dimensional Convolutional Neural Network) model on a set of temporal educational data by transforming the data into a colour-image-like structure [54]. This current research adopted 1D-CNN (One-dimensional Convolutional Neural Network) models, using hyperparameters *kernel* and *stride* to control the feature-extracting window size and the window slice step, to examine its capacity on temporal clickstream data. LSTM (Long Short-Term Memory) is a Recurrent Neural Network (RNN) designed for dealing with sequential data (e.g., time-series data) by ‘memorising’ earlier inputs. In complex settings, such as multidimensional data with inter-sequential or inter-temporal interactions, LSTM is more powerful than traditional models [55]. LSTM were selected for its capacity to handle temporal data and its outstanding performance in tabular clickstream data in prediction tasks [5]. This research used a stacked LSTM architecture (two LSTM layers, followed by one Fully Connected Layer).

M1 and M2 models. Two models were trained with WEEK and MONTH feature sets when using LR, k-NN, RF and GBT. One model did not use feature selection (denoted by M1 models in this research). Another model used Information Gain feature selection filter method (denoted by M2 models in this research). For 1D-CNN and LSTM, only one model was trained for each feature set (WEEK and MONTH) without using the feature selection method (i.e., M1 models). This is because 1D-CNN and LSTM have the capability to weight features within the neural network mechanism.

Cross-validation. To maximise the data used for training and obtain solid results, this research adopted 10-fold cross-validation. Specifically, for each fold, 90% of the data were used as a train set, and 10% were used as a test set.

Model evaluation metrics. The performance of the models were evaluated with accuracy, F1-score and AUC.

4. Results

The results are presented in three main aspects: model training implementation, model performance (i.e., model evaluation results) and feature importance. The first two aspects show how the models were trained, how well they perform, and which model is the best. The third aspect, feature importance, examines the dominant features of the best model to gain insights into teaching and learning.

4.1. Model Training Implementation

This session demonstrated the implementation process of M1 models (no feature selection) and M2 models (using Information Gain for feature selection).

M1 Models. LR M1 models adopted normalised input data (0, 1) and were trained using the default hyperparameters of the Logistic Regression operator in RapidMiner. k-NN M1 models also adopted normalised input data (0, 1) and used an optimal k value of 7, and a distance measure hyperparameter of MixedMeasures. RF M1 Models adopted original input data (i.e., without normalisation) and involved tuning two hyperparameters: *number_of_trees* is set to 350, and *maximal_depth* is set to 3. GBT M1 models adopted original input data and involved tuning three hyperparameters: *number_of_trees* is set to 61, *maximal_depth* is set to 3 and *learning_rate* is set to 0.1. 1D-CNN models, structured with an input layer, a 1D-CNN layer, a pooling layer, a fully connected layer and an output layer, used a *batch* size of 128, a *epochs* of 400, a *learning rate* of 0.001, and *dropout rate* of 0.4. The 1D-CNN models using input data with a shape of (1, 13) (for both WEEK and MONTH feature sets) have 897 trainable parameters. LSTM models, structured with an input layer, two LSTM hidden layers, a fully connected layer and an output layer, adopted an *optimisation function* of *Adam stochastic gradient descent*, a *loss function* of *categorical binary cross-entropy*, a *learning rate* of 0.0001, a *dropout rate* of 0.2, a *batch* size of 128, and an *epochs*

of 700. The LSTM models using input data with a shape of (40, 13) (i.e., WEEK feature set) have 32 hidden units in first LSTM layer and 8 hidden units in the second LSTM layer, with a total of 7209 trainable parameters. The LSTM models using input data with a shape of (10, 13) (i.e., MONTH feature set) have 32 hidden units in first LSTM layer and 16 hidden units in second LSTM layer, with a total of 9041 trainable parameters.

M2 models. The model training process involved (1) weighting features by Information Gain and acquiring weight scores of features, and (2) finding the best threshold of weight scores that enables a selection of the best subset of features. The implementation of this process involved two parts. The first part was obtaining weight scores for all click behaviour features using the operator *Weight by Information Gain* in RapidMiner. The results of this process were shown in Table 2. The second part of the implementation process involved training models to find the best threshold with the best model performance. For LR and k-NN using both WEEK and MONTH feature sets, the best threshold was 0.7. This indicated only one feature, *homepage* (Act4), was involved in the model. For RF and GBT using WEEK, the best threshold was 0.3. This indicated two features, *homepage* (Act4) and *forum* (Act1), were involved in the model. For RF and GBT using MONTH, the best threshold was 0.3, indicating that four features were involved in the model. These were *homepage* (Act4), *forum* (Act1), *subpage* (Act3) and *resource* (Act6).

Table 2. Weight scores of feature weighting by Information Gain for WEEK and MONTH feature sets (normalised in between 0 and 1).

Feature Name	Activity Category	Weight Scores in WEEK	Weight Scores in MONTH
Act1	forum	0.60	0.63
Act2	content	0.28	0.34
Act3	subpage	0.28	0.54
Act4	homepage	1.00	1.00
Act5	quiz	0.12	0.32
Act6	resource	0.22	0.43
Act7	url	0.13	0.19
Act8	collaborate	0.04	0.09
Act9	questionnaire	0.03	0.06
Act10	onlineclass	0.00	0.01
Act11	glossary	0.03	0.06
Act12	sharedsubpage	0.00	0.00

4.2. Model Performance

The model performance was evaluated using accuracy (Table 3), F1-score (Table 4) and AUC (Table 5). As 10-fold cross-validation was used in model training, the variances were also demonstrated in the model performance results. Overall, the results showed LSTM >1D-CNN >GBT, RF >k-NN, LR. The best model was the LSTM (M1) model using feature set WEEK, with an accuracy of 89.25% ($\pm 0.97\%$), F1-score of 92.71% ($\pm 0.62\%$) and AUC of 0.913 (± 0.014). Also, the variances of the model performance were relatively low. The second-best model was the LSTM (M1) model using feature set MONTH, with 88.67% ($\pm 1.27\%$) accuracy, 92.37% ($\pm 0.81\%$) F1-score and 0.906 (± 0.013) AUC. However, the rest of the models did not perform well. The models k-NN, RF, GBT, 1D-CNN with WEEK and MONTH showed low AUC scores, between 0.50 to 0.78 (Table 5). This range of AUC indicated that the model's ability is equivalent to a random guess or slightly better. Also, their corresponding accuracy ranges from 66% to 76% with F1-score ranging from 72% to 85%. Due to the imbalanced data (approximately 68% Pass, 32% Fail), this performance range is not ideal in practice.

Table 3. Model performance—accuracy (variances are demonstrated within the parentheses).

Algorithms	M1 Using Feature Set WEEK	M2 Using Feature Set WEEK	M1 Using Feature Set MONTH	M2 Using Feature Set MONTH
LR	70.24% ($\pm 0.02\%$)	70.25% ($\pm 0.00\%$) ¹	70.24% ($\pm 0.03\%$)	70.25% ($\pm 0.00\%$) ²
k-NN	66.29% ($\pm 0.30\%$)	66.10% ($\pm 0.32\%$) ³	76.46% ($\pm 0.48\%$)	76.46% ($\pm 0.49\%$) ⁴
RF	70.25% ($\pm 0.00\%$)	70.25% ($\pm 0.00\%$) ⁵	73.82% ($\pm 3.83\%$)	76.39% ($\pm 0.47\%$) ⁶
GBT	70.25% ($\pm 0.00\%$)	69.02% ($\pm 1.99\%$) ⁷	76.47% ($\pm 0.49\%$)	76.47% ($\pm 0.49\%$) ⁸
1D-CNN	70.25% ($\pm 0.27\%$)	n/a	77.55% ($\pm 0.88\%$)	n/a
LSTM	89.25% ($\pm 0.97\%$) [*]	n/a	88.67% ($\pm 1.27\%$) ^{**}	n/a

Features used in M2 models: ¹ Act4; ² Act4; ³ Act4; ⁴ Act4; ⁵ Act4, Act1; ⁶ Act4, Act1, Act3, Act6; ⁷ Act4, Act1; ⁸ Act4, Act1, Act3, Act6. * The best performance: LSTM algorithm with M1 using feature set WEEK. ** The second-best performance: LSTM algorithm with M1 using feature set MONTH.

Table 4. Model performance—F1-score (variances are demonstrated within the parentheses).

Algorithms	M1 Using Feature Set WEEK	M2 Using Feature Set WEEK	M1 Using Feature Set MONTH	M2 Using Feature Set MONTH
LR	82.51% ($\pm 0.01\%$)	82.53% ($\pm 0.00\%$) ¹	82.51% ($\pm 0.02\%$)	82.53% ($\pm 0.00\%$) ²
k-NN	72.94% ($\pm 0.25\%$)	72.67% ($\pm 0.27\%$) ³	84.06% ($\pm 0.37\%$)	84.06% ($\pm 0.38\%$) ⁴
RF	82.52% ($\pm 0.00\%$)	82.52% ($\pm 0.00\%$) ⁵	83.88% ($\pm 1.65\%$)	83.96% ($\pm 0.37\%$) ⁶
GBT	82.52% ($\pm 0.00\%$)	79.58% ($\pm 4.75\%$) ⁷	84.04% ($\pm 0.38\%$)	84.04% ($\pm 0.38\%$) ⁸
1D-CNN	82.52% ($\pm 0.18\%$)	n/a	85.24% ($\pm 0.82\%$)	n/a
LSTM	92.71% ($\pm 0.62\%$) [*]	n/a	92.37% ($\pm 0.81\%$) ^{**}	n/a

Features used in M2 models: ¹ Act4; ² Act4; ³ Act4; ⁴ Act4; ⁵ Act4, Act1; ⁶ Act4, Act1, Act3, Act6; ⁷ Act4, Act1; ⁸ Act4, Act1, Act3, Act6. * The best performance: LSTM algorithm with M1 using feature set WEEK. ** The second-best performance: LSTM algorithm with M1 using feature set MONTH.

Table 5. Model performance—AUC (variances are demonstrated within the parentheses).

Algorithms	M1 Using Feature Set WEEK	M2 Using Feature Set WEEK	M1 Using Feature Set MONTH	M2 Using Feature Set MONTH
LR	0.597 (± 0.007)	0.607 (± 0.006) ¹	0.482 (± 0.008)	0.500 (± 0.000) ²
k-NN	0.670 (± 0.006)	0.666 (± 0.007) ³	0.671 (± 0.008)	0.670 (± 0.010) ⁴
RF	0.690 (± 0.004)	0.674 (± 0.004) ⁵	0.751 (± 0.008)	0.734 (± 0.009) ⁶
GBT	0.698 (± 0.004)	0.690 (± 0.004) ⁷	0.763 (± 0.007)	0.763 (± 0.007) ⁸
1D-CNN	0.720 (± 0.005)	n/a	0.786 (± 0.006)	n/a
LSTM	0.913 (± 0.014) [*]	n/a	0.906 (± 0.013) ^{**}	n/a

Features used in M2 models: ¹ Act4; ² Act4; ³ Act4; ⁴ Act4; ⁵ Act4, Act1; ⁶ Act4, Act1, Act3, Act6; ⁷ Act4, Act1; ⁸ Act4, Act1, Act3, Act6. * The best performance: LSTM algorithm with M1 using feature set WEEK. ** The second-best performance: LSTM algorithm with M1 using feature set MONTH.

4.3. Feature Importance

The important features of the best model, the LSTM (M1) model using WEEK feature set, were examined by observing how the model's performance changes when each feature in the model is discarded. As a result, the model performance showed a dropped accuracy each time a feature was removed. The accuracy decreased significantly when the features Act2 (*content*), Act3 (*subpage*), Act4 (*homepage*) and Act5 (*quiz*) were removed. Therefore, these four features can be considered dominant. A comparison of the accuracy after each feature were removed was shown in Table 6.

Table 6. Feature importance analysis result.

Removed Feature	Activity Category	Model's Accuracy	Dropped Accuracy
Act1	forum	89.22% ($\pm 0.79\%$)	0.03%
Act2 *	content	89.03% ($\pm 0.68\%$)	0.22%
Act3 *	subpage	88.90% ($\pm 0.78\%$)	0.35%
Act4 *	homepage	88.90% ($\pm 1.27\%$)	0.35%
Act5 *	quiz	89.07% ($\pm 0.93\%$)	0.18%
Act6	resource	89.18% ($\pm 0.87\%$)	0.07%
Act7	url	89.12% ($\pm 0.89\%$)	0.13%
Act8	collaborate	89.16% ($\pm 0.97\%$)	0.09%
Act9	questionnaire	89.23% ($\pm 0.89\%$)	0.02%
Act10	onlineclass	89.16% ($\pm 0.83\%$)	0.09%
Act11	glossary	89.22% ($\pm 0.77\%$)	0.03%
Act12	sharedsubpage	89.22% ($\pm 0.69\%$)	0.03%

* The first dominant features are Act3 (*subpage*) and Act4 (*homepage*), the second dominant feature is Act2 (*content*), and the third dominant feature is Act5 (*quiz*)

5. Discussion

This research trained multiple predictive models using machine learning methods and clickstream data, achieving up to 90.25% ($89.25\% + 0.97\%$) accuracy. The results provide insights into effective ways to extract features, train and evaluate predictive models in student performance prediction tasks using students' clickstream data. From a data science perspective, this research contributes three major findings through answering its three Research Objectives: (1) Feature extraction, (2) Feature selection, and (3) Model evaluation. In addition, although this research was conducted based on a data science approach rather than with a pedagogical focus, the identified important features from the best model can inform future course design and teaching interventions.

5.1. Research Objective 1: Feature Extraction

In this research case, the best practice was to adopt the weekly view (i.e., the WEEK feature set, aggregating click counts based on weekly time intervals), even though in some cases, it did not perform as well as the monthly view (i.e., the MONTH feature set, aggregating click counts based on weekly time intervals). Panel data appeared to be unsuitable for all traditional machine learning (LR, k-NN, RF, GBT) and 1D-CNN, so the weekly and monthly views were not worth comparing for these algorithms. However, for LSTM, the weekly view showed the best model with 89.25% accuracy, significantly higher than the monthly view at 88.67%. Therefore, although traditional machine learning models learned features better from the monthly view, their accuracy were still lower than the model using the weekly view with the LSTM algorithm. This result is consistent with some current studies that use a weekly view to represent clickstream data and effectively conduct their prediction tasks [14]. The feature sets used in this research involve both time and activity dimensions, which can be seen as an effective way to conduct feature extraction. As suggested by previous research, using features from multiple dimensions is more likely to achieve better predictive results [56].

5.2. Research Objective 2: Feature Selection

In data science, feature selection is a powerful technique that reduces the number of features and makes the model easier to learn patterns [57]. In this research, features were selected based on their correlation with the label (in M2 models). However, the traditional machine learning models (LR, k-NN, RF, GBT) did not boost the results despite using feature selection. One potential reason is that the dataset structure may not be suitable for the chosen machine learning algorithms. Another possible reason is that removing the lower correlated features could lead to a loss of valuable information for prediction. In contrast, the LSTM (M1) model using feature set WEEK did not use the feature selection method but still achieved the highest accuracy. This finding suggests that feature selection

can be optional in student performance prediction with clickstream data, at least when the feature set is not high-dimensional. For high-dimensional feature sets, feature selection is commonly used for training prediction models [49]. As WEEK and MONTH feature sets only have the total of 12 features, they are not considered high-dimensional. Therefore, feature selection may not be necessary in this case.

5.3. Research Objective 3: Model Evaluation

The experiment results show the varying capacities of different machine learning algorithms when dealing with clickstream data with a panel data structure. First, k-NN is often used for course-specific prediction using event-stream data [9]. It did not produce good results when applied to clickstream data in this research case. This finding is consistent with previous clickstream data studies that used k-NN for student performance prediction and obtained poor performance [18]. Second, the 1D-CNN models had higher accuracy than the traditional machine learning algorithms, but it was still significantly lower than the best LSTM model in this study. This may be because 1D-CNN is not as well-suited for dealing with sequential data. Third, LSTM is effective for learning features from panel data with a matrix structure that indicates student click behaviours. This may be because LSTM can handle sequential observations in each panel member. Similar findings have been reported in other papers. For example, a study concludes that LSTM is a outstanding candidate for training customer prediction models using a form of panel data [55]. Also, LSTM can achieve the same effects as traditional machine learning with complex feature selection processes, without requiring manual feature selection. In this study, LSTM generated better results than the traditional machine learning with large feature selection workloads. Therefore, when using LSTM to predict student course results, feature selection may not be necessary.

Deep learning can be used in areas where analytical-result-driven decisions can be explained and used to affect individuals [36]. This research used LSTM to train models, then conducted feature importance analysis to generate explainable results (see the following section Implications for Learning and Teaching). Despite the perceived “black-box” nature of deep learning LSTM, this research demonstrated how it can provide explainable achievements for student performance prediction and support decision-making in teaching and learning.

5.4. Implications for Learning and Teaching

In student performance prediction tasks, feature importance analysis can reveal the factors that influence students’ performance. Based on the feature importance analysis of this research, the students’ click behaviours on the course homepage and subpages are the most important to the prediction tasks. The second-most important activities are the course content and quizzes. The rest of the activity categories demonstrated minor importance, meaning that students’ click behaviour patterns on those sites have a minor impact on predicting students’ academic results. These findings can inform teaching and learning in online courses with a similar structure, with the goal of improving the learning environment or facilitating teaching intervention practices. First, the identified dominant activity categories can be used to guide course design. Taking the findings in this study as an example, students’ click behaviours on the course homepage and its subpages may reflect students’ habits of interacting with the course learning environment, for example, student starting their learning by accessing the course’s homepage. Therefore, key course information can be placed on the homepage and subpages to align with students’ behaviour habits. Additionally, as the content and quizzes are identified as critical, educators or instructors can encourage students to engage with the learning content or materials and quiz activities.

6. Conclusions

This research investigates the potential of using clickstream data to predict student performance. Student performance prediction is a sub-topic of LA and EDM. The ability to predict student performance can be beneficial in identifying at-risk students and providing them with learning support. This research aims to build a student performance prediction model using clickstream data. In the experiments, multiple predictive models were trained and analysed, using aggregated click data (number of clicks in a weekly and monthly basis), machine learning algorithms (LR, k-NN, RF, GBT, 1D-CNN and LSTM) and a feature selection method. This research found that weekly-based click count aggregation in the form of panel data, together with the LSTM model, is the best practice for this student performance prediction case. Feature selection is optional in this case. Moreover, by analysing important features from the best model, this research found that clicks on the homepage, subpages, content and quizzes are significant in predicting student performance. Based on these findings, educators can consider improving the online learning environment by utilising the advantage of students visiting homepage and subpages of the course. Teaching intervention practices to help at-risk students are suggested to provide student support around learning materials and quizzes.

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Abbreviations

The following abbreviations are used in this manuscript:

LA	Learning Analytics
EDM	Educational Data Mining
LMS	Learning Management System
OULAD	Open University Learning Analytics Dataset
VLEs	Virtual Learning Environments
LR	Logistic Regression
k-NN	k-Nearest Neighbors
RF	Random Forest
GBT	Gradient Boosting Trees
CNN	Convolutional Neural Network
1D-CNN	One-dimensional Convolutional Neural Network
2D-CNN	Two-dimensional Convolutional Neural Network
LSTM	Long Short-Term Memory

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Article

Unplugging for Student Success: Examining the Benefits of Disconnecting from Technology during COVID-19 Education for Emergency Planning

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Abstract: The COVID-19 outbreak revealed the fragility not only of our species but also of society, which has demonstrated its ability to adapt to challenging conditions and to learn from disasters. One of the most pressing issues during the pandemic was the delivery of education during lockdowns. Education in emergency was established using various communication media, hastening the digitalization of education. However, this also highlighted the impact on the mental health of students, who were already experiencing overuse of the internet and electronic devices prior to the pandemic. In response, Tecnológico de Monterrey, a private Mexican university that also offers high school programs, launched the “Unplugged Day” initiative, which encouraged students to disconnect from electronic devices and participate in physical, cultural, creative, or reflective activities. This study applied a voluntary survey to 1850 students from March to May 2021 on a weekly basis, with the aim of analyzing symptoms of insomnia, emotions, perceptions of online education, sources of stress, and the need for professional support to manage their emotions in relation to their participation in Unplugged Day activities. Our results, obtained through a quantitative methodology, confirmed the impact of the emergency, lockdown, and forced remote education on the mental health of students. Furthermore, the results revealed that the Unplugged Day initiative is a strategy that promoted students’ well-being during online education. The respondents also suggested strategies for promoting mental health and well-being of learners, whether in an emergency or not. These findings provide valuable information for governments and educational institutions to implement policies and strategies for planning education in emergency situations and for addressing the ongoing global problems of stress and mental health, which are related to the increasing use of electronic devices and the volatility, uncertainty, complexity, and ambiguity of global society. It is our responsibility to improve education so that it can play its role in preserving cultural heritage, overcoming adversity, rebuilding after catastrophes, and shaping a better future for generations to come.

Keywords: emotional well-being; educational innovation; stress; education in emergency; insomnia; higher education

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1. Introduction

As educational institutions strive to be a driving force for social improvement in the future, it is crucial that we equip students with the skills necessary to navigate the challenges of a rapidly changing world characterized by volatility, uncertainty, complexity, and ambiguity. The current global landscape, marked by economic instability, poverty, pandemics, and social inequality, requires future citizens and workers to be resilient and adaptable. In recognition of this, the European Commission [1] has emphasized the importance of teaching students and workers about physical and mental health, risk exposure, as well as mechanisms and resources for healing and support in case of mental illness.

In addition, the ability to recognize and respond to threats to personal and community well-being is an essential skill, especially in light of potential future social or financial crises

and natural disasters exacerbated by climate change. Being able to identify, assess, and mitigate risks to mental and physical health and well-being, as well as to the community and environment, is a vital component of resilience and adaptability in an ever-changing world. Education not only plays a vital role in social improvement, but it is also crucial for protecting and preserving our culture and for recovering from catastrophe.

Given the increasing reliance on online education, it is essential that we implement policies and practices to promote the care and awareness of the mental health and well-being of our students. The COVID-19 pandemic has highlighted the need for such efforts and served as a catalyst for progress in this area.

The mental and emotional welfare of individuals was affected by the COVID-19 lockdown [2–4]. Young students are among the most susceptible groups in society that can be negatively impacted by the isolation and lockdown imposed by the pandemic [5–7]. Although adolescents were not initially considered to be at high risk for contracting COVID-19, research has shown that they are vulnerable to experience stress and depression and can be negatively affected by other psychological repercussions of the current pandemic [4,6,7]. As of 31 July 2020, a total of 31,453,440 students at all levels of education worldwide had undergone school closures due to COVID-19 contingency measures. The situation was particularly dire for students in the Americas (South, Central, and North) given that most countries within the continent did not open schools for more than 41 weeks [8].

Quarantine is a strong public health initiative to prevent the transmission of contagious illnesses [9], but it may also leave significant psychological impacts on those who experience it [10]. The longer the quarantine period is, the more severe its effects on the adolescents' social networks and behavior will be [5]. Another issue that requires the attention of stakeholders and decision-makers within the educational system is the fact that the negative consequences of COVID-19 lockdowns may not entirely disappear once the pandemic is over. Research-based evidence suggests that negative psychological and psychosocial impacts caused by isolation can be long-lasting and persist beyond the current pandemic [10–12], with the most adverse effects on the young population [4]. Therefore, it is a concern for education institutions to monitor the emotional well-being of students and provide support throughout the emotional fluctuations they may experience during the pandemic [13].

The transition to online classes has increased screen media usage for communication and access to educational materials [14]. We must acknowledge it as a relevant factor for increased anxiety and heightened stress, among other psychological challenges [15]. In fact, excessive evening smartphone use is associated with a higher risk of poor sleep and insomnia symptoms [11]. In conjunction with the threat of the pandemic, students have naturally faced academic stress [7], which has sharpened due to the cognitive overload and additional stressors caused by the transition to online learning [16,17]. This raises the question of the extent to which schools can play a role in the well-being of students, as there is a pressing need for educational institutions to carefully monitor students' emotions and mitigate the adverse consequences of quarantine [18].

Another contributing factor is the limitation of physical activities when aiming to alleviate students' mental health and energy level [5]. In that regard, Chen et al. (2020) suggested a multi-stepped intervention strategy to diminish psychological problems imposed by lockdown. The first three steps involve (i) delivery of positive epidemic-related information; (ii) reducing opportunities for negative reactions/behavior; (iii) stress management; these are ideal for large-scale interventions and could be delivered through online platforms. Other researchers have recommended that academic institutions deliver clear and informative messages to students, develop online networking events and activities, and prioritize call centers and student support services to mitigate the adverse effects of the lockdown [13,18].

Tackling the emotional challenges that come with the prolonged pandemic is a collective effort, and the immediate measures taken as part of quarantine planning evidently contributed to reducing the overall global mental health burden [17]. Public policies must

be implemented to raise public awareness on mental health, including healthy sleep habits and limited use of electronic devices [19], as well as promoting strategies in educational institutions to ensure the well-being of adolescents.

Tecnologico de Monterrey, a leading university in Mexico and Latin America, announced a day without the use of smart devices and internet for its students under the heading of Unplugged Day. The purpose of this initiative was to dedicate students' time and energy to activities that may help in elevating their energy level and promoting their emotional health and well-being. Unplugged Day was recommended for undergraduate students and mandatory for every high school student across the 34 campuses around the country. Amid the COVID-19 quarantine, high school students revealed a heightened level of stress and anxiety [13]. Therefore, Unplugged Day was established as a means for taking a break from regular online lessons to engage students in physical activities, such as cooking, running, yoga, and cycling, among others that do not require the use of internet or smart electronic devices. We tracked students through online weekly surveys from 1 March 2021 and for 11 subsequent weeks. The Unplugged Day activity took place once every month during this period, which allowed us to analyze variables including insomnia, stress, anxiety, general and academic emotions, and energy level of the students.

In this study, we hypothesized that through the implementation of the Unplugged Day initiative, the youngest members of our educational community who disconnected from the virtually driven world that they became deeply immersed in during the COVID-19 lockdown would experience improved levels of mental well-being and sleep quality. Additionally, we sought to gain insight into the most frequent stressors experienced by our students during remote learning. From this experience, we might learn how to ensure the mental health and wellbeing of our students, a relevant issue in online remote learning and in education during an emergency.

2. Background

2.1. Stress: A Global Health Problem

Stress is a natural part of human experience, but when it exceeds certain limits, it can have adverse effects on health and well-being. A beneficial or healthy response to stress is known as eustress, which can lead to high performance in sports and work [20]. Stress not only supports our survivor instincts, but also helps effectiveness and efficiency [21]. Even so, beyond a certain threshold, stress is only detrimental to an individual's health, mood, productivity, relationships, and long-term quality of life [22].

Humankind is currently facing an array of challenges, including wars, economic instability, poverty, pandemics, and social inequality, all of which can contribute to chronic stress and other mental disorders. Individuals who have limited access to resources or experience any form of inequality or segregation may experience heightened levels of stress and have fewer resources for coping with it [23,24]. Even in developed countries, the rapid pace of technological change and the demands of fast-paced and demanding schedules in modern life can also contribute to chronic stress. The competing demands of work, family, and social obligations can make it challenging for individuals to find adequate time for relaxation and stress management, thereby threatening individuals' well-being.

Stress is considered a public health problem due to its impact on people's physical and mental health and on society as a whole [23,25]. Chronic stress can contribute to a variety of health problems, including heart disease, diabetes, obesity, anxiety disorders and depression. Additionally, stress can also affect academic and work performance and can have a negative impact on interpersonal relationships and overall well-being. The World Health Organization (WHO) has recognized stress as a global public health problem and has launched various initiatives to address this issue [23]. WHO recommends a holistic approach to addressing stress, which includes preventative and treatment measures, as well as promoting healthy lifestyles and supporting people affected by stress. According to the National Institute of Mental Health (NIMH), stress disorders are common in the United States [26], and the Centers for Disease Control and Prevention (CDC) states that chronic

stress puts your health at risk. Recently, the WHO has launched a campaign on mental health and stress (2020), recognizing the importance of addressing stress as part of mental health.

2.2. *Adolescents and Academic Stressors*

Adolescents are often vulnerable to stress due to the individual and social transitions they experience. Adolescence has earned the nickname of the “storm and stress” [27], given the psychosocial and physiological changes a person goes through while an individual is yet to resolve their response to stressors [28].

Academic stressors comprise a large portion of what the younger members of academic family have to deal with [29]; in fact, it is the primary source of stress among adolescents [29,30] and represents a significant concern for secondary and tertiary education [31]. Exams, homework, and additional school-related work outside the classroom are some of the main sources of academic stress in addition to giving presentations, competing with classmates, meeting deadlines, and experiencing academic overload [13,32,33]. The Organization for Economic Cooperation and Development (OECD), as part of its Program for International Student Assessment (PISA), surveyed approximately 540,000 15-year-old students about their academic feelings in 2015. The results were alarming, as 66% of the students reported feeling worried about poor grades, 59% declared feeling concerned about tests, and 55% stated feeling anxious about exams even when they were well prepared [34]. More recently, a study on 150 adolescents reflected that no student was free from stress, and a considerable number (50.7%) were facing mild academic pressure [35].

Ongoing academic stress hinders students’ learning capacity, academic performance, sleep quality and quantity, and physical and mental health, while increasing the possibility of substance abuse and developing other destructive behaviors [31,36]. Students greatly rely on their executive functioning skills, such as paying attention, focusing on tasks until completion, and understanding different points of view, among others. However, these executive functions cannot be fully used under high stress levels [37]. In addition, the body’s natural response to elevated rates of stress is anxiety [38], which in turn may precede the onset of depressive disorders as they are highly comorbid [39,40]. The scientific community recognizes that stress is currently affecting students’ academic performance and overall well-being; however, together with anxiety, they threaten intellectual activity. Anxiety and stress decrease the working memory’s capacity and efficiency as a result of a degraded cognitive function in tasks involving the working memory [41]. Enduring stress in high school is a key factor in higher education continuity, as it inhibits engagement and increases the risk of dropout [31]. In 2014, 72% of first-year Australian college students considered deferring or withdrawing from school due to poor emotional health caused by stress [42].

2.3. *Consequences of Chronic Stress in Adolescents*

Studies have shown a correlation between stress in adolescents and sleep disorders, which exacerbated as a result of the COVID-19 lockdown. Isolation caused by the pandemic may impair sleep at all age levels [43,44]. However, the impacts on sleep and mental health were more pronounced in adolescents, who reported more severe insomnia symptoms, poor sleep quality, a delayed bedtime, longer sleep latency, higher daytime dysfunction, and a more prevalent disruption of sleep habits [43,45]. A national study conducted by Gualano et al. during the last two weeks of the first Italian lockdown from 19 April to 3 May 2020 found that depression (24.7%), anxiety (23.2%), and sleep disturbances (42.2%) were prevalent in the Italian population [46]. Particularly, insomnia and tiredness were found to negatively impact cognitive, learning, and emotional regulation skills [47]. Furthermore, the COVID-19 pandemic has led to a high prevalence of sleep problems among adolescents and young adults [43,48]. A survey of 4314 Italian children and adolescents conducted between 7 May and 15 June 2020 found a significant and homogeneous delay in sleep/wake schedules [49]. Additionally, a study of 122 American tenth graders conducted by Becker

et al. (2021) revealed concerning delays in sleep and wake times, as well as difficulties initiating and maintaining sleep during lockdown [50].

Unplugging refers to reducing the use of technology and digital devices and limiting exposure to social media and other digital content [51]. By unplugging, students aim to increase focus and productivity reducing academic stress and avoid developing or exacerbating psychological concerns, such as stress, anxiety, and depression. To break this cycle and reduce digital technology use, it is important to promote self-control, the willingness to increase overall performance, improve well-being, and maintain real-life relationships [52].

2.4. Communication and Information Technologies and Their Impact on Mental Health

While online learning leveraged technological advancements to benefit the students in various ways, including the emergency delivery of education amid COVID-19 lockdown, communication and information technologies have been threatening students' learning process and emotional health worldwide [13,33].

Throughout the COVID-19 pandemic, social media emerged as the primary means of communication [53,54]. In addition to connecting individuals with others, social networks have also served as a coping mechanism for dealing with the isolation caused by lockdowns [55]. However, social media also became an ideal platform to spread fear and anxiety related to the pandemic through the phenomenon of "infodemics", negatively impacting individuals' mental health [56].

A study involving 1018 senior high school students revealed that 56.9% believed that the effectiveness of emergency remote education was poorer than in-person modalities [7]. Social isolation can lead to increased anxiety, stress, low mood, fear, frustration, and boredom [25,57,58]. Furthermore, online learning and difficulties in completing schoolwork can further contribute to the onset or progression of psychological effects such as stress [59]. A survey conducted on 270 participants by Aguilera-Hermida (2020) revealed that the virtual setting constituted a major challenge for students, arguing that staring at the screen for extended periods caused fatigue which made bearing the class further difficult. On the one hand, educators may feel that they have lost control over the class dynamic, leading to an increase in homework and assignments to ensure the learning outcomes [59,60]. On the other hand, stress due to increased workload is a common issue in study-at-home programs, which can be a burden for students [59,61,62]. Another issue to be taken into consideration is the strict measures exercised by teachers and professors to prevent academic dishonesty in tests and exams, such as increasing their complexity and shortening exam times. It is noteworthy that academic stress is a concerning matter as it may lead to low self-esteem [32,63], which has been found to be correlated with suicidal ideation [63]. Studies have found that academic stress was present in 14% of youth suicide cases [64].

Amid COVID-19 lockdowns, several studies analyzed the response of the students to the sudden shift from in-person to online or virtual education. The identified effects range from decreased course completion for lower-performing and less-experienced students to declines in initial enrollment [65] and threats to the mental health and emotional well-being of the students. Wilczewski, Gorbaniuk and Giuri reported an increase in levels of loneliness among self-isolating students in online learning despite the positive influence of peers and family support [66]. A study conducted in Wuhan, China from 4 February to 9 March 2020, found that out of 286 high school students, most maintained good mental well-being levels [67]. However, the study also recognized that schools should train students to positively regulate their emotions and design counseling courses for psychological trauma, as developing post-traumatic stress symptoms (PTSS) became a possibility for many students [68]. Another study conducted in Iran from 14 to 31 March 2020 surveyed approximately 20,200 students from first to twelfth grade and found that despite the school closures, students reported an enthusiasm towards learning and school activities [69]. In contrast, a study conducted in Mexico with 1473 high school students found that they were not so enthusiastic about the stay-at-home education setup; meanwhile, the number

of weeks under quarantine played a critical role in students' mental health as well [13]. An online questionnaire applied from 13 March to 8 May 2020 showed that students suffered from negative feelings and low energy levels due to the lockdown and subsequent disruption of their social lives [13]. Another study performed on 8079 Chinese junior and senior high school students from 8 to 15 March 2020 demonstrated that there was a high incidence of depression (43.7%) and anxiety symptoms (37.4%), and a combination of both (31.3%), among the respondents [70]. A couple of months later, between 1 and 7 May 2020, researchers also detected an alarming frequency of depressive (52.4%) and anxiety symptomatology (31.4%), and a combination of both (26.8%), among 1,018 high school students from the Shandong province of China. These results are similar to those of the earlier study, highlighting the need for ongoing psychological support and attention for students during the COVID-19 pandemic [7].

The excessive and uncontrolled use of smart devices has been shown to have a negative impact on psychological well-being as it increases anxiety, depression, and stress symptoms, even prior to the COVID-19 outbreak [71]. In an effort to examine the correlation between the lockdown and internet usage, Duan et al. found that 22.28% of 3613 surveyed students reported experiencing depressive symptoms, while 29.58% declared to have spent more than five hours per day online [72]. Salfi, et al. demonstrated a direct relationship between the evening use of electronic devices and the development and exacerbation of sleep disturbances during home confinement due to the COVID-19 pandemic, independent of other psychological and circadian dimensions [19].

While the transition to virtual classes has resulted in reduced motivation, self-efficacy, and cognitive engagement [59], some used social media as a means of recovering academic effort. This can be beneficial if performed in moderation and outside of class time; however, inside the classroom, it can be a counterproductive distraction that may cause deviated attention and reduced student outcomes [73,74]. Locked inside their homes, where students have all types of smart devices at hand, social media usage represents a harmful obstruction to learning and well-being. Research shows that problematic smartphone and social media usage was correlated to reduced mental health during the pandemic [75]. Internet addiction can adversely affect cognitive processes, including decision making and creativity, and in some cases, users may develop an inability to be away from technology even for short intervals [76]. As such, there is an urgent need to promote digital detox among students [77].

In this study, we report on the implementation and outcomes of an initiative called "Unplugged Day" at a Mexican educational institution during COVID-19 pandemic. The primary goal of this initiative was to promote well-being and mental health among students forced to online education. The results might provide valuable insight on how to foster the development of self-awareness, a future skill, and a relevant topic in emergency education.

3. Methodology

The purpose of this study is to gain a deeper understanding of the emotional and well-being implications of full-time online education on adolescents and the impact of dedicated mental health and well-being interventions. This research took place amid COVID-19 lockdown and aims to address the following research question:

What is the impact of Unplugged Day as a dedicated mental health and well-being intervention on the emotional experiences and overall well-being of adolescents in full-time online education?

The findings of this study will contribute to the existing literature on the emotional and well-being experiences of adolescents in full-time online education and inform the development of interventions and policies to support the mental health and well-being of adolescents in the context of increasing online education. By providing answers to these research questions, this study aims to shed light on the emotional and well-being implications of education in emergencies as well as the effectiveness of dedicated mental health and well-being interventions in online remote education. At the same time, it

can inform the development of effective support for adolescents in emergencies or crisis situations, such as natural disasters, armed conflicts, or pandemics.

4. Unplugged Day Activity

The Unplugged Day initiative, implemented by Tecnológico de Monterrey (TEC), was designed to promote physical and mental well-being among students during the COVID-19 quarantine period. As part of the forced emergency remote education, this activity was designed for undergraduate students and high school students (HSS). The initiative aimed to encourage participants to disconnect from technology and engage in activities that promote physical and mental well-being, such as exercise, hobbies, and self-reflection.

To facilitate this, TEC organized various optional 30–60 min activities which were guided through webinars or streaming and recommended individual self-paced activities, such as crafting, table games, brain gym, and physical and mindfulness activities.

TEC implemented Unplugged Day during the spring semester of 2021 in 34 high schools and 26 campuses across Mexico. It was held on three non-consecutive days throughout the semester, on 25 February, 19 March, and 16 April 2021. Although participation in the initiative was optional for undergraduates, it was mandatory for HSS, and a percentage of their tutoring class grade was contingent upon their participation. TEC informed the parents of HSS about the Unplugged Day via email prior to the start of the semester. Furthermore, the institution reminded students and tutors about the event four days prior to each Unplugged Day.

5. Data Collection Procedures

We used an online survey powered by Qualtrics to collect data weekly from 1 March to 17 May 2021. According to the school calendar, the survey took place from the seventh to the seventeenth week of classes—identified as W1 to W11. A total of 6500 high school students (HSS) were selected to respond to the survey on a weekly basis and were randomly assigned numbers matching the institutional student identification to avoid duplicated responses. The invited students belonged to the 34 TEC high schools across Mexico.

It is noteworthy that while the Unplugged Day held a value in students' grade for tutoring class, participation in the survey was entirely voluntarily, with an approximate participation rate of 2–4% in relation to the total number of invitations sent. These sample sizes provide confidence intervals between 6% and 9% at a 95% confidence level. Table 1 shows the number of HSS respondents per week.

Table 1. Mexican high school students that responded to the survey by week (week 1 corresponds to 1 March to 17 March 2021, while week 11 corresponds to 11 May to 17 May 2021).

Week	Number of Respondents
W1	176
W2	193
W3	166
W4	152
W5	113
W6	160
W7	245
W8	125
W9	198
W10	177
W11	140
Total	1845

The personal information collected, stored, and analyzed from students was confidential. The students provided informed consents prior to the initiation of this project. The research project received approval from the Institutional Research and Ethics Review Committee within the Office of the Vice President for Research and Technology Transfer of

Tecnologico de Monterrey. We also adhered to the Declaration of Helsinki for research on human subjects. A total of 1850 HSS voluntarily answered the survey over 11 subsequent weeks. We removed five incomplete records from the database. Table 1 displays the number of Mexican high school students who answered the survey per week, while Table 2 displays their participation, grade (1st or Freshman, 2nd or Sophomore, and 3rd or Senior), and gender.

Table 2. Mexican high school students in relation to participation in the Unplugged Day initiative during mandatory online distance education implemented during COVID-19 lockdown.

Unplugged Day Participation	Year in High School	Gender		Sum
		Female	Male	
Partially unplugged from electronic devices	1	390	183	573
	2	177	86	263
	3	194	92	286
Entirely unplugged from electronic devices	1	106	66	172
	2	63	39	102
	3	45	36	81
No participation	1	99	73	172
	2	58	39	97
	3	51	48	99
	Sum	1183	662	1845

6. Survey

TEC proposed Unplugged Day to promote improved mental health and well-being among HSS during forced online education due to the COVID-19 lockdown. Studies had shown that students were experiencing symptoms such as tiredness, insomnia, anxiety, and stress as a result of the lockdown and online education [13,78]. Educators and educational institutions were seeking strategies to promote their mental health and well-being. We aimed to investigate the impact of Unplugged Day on HSS's emotional well-being and to identify potential ways of alleviating stressors associated with the forced online modality.

To gather information on students' perception of their well-being, we designed a survey in Spanish inspired by their most relevant emotions associated with confinement [13], school-related or academic emotions [79], sleeping quality [70], and academic stress [80]. Due to the pressing situation, we applied a preliminary version of the survey to 207 HSS from 22 February to 26 February 2021. From these preliminary results, we designed the final Spanish version of the survey in a timely and efficient manner (Table 3).

Table 3. The survey that was distributed among high school students of different campuses across Mexico under forced online lessons due to COVID-19 lockdown.

#	Question	Options
Q1	What was your energy level this week?	Very low, low, neutral, high, very high
Q2	Which of the following phrases do you identify with the most? This week I felt ...	Very stressed, stressed, neither stressed nor relaxed, relaxed, very relaxed
Q2.1	Which of the following situations made you feel stressed during the week?	Homework and assignments, grades, confinement, virtual classes, infection of relatives, familiar finances, familiar relationships, my relationship, personal appearance, death of a relative, my health, other

Table 3. Cont.

#	Question	Options
Q2.2	What do you think Tec de Monterrey could do to reduce your stress? Please select those options that best apply for you.	Dynamic teaching, better class explanations, less collaborative work, less homework, flexibility in deadlines, class activities focused on relaxation, empathetic teachers, planned activities, fewer mid-term exams, fewer quizzes, more unplugging, hybrid classes, face-to-face classes, is not a university problem, other
Q3	Which of the following phrases do you identify with the most? This week I felt ...	Very tired, tired, neither tired nor rested, rested, very rested
Q4	Based on the following list of emotions, which of them did you experience most frequently this week?	Tranquil, happy, upset, sad, scared, surprised, angry, other
Q5	Based on the emotion you experienced during the week, do you think you need any help to manage it? (only for those respondents who experienced negative emotions)	Yes, No
Q6	Have you experienced insomnia in the last week (issues to fall asleep)?	Yes, all weekdays; yes, almost all weekdays (5–6 days); Yes, some days during the week (3–4 days); yes just a few days during the week (1–2 days); no, I have not experienced insomnia during the week
Q7	Had you experienced insomnia before the COVID-19 pandemic?	Yes, all weekdays; yes, almost all weekdays (5–6 days); Yes, some days during the week (3–4 days); yes just a few days during the week (1–2 days); no, I have not experienced insomnia during the week
Q8	How was your experience with online classes this week?	Very unsatisfactory, unsatisfactory, neutral, satisfactory, very satisfactory
Q9	Thinking about your academic experience during this week, what was the emotion you felt most frequently?	Worry, frustration, nervousness, satisfaction, boredom, joy/, confidence, uncertainty, enthusiasm, fun
Q10	Have you participated in “Unplugged day” activities?	Yes, no
Q11	Did you completely unplug from your electronic devices? (only for those respondents that did participate in “Unplugged day”)	Yes, no

7. Data Analysis

The collected data underwent thorough cleaning to eliminate incomplete records, thus ensuring the validity of the results. Quantitative analysis was performed, including both descriptive and inferential statistics. Descriptive statistics were represented using bar and radar charts to showcase the distribution of categorical data, while inferential statistics were calculated using chi-squared tests (with a 95% confidence level and significance levels of 0.05 *, 0.01 **, or 0.001 ***) to examine the relationship between variables and insomnia symptoms and participation in the Unplugged Day activity. This approach ensured the reliability of the results by considering both the significance level and confidence level of the findings.

8. Results

From the total number of respondents, 50% belonged to the first year of high school (freshmen), while 25% corresponded to the second year (sophomores,) and the remaining to the third year (seniors).

HSS who responded to the survey were instructed to disconnect from all electronic devices for one day and engage in alternative activities such as cooking, yoga, baking, walking, cycling, and exercising, among others. Despite the value of the activity in students' grades and the purpose of the Unplugged Day being clearly communicated to the students, 20% of them refused to participate. Of the 80% who chose to participate in this initiative, 61% did not fully disconnect and only 19% abstained from all electronic devices for one day (Table 2). Additionally, the data show that among the participants, female students (64%) participated in Unplugged Day more than their male counterparts (35%).

Our analysis of high school students (HSS) in a private institution in Mexico revealed an alarming rise in the level of insomnia among those who reported experiencing this problem 'always' or 'frequently' throughout the course of the pandemic. Figure 1 reports insomnia's incidence in high schoolers pre- and intra- COVID-19 outbreak.

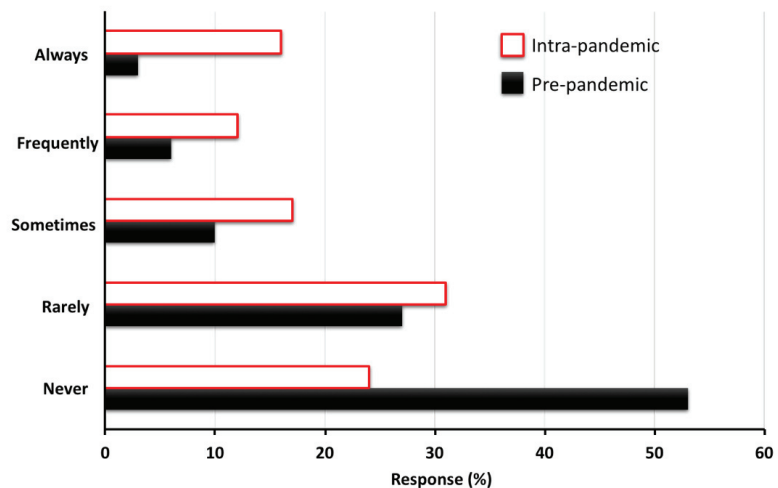


Figure 1. Insomnia incidence reported by Mexican high school students prior to the COVID-19 outbreak and after one year under COVID-19 lockdown (from 1 March to 17 May 2021).

Further study on students' sleep through a chi-squared test revealed a dependency between insomnia and crucial factors, including energy level, tiredness, stress, dominant emotions, and the online component of their education (Table 4). This is of considerable importance, as a number of actions can be designed by not only the students or parents within the household, but also by educational institutions in order to improve the quality and duration of sleep.

Our study found that HSS who participated in the Unplugged Day initiative had higher energy levels and lower levels of stress and tiredness compared to those who did not participate. Thirty-five per cent of non-participants reported low energy levels, while only 27% of participants did. Stress levels were also 7% lower among participants, and they felt more relaxed and less tired compared to non-participants (See Figure 2). This finding is significant since in our past studies [13] we identified stress as one of the most alarming negative emotions that required specific attention from higher education institutions.

Table 4. Statistical test (chi-squared, confidence level 95%, significance level 0.05 *, 0.01 **, or 0.001 ***) for the independence of different variables with insomnia among HSS during COVID-19 lockdown.

Variable	χ^2	<i>p</i>	
Level of energy	330.27	0.0000	***
Tiredness	278.44	0.0000	***
Stress	161.56	0.0000	***
Insomnia before lockdown	535.74	0.0000	***
General dominant emotion	216.12	0.0000	***
Positive/negative emotions with/without the need for professional help	183.69	0.0000	***
School-related emotion	249.08	0.0000	***
Online education experience	128.94	0.0000	***

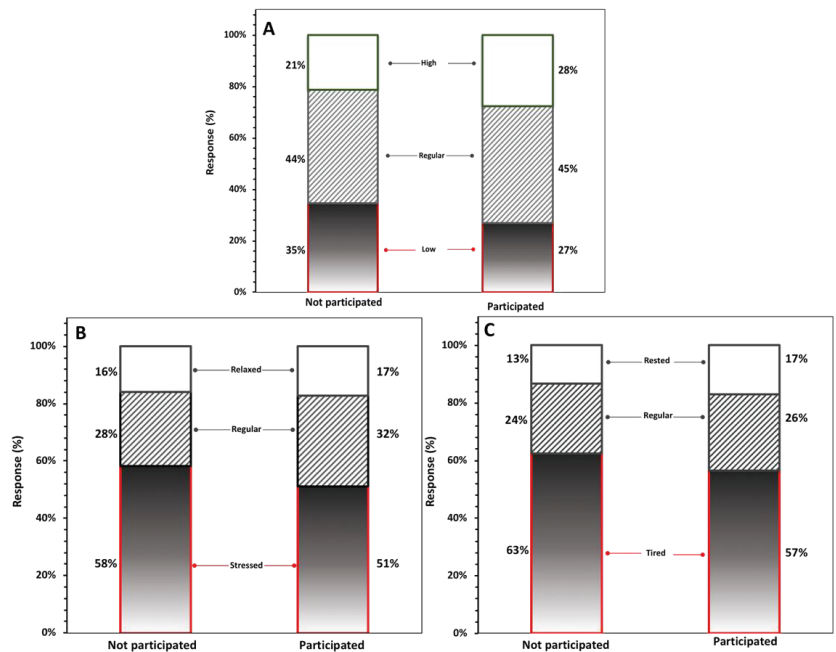


Figure 2. Energy (A), stress (B), and tiredness (C) levels of the high school participants of Unplugged Day versus those who did not take part in this mandatory initiative during online lessons due to COVID-19 lockdown.

High school students (HSS) who participated in the Unplugged Day activity reported more positive general and school-related emotions, as indicated in Figure 3. In comparison to non-participants, a higher percentage of Unplugged Day participants reported feeling “happy” (feliz) and “calm” (tranquilo(a)), while a lower percentage reported feeling “sad” (triste) or “disgusted” (disgustado(a)). Furthermore, a slightly higher percentage of participants reported experiencing “joy” (felicidad), “enthusiasm” (entusiasmo), and “satisfaction” (satisfacción) in relation to their school experience but significantly less “frustration” (frustración) and “boredom” (aburrimiento).



Figure 3. General (A) and school-related (B) emotions of the Unplugged Day participants and those who did not participate in the mandatory initiative during online lessons due to COVID-19 lockdown (1 March to 17 May 2021).

The HSS who participated in the Unplugged Day reported higher levels of satisfaction with their online education than those who did not participate. Both groups were generally satisfied with their education, but the satisfaction levels were more skewed towards the satisfactory side for those who participated in the Unplugged Day, as shown in Figure 4.

Participants in the Unplugged Day initiative reported a lower need for professional assistance in managing negative emotions, as shown in Table 5. This is consistent with the results in Figure 3, which indicate that participants in the Unplugged Day felt calm and content while non-participants reported feeling displeased or even sad. This finding highlights the potential benefits of the Unplugged Day initiative in promoting mental health and well-being among students.

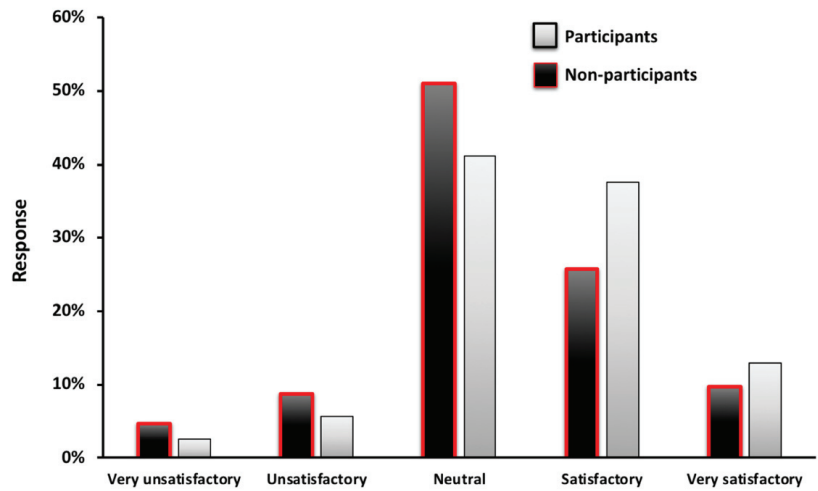


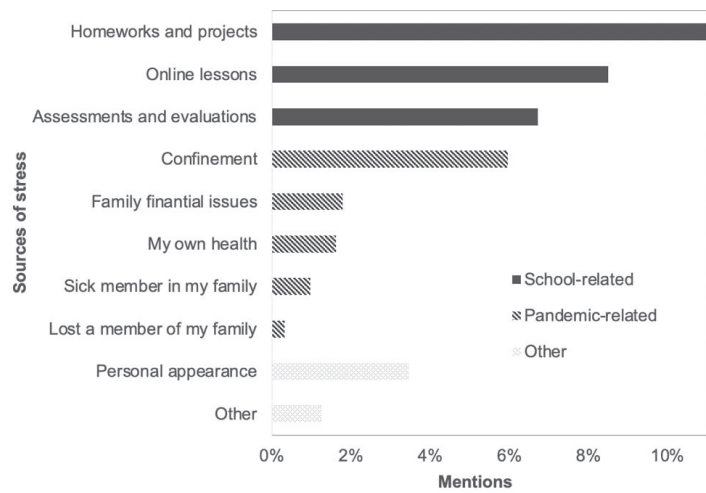
Figure 4. Percentage of Unplugged Day participants (N = 1477) and non-participants (N = 368) according to their satisfaction with online lessons during COVID-19 lockdown (1 March to 17 May 2021).

Table 5. The positive and/or negative emotions of the HSS during COVID-19 lockdown.

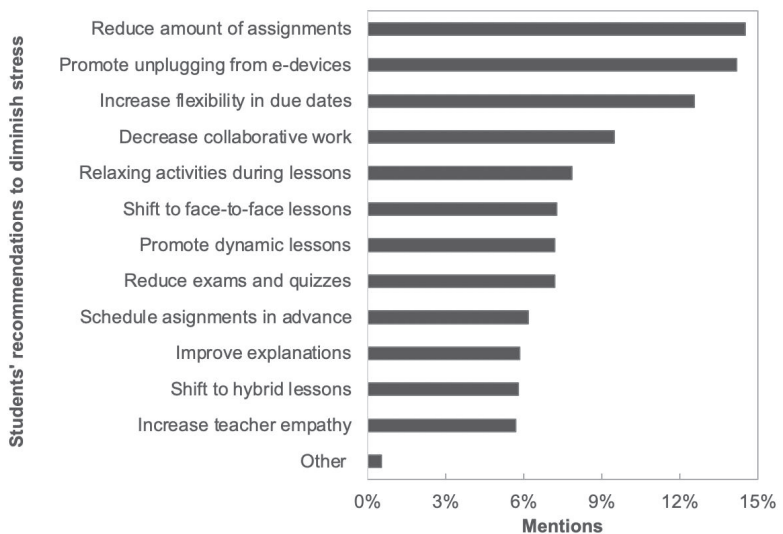
	Non-Unplugged Day Participants	Unplugged Day Participants
Positive emotions	184 (50%)	945 (64%)
No professional help needed to deal with negative emotions	158 (43%)	455 (31%)
Professional help needed to deal with negative emotions	26 (7%)	77 (5%)

Statistical analysis of our results confirms that participation in Unplugged Day is not independent of several descriptors of students' mental health and well-being. Table 6 reports the chi-squared test (confidence level 95%) for the participation in the Unplugged Day and different variables analyzed in this study. The most frequent emotion, psychological help needed, perception of online education, level of energy, tiredness, academic emotion, insomnia during lockdown, anxiety and stress for HSS are not independent from their participation in Unplugged Day. This dependency is also true for gender; female students have committed themselves to the Unplugged Day at a far more significant level than their male counterparts. Concerning the academic year, and therefore the age, the test is not conclusive on whether they depend on each other. Further research is needed to verify its validity for other adolescents, e.g., first-year undergraduates.

Regarding the stressors during the COVID-19 lockdown (Q2.1), high school students (HSS) reported being more stressed by school-related situations than by pandemic-related situations. The results shown in Figure 5A indicate 6% of the HSS identified the confinement as a source of stress; however, almost twice of them mentioned school-related sources of stress. This observation demands the action of educational institutions, since school added stress to the one caused by the emergency itself.



(A)



(B)

Figure 5. The main stressors of high school students during the COVID-19 lockdown (A) and their suggestions to reduce their stress level (B). During forced online distance education, the top two suggestions refer to diminishing the use of electronic devices.

HSS have identified reducing screen time and decreasing the number of assignments as the top recommendations to alleviate stress during emergency education. To co-create an optimal learning environment for students, we asked for their input on what considerations would make emergency education less stressful (Q2.2). While most of their suggestions can be applied regardless of whether it is an emergency, only two of them, moving to in-person and hybrid modalities, are related to lockdowns. Figure 5B summarizes their responses, showing that the top two recommendations are fewer assignments and more opportunities to unplug. Both indirectly and directly suggest moderation in the use of electronic devices. These results are important and can guide educational institutions in

implementing initiatives that promote the mental health and well-being of adolescents both during and outside of emergency education.

Table 6. Statistical test (chi-squared, confidence level 95%, significance levels of 0.05 *, 0.01 **, or 0.001 ***) for independence of variables and participation in the Unplugged Day (partially/totally/no participation).

Variable	χ^2	<i>p</i>		Dependency on Participation in Unplugged Day
Most frequent emotion	53.14	0.0000	***	Not independent
Psychological help needed	31.74	0.0000	***	Not independent
Perception of online education	36.98	0.0000	***	Not independent
Gender	18.20	0.0001	***	Not independent
Level of energy	28.79	0.0003	***	Not independent
Tiredness	28.56	0.0004	***	Not independent
Academic emotion	42.19	0.0010	**	Not independent
Insomnia during lockdown	23.47	0.0028	**	Not independent
Anxiety	10.45	0.0107	*	Not independent
Stress	16.89	0.0132	*	Not independent
Academic Year	5.77	0.2166		Inconclusive

9. Discussion

The COVID-19 pandemic has brought attention to the need for preparedness and response to future emergencies. A variety of potential future emergencies that humans may face have been identified, including natural disasters such as earthquakes, volcanic eruptions, hurricanes, tornadoes, and tsunamis, as well as extreme weather events resulting from climate change, such as severe floods, droughts, and storms. Additionally, the emergence and rapid spread of other infectious diseases across the globe is a potential concern. There is also a risk of technological disasters, including accidents or malfunctions in critical infrastructure systems, such as power grids, chemical plants, transportation systems, and financial systems. Furthermore, food and water scarcity may be exacerbated by overpopulation, political instability, and civil unrest, and armed conflicts may lead to humanitarian crises. Preparing for and addressing these potential future emergencies is crucial for mitigating their negative impact on individuals, communities, and society as a whole [81].

The following discussion focuses on the impacts of Unplugged Day as a dedicated mental health and well-being intervention on the emotional experiences and overall well-being of adolescents in full-time online education due to emergencies.

10. Insights on Adolescent Sleep during Quarantine and Implications for Future Crises Management

In agreement with the obtained results from Italy and United States, our study demonstrated an increase in the level of insomnia among the evaluated HSS during COVID-19 quarantine (Figure 1). Adolescents, during their high school years, naturally undergo psychosocial and biological changes that may disturb their sleep [47]. From the biological perspective, changes in the sleep/wake schedule, sleep phase delay, decreased sleep duration, and later endogenous circadian system are associated with adolescence [47,50]. Moreover, the desire to remain active and participate in multitude of experiences in their lives often leads to sacrificing sleep hours to socialize [82], stay connected to social media [46,83,84], or meet academic demands [85,86]. The COVID-19 outbreak, in nature, was a stressful event that imposed elevated levels of daytime stress, anxiety, and depression and contributed to sleep disruption as a natural byproduct [87]. Light exposure during the day plays a significant role in the nighttime melatonin hormone release to induce sleepiness [87]. Social distancing provoked the reduction in exposure to sunlight which

triggered an inconsistent sleep routine [88]. Using the bedroom as a workplace environment was another consequence of emergency remote learning and a threat to good quality sleep. These factors negatively impacted bedtime and sleeping behavior [87]. Confinement also exacerbated the use of technological devices at bedtime and promoted low activity levels, thus negatively affecting sleep, shortening the sleep duration, and lowering the sleep quality of the individual [87,89,90].

HSS who participated in Unplugged Day reported less frequency of insomnia. Interestingly, 16% of those who did not attend the Unplugged Day and remained attached to their devices stated that they slept well (reporting 'never' for insomnia throughout the night) compared to 11% who responded to the call positively and mentioned the same. This did not come as a surprise to us. In 2013, the term 'fear of missing out' (FoMO) was characterized as a "pervasive apprehension that others might be having rewarding experiences from which one is absent" [91]. In short, FoMO, a rapidly spreading term among the population, stands for 'fear of missing out' on experiences that others may have [92,93]. Digital dependency is a serious phenomenon to which the literature points out with several supporting studies; one of these studies indicates that college students faced significantly higher anxiety levels as time went by without having access to their smartphones [94]. Another study asked undergraduate students to leave their mobile phones unattended while performing a cognitive task; participants' heart rate and blood pressure increased as they heard their mobile phones' notification tones [95]. While online education offers its share of stress, using electronic devices as a means for effort recovery can account for an effective communication method to remain connected to the academic and social environments [46,73,78]. The FoMO, in essence, is selecting an option or activity at the expense of others, usually promoting the use of social networks for problematic behavior [74,93]. Therefore, we speculate that those who refused to join the Unplugged Day were victims of anxiety, fatigue, and FoMO.

11. The Impact of COVID-19 Quarantine and Unplugged Day on Energy Level, Stress, and Tiredness

The COVID-19 pandemic represented a unique threat that confronted us with unprecedented fragility and the efforts to contain it ushered in imminent mental and behavioral challenges [96]. Several countries worldwide adopted quarantine, which refers to strict isolation, as a step to mitigate the spread of COVID-19 [9]. Its purpose was to safeguard physical public health; however, undoubtedly it left an adverse psychological burden on individuals [97,98]. The COVID-19 lockdown obstructed humans' fundamental need for social connection [99]. This lockdown, as any other in case of disaster or crises, elevated loneliness levels and depression [25,57]. Under such circumstances, digital technologies became the greatest allies to bridge social distance, reach out to other fellow human beings, and ensure the continuation of social communication, work, and education [87,96,100]. Internet usage and social media exposure arose during lockdown [46,59]; they are positively correlated to an elevated incidence of mental health challenges as well [46,75,101]. It was the young population of students who faced the greatest difficulties since they excessively use electronic devices while their school duties remained the same if not increased [14]. Ironically, when the digital natives needed a break from the technological environment more than ever, they were demanded to stay connected.

Figure 3 reveals that participation of students in the Unplugged Day activity resulted in a reduced level of stress and tiredness. Our observations are in line with other studies conducted on college and university students during July 2020, which revealed that factors affecting psychological well-being, such as poor sleep, anxiety, and depression, were positively correlated with problematic smartphone and social media usage [75].

Today's adolescents have a tight connection with the internet, as Generation Z has had widespread access to technology throughout their upbringing [102]. While the internet has facilitated learning for individuals across age demographics, problematic internet and social media usage has a profound effect on young students' mental health and lifestyle [103,104].

Excessive use of electronic media and high screen exposure time is associated with adverse effects on sleep [105], tiredness [106], depression [105,107], and anxiety [108]. In addition, short-term consequences of such afflictions are poor academic performance, compromised physical, emotional, cognitive, and psychosocial health, in addition to risk-taking behavior [109,110]. The COVID-19 confinement further led to an overwhelming rise in the use of social media, streaming services, and gaming in adolescents [89,111,112]. Such activities, to a certain degree, served as a coping mechanism to alleviate stress and negative emotions [113]. Despite the short-term beneficial effects that the use of electronic devices provides, the long-term results can be devastating. Gaming addiction, compulsive internet usage, and high social media usage during the COVID-19 outbreak were found to be correlated with increased loneliness, poor sleep quality, and pandemic-related anxiety [89]. Therefore, governments and educational institutions must be aware of the impact of virtual social networking and device-based activities and the psychological complications they may impose on adolescents under confinement in emergencies.

12. The Impact of COVID-19 Quarantine and Unplugged Day on Adolescents' Emotions

The COVID-19 pandemic, as any other potential emergency, constituted a collective continuous traumatic stressor [114]; individuals faced uncertainty and preoccupation about the situation and its duration while experiencing stress and health-related concerns with their frequent and sudden changes in their routines [87]. Particularly, students were extensively exposed to the psychological burden imposed by COVID-19 lockdown [5–7]. The causes include school closures, online classes, and reduced physical activities [70], which resulted in a loss of stimulation and social support provided by their friends and social network, thus missing out on some fundamental necessities for optimal mental health [115]. The unprecedented uncertainty and stress [116], in addition to the unforeseen circumstances, bestowed them with anger [13], anxiety [2,3,6,7,13,78,115,117], boredom [13], depression [2,3,6,7,13,115], fear [5], frustration [13], sleep disorders [48,50,78], stress [2,3,6,13,78], tiredness [13], and overall poor mental health [115]. Research demonstrates a correlation between the isolation policy and the emergence or exacerbation of more severe psychological symptoms, such as obsessive-compulsive disorder, hypochondria, neurasthenia, and post-traumatic stress syndrome [5,96]. Our findings indicate that one out of six HSS who experienced negative emotions expressed the need for specialized support to manage their negative emotions.

13. The Urgent Need to Address Student Stress in the Online Learning Environments

According to our survey, students identified homework, assignments, grades, confinement, and the very nature of virtual classes as significant sources of stress. The effectiveness of web-based learning is known to be highly related to the user's degree of acceptance [118]. For that reason, it was expected that the students who were suddenly forced to switch from in-person to remote lessons would experience decreased motivation, self-efficacy, and cognitive engagement [59]. Students perceived the online learning environment as a major challenge that caused low study efficiency and negatively impacted their emotional well-being [7,59,78]. A study conducted on 358 students on 15 September 2020, revealed that online education was also causing stress and affecting the students' sleep due to excessive screen time (74.6%) [78]. Stress and sleep disturbances were proven to be associated with poor academic performance [31,119], thus leading to additional stress. Research suggests that academic workload also had a negative effect on students' health [62], which was alarming given the trend among educators to increase homework and assignments within the study-at-home learning scheme [59,61,62]. This prompted a call for sustained attention from every educational stakeholder to take these observations into careful consideration during decision making and to implement new practices that eliminate or minimize such stressors.

14. Strategies for Safeguarding the Mental Well-Being of Young Students

The literature has agreed on the need for intervention of the emotional and psychological ravages caused by crisis and emergencies such as pandemics; it proposed several alternatives to safeguard the mental well-being of young students during this and other emergencies. Chen et al. (2020) suggested a six-step large-scale strategy to address mental health during pandemics that can be extended to other emergencies; it consisted of (1) delivering positive emergency-related information; (2) reducing chances for negative behavior; (3) stress management; (4) improving family relationships; (5) cultivating positive behavioral habits; (6) adjusting academic expectations [5]. Aguilera-Hermida (2020), on the other hand, emphasized the role of educators in bringing aid to their students, promoting a positive attitude, encouraging motivation, supporting students to comprehend the importance of coping approaches, and promoting autonomous self-regulated learning that considered the learning methods and needs of each student [59,120]. A study conducted on 1975 HSS in New Zealand amid the COVID-19 pandemic demonstrated that supportive pedagogies implemented by educators were key to enhancing students' academic progress and well-being [121].

The psychological impact of emergencies, such as pandemics, crises, and war, on young students, cannot be ignored. In the past, it was noted that support for students during these times is crucial for their mental well-being [13]. To address this, it is important to provide validated, adequate, and timely information regarding the emergency [25]; improve communication with students and their parents; provide psychological assistance [25]; implement engaging methods to reduce boredom; and promote positivity and optimism. Moreover, the opinions of students should be taken into consideration in order to refine current strategies and inform future decision-making processes in educational institutions of all levels. This highlights the significance and relevance of addressing the emotional and psychological needs of students during emergencies for the betterment of society.

The results of our study indicate that participation in the Unplugged Day initiative implemented by Tecnológico de Monterrey during online remote education had a significant impact on the mental health and well-being of students. Our statistical analysis confirmed that participation in Unplugged Day was related to several positive aspects including higher energy levels, lower stress and tiredness levels, and more positive emotions compared to those who did not participate. Our study also found that female students participated in the Unplugged Day at a higher rate than male students and that further research is needed to verify the validity of the results for students of different ages. Even more, the top recommendations from students for reducing stress in remote learning were less homework and more unplugging initiatives. These findings emphasize the crucial role of student well-being in the design of educational environments, especially in emergency situations, and suggest incorporating such considerations into online remote education which will become increasingly prevalent in the future.

Modern life poses a significant threat to mental health and well-being, even in normal or secure conditions. Studies have shown that factors including social isolation, job insecurity, and technology overload can contribute to mental health issues such as depression, anxiety, and stress [122]. For example, a study published in the *American Journal of Epidemiology* found that social isolation increases the risk of premature death from all causes, including mental and physical health [123]. Additionally, research has shown that job insecurity is associated with increased mental health problems such as depression and anxiety [124,125]. Furthermore, technology overload, or the excessive use of technology, has been linked to negative effects on mental well-being, such as sleep disorders and decreased ability to focus, as previously discussed.

It is important to note that these negative effects are not limited to individuals in vulnerable or precarious situations but can also affect those in normal or secure conditions. For example, a study stated that the relationship between mental health and income for people living in high-income countries is not clear and has produced somewhat conflicting results [126]. This highlights the need for a comprehensive approach to addressing the

mental health impacts of modern life, including addressing social and economic factors that contribute to mental health problems and promoting healthy coping mechanisms and self-care practices.

Stress, depression, and anxiety are considered public health problems due to their impact on individuals' physical and mental health and on society as a whole [25]. For example, chronic stress can contribute to a variety of health problems, such as heart disease, diabetes, obesity, anxiety disorders, and depression. It can also affect academic and work performance and overall well-being. Therefore, it is important to take measures to address mental health issues and promote healthy lifestyles in order to improve the health and well-being of individuals and society as a whole.

Universities, as leaders of social change, should include policies and actions to promote self-care, health, and well-being among their students and graduates. These actions can include specific courses and programs in the curriculum designed to address the specific needs and challenges of university students and should be easily accessible to all.

15. Limitations and Future Directions

The present investigation into the academic practices of Mexican secondary and tertiary educational institutions aimed to promote the mental health and well-being of students during the COVID-19 lockdown was, to the best of our knowledge, the first of its kind. However, we must acknowledge that a primary limitation of our study was that the sample consisted of only those who voluntarily responded to the survey. This voluntary nature of the study may have introduced bias in the information obtained from students, since mood has been shown to affect the participation and information processing [127,128]. Additionally, the study was performed within a private university, where 54% of the students benefit from scholarships and financial support programs. Hence, this study does not consider the socioeconomic context of the students, despite the known direct link between socioeconomic inequity and poor mental health [129].

This was neither conducted as a longitudinal study nor as an experimental design. We hope that the catastrophic conditions will not be replicated under any circumstances. However, the appropriateness, pertinence, and timing of the research enabled us to gain insights from the COVID-19 pandemic emergency. The results are highly valuable and will assist us in preparing for and delivering education during quarantine, emergency, or catastrophic circumstances.

It is important to further explore initiatives aimed at promoting mental health and well-being. Self-awareness, which involves recognizing and understanding one's own emotions, thoughts, personality, and health needs, is a critical skill required for many future job prospects. However, as noted by Rasheed, Younas, and Sundus in their study [130], there is a lack of educational and personal strategies for enhancing self-awareness.

With the increased use of technology and online education, it is essential to ensure the mental health of students and enhance self-awareness. The effectiveness of initiatives such as Unplugged Day, which promote disconnection from technology and involvement in physical and reflective activities, should continue to be studied. As online education becomes more prevalent, it is crucial to ensure that mental health and self-awareness are prioritized and addressed not only to meet future job prospects but to ensure the mental health and well-being of future generations.

16. Conclusions

Education plays a crucial role in driving societal change, especially during times of crisis. It is the key to preserving our cultural heritage, overcoming adversity, rebuilding, and improving our future. In response to the COVID-19 pandemic, governments and educational institutions quickly developed and implemented emergency plans to ensure that education could continue even during lockdowns.

Amid COVID-19 lockdown, Tecnológico de Monterrey, a private Mexican university also offering high school programs, transitioned to online remote education and imple-

mented various strategies to support the mental health and well-being of its students. One of these strategies was the “Unplugged Day” initiative, which encouraged students to disconnect from electronic devices once a month and participate in physical, cultural, creative, or reflective activities.

We conducted this research to analyze the perceptions of students on their sleep quality, emotions, sources of stress, and need for professional support from 1 March to 17 May 2021, across 34 campuses nationwide where Unplugged Day was implemented. The analysis included descriptive and inferential statistics on data collected from a voluntary survey applied to 1845 Mexican high school students.

Respondents showed an increased incidence of insomnia, in line with previous research conducted globally. This is a cause for concern for educational institutions, as the study results showed that insomnia is interdependent with important indicators of well-being, including school-related emotions and the online education experience.

The Unplugged Day initiative had a positive impact on the emotional experiences and overall well-being of adolescents enrolled in full-time online education during the COVID-19 crisis. Despite its value in students’ grades, only 19% of students fully participated; 61% partially participated; and 20% did not participate at all. Female students were found to engage more in the Unplugged Day initiative than male students. Students who participated in the Unplugged Day reported higher levels of positive general and school-related emotions, higher levels of satisfaction with online education, and a lower need for professional assistance in managing negative emotions.

The study also found that high school students reported being more stressed by school-related situations than by pandemic-related situations during the COVID-19 lockdown. This highlights the relevant and pertinent actions of Tecnológico de Monterrey addressing mental health and well-being of its community towards avoiding increasing the natural stress caused by the health crisis. The students recommended reducing screen time and the number of assignments as the top ways to alleviate stress during emergency education, suggesting moderation in the use of electronic devices. While most of the recommendations can be applied regardless of the emergency, only two of them, i.e., transitioning to in-person or hybrid modalities, were related specifically to lockdowns.

Despite the limitations of current research and the need for further research, the findings provide valuable insights into education during emergencies and can guide educational institutions in implementing initiatives that promote the mental health and well-being of adolescents both during and outside emergency education. This will help to build a better future for our learners by fostering their self-awareness and developing skills that are increasingly important in future job prospects.

The COVID-19 pandemic has been a catastrophe for humankind, but it has also brought about new gains: healthcare, technology and digitalization, global cooperation and solidarity, and the environment. Educational institutions must not be left behind; they must identify and leverage these gains to provide quality emergency education and enhance future skills in our learners. This will ensure that education keeps playing its role in building a better future for all.

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Article

Exploring the Impact of University Student Engagement on Junior Faculty's Online Teaching Anxiety and Coping Strategies during COVID-19

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Abstract: (1) Background: When online teaching or blended teaching becomes the new normal in college teaching and learning during the pandemic phase, how to cope with teaching anxiety and enhance online student engagement has been frequently discussed among scholars and practitioners. (2) Methods: This qualitative study aims to investigate the impact of online college student engagement on junior faculty's online teaching anxiety in the pandemic era, with an emergent shift to online teaching as a new normal for higher education. The study analyzed the ways junior faculty adapted to enhance online student engagement and cope with anxiety-provoking sources. (3) Results: Online teaching anxiety may occur at the beginning of the semester or during a large amount of assessment and marking and can also occur with student complaints and the inactive online engagement of students. Student engagement is the most challenging pedagogical issue during online teaching, especially social and emotional engagement. (4) Conclusion: This study recommends that peer mentoring and university-level faculty professional development services are effective strategies to reduce junior faculty's teaching anxiety. Pedagogy training and support should provide faculty with hands-on activities with problem-solving toolkits that they can take away to their own teaching.

Keywords: teaching anxiety; online teaching; student engagement; coping strategies

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1. Introduction

When online teaching has become the new normal in higher education during the pandemic, online teaching anxiety is growing among the junior faculty, who are facing more complicated challenges than classroom teaching. Among all the pedagogical difficulties, student engagement is one of the most challenging tasks, which is listed as a university policy and teacher evaluation criteria. Student engagement is identified as an important indicator of the student experience in higher education [1] which requires new initiatives from individual faculty and higher education institutions during the shift to emergency online teaching necessitated by the global pandemic.

This paper begins by presenting scholarly literature about teaching anxiety and online student engagement. After discussing the objectives and research questions, the qualitative approach with semi-structured interviews was discussed in the method section. Next, findings regarding the pattern of teaching anxiety and how student engagement may influence faculty's teaching anxiety were portrayed. Finally, discussions on the meanings and values of the findings and recommendations on the courses of action for faculty members, decision-makers for individual support, and unit-level support were proposed.

2. Literature Review

The literature review section will first present teaching anxiety and its relevance to teacher anxiety, emphasizing the online teaching environment during COVID-19. Then, literature on student engagement, especially online student engagement, was synthesized and presented.

2.1. Teaching Anxiety

Prior to the COVID-19 crisis, teaching had been widely described as an anxiety-inducing profession [2], and the issue of teaching anxiety has been an age-long affair [3]. The concept of anxiety has received much attention in teacher education because of its significant role and undeniable effects on the process of teaching and learning. Anxiety is defined as an emotional and affective state in which a person feels powerless, tense, fearful, and apprehensive [4]. Researchers classified anxiety into two types: trait and state anxiety [5]. Trait anxiety is related to personality, whereas state anxiety is felt at a particular moment as a reaction to a definite situation [4,6]. Teaching anxiety may lead to inappropriate and ineffective teaching behaviors and even affect the instructor's wellness [7]. Gardner and Leak [8] conceptualized teaching anxiety as anxiety experienced about teaching activities that involve the preparation and execution of classroom activities.

Due to the outbreak of the COVID-19 pandemic, universities and faculty members had to respond quickly to an abrupt shift to online teaching, and the prevalence of anxiety disorders was revealed in primary school teachers, secondary education teachers, and university teachers [9]. Liu and his team [10] reported a persistently higher level of online teaching anxiety among foreign language teachers in China. Pressley et al. [11] surveyed 329 elementary teachers in the fall of 2020 from across the United States, and the teaching anxiety remained unchanged or increased for over half of the sample even when they were able to return to school. Teachers providing all-virtual instruction felt the most anxiety compared to hybrid teaching and all-in-person teaching.

Besides the definition and symptoms of teaching anxiety, the anxiety-provoking factors for teachers have received researchers' attention for a long time [7,12]. The potential challenges and negative feelings experienced in the teaching process can result in teaching anxiety [10]. Teacher anxiety could be attributed to many sources, such as the under-resourced working atmosphere, the inadequate mastery of manipulating modern-technology-driven teaching equipment, a lack of teacher training, and working burnout [8,10,13]. There was no apparent difference in the sources of anxiety between onsite teaching and online teaching [11,14].

Pedagogical issues also strongly influence teacher anxiety, including evaluation and classroom management [15]. Agustiana [16] collected data from 50 Indonesian pre-service teachers on their teaching anxiety. Peer observation, a lack of teaching experience, large-sized classes, and student questions were the major sources of anxiety. For virtual learning settings, including synchronous and asynchronous learning, the issue of student engagement became more demanding than other factors [17].

This study aims to explore the online teaching anxiety of new junior faculty from different schools and departments at one university as the case. Teaching anxiety influences both pre-service teachers and in-service teachers, particularly new teachers with limited experience and knowledge of teaching and learning. Junior faculty in universities, including lecturers and assistant professors, are more likely to experience teaching anxiety based on their teaching expertise. Moreover, most teacher anxiety research is on the subject of perspectives, such as in foreign language and math education. However, there are limited discussions on general faculty professional development, particularly from the lens of junior faculty who had recently started their teaching career in universities with a huge passion for teaching and learning. They are also the primary target for most professional development programs for faculty within higher education institutions. Specific needs analysis on teacher anxiety and discussions on adequate support are beneficial for continuous educator development and staff retention.

2.2. Online Student Engagement

Student engagement has been reported to be crucial to student experience, including student academic achievement, satisfaction, development, and lifelong learning, which are listed as university policies and teacher evaluation criteria in many higher education institutions [18,19]. Although engagement is widely used, the meaning and interpretation

of student engagement vary in different periods and contexts [19–21]. Kuh [22] defined engagement as involvement in learning. Trowler [23] correlated engagement with “the interaction between the time, effort and other relevant resources invested by both students and their institutions intended to optimize the student experience and enhance the learning outcomes and development of students and the performance, and reputation of the institution” [23].

There are a number of factors affecting student engagement, and interaction is a key influencer [18,24]. Interaction enacts students to communicate and construct meaning individually and with others [18]. Research revealed that the learners’ interactions with content, peers, and instructors could improve their online engagement in course learning [18,25]. Student online interaction is classified into three types: student–content interactions, student–student interactions, and student–instructor interactions. Student–content interactions enable students to work on interactive tutorials and simulations. Student–student interactions promote students’ collaborative projects and active participation in discussions. Student–instructor interactions allow students to communicate directly with the instructor synchronously and asynchronously [26].

Teacher beliefs and instructor–student bonds also contribute to student engagement [27]. Aligned with this view is an expectation around staff teaching engagement and the role of instructors as facilitators of conversations [19]. Fleckhammer and Wise [28] stated that “online students . . . need to be able to engage with their learning in an independent style, but it may be that overall academic engagement can be facilitated for this cohort by developing a greater sense of social engagement” [28]. If academics are convinced that they can improve student engagement, the possibility of having teaching initiatives for engagement increases. Self-efficacy can grow when someone experiences success [29]. In addition, Bandura [29] suggests that a pep talk or good feedback could help to enhance self-efficacy. Experience and feedback could be combined using direct coaching [27].

A great deal of literature about online engagement incorporates three key areas of behavioral, emotional, and cognitive engagement because of their impact on students’ attitudes and motivations [1,30]. Nevertheless, Lawson and Lawson [21] suggested that there is a need for a “more nuanced and less formulaic conception of student engagement” [21]. Based on a review of the relevant literature that explores engagement in educational contexts, Redmond and his colleagues [19] developed an online engagement framework for higher education involving five key elements: social engagement, cognitive engagement, behavioral engagement, collaborative engagement, and emotional engagement (see Table 1). Social engagement can be illustrated through actions that build community, such as social forums and developing relationships with peers and instructors [19]. Cognitive engagement is the active process of learning. Fredricks et al. [1] identified cognitive engagement as students engaged in the learning process to “comprehend complex ideas and master difficult skills” [1]. Behavioral engagement refers to academic engagement, learning presence, and self-regulating behaviors [31]. Collaborative engagement involves developing different relationships and networks that support learning, including collaboration with different educational stakeholders. Online learners must collaborate online because of the limitation of geographical distance from peers [19]. Emotional engagement is defined as students’ emotional reaction to learning, including any feelings and attitudes toward learning [19]. Emotional engagement includes “interest, values, and emotions” [1]. This study has used Redmond et al.’s [19] framework as the theoretical framework (see Table 1).

Table 1. Online Engagement Framework for Higher Education [19].

Online Engagement Element	Indicators (Illustrative Only)
Social engagement	Building community Creating a sense of belonging Developing relationships Establishing trust
Cognitive engagement	Thinking critically Activating metacognition Integrating ideas Justifying decisions Developing deep discipline understandings Distributing expertise
Behavioral engagement	Developing academic skills Identifying opportunities and challenges Developing multidisciplinary skills Developing agency Upholding online learning norms Supporting and encouraging peers
Collaborative engagement	Learning with peers Relating to faculty members Connecting to institutional opportunities Developing professional networks
Emotional engagement	Managing expectations Articulating assumptions Recognising motivations Committing to learning

2.3. Research Objectives and Questions

The primary purpose of this study is to investigate the impact of online college student engagement on junior faculty's online teaching anxiety in the pandemic era of emergent online teaching as a new normal for higher education. The study will also analyze the ways junior faculty adapted to enhance online student engagement and cope with anxiety-provoking sources, aiming to discuss the implications of effective practices in enhancing online student engagement and how such anxiety could be alleviated with the efforts of individual faculty members, departments, and universities.

This study is guided by the following three research questions:

1. What are the university junior faculty's perceptions of online teaching anxiety during COVID-19?
2. How does university student engagement influence junior faculty's online teaching anxiety during COVID-19?
3. What coping strategies do junior faculty members take to enhance online student engagement and alleviate online teaching anxiety?

3. Method

3.1. Data Source

The data were collected from Sunshine University (pseudonym) in Southern China. Sunshine University is a transnational university that uses English as the medium of instruction (EMI) and embraces diversity and internationalization. Sunshine University employed online and onsite blended teaching and learning in the current academic year when the authors conducted this study as a response to the COVID-19 pandemic situation as the new normal. Sunshine University emphasizes teaching innovation and student engagement and launched a guideline on fostering student engagement in learning in the current academic year.

3.2. Samples

Purposive sampling, specifically homogeneous sampling, was used in this study when confirming the number of participants. Purposive sampling is a nonrandom technique that researchers will set out what experiences and knowledge of potential participants can contribute to what needs to be known in the study [32]. Bernard [32] also emphasized that the participants' capacity and willingness to share and communicate their knowledge and experience accurately and deliberately is essential for a study using purposive sampling. Homogeneous sampling "focus on candidates who share similar traits and characteristics" and "precise similarity and how it relates to the topic being researched" [33].

We understand the argument on the disadvantage of purposive sampling caused by relying on the researcher's judgmental subjectiveness. The argument about purposive sampling be that "not a good defense when it comes to alleviating possible researcher biases, especially when compared with probability sampling techniques that are designed to reduce such biases" [34]. However, the researcher's judgmental subjectiveness may become a major concern when the selection criteria are unclear [34].

After clarifying and agreeing on the definition of "junior faculty" in this study, the authors discussed the criteria for inviting interviewees as samples. First, participants should either be assistant professors or lecturers. Second, participants should come from different majors. Third, participants should teach courses online in the past academic year due to COVID prevention at Sunshine University. Eight junior faculty from different majors who taught courses online at Sunshine University were initially identified.

We emphasized data saturation when evaluating the number of interviews needed for our qualitative study using purposive sampling. According to Burmeister and Aitken [35], data saturation is more about the depth of the data instead of the numbers or the thickness of the data. Bernard [36] claimed that the number of interviews needed for a qualitative study to reach data saturation was a number he could not quantify. "If one has reached the point of no new data, one has also most likely reached the point of no new themes; therefore, one has reached data saturation" [37]. Therefore, we analyzed the data throughout our study and stopped engaging more participants whom we initially identified when no new information about our research questions was forthcoming. Finally, we ended up with five participants. Please see Table 2 for a detailed sample description.

Table 2. Descriptions of Interviewees.

Participant	Gender	Overall Length of Teaching Experience	Length of Teaching at this University	Discipline	Academic Rank
A	Male	1 year	1 year	Electronic Engineering	Lecturer
B	Female	1 year	1 year	Math	Lecturer
C	Female	2 years	2 years	Film	Lecturer
D	Female	3 years	2 years	Linguistics	Lecturer
E	Female	6 years	0.5 year	Architecture	Assistant Professor

3.3. Measures

This study employs a qualitative approach with one-on-one semi-structured interviews, which allows researchers to have an in-depth understanding of participants' experiences and perceptions [38]. Our interview questions were composed of three themes: (1) faculty's perceptions of online teaching experiences and their anxiety, if any, in the past academic year; (2) faculty's perceptions of online student engagement and faculty's thoughts on the impact of online student engagement on their teaching anxiety and their employed strategies in enhancing online student engagement; (3) faculty's strategies for coping with teaching anxiety and expecting support from the department and the univer-

sity. The interview questions were pilot-tested before using for formal interviews. Detailed interview questions for the semi-structured interviews can be found in Appendix A.

3.4. Data Collection

The semi-structured one-on-one interviews took place online via video conferencing. Each interview lasts between 40–60 min. The participant information sheet, consent form, and guiding interview questions were given to the interviewees beforehand. The interviews were recorded and transcribed into text scripts. The interview language was chosen based on the language the interviewees felt comfortable with (Chinese or English).

3.5. Analyses

Thematic analysis was used to tease out common themes of the responses. The authors conducted thematic analysis in six steps: (1) becoming familiar with the transcripts, (2) coding, (3) generating initial common themes, (4) reviewing initial themes as a research team, (5) defining and labeling common themes, (6) writing up findings. To ensure the validity and trustworthiness of the study, we applied member checks to ensure the transcripts and the interpretations of interviewees' perceptions were accurate. We often discussed the themes and coding generated from the transcripts and adjusted our codes at different levels when needed. To answer the first research question, in addition to presenting the thematic analysis results in the findings section, the authors also described the change in teaching anxiety over time in one academic year and self-reported anxiety.

4. Results

Based on the interviews, all participants had experienced teaching anxiety in at least one online academic semester, with different anxiety levels, developments in online teaching anxiety during the semester, influential factors of online teaching anxiety, and coping strategies to alleviate the anxiety.

Starting the New Semester with Anxiety. Four out of the five participants had high teaching anxiety at the beginning of the online semester. Based on their self-reported data in the interviews, participant C expressed the strongest anxiety with her words "very anxious", and participant B had the mildest anxiety by reporting "not very worrisome". When the online semester started, the anxiety levels of participants A, C, D, and E had obviously decreased, with some differences in duration and range. Participant A was not anxious and felt comfortable about teaching after two weeks of online teaching. Participant C took the first half of the semester, mostly seven weeks, to adapt to the online teaching with an "acceptable anxiety level" in her words. Participant D decreased her anxiety in one month and ascribed such change to "the familiarity of the online teaching platform and the university pedagogical culture". Participant E experienced a sharp decrease in the first week of online teaching, and some slower drops continued until reaching the bottom of her anxiety in the first month of her online semester. Participants C and E described that their anxiety toward online teaching reached a peak one day before the first online lessons.

Increased Anxiety during the Assessment Period. Participants A, B, and D claimed their anxiety levels increased during the assessment. Participant A was very concerned about students' academic performances, which were regarded as an essential element in his self-evaluation of online teaching quality. The subject difference might be the reason due to the assessment design. From the perspective of content knowledge, both participants A and B mentioned that formulas in engineering and science majors were difficult for students to understand and use. Participant B thought her course was more difficult for online learning because principles were easy to understand through lab experiments; however, the assessment format was another reason for her rising anxiety level. Participants A, B, and D had more summative assessments, such as multiple-choice questions and open-ended questions in written tests while the other two participants evaluated students more on a formative basis. For example, participant C claimed her classes and assessments were project-based. Students worked on projects on filming and editing. Participants A, B, and D

evaluated students on their individual performances, while participants C and E provided more chances for group projects and assessments.

Increased Anxiety Toward Various Student Interactions. All of the participants reported that their anxiety status was directly related to students' interaction, including students' feedback, complaints, and online learning engagement. All of the participants expressed that they took every student's comment and feedback seriously. Participant B said she felt very anxious when students reported learning difficulties and inactive participation in the course. She was surprised and sad when students complained to her that some learning content was hard in the middle of the semester. According to participant C, she encouraged students to share their feelings about course learning and university studies, which was very helpful in knowing and therefore meeting students' needs, particularly during a difficult time of online learning. However, she also pointed out that the "side effect" was that students' negative feelings toward online education could be contagious, distracting her attention from course-based thinking to general online education during COVID-19. The anxiety increased based on her feeling of powerlessness and doubts about the online university education.

4.1. Student Engagement as the Most Challenging Pedagogical Issue during Online Teaching

All five participants claimed that student engagement was crucial to their online teaching anxiety, as they all used student engagement as the key indicator of student learning and teaching quality. Class attendance, in-class participation, learning commitment, student motivation, student interaction, and learning with peers are illustrators of online student engagement as behavioral engagement, emotional engagement, social engagement, and collaborative engagement. Cognitive engagement was not mentioned at all by the participants.

Based on the interviews, social engagement was the most concerning element of online student engagement by all five participants. Participant A believed social engagement, such as "interaction and good relationships between students and faculty", was the most crucial element of online engagement. Participant B expressed her expectation of having more "in-class and synchronous student-student interaction and student-instructor interaction because it is more direct for faculty to know students' learning difficulties and needs based on such online engagement". Participant C claimed social engagement is the most essential element of her students' online engagement, as her course was project-based, and students needed to "build up a community and trust from the classmates for the smoother group and individual projects". Participant D, who had six years teaching experience in higher education, said that "student interactions with classmates and instructors in class time could represent their status of involvement in learning especially online learning". Participant E believed "student-instructor relationship is the key to all online engagement elements".

Emotional engagement was another element of online student engagement mentioned by all five instructors. "Learning commitment" and "student motivation" were key indicators. Students were reported as "less motivated" and "indifferent" to their studies during the online learning semesters. Participant D said, "I feel anxious about students' negative feelings of learning such as no learning commitment and would try my best to motivate them by sharing my learning stories and fun cases in architecture". Participant D believed student motivation, especially "intrinsic motivation," was the core of learning after their university studies. She also said, "it is the instructor's responsibility to ignite students' learning passions and ideas of knowing what to learn".

Behavioral engagement was not recognized by the five participants as an effective element of online student engagement; however, all of the instructors talked about attendance, which was coded as an indicator of behavioral engagement in the first place. Two out of the five instructors, participants B and E, with a lower attendance rate, used attendance to evaluate student engagement. Participant B said, "the synchronous learning of attending the online seminar was more efficient than asynchronous learning such as watching a recording because they could raise any concerns while working with me for the formula

derivation". To improve students' attendance rate, participants B and E reminded students every week by emails and some messaging applications. Participant E also described how she fostered students' behavioral engagement by using strategies for social engagement like "creating a closer and friendly student-instructor relationship to motivate students to join the classes". Her strategies for increasing student online class attendance include "not asking all students to turn on their cameras because they may feel anxious in front of the camera" and "chatting with students on social media platforms frequently to know students' feelings at the first time".

Although participants A, C, and D had good student attendance records in their first online teaching semester, they thought attendance, which usually represents students' behavioral engagement, could be faked in online lessons. Participant A said, "when students have online classes, attendance cannot explain student engagement. With their cameras off, you don't know whether students are listening".

The collaborative engagement was only discussed by three participants, A, C, D, and they wanted their students to engage in course learning by "having more possibilities of peer learning" and "getting support and ideas from classmates and peers". Participant C pointed out that "students majoring in filming should seize the chance of building their professional network from a very early stage" and "their universities classmates and teachers are their first human resources in the film-related industries".

4.2. Efforts and Expectations of the Coping Strategy

Reflections were mentioned by all of the participants as individual strategies. Three participants were aware of their reflective procedures and had taken actions to solve pedagogical issues.

Participants B and E reported the effectiveness of mentorship and peer talk provided at the department level. In contrast, another two participants expressed their expectations of having one-on-one support from experienced faculty in the same department. All five participants mentioned the university-level faculty professional development service as a strategy to reduce junior faculty's teaching anxiety. They had participated in at least one supporting service, such as the new faculty orientation, a postgraduate certificate program in teaching and supporting learning in higher education, continuous professional development workshops, and pedagogies-related communities of practice.

5. Discussions and Recommendations

5.1. The Moment When Teaching Anxiety Mostly Occurs

This study explored the results from a qualitative view of investigating the moment and influential factors of junior faculty's online teaching anxiety. Previous studies indicate that online teaching anxiety remained unchanged for most elementary school teachers in the United States and persistently high for Chinese teachers teaching foreign languages [10,11]. Differently, moments of online teaching anxiety can be captured based on the descriptive data provided by junior faculty in one academic semester during the online teaching period of COVID-19. The beginning of the first online semester is the moment with the most and highest anxiety based on the five participants' self-reported data. The assessment period and moments involving student interactions are also the moments when junior faculty feel anxious, powerless, and self-doubted.

The under-resourced working environments and pedagogical issues are the main resources of teacher anxiety, which are consistent with findings of other studies [8,13,39]. Being new to university teaching and unfamiliar with the technology-based online teaching platform amplifies the junior instructors' initial fear of online teaching. Positive feelings such as confidence and self-efficacy dominate junior faculty's psychological status when online teaching starts, and the teacher anxiety decreases to the bottom with individual differences in the time and amount. Once the teaching starts, the junior faculty's attention has been shifted from the general teaching environment to students and lessons. The pedagogical issues become the primary focus, and instructors are devoted to their sat-

isfying teaching based on their teacher beliefs. Student engagement is regarded as the most challenging and widely discussed issue in online pedagogy. Teacher reflection and actions are taken with high frequency and on a task basis to foster student engagement in online classes.

5.2. *The Impact of Faculty Beliefs of Student Engagement on Teaching Anxiety*

According to Redmond et al. [19], online student engagement can be categorized into five elements: behavioral, emotional, cognitive, social, and collaborative. The instructors in this study have different perceptions and priorities of online student engagement, which is consistent with previous studies. Research has demonstrated that teachers describe student engagement in different ways and prioritize pedagogies supporting different engagement elements [40,41]. This is important because teachers may need to focus on improving specific dimensions of engagement to support student outcomes and success [42]. A teacher's level of experience and the demographic of the students in a school may also influence how teachers prioritize pedagogies that support student engagement [30].

While Bowen [43] stated that cognitive engagement is the most fundamental form of engagement, social engagement and emotional engagement are reported to be the most influential element of online student engagement by the five instructors. Among all the key illustrators of social engagement in Redmond et al.'s framework [19], students' in-class participation and active interaction are major indicators. While both student–faculty and student–student interactions are highly valued by junior faculty, self-learning, which normally features student–content interaction, received little attention in this study. Although both asynchronous and synchronous teaching can foster student interaction and engagement online [26], junior academics prioritize synchronous lessons and live participation as more effective and controllable for university students' learning. Cleveland-Innes and Campbell [44] indicated that “emotion is identified as important to student adjustment to the role of the online learner” [44]. Junior instructors were aware of encouraging and supporting students' online emotional engagement through various effective learning activities, such as gamified surveys, project-based learning tasks, and fun case studies. Students' emotional status, including their commitment to learning and self-recognized motivation, positively correlates with instructors' online teaching anxiety.

5.3. *Activating Lesson-Based and Semester-Long Teacher Reflection for Instructors*

Effective teacher reflection across the first online teaching semester allows junior academics to continually think about their online teaching and then modify actions accordingly. This ongoing process taken by instructors is consistent with what Schön [45] conceptualizes as a reflection in action. As Howard [46] stated, the very nature of teaching is to revisit curriculum, pedagogy, and assessment. Junior faculty should be aware of such nature by attending the tailored teacher inductions and training, encouraging academics to improve their reflective practice continuously.

5.4. *Reinforcing Mentor-Mentee Nexus within the Department*

Compared with the high teacher anxiety of most of the participants, one instructor reported low anxiety at the beginning of the semester due to the prompt support from her Shifu, who had provided one-on-one mentoring before and after her first online lesson. Mentorship is widely used in primary and secondary education for novice teacher development, while some higher education institutions foster peer support between novice and experienced teachers by encouraging mentoring programs. More and more universities have established the “buddy system” or “mentor system” among senior faculty members and junior faculty members and between new faculty and returning faculty.

All interviewees' identity as the junior faculty may also be relevant to their online teaching anxiety. They may be under the pressure of performance evaluation and academic promotion. Their online teaching anxiety might come from being perceived as underperformed by their line manager or receiving poor course evaluations from students due to

inactive online student engagement. Therefore, the buddy system or the mentor system in the department may allow senior faculty members to help junior faculty members establish confidence in teaching by sharing effective practices.

5.5. *Creating Task-Based University Program*

Although Sunshine University has provided credit-based in-service training programs, participants expect to have more task-based training programs targeting specific pedagogical issues or stages of teaching. For example, student engagement is a popular teacher training topic, which could be specified into behavioral, social, cognitive, collaborative, and emotional elements. Teaching strategies and recommendations should be different, considering the unique features of each element. Workshops on learning theories and general pedagogies are less efficient than a hands-on activity of problem-solving. Besides the taught training programs, instructors can benefit from peer learning at the university level. Community of practice and teaching showcase events themed on specific teaching challenges have many potentials.

5.6. *Limitations and Future Studies*

Although this study has promising and inspiring findings, there are two limitations that the readers should be aware of. First, our interview questions asked participants to describe their teaching anxiety. Participants used the words “strong,” “high,” or “low” to describe their self-perceived anxiety and changes in teaching anxiety over time. Our focus was to illustrate the changes in teaching anxiety over the academic year that were associated with key moments rather than compare the anxiety level of participants with each other. Future studies could utilize an existing instrument or develop a new instrument to measure faculty’s online teaching anxiety with a quantitative approach and compare individuals’ anxiety levels with each other across discipline and teaching experiences. Second, due to the pandemic prevention, all of the interviews were conducted online instead of in person. If we were to have an opportunity for in-person interviews, the authors could be more observant of the interviewees’ facial expressions and body language.

Building on this study, we will expand our study by furthering the qualitative approaches with a larger faculty sample size. In addition, a quantitative approach may also be added to the existing qualitative study in a mixed-method study in the future. First, a quantitative approach can be employed to measure online student engagement, specifically, social engagement, cognitive engagement, behavioral engagement, collaborative engagement, and emotional engagement. Under these five dimensions, we will also focus on online student engagement with the curriculum, instructors, and peers. Second, the teaching anxiety level is related to the extent of student engagement in the above five dimensions with the anxiety level using the quantitative approach. This method will allow authors to confirm the findings about student engagement and online teaching anxiety. Third, future studies may create a predictive module with various factors that may influence junior faculty’s online teaching anxiety.

6. **Conclusions**

As online-onsite blended teaching and learning become the new normal in higher education globally in the pandemic era, faculties are constantly observing and reflecting on their own approaches and experiences in online teaching and seeking strategies to cope with online teaching anxiety. Online teaching anxiety may occur at the beginning of the semester or during a large amount of assessment and marking and can also occur with student complaints and inactive online engagement of students. Student engagement is the most challenging pedagogical issue during online teaching, especially social and emotional engagement. It is recommended that universities and departments should encourage peer mentoring among faculties members for peer support and come up with strategies and resources to leverage online student engagement. Finally, the pedagogy training and

support should provide faculty with hands-on activities of problem-solving toolkits that they can take away to their own teaching.

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Data Availability Statement: Not applicable.

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Appendix A

Semi-structured Interview Questions

1. What would you describe your feelings and experiences of online teaching in the past Spring semester in AY2021-22?
2. Have you ever had online teaching anxiety during Spring 2022? In terms of online teaching anxiety, I meant negative feelings such as fear, apprehension, and doubts about online teaching, particularly on learning activities, students online learning performance, and therefore your teaching skills.
3. What is the root cause of your online teaching anxiety?
4. What would you rate the engagement of your students while teaching and learning online?
5. Did online student engagement level influence your teaching anxiety (e.g., low attendance or inactive engagement in online classes)?
6. What strategies have you employed to engage students during online teaching?
7. Have you experienced any difficulties or problems in engaging students in the first month of online teaching? If so, would you please elaborate it?
8. What have you done to solve those (in Question 7) difficulties or problems? Were there any supports from your unit and the University?
9. How do you evaluate your solutions to solve those difficulties or problems?
10. What are your expectations of online teaching professional development from individuals, departments, and the University?

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Article

Using Interactive Online Pedagogical Approaches to Promote Student Engagement

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Abstract: The COVID-19 outbreak in late 2019 required a complete shift to online learning across all educational institutions, including universities. The rapid transition to online learning globally meant that many educators were suddenly tasked with adapting their classroom-based pedagogy to the online space. While this was undoubtedly challenging for teachers and students, it also opened up possibilities for reimagining the delivery of content, along with creating increased access for students who had barriers for studying remotely before the impact of COVID-19. The study discussed in this paper examines the experiences of students studying at a regional Australian university that already offered online courses, and whose instructors were already using a diverse range of online delivery tools. Specifically, the study sought to investigate how instructors used interactive strategies to promote student engagement, and how the interaction between learner and content influences student engagement. With research showing that online students typically have higher attrition rates than their on-campus counterparts, engagement has been identified as an important factor in online learning. Online interaction in particular is considered to be instrumental in influencing student engagement and positively impacting student satisfaction, persistence, and academic performance. Data collected from interviews conducted with two different cohorts of students, studying two different courses (mathematics education and Chinese language) at the same university, demonstrated ways instructors utilised interactive online pedagogies to engage students with potentially challenging course content. The study has implications for online educators who are looking for ways to adapt their on-campus courses to online delivery, with a focus on engaging and maintaining online students' interest and ongoing participation in their courses.

Keywords: online learning; higher education; engagement; interactive strategies

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1. Introduction

The impact of the COVID-19 situation has led to an increased uptake of online learning by students, both nationally and internationally. As a result, higher education instructors have been tasked with engaging online students, designing online materials, and communicating and interacting with students in mostly asynchronous ways. Universities' teaching staff were required to adapt their courses to online versions to cater to students who could no longer attend on campus. Many continued to offer online courses and/or blended learning models, even when on-campus study resumed (Hamer & Smith, 2021; Martin, 2020) [1,2]. This increased availability of online learning has enabled wider access and participation internationally and nationally in higher education in Australia for a diverse range of students. Issues of engagement, participation, commitment, integrity, and quality, however, continue to be concerns when discussing online learning (Kehrwald & Parker, 2019) [3]. It is often assumed that providing online digital tools for learning will have a positive influence on student engagement, yet student engagement is reflexive and based on individual goals (Kahn et al., 2017) [4]. Online learning offers flexibility and convenience,

giving students the opportunity to balance study with other demands and responsibilities (Stone et al., 2016) [5]. Attrition rates remain a concern for online students. In 2017, for example, Australian online students in the higher education sector had an attrition rate of 29.64%, compared with an on-campus rate of 12.23% (Department of Education, Skills & Employment, 2018) [6]. Research indicates that the convenience offered by online study is diminished by negative factors such as a lack of interaction with tutors and other students, problems with instructional materials, technical problems, and challenges of work, health, and family commitments (Greenland & Moore, 2014; Ilgaz & Gulbahar, 2015) [7,8]. Feelings of alienation, perceived lack of relevance, and the drudgery of study have also been identified by students as impacting on the quality of the online learning experience (Wimpenny & Savin-Baden, 2013) [9]. A strong teacher presence (Stone, 2017) [10] and course design that “engages and connects students with their teacher, other students, and the course material” (Stone, 2017, p. 39) [10] can mitigate some of the negative issues associated with online learning, at least in the Australian context.

Contemporary views about online learning highlight the disconnect between the ‘new’ flexible learning, and the traditional or established approaches to teaching and delivery (Kehrwald & Parker, 2019) [3], such as on-campus one-hour lectures. The increase in online learning has necessitated a shift in teaching approaches, but such shifts require an understanding that on-campus-appropriate teaching pedagogies are not equally effective in the online environment. Historically, without training, instructors are inclined to replicate existing course design and pedagogical practices when they move from face-to-face delivery to blended or online instruction (Bonk & Dennen, 2003) [11], without capitalising on the dynamic nature of a technologically enhanced teaching and learning environment (Redmond, 2011) [12].

Dissatisfaction and concerns about the efficacy of online delivery have also been raised by instructors who may be facing “overwhelming and downright frustrating” technical and pedagogical challenges in designing, developing, and delivering engaging experiences (Stoff & Mozer, 2016, p. 152) [13]. There are also concerns about the quality of online teaching provided, in that, despite the advancements in technology, pedagogy, and practice, there is widespread variability in practice (Kehrwald & Parker, 2019) [3].

It is recognised that the instructor, and in particular, learner–instructor interaction, is a significant predictor of student satisfaction, engagement, and achievement in online learning (Martin et al., 2018) [14], and this has been identified globally during the COVID-19 pandemic (e.g., Roque-Hernández et al., 2021; Alla et al., 2022) [15,16]. In a study that investigated award-winning online teaching practices, expert instructors were characterised as understanding what worked in the online format, having confidence in online teaching, not being limited by technology, and knowing how to adapt materials for an online format (Kumar et al., 2019) [17].

Kehrwald and Parker (2019) [3] recently highlighted the need to utilise evidence-based academic practice to improve online learning, with innovative and progressive features of contemporary university online learning and teaching, such as those documented in case studies. The study discussed in this paper answers that call. It draws upon Moore’s (1993) [18] and Martin and Bolliger’s (2018) [19] subsequent construct of instructional strategies to demonstrate how interactive online pedagogies can be used to promote interaction between learner and learner, learner and instructor, and particularly learner and content. Two case studies were selected to illustrate the impact of the instructor on engaging learners with challenging content material and how this can be achieved in a fully online environment. Specifically, the study sought to address the following research questions:

1. In what ways do two online instructors use interactive pedagogical approaches to engage their student cohorts with learning challenging course content?
2. What are these online students’ perceptions of the impact of these approaches on their learning and engagement?

It is anticipated that documentation of these case studies will be of relevance to course developers and higher education institutions who are looking to improve their online

course offerings, and provide better student support, experiences, and outcomes, which will ultimately lead to an increase in student retention. In addition, online instructors who may be finding the transition to online pedagogy challenging will gain insights into how course content can be creatively adapted to accommodate online delivery and teach core content, while still maintaining student engagement.

2. Literature Review

This section examines the literature related to the role of the instructor in designing and delivering courses that foster student engagement. The design of blended and online courses requires a different pedagogical approach to that for on-campus delivery. Engaging students in a digital world can be challenging, so a number of pedagogical frameworks have been proposed to support effective student engagement in online learning (e.g., Redmond et al. 2018) [20]. Effective online delivery utilises a range of digital tools and approaches, and multimedia has been shown to increase student engagement and learning (e.g., Martin & Bollinger, 2018; Martin et al., 2018) [14,19].

2.1. Instructor Presence

It has been suggested that instructor presence is essential to the success of online courses (Martin et al., 2018) [14]. This has been particularly important during the COVID-19 pandemic, where teacher presence has been found to have a positive impact on student engagement and learning (e.g., Rapanta 2020) [21]. Teacher presence may be perceived differently by educators and students in an online environment (Wang et al., 2021) [22], however, if implemented effectively, teacher presence is perceived by students as highly beneficial to learning (Martin et al., 2018) [14].

Research findings consistently show that instructor presence enhances students' motivation to learn, increases the depth and quality of students' interactions and discussions, and can reduce a sense of loneliness (e.g., Martin et al., 2018) [14]. Instructors and subjects that stimulate interest have a positive effect on engagement (Park & Choi, 2009) [23], with previous research conducted in this area showing that "it is the presence and behaviour of the lecturer, rather than peers, which is key to student engagement online" (Muir et al., 2019, p. 12) [24]. Instructor or teaching presence is theorised to consist of three components: instructional design, facilitation, and direct instruction (Anderson et al., 2001) [25]. Research findings indicate that instructional design, and clearly defined roles of instructors, are critical in facilitating cognitive presence, particularly in online discussions (e.g., Garrison & Cleveland-Innes, 2005; Gasovic et al., 2015; Garrison, 2016) [26–28]. Collaboration is also key to successful instructor presence in both online and blended learning frameworks (Vaughan et al., 2013) [29].

Instructors can utilise facilitation strategies to enhance instructor presence and instructor connection (Martin et al., 2018) [14]. Martin et al. (2018) identified twelve different facilitation strategies that influenced engagement and learning in the online environment [14]. The facilitation strategies were aligned to four dimensions: social, managerial, pedagogical, and technical. These strategies include aspects such as video-based instructor introductions, instructors' presence in discussion forums, interactive visual stimuli, instructors' use of various features in synchronous sessions to interact with students, and instructor-created content in the form of short videos/tutorials.

2.2. Use of Multimedia

Multimedia technology empowers education, providing opportunities for interactions between teachers, student, and content that are flexible and authentic (Almara'beh, et al., 2015) [30], with digital tools often providing simulation opportunities to enhance learning (e.g., Vagg et al., 2020) [31]. Using multimedia in online courses has been shown to have a positive impact on education (e.g., Kostolanský et al., 2019) [32] and increase student engagement and learning (e.g., Martin et al., 2018) [14]. King (2014) [33] found, for example, that mini-videos and screen-casting that make instructors more visible had

pedagogical benefits, and video-based instructor introductions can help form relationships with instructors, resulting in more positive course evaluations (Jones et al., 2008) [34]. Mobile and digital technologies can offer considerable benefits and affordances within learning environments, such as building and supporting creative, collaborative, critical, and communicative capacities (Cobcroft et al., 2006) [35]. Inclusion of media tools or interactive videos (Havice et al., 2010) [36] may stimulate learners' motivation to learn and in turn increase student interaction with course content; however, it has often been observed during the COVID-19 pandemic that instructor unfamiliarity with digital tools may dampen student learning (Chu et al., 2021) [37].

Videos have been recommended as a medium for building social, cognitive, and teaching presence (Di Paulo et al., 2017) [38], with asynchronous video being effectively used to develop students' perceptions of teaching presence and immediacy (Crawford, 2018) [39]. This may be particularly relevant to language learners. Within online engagement literature, research suggests that students' exposure to a web-based learning platform (a virtual world) in the target language helps to reinforce their linguistic, pragmatic, and intercultural development, as they learn to navigate and comprehend the target language and culture through real-world tasks (Grant et al., 2013; Henderson et al., 2012). [40,41] The virtual world can provide opportunities for success in an environment that minimises unhelpful anxiety about foreign language production (Lin et al. 2014) [42]. This kind of learning activity offers particular benefits for beginning learners, who have not yet integrated large numbers of fluent speakers of the target language into their social networks (Pasfield-Neofitou et al., 2016) [43].

Use of multimedia has also been shown to result in more active contributions to discussion boards (Martin et al., 2018) [14]. Discussion boards provide the primary forum for learner–learner and learner–instructor interaction and can be an important tool to foster student engagement (Baldwin & Sabry, 2003) [44]. Although a sense of online instructor presence is essential to enable positive learner–instructor participation (Shea & Bidjerano, 2010; Chen et al., 2019) [45,46], both students and instructors have been critical about the quality of interaction and content in online asynchronous discussion forums (Thomas & Thorpe, 2019; Douglas et al., 2020) [47,48]. While there is little agreement about what constitutes instructor presence in terms of minimum numbers of postings, recommendations include starting major discussion threads, narrowing down topics, and responding promptly to students' posts (Martin et al., 2018) [14].

In summary, the research literature depicts instructor presence as being key to student engagement, with the expectation being that instructors utilise a range of engaging strategies, including the use of multimedia, to facilitate learning. What is less evident from the research is accounts of actual case studies which illustrate and document how instructors utilise these strategies within the context of different discipline areas. The research described in this paper builds on the existing research which highlights the importance of instructor presence through describing accounts of how this is enacted in practice and the impact it had on students' engagement.

3. Theoretical Framework

Moore (1993) [18] identified three types of interaction that foster student engagement: learner–learner, learner–instructor, and learner–content. Other researchers have used this construct to understand how online learners can be assisted to be more active and engaged (e.g., Lear et al., 2010; Martin & Bolliger, 2018) [19,49], and we used this framework as a tool for analysing the data for the study discussed in this paper. Figure 1 shows the types of interactions, based on Moore's (1993) [18] framework and adapted by Martin and Bolliger (2018) [19].

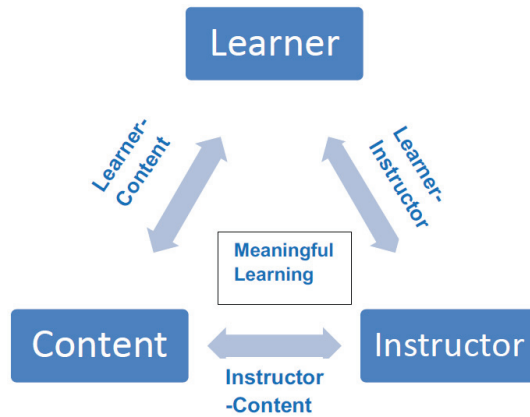


Figure 1. Types of interactions.

Learner–learner interaction refers to the opportunities provided for students to learn from one another through the exchange of resources, discussion, sharing of experiences, and ideas (Bolliger & Martin, 2018) [50]. Learner–learner interaction can be facilitated by strategies such as constructing interactive introduction activities at the beginning of a course, utilising videoconferencing or chat rooms, and using discussion boards. Such activities can assist students with feeling connected and can create a dynamic sense of community (Martin & Bolliger, 2018) [19].

Learner–instructor interaction in the online environment can be enacted through the instructor modelling online behaviours and establishing presence through creating and facilitating online discussions (Bolliger & Martin, 2018) [50]. Rapport and collaboration between students and instructors are important influencers in student engagement (e.g., Martin & Bolliger, 2018; King, 2014) [19,33]. Studies show that students who have a strong connection with their instructors achieve good learning outcomes and are more confident than those who consider their instructors to be less supportive (e.g., Creasey et al., 2009) [51].

Learner–content interaction refers to the way in which students engage with instructional materials and planned activities. Learner–content interaction can occur when students are watching instructional videos, interacting with multimedia, and searching for information (Abrami et al., 2011) [52]. It is recommended that online instructors make the content come alive using appropriate technologies and be critical when choosing material and content (Revere & Kovach, 2011) [53]. Course management system features, and effective communication and course facilitation strategies, have all been shown to engage online students (Dixon, 2010) [54].

To date, there has been a lack of research on learner–content interaction (Bolliger & Martin, 2018; Xiao, 2017) [50,55], with most studies focused on the first two interaction types. Learner–content interaction is crucial for learning in any environment, with Xiao (2017) [55] suggesting that further investigation into how students interact with content is required. The study discussed in this paper addresses this need through its focus on learner–content interaction and how this interaction is facilitated by the instructors in two cases. The cases were selected as they both involve the teaching of challenging course content through the utilisation of facilitation strategies and showcase what innovative pedagogical approaches are possible in completely online environments.

4. Methods

The research reported in this paper was part of a larger cross-disciplinary ethically approved study undertaken by researchers from a regional Australian university who investigated the use of interactive pedagogical designs in online courses. The study was given institutional ethical approval in 2019, with permission to publish results from smaller

elements of the research. This paper focuses on the qualitative data collected from online students enrolled in two units taught by the researchers during 2019. These data were from semi-structured, in-depth interviews with students and instructors undertaken during 2019–2020, as well as anonymous university-solicited student evaluation data (eVALUate comments) submitted to the university teaching and learning administration by students from the researched units at the conclusion of semester instruction. The use of both forms of qualitative data enabled data triangulation, to strengthen the legitimacy of the study findings (Bryman et al., 2008; Flick, 2018) [56,57].

4.1. Interview Data

From a total population of 80 and 60 online students, respectively, 9 students from the first subject (Teaching Primary Mathematics) and 4 students from the second subject (Introduction to Chinese) were interviewed. Interviews were conducted face-to-face, by phone and video call, and lasted between 30 and 45 min. They were digitally recorded, fully transcribed, and member-checked by participants for accuracy. The interview samples were not probability-based (Kohler, 2019) [58]. Participants volunteered to be part of the study, and not every member of the population had a chance of being included. The small sample size of interview participants limited generalization and transferability of the study results. However, it is submitted that the research provides useful insights into pedagogical tools which can support online student engagement.

To ensure that the results were not compromised by the learners' participation in courses taught by the researchers, potential interview participants were identified by the researchers and contacted after completion of the semester by the study Research Assistant. Students who had actively engaged with the pedagogical strategies implemented by the researchers in the focus units were offered the opportunity to discuss their experiences in an interview. This purposive sample (Denieffe, 2020) [59] ensured that participants had experience and first-hand knowledge of the teaching and learning strategies being investigated. Interested students self-selected and participated voluntarily.

4.2. eVALUate Data

In addition to the interview data provided by participants, this study also collected relevant qualitative data from eVALUate comments submitted by students from the two focus subject units. All students enrolled in the units were advised at the start of semester that their anonymous eVALUate comments may be utilised for this research and were afforded an opportunity to refuse such use by directly contacting the study Research Assistant. Instructors did not have access to any student decisions as to the inclusion of their data and were privy only to anonymised comments. No student refused use of their eVALUate data. eVALUate data were received from 25 students (40% response rate) for Teaching Primary Mathematics, and from 21 students (33% response rate) for Introduction to Chinese.

4.3. Data Analysis

Interview transcripts and student eVALUate comments were fully de-identified before analysis and were analysed using a thematic analysis process with constant comparison (Terry et al., 2017) [60]. This approach, which adopts pragmatic abduction (combining both deductive and inductive logic), enabled the researchers to consider the data in light of pre-existing themes identified from the literature, while at the same time being sensitive to new patterns that emerged during the analysis (Earl Rinehart, 2021) [61].

The qualitative data reduction involved the systematic allocation of codes to the data which were subsequently developed into higher-order themes (Elliott, 2018) [62]. Initial codes were assigned to words, phrases, and sentences in the text material that seemed to "stand out" (Bryman et al., 2008, p. 298) [56]. As the data were continually reread and compared, those descriptive topic codes were replaced with more abstract categories (Kennedy, 2016) [63]. The data were then examined to identify the emergent

interconnections and patterns. Corresponding patterns were placed together, and direct quotes were identified from the data to illustrate the categories (Bryman et al., 2008; Genapathy, 2016) [56,64]. The patterns within the data were then examined for overarching themes, operating at a higher level of abstraction again, and data were gathered under those themes (Belotto, 2018) [65]. Throughout the qualitative analysis process, the researchers remained mindful of the research questions for this study which helped to shape their subjective decisions in coding and categorising the data (Vaismoradi et al., 2013) [66].

Initial coding of the qualitative data focussed on the online pedagogical strategies and teaching tools employed in the two instructional units. That was subsequently refined based on the needs reported by students for online learning support, conceptualised as academic, social, and pastoral support domains. The strategies and tools utilised by the unit instructors were further coded in relation to online student support, with additional filtering in relation to such support reflecting engagement through student–teacher, student–student, student–self, and student–learning content interactions.

5. Results

5.1. Case Study 1: Teaching Primary Mathematics

Learning content for the subject ‘Teaching Primary Mathematics’ was presented to students weekly through the university online learning management system. It typically contained a narrated PowerPoint presentation or lecture, required readings, and activities. There was an expectation communicated by the instructor that students would progress through the learning content at their own pace and contribute to the discussion board topics for that week. The following results include excerpts from student interviews that provide insights into the ways the lecturer attempted to engage students with the content, and the impact this had on their learning.

5.1.1. Engaging with Content through Activities

Each week, students were provided with a variety of activities that helped to demonstrate or reinforce mathematical understandings, and skills, related to that week’s topic. For example, in Week 4, students were asked to play ‘Nasty Games’ (a game involving throwing a dice and designating the numbers thrown with the value of ones, tens, or hundreds) with their peers or children to develop an understanding of place value:

“There were certain things that she would have us maybe experiment with the children that we had, so my kids were my guinea pigs. You know, ‘Can you solve this? What do you think about this?’ kind of thing. So, it was, on a personal level, it was simple enough that I could do it on a week to week, I could use my kids as well in it. So, I could learn about how they saw it and how I understood it kind of a thing.”

(Jasmine)

“I really enjoyed the questions [and] weekly activities that the lecturer gave us . . . She really encouraged the whole thinking out of the square, and not just doing formal algorithms, explaining how you would solve a problem. I really enjoyed that because it just proves that there’s not a right way to do a maths problem . . . and reading how the other people solve their problems was really an eye-opener. Every week I jumped on [to the discussion board] to see what other people had done, or how they’d solved the problem to compare it to how I had.”

(Patricia)

A regular feature each week involved the opportunity to ‘Let’s do some maths’, where students worked individually to solve a challenging problem or puzzle, and then posted their response to the discussion board. For example, in Week 3, students were asked to solve the following problem: It takes $3\frac{1}{4}$ hours to ride from Melbourne to Geelong. It takes $\frac{1}{2}$ an hour longer to ride from Melbourne to Werribee than it takes to ride from Werribee to Geelong.

How long does it take to ride from Melbourne to Werribee? Feedback from the students indicated that they enjoyed the opportunity to actually engage in some mathematics:

“I think I really liked the fact that it was not just all the theory stuff, you know, knowing harder teachings, but also she had us do some Maths . . . So, I really liked that. Just that, I don’t know, to me it was like, a bit of fun.”

(Kayla)

“I was really, really happy with the way it was set out in terms of, it wasn’t all reading nor all lectures, and only very, very short lectures, and then there were videos and quizzes, and resources, and it was a lot of different things, which kept it interesting.”

(Lisa)

5.1.2. Engaging with Content through Multimedia

Each week the instructor prepared an overview video which showed her talking to the camera about what to expect and focus on in that week’s topic. Students appreciated the inclusion of the videos, as the following comments illustrate:

“I like the fact that every week, there was an introductory video which was current . . . it made you feel like you were having a conversation with her, and she was talking about things that had actually happened the week before.”

(Kayla)

“I made sure those videos were the first things I watched every week before I did the rest of the content. I thought they were a really good overview, but I think, all over, it could’ve been a bit more focussed on . . . Like, maybe just even a couple of minutes explaining how to approach the maths before we learn how to teach it, if that makes sense . . . But, yes, I did watch those videos.”

(Lisa)

“I thought they were good . . . I like the idea of having an instruction video because it set the tone for the week. Especially . . . some of the content was incredibly new for me. The introduction video was at least a way to comprehend the whole week’s work.”

(Marissa)

In addition, the learning content usually included links to online videos, such as TED talks, or videos produced by the instructor to demonstrate mathematical concepts or skills. For example, one short video showed the instructor playing a game of Tenzi™ to demonstrate probability concepts. Another showed a step-by-step guide to using MAB (multi-based arithmetic blocks) to solve an addition algorithm. In this way, the videos provided an opportunity for online students who could not attend on-campus classes to see modelling of materials or participate in game-playing.

“The videos were good for me because when it comes to math . . . it was not my strength, it really wasn’t my strength growing up . . . I was like, ‘Oh my God. This was something I learned about 100 years ago or something,’ . . . So, the videos really helped. I could go back and I could be like, ‘Oh, is that how they do that?’ . . . So, all these physical equipment that they use, it was good to see what it looks like and how they can manipulate them and things like that, so the videos were the best for me.”

(Jasmine)

“I know sometimes I’ve got to interpret words or activities in my own way. But if she demonstrated it, then you know exactly what she was talking about.”

(Oscar)

5.1.3. Engaging with Content through Discussions

Discussion boards were the primary forum for students to respond to the learning content. Each week, the instructor presented three or four suggested discussion topics and the students could choose to respond to any or all. There was an expectation that students would continue to build on discussion threads that were created, rather than starting new ones. Student feedback showed that, in addition to discussing more general topics, students were also able to use the forum to focus on content-related discussions:

“I had completely forgot how to do fractions, for example. And so, it was really good to read other people’s posts, and I was like ‘Oh right! That’s how you do it. I forgot that rule.’”

(Harry)

“I think that it is important to have that discussion board because sometimes when you have absolutely no idea what that particular topic was about, you can go and you can see what someone else has written and be like, ‘Oh yeah. That makes sense.’”

(Jasmine)

“I like how the lecturer encouraged us to think outside the square. There’s no right way or wrong way to do things, as such. So, I posted weekly with explanations and trying to get the way that I do maths across to the other students because I think that I do it a little bit differently to other people.”

(Patricia)

The following comment, however, demonstrates that perhaps not all students felt comfortable with posting to the discussion boards, and highlights the limitations associated with relying on discussion board contributions:

“Maths does have a right and wrong answer, even though we’re being taught that there’s a number of ways to get to answers . . . We felt a bit stupid. We didn’t want to make mistakes because there were people there that were quite capable . . . Our contributions were sort of making us . . . feel a bit inadequate.”

(Marissa)

5.1.4. Summary of Results for Case Study 1

This case study examined the relationship between the learner and the content through a wide range of interactive strategies in a Teaching Primary Mathematics course. The results show that the instructor used a variety of strategies, such as overview videos and interactive activities, to effectively engage the learner with the content of the course. To engage learners and maintain their engagement, the instructor was cognizant of making the content relevant and interactive, and maintaining a consistent instructor presence throughout the semester, even though online activities were often asynchronous.

5.2. Case Study 2: Introduction to Chinese

As in the first case study, learning content for the subject ‘Introduction to Chinese’ was traditionally outlined in a weekly schedule through the University’s learning management system. The weekly content consisted of a series of short lecture and tutorial videos along with accompanied notes in PDF format, selected digital learning tools, various types of learning activities, discussion areas to share learning experience and resources, and self-reflection on learning for that week. It was anticipated that students would self-pace their learning throughout the semester by engaging with the weekly content in their own time.

Interactions are the central emphasis in language learning (Lin et al., 2017) [67]. The integration of a wide range of interactive strategies, therefore, was a deliberate approach designed to scaffold content structure to make Chinese language learning manageable and successful. A student interviewee commented on this approach:

“I think that having a range of different resources is really important for online and I like things being kind of bite-sized so that you don’t necessarily have to sit down and watch a 50 min lecture but making things a bit more modular is really beneficial in the online space.”

(Natalia)

“There’s a lot of content online and I know some students don’t really use it, that extra content, you know, and I’m probably specifically talking about Chinese, you know, Lecturer puts up videos and all this extra little stuff there for us.”

(Olivia)

Benefits of the approach were also identified in post-learning evaluation by students:

“The unit [subject] helps me understand the basics of the Chinese Language and build a proper foundation. The interactive questions in the modules which give me a chance to test my learning.”

(Student, eVALUate comment)

5.2.1. Engaging with Content through Digital Tools

Compared to European languages, learning Chinese requires relatively large cognitive adjustments to sounds and forms of writing (Orton, 2010) [68]. Two digital tools were used to assist beginners in learning the Chinese language phonetic system and character writing. One tool was a “Chinese Writing Skills CD” (later converted to a web page) developed by the instructor, featuring animation, audio, and text (see Figure 2). It included a printable vocabulary list, and seven modules on the fundamentals of Chinese writing. The resource enabled beginners to independently practise and improve their Chinese writing and reading skills. The feedback from students was very positive. For example, a first-year student stated: “I have used almost all of the components and think this is a great resource for helping students to better learn Chinese.” (Student, personal communication).

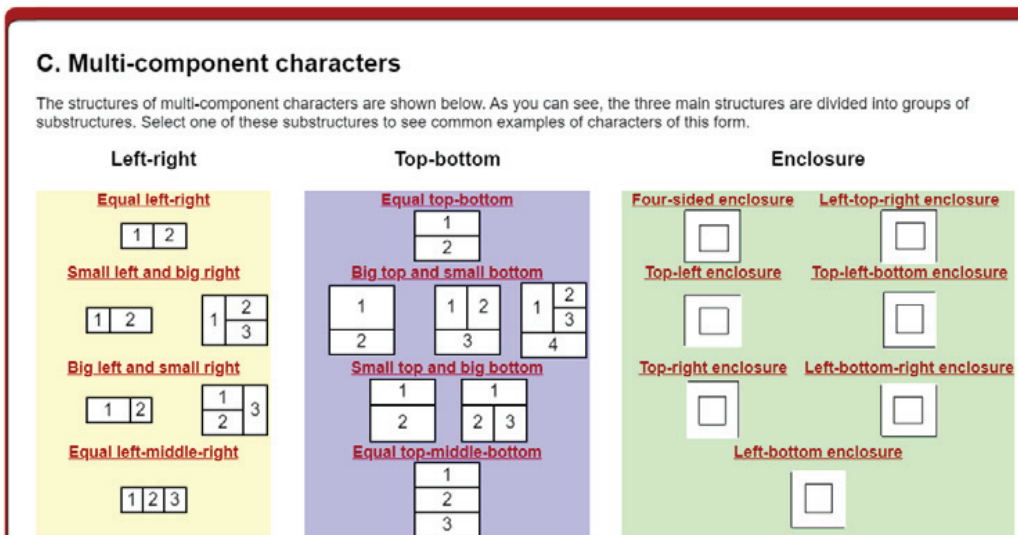


Figure 2. A snapshot of Chinese Writing Skills CD. Reproduced with author’s permission.

The other digital resource used in the subject was an e-learning tool: “Mastering Mandarin Pronunciation Through E-learning” (Yeh and Chen, 2010) [69], that helped enhance the students’ acquisition of Chinese pronunciation. A student stated: “The tool allows for more interactive learning which increases time spent studying Chinese, so it is definitely beneficial for this beginner Chinese unit.” (Student, eVALUate comment). Specifically, all learners agreed that this tool was visually attractive, easy to follow, interactive, and engaging. As one student observed: “Words and buttons are spaced out and large, making it easy to use.” (Student, eVALUate comment).

5.2.2. Engaging with Content through Multimedia

To connect language to the real world, a range of authentic materials were incorporated into the learning content. These included short video clips with a focus on words, grammar, and sentence patterns, and the use of an immersive 3D virtual world. Students acknowledged the effectiveness of the short video clips: “Through the use of short videos, the teacher ensures that lectures and tutorials are always fun and interactive.” (Student, eVALUate comment).

Chinese Island (Monash University, 2007) [70] is an extant immersive 3D multiuser virtual world (MUVW) created in Second Life, developed by a major urban Australian university. It enables students to use Chinese language in an environment resembling real-life geographic locations and simulate real-life experiences (Peterson, 2011) [71]. The virtual environment allows users to engage in cultural experiences such as dining in a restaurant and visiting markets and streets, with sounds and music enhancing the reality of the experience (see Figures 3 and 4).



Figure 3. “Mohai Academy”, Chinese Island image featuring stone lions. Reproduced with the creator’s permission.



Figure 4. Chinese Island image showing marketplace. Reproduced with the creator’s permission.

Chinese Island was deliberately chosen as a tool for learners to develop language acquisition, based on recommendations from research that the virtual world can assist with alleviating anxiety about foreign language production (Lin et al., 2014) [42]. By adapting task-based language-learning methods to a 3D MUVW environment, the learning tasks were a combination of learnt textbook-based content with authentic scenarios, and new content from real life. It provided students with the opportunities to internalise their learning through revision, practice, consolidation, and extension. Immersion in this virtual world had a positive impact upon students’ learning, as the following interview quotes illustrate:

“When you go into this space on the computer, online, it’s very immersive . . . it’s virtual technology . . . you can imagine, and you can see the streets and all the signs and there’s the markets. And there’s all these little experiences that you wouldn’t have been able to have any other way. There are those little things that you get to learn about the culture from a—yeah, in a native way, not so much a tourist, you know, and also within that island you also can increase your language skills by engaging in conversations.”

(Olivia)

“I think as a beginner, vocabulary is one of the most important things. Being able to click on objects and retrieve the vocab/further info was something I found quite useful, which complemented my more ‘traditional’ approach to learning.”

(Darren)

“It helped reinforce what I’d already learned, and it taught me new characters as well.”

(Kathleen)

5.2.3. Engaging with Content through Instructor Interaction

In addition to interacting with students as they navigated their way through Chinese Island, the instructor also made use of discussion boards. The purpose of the discussion boards was to provide an opportunity for students to engage in dialogue with the instructor

and other students beyond any synchronous opportunities. It also allowed for prolonged engagement with the content, as students could return to the forum over days, or even weeks. The uptake from students was mixed, with feedback not always positive:

“The second you put all these discussion boards and all the rest of it open for everyone to see, you’re kind of like—which is weird because in real life, we don’t have a problem often conversing with one another, but then the second it’s online, it’s almost like there’s that kind of stigma of the oversight of the lecturer, I can’t say what I want to be seen and it’s there forever and things like that. I think it’s a difficult problem.”

(Andre)

“Sometimes I think they’re not people’s real opinions, they’re what they want people to think they think. I think there’s all a falseness that goes on in discussion boards or what the lecturer wants to hear. There’s a lot of conformity around.”

(Olivia)

Adoption of a more personal approach, including regular individual emails and phone conversations, assured students that the lecturer was accessible and cared about their learning. The following quotes demonstrate that students appreciated the individual support provided:

“For some reason I couldn’t attend that first lecture, but—and I’ve never received an email from a lecturer before that said ‘I was expecting to see you today. Are you coming tomorrow?’”

(Olivia)

“I guess for me, the kind of accessibility to interacting with lecturers, I think, is something I value in lecturers, approachable, personable . . . even if it’s outside of consultation times or whatever—generally being accommodating and trying to work with you to get whatever outcome you’re working towards is something I’ve personally really valued.”

(Andre)

5.2.4. Summary of Results for Case Study 2

This case study examined the relationship between the learner and the content through a wide range of interactive strategies in an introductory Chinese language subject. The results suggested that students perceived these types of interaction as having a positive influence on their learning. The use of an interactive multimedia platform, Chinese Island, was most beneficial for learners to study Chinese language. It provided opportunities for students to interact with objects and non-player characters, reflecting ‘real language’ and ‘real life’ in the target language environment.

6. Discussion

6.1. Instructors’ Use of Interactive Strategies

Both case studies illustrate how the instructors utilised a variety of interactive pedagogical approaches to engage online learners with the learning content. In the Teaching Mathematics subject, for example, games and activities were used to foster students’ engagement with mathematical content, by requiring them to interact with children or peers. In addition, reporting or sharing the experiences through discussion boards provided opportunities for learner–instructor and learner–learner interactions to occur (Moore, 1993) [18]. Similarly, the provision of digital tools, multimedia, and the Chinese Island 3D MUVW allowed beginning Chinese language students to engage with language learning in creative and novel ways. This finding is consistent with other literature which shows that the use of multimedia particularly stimulates learners’ motivation to learn and engage with course content (e.g., Havice et al., 2010; Vagg et al., 2020) [31,36]. As shown in Figure 1, meaningful learning is influenced by the interactions between learner and instructor, learner and

content, and instructor and content. Interactive strategies, as used by the two instructors, provided examples of all three aspects.

6.2. Instructor–Content

Both instructors deliberately designed their courses to incorporate appropriate online pedagogical practices that allowed students to interact with the learning content. Technical facilitation strategies were particularly evident through instructor-created materials in the form of short videos/multimedia (Martin et al., 2018) [14]. As reported by Martin et al. (2018), instructor-made videos can help students understand instructional material, as was found to be the case in the Teaching Mathematics subject [14]. While the Chinese language instructor devised a component of the learning materials, she also made use of a range of digital resources, such as the writing skills resources and e-learning tools. The immersive Chinese Island provided opportunities for the instructor to interact with learners as they navigated their way through the virtual environment. Both cases demonstrate the importance of the instructor utilising appropriate interactive content to assist their students' learning. Such content may, but does not have to, be instructor-created to be effective.

6.3. Learner–Content

As Figure 1 showed, meaningful learning occurs when the learner engages with the content of a course. Multimedia-based e-learning environments encourage more learner–content interaction than do traditional learning settings (Zhang, 2005) [72], and this was evident in the use of the Chinese Island in the Chinese language subject. Students commented on the impact of the immersive environment in reinforcing previous learning and improving their vocabulary skills. These findings point to similar benefits relating to interactive visual stimuli identified by others (e.g., Di Paulo, et al., 2017; Havice, et al., 2010; Martin et al., 2018) [14,36,38], including increased student interaction with course content.

While the Chinese language students experienced a virtual target language environment, learners in the Teaching Mathematics subject were able to engage with the content through existential experiences, such as videos showing how games were played and how materials were used to teach mathematical concepts. In this way, the instructor provided her students with online activities that without technology, would require in-person participation.

6.4. Learner–Instructor

As the research indicates, instructor presence is the key to student engagement (e.g., Muir et al, 2019; Park & Choi, 2009) [23,24], and feedback from students in both case studies supports this finding. One of the most influential facilitation strategies in terms of instructors making connections and establishing relationships with students was through the use of video-based instructor introductions (Martin et al., 2018) [14]. This provides an example of how an interactive strategy, designed initially for instructor–content purposes, also helped to facilitate learner–content and learner–instructor engagement. Students in the Teaching Primary Mathematics subject in particular commented on how the videos helped them to comprehend the weekly work, and that they appreciated the relevance and currency of the videos. In addition, these learning materials helped to create a personal relationship between the learner and the instructor, as “it made you feel like you were having a conversation with her” (Kayla). This finding supports Jones et al.'s (2013) [73] research, which found that video-based instructor introductions helped form relationships with instructors. While the Chinese language instructor did not create introductory videos each week, she facilitated learner–instructor interaction through emails and one-on-one consultations with individual students. Overall, the findings indicated that, consistent with other research (e.g., Alla, et al., 2022; Martin et al., 2018; Roque-Hernández et al., 2021) [14–16], learner–instructor interaction was important for students, and perhaps particularly appreciated during the COVID-19 pandemic (Alla et al., 2022) [16]. The major forum for learner–instructor interaction in Teaching Primary Mathematics occurred through the use

of the subject discussion boards. As Shea and Bidjerano (2010) [45] (and Douglas et al, 2020) [48] found, a sense of an online presence from instructors is essential to enable positive learner–instructor participation, and the Teaching Primary Mathematics instructor maintained a consistent presence in the discussion board space, as evidenced by student feedback. The results show that the instructor provided a variety of strategies to encourage students to engage with, and discuss, the content through the discussion boards, which were generally regarded as valuable by the students. The comment by Marissa, however, is a reminder that discussion boards by their very nature may lead to a reluctance to post. Unlike the students and instructors in Thomas and Thorpe’s (2019) [47] study, Marissa’s feedback was not directed at the quality of the interactions or content, but rather the nature of the subject itself. The students in the Chinese language course were also able to interact with their lecturer through discussion boards, with their feedback highlighting concerns about the quality of the interaction (Thomas & Thorpe, 2019) [47]. This quality of interaction is essential in the success of discussion boards, particularly when online discussion is incorporated into the curriculum to mirror an authentic real-world activity (Gay & Betts, 2020) [74].

7. Conclusions and Implications

The case studies presented in this paper examined how meaningful learning is influenced by three types of interaction (Martin & Bolliger, 2018; Moore, 1993) [18,19], with a particular focus on the instructors’ strategies to promote the learners’ interaction with the content. The two case studies were selected as they showcase how it is possible to use interactive pedagogies to teach challenging course content. In addressing the first research question, the findings from this study indicate that instructors utilised a variety of interactive methods to promote the learners’ interaction with the content, such as games, weekly challenges and puzzles, videos, discussion boards, and unit-specific digital tools. In response to the second research question, interview data provided empirical evidence towards the extent to which students perceived these online and pedagogical strategies to be beneficial to their learning. The results suggest that improvements in learner–content interaction, fostered by approaches such as providing personal support to students, being present to stimulate student engagement, and encouraging regular student communication opportunities, may help to enhance students’ engagement. These findings have important implications for the design of online courses for university students. We acknowledge that the research is subject to a number of limitations with respect to its generalizability, based on the small sample size of interview participants and their self-selection. It is submitted, however, that the results nevertheless offer useful insights into pedagogical opportunities which facilitate online student engagement in their learning.

The insights gained from the findings may assist instructors in understanding learners’ interaction with online content, as well as the impact of learner–content interaction on the learners’ progress. Lin et al. (2017) [67] stated that learner–content interaction was the only factor that affected perceived progress. In addition, Kuo et al. (2013) [75] argued that student–content interaction was one of strongest predictors of student satisfaction with online courses. This study has demonstrated that meaningful learning can occur when attention is paid to all three areas of interaction, and instructors’ use of interactive pedagogies can influence learners’ propensity to engage with the content. This is supported by Alla et al. (2022) [16], who report that all three elements, and especially teacher presence, impact positively on the quality of online teaching in higher education. Teaching subjects that are inherently challenging calls for instructors to be creative, in terms of providing engaging course materials, and attentive in relation to regular communication with students and offering ongoing support and guidance. While, arguably, any instructor can select and provide appropriate content material, it is the role and presence of the instructor that is vital to engaging students with that content. For instructors that are new to online teaching, it is recommended that particular attention should be paid to establishing relationships which can be facilitated by regular learner–instructor interaction. Designing content that

is interactive and engaging, such as the examples detailed in this study, can also promote engagement, and provide opportunities for learner–instructor interaction. Considering the positive effect of learner–content and learner–instructor interactions on both student satisfaction and perceived progress, more research on content-related methods of engaging online students needs to be undertaken, to enable online educators to better facilitate online learning.

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Article

Pilot Research into the Perceived Importance of Educational Elements and an Application for Detecting Progress through the Perspective of Practice

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Abstract: Data analysis and the development of learning skills based on monitoring students' progress are aspects in demand by schools and students. Quite a lot of studies deal with Learning Analytics Dashboards. There is a limited number of studies that take into account the supply of such tools on the market. In this pilot study, the researchers present findings on the attitudes of 19 higher education institutions from the Czech Republic, Belgium, Germany, Greece, the Netherlands and Poland, along with 14 secondary schools from the Czech Republic, towards the proposed web-based application for supporting learning and providing automated feedback on student progress in accounting education. The aim of this section was to find out how schools perceive the importance of the proposed application and its specific parameters. The study also presents the current product offer on the Czech market and the interest among 112 companies in developing such an application. The findings revealed that there is no such tool offered on the Czech market, and the majority of the analyzed companies are interested in its development. The schools evaluated the learning tool as being most important in the area of distance learning, and most useful for the visualization of accounting methods based mainly on imagination. The value of such an application is seen in supporting self-study, providing information on attitudes and current abilities, and tracking students' learning progress.

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Keywords: distance learning; visualizing web application; progress in learning; perceived usefulness; companies; accounting

1. Introduction

Recent education, regardless of the level or type (distant or in the classroom), or the age of the lecturer, is strongly impacted by digitalization [1–3]. The digital transformation is viewed as an imperative; it represents, according to [4] (p. 5) “a series of deep and coordinated culture, workforce, and technology shifts that enable new educational and operating models and transform an institution's operations, strategic directions, and value proposition”. Formative assessment and continuous feedback to students on their progress in their studies is becoming increasingly important. Universities and secondary schools have experienced pressure to change teaching methods and forms in order to adapt them for the online environment [5] in which teaching has taken place and often still takes place. However, schools and teachers are less aware that there is also an increasing need to change the methods and forms of learning to be student-centered [6]. The researchers support the argument of the authors [5] that learning does not only take place within a person but within and across virtual space. Therefore, providing formative feedback and

monitoring student progress based on behavioral, emotional, and cognitive dimensions is an essential part of today's modern education [7]. The study [5] points out several major challenges. There is no systematic feature for tracking and evaluating students' online learning activities in a web-based interactive environment in order to show student progress. There is also a lack of immediacy, personal feedback and self-reflection. Few researchers have empirically examined, so far, how students perceive informed learning progress in solving a complex problem [8]. The use of a web-based interactive environment for learning itself allows the research to be based on the data produced by users through their interaction with the application. Two research areas, namely Educational Data Mining and Learning Analytics, deal with this modern direction of research on learning and cognition. Their anchoring, as a separate research field, was noted in the year 2013 [9]. Data-driven research is widespread in university settings. For example, this field can be used to understand the causes of student performance, to predict at-risk students at an early stage [10], or to prevent students' dropout in higher education [11].

In the economic sciences, which include the field of accounting, it is important to promote thinking. It is an important prerequisite in order to achieve better academic and professional outcomes, and it strongly affects learning and teaching strategies [12,13]. Already, J. M. Keynes has pointed out that economics is a tool of thinking in order to make the right conclusions, and is relevant in relation to the economic problem at hand [14]. The study of accounting is oriented towards inference, imagination, visualization, evaluation, discovery, or rationale [15]. In order for the efforts of the teacher and the student in accounting science to be capitalized, the necessary cognitive dimensions need to be adequately developed, especially through the previously mentioned cognitive processes [16]. This could be fulfilled by visualization tools in an interactive environment. The authors [17] defined cognitive skills that can be developed in accounting disciplines through mobile devices in a university setting. These authors [17] built on their 2019 research and took it to a professional level, in a labour market environment. They incorporated not only human information processing theory (HIPT) but also components such as worker satisfaction and motivation into the model. Their research has implications for improving jobs in finance and accounting. In the context of turbulent technological advances, a visualization web application in an interactive environment could be considered to transform the current learning-based accounting education not only into a deeper level of thinking but also to support students' self-studying and inform them of their learning progress.

1.1. Formative Feedback for Learning Progress

One way to define learning is in terms of the components it involves. Thus, learning involves the purposeful improvement of cognitive, affective, or behavioral skills [18–20]. Formative assessment, which is an effort to detect improvement by diagnosing the quality of student responses, is important for effective learning. It is an effort that encourages formative feedback toward learning goals [21–24]. The formative function of assessment is understood as a set of activities following a logical sequence [25]: (a) clarify learning objectives and success criteria so that students understand them; (b) prepare questions, tasks and activities, and effectively guide discussions and activities so that evidence of learning emerges during them; (c) provide feedback that enables students to move forward; (d) activate students to become a source of learning for each other; and (e) activate students to take ownership of their learning. Formative feedback is based on providing information on how the student should improve. The studies [26,27] identified several assumptions underlying formative assessment that must be simultaneously met in order for it to be functional: (i) Formative assessment must be domain-specific; therefore, it is not the same across grade levels and settings. (ii) Teachers must display sufficient cognitive and professional skills in relation to the educational domain (in particular, what conclusions to draw from student performance, and what actions to take). (iii) A more conscious approach to students' own learning. Students need to rethink their current attitudes to learning and teachers need to change the way they have been teaching. Feedback is an essential factor

for learning and teaching, and can greatly enhance learning. Reviews and meta-analyses show that the range of effects of studies comparing different types of feedback varies from moderate negative to large positive effects. The effects of feedback strategies can vary depending on contextual factors such as task complexity, and individual factors such as knowledge or motivation [22,28,29].

1.2. Formative Feedback Based on Learning Analytics

Technology-based formative feedback has been defined and its test prototype developed through research [8] based on the findings of several researchers who have developed learning dashboards to visualize learning progress in terms of long-term change [30–33]. Formative feedback is based on a series of students' responses to a pre-specified problem-based task. Thus, both teacher and student have information about the student's progress towards a solution, for example, in the level of expert understanding of the situation. The study [34] proposed a Learning Analytics Dashboard (LAD) and examined critical factors of the perceived usefulness of a Learning Analytics Dashboard for distance university students. Their research was based on interviews with 21 students.

Their findings revealed that amongst the LAD features favoured by students was the potential to receive study recommendations, whereas comparison with peers was amongst the least favoured elements, unless informed by qualitative information. Factors including information trust, attitudes, age, performance and academic self-confidence were found to explain these perceptions. [34] (p. 1)

However, the study did not emphasize other important parameters such as student individualization (i.e., tailoring instruction to students' needs and goals), student–teacher cooperation, or cooperation among students. Detected student progress helps teachers determine instructional sequencing and strategies. Learning progress is an empirically testable framework that defines the learning pathways through which students move from simple to more sophisticated concepts or practices in a domain [35]. The automated tracking of learning progress is based on the Learning Analytics system [9], which enables the use of technology-enhanced formative assessment and feedback applications. Such a system helps students to take control of their learning [8,36], and students become the source and subsequently the owner of their learning [25]. It is a prerequisite that students are equipped with digital competence, and that they can face the requirements of a changing educational model [37]. Learning Analytics can be used to identify at-risk students and define practices to improve teaching and learning [38]. The studies mentioned above do not reflect the existing supply of these mobile and web-based applications and programs in the market, nor the interest of manufacturers in such products. Hence, this study is oriented in the given context and extends the knowledge with the perspectives of the representatives of the application domain, and their needs and interests.

1.3. Research on Accounting Education and Learning Strategies

From a methodological point of view, accounting education is closely related to mathematical sciences, as it is based on mathematical laws and logic theory, and the typical gnoseological procedures are deduction, analogy, abstraction, and imagination, etc. [16]. The importance of image-based reasoning in mathematical understanding and problem solving has been recognized, for example, by the authors [39,40]. This claim is supported by a study [41] which examined the relationship between mathematical and economic (financial) literacy, and confirmed a significant positive association. Past research [15,42] at the science level has already been directed towards exploring the concepts and links between accounting and mathematical laws. Their research shows that accounting functions in their interactions are underpinned by alternative mathematical–analytical models. Often, accounting is taught based on trivial, passive, intuitive practices [43,44]. It cannot be argued that teachers do not make an effort to guide students to logical thinking and deduction, but traditional teaching tools without interaction, imagination, and visualization will not achieve the necessary development of accounting thinking, e.g., [45]. If the core of

accounting thinking is the ability of students to see the duplicity of accounting entries in all three possible types of representations [43]—debit and credit side pre-contracting, double-sided entries in accounts, and accounting statements—then the results of research with Czech undergraduate students are worrying. In no year of study were the three forms of understanding of accounting correlations even remotely balanced [46]. The above findings from 2013 are confirmed by more recent research from the foreign higher education field [44]. The study described the current state of accounting education in higher education institutions, which is not in line with the development of accounting thinking described above.

From the above findings, it is evident that the teaching of accounting, whether at higher education institutions or secondary schools, needs innovation in the use of modern digital tools, which, above all, will help to increase the clarity of the presented curriculum, leading to understanding and the development of thinking. Animations, simulations, and visualizations are appropriate means not only of presenting the issues but also of capturing students' progress. International studies [8,34] point to prototypes of similar instructional panels for tracking students' progress in terms of long-term change, which serve as an information channel for effective decision making by students regarding learning and teachers regarding teaching.

1.4. Aim of the Research, Development of Hypotheses and Research Questions

The aim of our study is to find out how secondary school, higher economic education institutions, and representatives of the application sphere perceive the importance of educational elements and visualization web applications that should serve not only to monitor and evaluate students' online learning activities in a web-based interactive environment but also to support (i) self-study, cooperation and students' ability to learn by detecting their progress in competencies and attitudes towards learning through formative assessment, continuous feedback and self-reflection; (ii) students' thinking in accounting disciplines; and (iii) teachers' decision making about their future teaching, enabling the selection of relevant teaching methods that will be directed towards effective student learning.

The purpose of such a web application is to support a modern way of teaching at the secondary and higher education level in the Czech Republic and beyond based on Learning Analytics. This approach is challenging but very useful, and is used in teaching practice. The study concept is based on pilot research focusing on the current attitudes and needs of schools and representatives of application spheres, but not on defining parameters for the assessment of students' progress in the long term, with implications for learning outcomes. The design of the study is based on a pilot survey that focuses on the current attitudes of representatives of the application sphere and partner secondary and higher education institutions with which the researchers work closely in educational projects, but not on defining parameters for assessing students' progress in the long term, with implications for learning outcomes.

The first part of the research was processed using quantitative research methods: the subject of the analysis of attitudes of schools was to test the following substantive hypotheses:

- H1: School representatives' attitudes towards the need for a visualization web application for learning vary by country and level of education.
- H2: School representatives' attitudes towards the specific parameters of a web-based learning application vary depending on the country and level of education.
- H3: School representatives' attitudes towards the importance of educational elements for the teaching of accounting vary depending on the country and level of education.
- H4: School representatives' views on the absence of educational elements in the teaching of accounting vary depending on the country and level of education.
- H5: There is a correlation between the need for a visualization web application and the perceived absence of educational elements to teach accounting.
- H6: There is a correlation between the perceived importance of specific parameters of a visualization web application for the teaching of accounting.

The second part of the research was processed using qualitative research methods. The subject of the analysis of companies' opinions were these research questions:

RQ1: Is there such a web application for the teaching of accounting on the Czech market?

RQ2: Do relevant companies perceive the development of such a web application as beneficial?

2. Materials and Methods

2.1. Procedure of Research

The research was carried out as pilot research related to the determination of the attitudes of representatives of secondary schools and higher education institutions towards the relevance of the proposed visualization web application for the teaching of accounting. Furthermore, the research was focused on representatives of the application sphere in order to find out their interest in the development of such an application on the Czech market. The Czech market was chosen because of the existence of a similar web visualization application in the international environment, where it is either being worked with or its prototype is being tested. This fact has emerged from international studies, e.g., [8,34]. Therefore, this study focuses on identifying the current supply of such a product on the Czech market because such knowledge is lacking in studies. The pilot research was conducted from October to December 2021.

The subject of the research was the perception of the importance of educational elements in the teaching of accounting and the specific parameters of the researchers' proposed web application for the development of accounting thinking in an interactive environment, monitoring student progress and supporting their self-study and learning ability. The proposed web application and other educational elements were presented to the subjects in the form of a description, not in the form of a prototype intended for pilot testing. From this pilot research, it was possible to identify the interdependence of the need for such a didactic digital tool with the limitations in the teaching of accounting, and therefore to adapt the proposed didactic tool more effectively to current educational needs.

Among the learning elements, in light of the analysis of the current state of knowledge [6,8,9,34] and examples of good practice from the pandemic era and accounting education, the following were selected and labelled as follows:

- INDIVID: Student-centered individualization (i.e., teaching and learning are tailored to the interests and goals of individual students and their learning needs).
- COOP STUD: Cooperation among students during instruction in practical activities and studies.
- COOP TEACH: Cooperation between the student and teacher during the lessons in instructions and practical activities.
- ATTITUDES STUD: Computer-automated detection of student attitudes (i.e., obtaining continuous information about what the student enjoys, is interested in, is surprised by, finds difficult, etc.); after a certain period of time (class, semester) the student evaluates their attitudes towards the teaching of the subject.
- PROGRESS LEARN: Using computer automation, we obtain information about each student's current abilities and progress, through which the student can make decisions about their future learning and choose effective learning methods.
- PROGRESS TEACH: Using computer automation, we obtain information about each student's current abilities and progress, using which the teacher can make decisions about their future teaching and choose effective teaching methods.
- SW: Learning software to support learning.
- SIMULATION: Simulations of accounting activities supporting the ability to learn, for example in the form of project-based learning.
- PC GAMES: Didactic computer games to support learning.
- ANIMATION: Animation of the accounting view and transaction reporting to support the ability to learn.
- COMMENTARY: Spoken explanatory commentary supporting the ability to learn.

- COMBINE: Combination of spoken explanatory commentary with animations to support learning.

The above variables are closely related to the teaching process, and must be taken into account when conceptualizing the design description of a web-based learning application [6,8,9,34]. Exploring their relations will help us to better understand the factors influencing teaching, for the time being at the level of the perception of their importance and absence in teaching from the perspective of tertiary and secondary education representatives.

Among the specific parameters of the web application with respect to studies [17,18] and past experience, the following were selected and labelled as follows:

- APP FREE: Free version of the app.
- AUTOMATING ACCOUNT: Automating the transition between three formats for displaying accounting transactions—(i) pre-accounts, (ii) T-accounts, and (iii) financial statements.
- VISUALIZATION: Visualization of account parameters in the accounting books (i.e., turnover, opening/ending balances, number of counter-accounts) and reconciliations (amount, impact of the transaction on the statements) using the size, width and colour of objects representing accounts and reconciliations.
- INTERACTIVITY: Interactive environment for student self-learning, i.e., providing information about each student's attitudes, current abilities and progress.
- FACE TEACHING: Usability of the application in full-time (face-to-face) teaching.
- DIST TEACHING: Usability of the application in distance learning (self-study).

The above parameters are linked to a web application that should serve the teaching of the accounting subject and help in understanding the relation between accounting and the reporting of economic information. Based on the analysis of current knowledge [43–46], they were selected in order to further explore the attitudes of representatives of tertiary education, secondary education, and the application sphere.

The examined educational elements and the proposed web application for the teaching of accounting, which carries the above specific parameters, are closely related. Their interconnectedness is based on Learning Analytics. Such an application would build on these principles, allowing students to move around in an interactive environment that would enable them to study the subject of accounting effectively, with immediate feedback impacting on learning outcomes and monitoring their attitudes towards learning. This also requires teachers and students to work together, to be able to detect student progress in knowledge and skills, and to use the ongoing results to improve student learning and teacher teaching. Thus, these principles come down to the teacher's individual approach towards students. It is important that the application can be used for both contact and distance learning.

Information about the companies was the main subject of the qualitative research focused on the interest of representatives of the application sphere in the development of the proposed visualization web application on the market, especially the field of business and previous experience in the field, including the product portfolio, based on archival and publicly available data from official company websites.

2.2. Characteristics of Respondents

A total of 33 representatives of secondary and higher education institutions participated in the pilot research, and they were from the following countries: Czech Republic, Belgium, Germany, Greece, Netherlands, and Poland. They participated in the quantitative research. A total of 26 Czech schools took part in the pilot survey, which also corresponds to the number of secondary schools and higher education institutions contacted, which at the same time are partner schools within the framework of educational projects. In addition, 7 representatives of universities from other countries took part. The researchers have focused the research on the partnering universities that have been cooperating within the International Business Network (IBW). The Network was established 21 years ago by the Belgian University College Leuven (University College Leuven-Limburgh since 2015) and the French Institut Universitaire de Technologie de Saint-Denis, a part of the

University Sorbonne Paris Nord. In 2021, there were 13 members from Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Latvia, Netherlands, Poland, Portugal and Ukraine. Each partnering university or college organizes on a regular basis a week of student activities—an international business week, during which students cooperate on an international business case [47]. For the purpose of this research, the researchers have approached selected members of the IBW Network (Wroclaw School of Banking, Poland; University of Applied Sciences Kaiserslautern, Germany; West Attica University in Athens, Greece; Rotterdam University of Applied Sciences, Netherlands; University College Leuven-Limburgh, Belgium), based on the specialization of their international business weeks (accounting and finance).

Within the Czech Republic, not only higher education institutions with an economic focus were contacted but also secondary schools with an economic focus. The selection of these schools was intentional, as the researchers targeted economic study programmes, based on proven partnerships with these schools. In total, there were 14 secondary schools and 12 public higher education institutions from the Czech Republic, the questionnaire was completed for each school by one representative at the school management level, competent for strategy and pedagogical activities. In total, there are 26 public higher education institutions in the Czech Republic. Thus, the sample consisted of subjects (schools) represented by one representative each. With regard to such a selection of respondents at the school level, the researchers based their selection on the centralized development projects of the Ministry of Education, which have been launched in the Czech Republic since 2021, and in which all public higher education institutions are involved. In these projects, the sample consists of one representative of the higher education institution. A representative of the institution of higher education (rector, vice-rector, or dean) and secondary schools (principal or deputy principal) commented on distance education issues at the strategic level of the institution. In this pilot study, the researchers worked with such secondary schools from the Czech Republic that are also their partners in the IBW. As they do not have partner secondary schools in other countries, it was not possible to direct the research to secondary education in other countries for the time being. For this reason, the study is considered to be a pilot study, and based on the results the researchers will adjust the methodology for the comprehensive research. Taking into account some characteristics (country and level of education) will better identify differences in the views of the different institutions, and will thus be able to better detect the specific needs of different user groups. Table 1 illustrates the research sample in terms of the characteristics studied.

Table 1. Profiles of the research sample.

Variable	Frequency	Percentage
Level of education		
Secondary	14	42.40
Tertiary	19	57.60
Country		
Czech Republic	26	78.80
Belgium	3	9.10
Germany	1	3.03
Greece	1	3.03
Netherlands	1	3.02
Poland	1	3.02

Representatives of companies that were relevant to the research project represented the second group of the research group within the qualitative research. Their selection was conditioned by their business sector and previous experience in the industry, including their product portfolio, based on archival and publicly available data from official databases. Thus, the firms were selected in an intentional manner with the research objective in mind. The total spectrum of firms operating in the Czech market was narrowed down to

112 entities, which is in line with the intention. These entities were classified as micro-, small- and medium-sized firms, and are also represented by individual entrepreneurs and natural persons. Because firm size was not important for the research design, the frequency of firms by size is not reported in the paper. The professional focus and line of business of these entities was a crucial criterion for the research. Thus, these are firms engaged in application development and software development for commercial and educational purposes. Their professional orientation can be summarized in the following activities:

- the development of accounting and economic software and systems;
- the development of customized web applications and databases;
- the development of web applications for educational purposes oriented to students and teachers;
- the development of web applications and software for marketing purposes, internet commerce, and the development of POS systems;
- the development of information and transaction systems in Java and JavaScript;
- the development of mobile applications, the provision of cloud services, and system integration;
- the development of computer games.

2.3. Methods and Instrument

The first part of the pilot research was the survey, which took the form of a three-month online survey using a web-based questionnaire that was sent to the email addresses of representatives of secondary schools and higher education institutions. The questionnaire surveyed the following areas:

- factual data on secondary and higher education institutions in terms of the level of education and country;
- the perception of the need for the proposed visualization web application to develop accounting thinking, promote self-study and student learning, and monitor student progress through the viewpoint of representatives of secondary and higher education institutions;
- the perceived importance of the specific parameters of the web application the researchers designed from the viewpoint of representatives of secondary and higher education institutions;
- the perceived importance of the educational elements selected by the researchers for the teaching of accounting from the perspective of representatives of secondary and higher education institutions;
- the perceived absence of the educational elements selected by the researchers for the teaching of accounting, from the perspective of representatives of secondary and higher education institutions;
- the attitudes of representatives of secondary and higher education institutions towards the reasons for not adopting the proposed web application.

A five-point Likert scale of 1–5 was used to subjectively assess the selected variables, and the respondents were asked to omit (as far as possible) a neutral answer—level 3. The reason was to detect the most accurate definition to the proposed application of the contacted secondary schools and higher education institutions of economics. Another scale was used to assess the need for the proposed web application: strongly agree, agree, disagree, or strongly disagree. It is no longer a five-point Likert scale, as the researchers needed to find out the verbal attitude.

In order to assess the importance of specific parameters of this web application and the selected educational elements for the teaching of accounting, the following scale was used: 1—not important; 5—most important. In order to assess the absence of the selected educational elements in the teaching of accounting, the following scale was used: 1—not missing at all; 5—most missing.

The questionnaire offered respondents a choice of predetermined reasons for not adopting the proposed web application in secondary and higher education settings. The respondents were also given the opportunity to provide another, personal reason that was not listed in the offer. The following reasons were selected for the predefined offer:

- Teachers' time spent on learning to use the app.
- Time spent on learning how to use the application on the part of the students.
- Teacher disinterest.
- Student disinterest.
- Bad experience with the use of digital, interactive applications.
- General disruption to your teaching.
- Overall disruption of students' learning styles.
- Duplication of didactic means for the teaching of accounting.
- I don't see the benefit of the web app.

All of the sensitive data have been anonymized and encrypted. Prior to the actual research, a pre-survey was conducted with a sample of 10 teachers from secondary schools and higher education institutions with the characteristics of the respondents from the main survey, thereby increasing the content validity of the research instrument. The reliability of the questionnaire was measured by computing Cronbach's alpha [48]. The questionnaire was evaluated as reliable, as Cronbach's alpha was 0.907.

Within the framework of pilot research oriented to representatives of the application sphere (the first part of the pilot research), the analysis of archival and publicly available documents was chosen. The selection of entities was made using the commercial and trade register in which the companies are registered, with regard to the field of business relevant to the research project. This was followed by an analysis of the websites of the 112 shortlisted businesses. This analysis was supplemented by direct meetings between the researchers and a representative of the company in order to substantiate the relevant selection and compile the final research sample from among representatives of the application sector. The aim of the direct interviews was to find out:

- the current availability (offer) of the designed visualization web application on the Czech market,
- the interest of selected companies in the development of web applications designed by the researchers.

2.4. Data Analysis

In the context of this study, the researchers equate the terms 'need' and 'meaning'. Quantitative research methods and relevant statistical tests were chosen for data analysis, taking into account the nature of the data. These hypotheses are related to the pilot analysis of the attitudes of school representatives. The above substantive hypotheses were verified at the 5% significance level, and for this purpose were formulated as null hypotheses:

- H_{0-1} : School representatives' attitudes towards the need for a visualization web application for learning do not vary by country or level of education.
- H_{0-2} : School representatives' attitudes towards the specific parameters of a web-based learning application do not vary by country or level of education.
- H_{0-3} : School representatives' attitudes towards the importance of educational elements for the teaching of accounting do not vary by country or level of education.
- H_{0-4} : School representatives' views on the absence of educational elements in accounting education do not vary by country or level of education.
- H_{0-5} : There is no correlation between the need for a visualization web application and the perceived absence of educational elements to teach accounting.
- H_{0-6} : There is no correlation between the perceived importance of specific parameters of a visualization web application for the teaching of accounting.

The original data obtained from the questionnaire survey are of several types. The variables expressing the descriptive characteristics of the respondents—i.e., country and

level of education—are nominal variables, and are used as a sorting factor to perform comparative analyses. The data contain mainly ordinal variables, expressed on a five-point Likert scale from 1 to 5. The relevance, the absence of educational elements for the teaching of accounting, the need for a web application and its specific parameters for educational purposes are described using the arithmetic mean. Because these characteristics do not meet the requirement of normality (verified by the Shapiro–Wilk test) but meet the requirement of homogeneity of variances (verified by the Levene test), the non-parametric Mann–Whitney U-Test was selected from the two-sample tests to assess the hypotheses H1 and H4. A correlation matrix was constructed to establish the correlation relations between the variables in the case of testing hypotheses H5 and H6. The tables presented in the Results section show only parts of it. The field inside the body of the table always contains the value of Pearson’s correlation coefficient r , which is usually used for this type of data [48]. Statistical analysis was performed using SPSS software.

The research questions RQ1 and RQ2 were set in close relation to the sub-questions from the face-to-face interview. A description of the parameters of the visualization web application was presented to the individual subjects from the application sphere, and then the researcher who conducted the interview asked the following questions:

- Do you offer or have you ever offered a product with similar features to the proposed visualization web application?
- Would you as a company be interested in developing such an application?
- Do you perceive the visualization web application designed by the researchers as being beneficial for education?

Qualitative research methods and relevant statistical tests were chosen for the data analysis, taking into account the nature of the data. Because the data from this section were obtained in the form of data description and a transcription of summary responses from the subjects, mathematical and statistical tools were not used for their processing.

3. Results

3.1. Descriptive Statistics—Research Focused on the School Environment

The results of the perception of the importance of a visualization web application for the development of accounting thinking, to support students’ self-study and learning ability and their progress in accounting disciplines, and the importance of specific parameters of this web application in partner secondary and higher education institutions in the Czech Republic and other countries are presented in Table 2.

Table 2. Perception of the importance of a visualization web application and its specific parameters for the teaching of accounting from the perspective of schools ($n = 33$).

Variable	Mean	Median	Mode	Standard Deviation	Variance
The need for a visualization web application (NEED APP)	3.36	3.00	3.00	0.60	0.36
APP FREE	4.12	4.00	5.00	1.14	1.30
AUTOMATING ACCOUNT	4.06	4.00	4.00	0.90	0.81
VISUALIZATION	4.27	4.00	4.00	0.76	0.58
INTERACTIVITY	4.27	5.00	5.00	0.94	0.89
FACE TEACHING	4.00	4.00	5.00	1.17	1.38
DIST TEACHING	4.58	5.00	5.00	0.79	0.63

The results show that the proposed web application is necessary for the representatives of secondary schools and higher education institutions involved in the pilot survey, which corresponds to an average value of 3.36. The mean values expressing the importance of

the web application parameters exceeded level 4, which indicates their high necessity for accounting education, especially for distance education needs.

The perception of the importance and absence of educational elements in the teaching of accounting in representatives of partner secondary schools and higher education institutions in the Czech Republic and other countries was also described using descriptive statistics. The results are presented in Tables 3 and 4.

Table 3. Perceptions of the importance of educational elements in the teaching of accounting from the perspective of school representatives ($n = 33$).

Variable	Mean	Median	Mode	Standard Deviation	Variance
INDIVID	3.58	4.00	5.00	1.30	1.69
COOP STUD	3.88	4.00	4.00	1.05	1.11
COOP TEACH	4.52	5.00	5.00	0.67	0.45
ATTITUDES STUD	3.42	4.00	4.00	1.32	1.75
PROGRESS LEARN	3.85	4.00	4.00	1.15	1.32
PROGRESS TEACH	3.73	4.00	4.00	1.18	1.39
SW	3.88	4.00	4.00	1.24	1.55
SIMULATION	4.18	4.00	4.00	0.98	0.97
PC GAMES	3.79	4.00	4.00	1.08	1.17
ANIMATION	3.76	4.00	4.00	1.00	1.00
COMMENTARY	3.73	4.00	5.00	1.28	1.64
COMBINE	4.27	4.00	5.00	0.94	0.89

Table 4. Perceived absence of educational elements in accounting education from the perspective of school representatives ($n = 33$).

Variable	Mean	Median	Mode	Standard Deviation	Variance
INDIVID	3.03	3.00	4.00	1.40	1.97
COOP STUD	2.91	2.00	2.00	1.31	1.71
COOP TEACH	2.79	2.00	2.00	1.36	1.86
ATTITUDES STUD	3.27	4.00	5.00	1.46	2.14
PROGRESS LEARN	3.58	4.00	4.00	1.30	1.69
PROGRESS TEACH	3.24	3.00	2.00	1.30	1.69
SW	3.30	4.00	4.00	1.45	2.09
SIMULATION	3.48	4.00	2.00	1.28	1.63
PC GAMES	3.36	3.00	3.00	1.29	1.68
ANIMATION	3.12	3.00	4.00	1.24	1.55
COMMENTARY	2.67	2.00	2.00	1.34	1.79
COMBINE	3.06	4.00	4.00	1.37	1.87

Representatives of secondary schools and higher education institutions perceive the most important elements of accounting education to be the collaboration between student and teacher, the combination of spoken explanatory commentary with animations to visualize the explanation, and the simulation of accounting activities. For these elements, the average values reflecting the perceived importance of secondary schools and higher

education institutions are higher than grade 4. No element examined was found to have a value lower than 3, even for our proposed visualization web application, which can be considered to be a result that reflects some importance for accounting education.

According to the school representatives, the least lacking elements in accounting teaching are collaboration between students and teachers (COOP TEACH), which is pleasing, as this element is also considered the most important for the teaching of accounting. It is also the cooperation between students with each other (COOP STUD) and the combination of spoken explanatory commentary with animations (COMMENTARY). For the other elements, the average value exceeded grade 3, which indicates some absence of them in accounting teaching, which may make it difficult to achieve effective teaching (RQ3). It should be noted that schools assign a higher importance for the simulation of accounting activities (Table 3), but this is not much used in the teaching of accounting (3.48).

3.2. Attitudes of Secondary Schools and Higher Education Institutions towards Reasons for Disinterest in a Visualization Web Application

Furthermore, the attitudes of secondary and higher education institutions towards the reasons why a visualization web application might not be adopted by a given school were surveyed and described. The results are presented in the form of percentages at the level of each variable and are presented in Table 5.

Table 5. Reasons for not being interested in a visualization web application for the teaching of accounting in % ($n = 33$).

Variable	Yes	No
Teachers' time spent on learning how to use the app	36.4	63.6
Time spent on learning how to use the app on the students' side	33.3	66.7
Teacher disinterest	39.4	60.6
Student disinterest	30.3	69.7
Poor experience of using digital, interactive applications	9.1	90.9
General disruption of studies and teaching	9.1	90.9
Overall disruption in the way students learn	0.0	100.0
Duplication of didactic means for teaching accounting	21.2	78.8
There is no benefit of a web application	3.0	97.0

The results show that an overwhelming majority of school representatives are of the opinion that the researchers' proposed web application would be beneficial for teaching and learning from their point of view, and would not represent a problematic didactic tool that would somehow interfere with established teaching methods or would significantly reduce the time teachers and students would spend on learning the new application.

3.3. Comparison of the Perceived Importance of Web Applications and Educational Elements for the Teaching of Accounting in Terms of Countries and Level of Education (Hypotheses H1–H4)

Furthermore, the Hypotheses H1–H4 were verified, i.e., there were statistically significant differences in the attitudes of the representatives of partner secondary schools and higher education institutions towards the need for a web application for accounting education, and the importance and absence of educational elements in accounting education in terms of differences between countries and levels of education in secondary and higher education were examined. The differences between countries were tested, i.e., between the Czech Republic and the other countries (i.e., Belgium, Germany, Greece, Netherlands, Poland) where the partner higher education institutions are located. The hypotheses were tested using a T-Test. Tables 6 and 7 show the results.

Table 6. Differences in schools' attitudes towards the need for a web application for the teaching of accounting, and the specific parameters of this application ($n = 33$).

Variable	Country (p)	Level of Education (p)
The need for a visualization web application	0.282 *	0.603 *
(NEED APP)		
APP FREE	0.498 *	0.033 *
AUTOMATING ACCOUNT	0.464 *	0.659 *
VISUALITION ACCOUNT	0.960 *	0.711 *
INTERACTIVITY	0.398 *	0.666 *
FACE TEACHING	1.000 *	0.135 *
DIST TEACHING	0.987 *	0.644 *

* The differences are significant at the 0.05 level.

Table 7. Differences in school representatives' attitudes towards the importance and absence of educational elements for the teaching of accounting ($n = 33$).

Variable	Importance of Educational Elements		Absence of Educational Elements	
	Country (p)	Level of Education (p)	Country (p)	Level of Education (p)
INDIVID	0.742 *	0.804 *	0.595 *	0.108 *
COOP STUD	0.738 *	0.376 *	0.840 *	0.738 *
COOP TEACH	0.705 *	0.144 *	0.284 *	0.619 *
ATTITUDES STUD	0.347 *	0.807 *	0.587 *	0.848 *
PROGRESS LEARN	0.454 *	0.573 *	0.515 *	0.804 *
PROGRESS TEACH	0.749 *	0.350 *	0.824 *	0.917 *
SW	0.535 *	0.933 *	0.747 *	0.954 *
SIMULATION	0.908 *	0.874 *	0.844 *	0.630 *
PC GAMES	0.568 *	0.332 *	0.411 *	0.981 *
ANIMATION	0.900 *	0.238 *	0.337 *	0.523 *
COMMENTARY	0.768 *	0.625 *	0.678 *	0.732 *
COMBINE	0.968 *	0.666 *	0.665 *	0.772 *

* The differences are significant at the 0.05 level.

Significant differences were found between secondary and higher education institutions in the opinions of schools on the need for the web application and the importance of the proposed specific parameters of this application at the 5% level of significance in the case of the parameter 'freely available version of the application'. Furthermore, according to the arithmetic mean, it was found that this parameter is more important for secondary schools to teach accounting (4.57) compared to higher education institutions (3.79). Considering the opinion from the point of view of the Czech Republic and other countries, the schools do not differ in their attitudes towards the need for web applications and the importance of their parameters, which was surprising to the researchers, as there is a difference in the approach to education in the Czech Republic and at the researched higher education institutions abroad. Possible reasons for this result are discussed in the Discussion section.

At the 95% significance level, the researchers do not reject the null hypothesis H_{0-1} . At the 95% significance level, the researchers reject the null hypothesis H_{0-2} in the case of the parameter 'free version of the web application', and in the case of the degree of education.

There were no significant differences at the 5% level of significance in the views of the representatives of partner secondary schools and higher education institutions on the importance and absence of educational elements in accounting education by country and level of education. The partner schools in the Czech Republic and in other countries

perceived the importance and absence of the elements studied in the same way. At the 95% significance level, the researchers do not reject the null hypotheses $H_{0.3}$ and $H_{0.4}$. Possible reasons for these results are discussed in the Discussion section, as they are surprising to the researchers and refute the original hypotheses.

3.4. Analysis of the Correlations in School Representatives' Attitudes towards Web Applications and Educational Elements for the Teaching of Accounting (Hypotheses H5 and H6)

Pearson's correlation coefficient r was used first to establish correlations between the perceived importance for a visualization web application to develop accounting thinking in an interactive environment and the perceived absence of educational elements in accounting education. This made it possible to establish the correlation between the need for such a didactic digital tool and the limitations in accounting education, and thus to adapt the proposed didactic tool more effectively to the current educational needs. Statistical analysis was performed at the 95% significance level. The results are illustrated in Table 8, in the form of a correlation matrix.

Table 8. Correlation matrix—relationship between the perceived importance of specific application parameters.

		APP FREE	AUTOM. ACCOUNT	VISUALIZ. ACCOUNT	INTERACT.	FACE TEACH
APP FREE	r	—				
	p	—				
AUTOMATING ACCOUNT	r	0.176	—			
	p	0.328 *	—			
VISUALIZATION ACCOUNT	r	0.069	0.340	—		
	p	0.704 *	0.053 *	—		
INTERACTIVITY	r	0.085	0.127	0.284	—	
	p	0.640 *	0.481 *	0.109 *	—	
FACE TEACHING	r	0.140	0.237	0.245	0.310	—
	p	0.436 *	0.184 *	0.169 *	0.079 *	—
DIST TEACHING	r	0.197	0.213	0.457	0.369	0.202
	p	0.271 *	0.234 *	0.007 *	0.035 *	0.260 *

* Correlation is significant at the 0.05 level.

The correlation analysis shows a significant direct relation ($p = 0.007$; $r = 0.457$) of the usability of the web application in distance learning with the visualization of account parameters (i.e., turnover, opening/ending balance, number of contra-accounts) and reconciliations (amount, impact of the transaction on the statements) using the size, width, and colour of the objects representing the accounts and reconciliations. Statistical significance was also detected between these specific parameters—the usability of the web application in distance learning and the interactive environment offered by the application for student self-study, in order to provide information about their attitudes, current skills and progress in accounting disciplines. Although a significant ($p = 0.035$) direct relation was found between these variables, the correlation coefficient was not strong ($r = 0.369$).

At the 95% significance level, the researchers reject the hypothesis $H_{0.6}$ in the case of the following pairs of specific parameters: the usability of the web application in distance learning and visualization of account parameters, and the usability of the web application in distance learning and interactive environment for the self-study of the student, providing information about his/her attitudes and progress.

Furthermore, correlations were found between the perceived importances of specific parameters of this visualization web application. Statistical analysis was performed at the 95% significance level. The results are illustrated in Table 9, extracted from the correlation matrix.

Table 9. Correlation matrix—relation between the need for a web application and the perceived absence of educational elements in accounting education.

NEED APP	Pearson's <i>r</i>	<i>p</i> -Value
INDIVID	−0.050	0.781 *
COOP STUD	−0.036	0.842 *
COOP TEACH	−0.055	0.760 *
ATTITUDES STUD	0.451	0.008 *
PROGRESS LEARN	0.362	0.038 *
PROGRESS TEACH	0.323	0.067 *
SW	−0.023	0.900 *
SIMULATION	0.210	0.240 *
PC GAMES	0.025	0.888 *
ANIMATION	0.064	0.722 *
COMMENTARY	0.271	0.127 *
COMBINE	0.200	0.265 *

* Correlation is significant at the 0.05 level.

Furthermore, the correlation analysis shows a significant ($p = 0.008$) direct relation between the perceived need for a visualization web application and the computer automated detection of student attitudes, i.e., obtaining ongoing information about what the student enjoys, is interested in, is surprised by, is having trouble with, etc. in accounting. The correlation coefficient for this direct relation is $r = 0.451$. The need for a visualization web application correlate ($p = 0.038$) with computer automation to have information about each student's current abilities and progress on which the student can make decisions about their future learning and choose effective learning methods. This is a positive relation between these variables that is not very strong ($r = 0.362$). There was no significant correlation between the other variables.

At 95% significance, the researchers reject the hypothesis $H_{0.5}$ for the following pairs of variables: the need for a visualization web application and computer automated detection of student attitudes, and the need for a visualization web application and computer automation to have information about each student's current ability and progress on which they can make decisions about their future learning.

3.5. Interest in the Development of the Visualization Web Application on the Czech Market (RQ1 and RQ2)

From the analysis of archival and publicly available documents of representatives of the application sphere relevant to the research intention ($n = 112$), it was found that the proposed visualization web application is not available on the Czech market, or there is no similar product for the teaching of accounting or other educational needs. For this reason, direct interviews were conducted with representatives of these companies in online or contact form in order to supplement and refine the results regarding their interest in the development of the proposed web application that would incorporate the specific parameters.

Assessment of RQ1: *Is there such a web application for the teaching of accounting on the Czech market?*

From face-to-face interviews, it was confirmed that the proposed visualization web application is not yet available on the Czech market. In total, 69 subjects (61.6%) expressed that they implement web and mobile applications for educational purposes of other kinds. The most frequently mentioned were existing offers of accounting and economic software, mobile applications, provision of cloud services, and computer game development. The other 43 subjects (38.4%) said that they were not currently involved in this area.

The most frequently recurrent direct responses of the subjects are summarized as follows:

"We are involved in other products such as mobile applications, cloud services and the development of accounting and economic software. Your idea seems interesting to us, but we have no links to this idea at the moment."

Assessment of RQ2: *Do relevant companies perceive the development of such a web application as beneficial?*

The companies contacted agree on the benefits of the web application for educational purposes. Although 43 companies out of the total sample of 112 are not currently directly involved in this matter, the design of this web application seems interesting to these companies, and they have expressed interest in possible cooperation on the research project. However, all of the firms agree that this will be a financially demanding activity.

The most recurrent direct responses of the subjects are summarized as follows:

"We do not produce the application, but we are not afraid to implement it according to your specifications. We see it as an asset." We see the benefit in the application, but it will be a financially demanding activity." We have tried to design something similar in the form of a prototype, we see the benefit in such things, but it has never been converted into current modern programs."

It can be summarized that, currently, the proposed web application is not available on the Czech market, but the representatives of the application sphere from the Czech Republic, who are relevant for the given activity, perceive the proposed web application for educational purposes as important and as an interesting product for future development.

4. Discussion

The pilot study focused on finding out, on the one hand, how secondary and higher education institutions in the Czech Republic and higher education institutions in other countries (Belgium, Germany, Greece, the Netherlands, Poland) perceive the importance of educational elements and visualization web applications that should serve to develop students' accounting thinking in an interactive environment, in order to support self-study and the student's ability to learn and monitor their progress in accounting disciplines, and, on the other hand, how interested the representatives of the application sphere in the Czech Republic are in the development of such a web application. It should be noted that the survey was designed as a pilot in order to obtain the first results, on the basis of which the methodology will be modified for comprehensive quantitative research with a long-term impact of the proposed web application on students' learning outcomes.

All of the representatives of partner secondary and higher education institutions ($n = 33$) perceived the proposed web application as necessary for the teaching of accounting, and beneficial for teachers' teaching and students' learning. These findings are consistent with the work of researchers who have developed instructional dashboards for the visualization of learning progress [8,34], and are consistent with the principles of Learning Analytics [9]. The results of the pilot study signal that the app would not represent a problematic didactic resource that would somehow disrupt established teaching methods or significantly reduce educators' and students' time spent on mastering the new app. Opinions on the need for the web application and its specific parameters do not differ by country at 95% reliability, divided into representatives of Czech schools and representatives of schools from other countries. This finding is surprising, as the experience of the authors of the study showed that the approach to education at the Czech and foreign higher education institutions is different in the global context. However, this result is explained by a longer-term cooperative relationship between Czech and foreign representatives, and joint projects and ongoing discussions between representatives on pressing issues of educational strategies and approaches. Thus, the partner schools may have influenced each other, which may have resulted in similar responses from the school representatives. It should be noted that this result is not considered a conclusion, but rather a necessity to verify it on the basis of quantitative research. Given that all of the school representatives assessed the concept of the web application as necessary and beneficial, the above result on the undetected differences by country indicates that the needs in teaching accounting in the schools surveyed are the same, and thus teachers and students may encounter similar or the same problems and constraints in teaching and learning, according to the schools' statements. This was also evidenced by an international study [8,34], the main interest of

which was also to examine attitudes towards a visualization-based learning dashboard with learning progress detection. A significant difference was found by the level of education, broken down into secondary and higher education institutions, at the 95% significance level for the parameter of the freely available version of the app. In the research setting of this pilot study, the finding was that this parameter is more important for secondary schools compared to higher education institutions. This may be linked to the way secondary and higher education institutions are funded, and the current needs of schools, which differ, for example, according to the strategic objectives of the school in the context and the demands placed on students. The willingness of colleges to possibly proceed to a paid version of such an application is higher.

The pilot study supported the recognition that higher education institutions consider student–teacher collaboration [8,33], the combination of spoken explanatory commentary with animations to visualize the explanation [33,45], and the simulation of accounting activities [44] to be the most important aspects of accounting instruction. At the same time, this pilot study brings the overlap of this topic to the secondary level of education, which is not mentioned in the studies [8,32–34,42]. In these areas, the researchers see an opportunity for further research based on quantitative research. The representatives of the secondary and higher education institutions involved in the research reported a lack of the ability to have computer-automated information about each student’s current abilities and progress in accounting classes, based on which the student can make decisions about his/her further learning and choose effective learning methods, and at the same time, based on which the teacher can make decisions about his/her further teaching and choose effective teaching methods. Furthermore, it is student-centered individualization and the computer-aided detection of student attitudes, i.e., what the student enjoys, is interested in, is surprised by, or finds difficult in accounting cf. [8,34]. Beyond studies [43,44], accounting simulations and computer games were also found to be missing elements in accounting education to support learning. What is surprising to the authors of the study is the absence of the simulation of accounting activities in the teaching of the accounting subject, as such activities are one of the building blocks on which the subject is based. Such activity is also very important for practical preparation for the accounting profession. It will be necessary to examine the frequency of the elements included, which was not dealt with in this study. Furthermore, animations of accounting displays are among the missing elements. The authors [39,40,42] point out the importance of animations for mathematical principles. Furthermore, the reporting of transactions to support learning ability, cf. [16], and the combination of spoken explanatory commentary with animations to support learning ability in accounting courses, cf. [17], were considered to be missing elements. The results indicate that the teaching of the subject of accounting is still close to the traditional mode of education. The researchers consider the above educational aspects in combination with the proposed web application for the teaching of accounting to be important, as it was necessary to establish the interdependence of the need for such a didactic digital tool with the constraints in the teaching of accounting. This leads to the practical implication of the pilot study, i.e., to adapt the proposed didactic tool more effectively to the current educational needs of secondary and higher education institutions.

The correlation analysis shows a significant direct dependence of the usability of the web application in distance learning with the visualization of account parameters (i.e., turnover, opening/ending balance, number of counter-accounts) and reconciliations (amount, impact of the transaction on the statements) using the size, width and colour of objects representing accounts and reconciliations. These parameters are generally important, and the findings support the arguments of the study [45]. Statistical significance was also detected between these specific parameters—the usability of the web application in distance learning and the interactive environment that the application offers for student self-study, in order to provide information about their attitudes, current skills and progress in accounting disciplines, cf. [34]. The surprising result for the researchers is that the need for a web application is not related to the absence of animation and simulation in the subject

of accounting, which is evident from the above presented research. This again reveals a style and approach to the teaching of the subject of accounting in which there is still a prevalence of teaching without digital technologies that can support the development of students' thinking and learning styles, especially by increasing visualization.

A new finding of this study is a significant direct relation between the perceived need for a visualization web application and the computer-automated detection of student attitudes, i.e., obtaining ongoing information about what the student enjoys, is interested in, is surprised by, or is having trouble with, etc., in accounting. The need for a visualization web application correlates positively with the computer automation of having information about a student's current abilities and progress, based on which the student can make decisions about his/her future learning and choose effective learning methods.

This study revealed that, beyond the studies [8,30–34] that have addressed the automation of the visualization of learning progress, according to application domain representatives ($n = 112$), the visualization web application the researchers designed is not available on the Czech market, or there is no similar product for the teaching of accounting or other educational needs. The interviewed companies agree on the benefits of the web application for educational purposes. Although 43 companies out of the total sample of 112 are not currently directly involved in this matter, the design of this web application seems to be interesting to these companies, and they have expressed interest in possible cooperation on the research project, which will be a financially demanding activity.

Limitations and Future Work

There are some limitations of this pilot study that point to a number of opportunities for future research. The researchers explored attitudes towards the proposed web application and the educational elements for the teaching of accounting first at partner secondary and higher education institutions. Research oriented towards secondary and tertiary education carries findings from one school representative which is competent in the field of educational strategy and pedagogy, not from every teacher who teaches an accounting subject at that school, which may be a limitation to some extent. The researchers are currently working on this aspect, and are extending the research into quantitative research with the teacher's perspective. They are also targeting secondary schools from other countries in the future, as part of the extension of the IBW programme specifically to the secondary level. In addition, the research will include secondary and tertiary education students who have studied or are studying accounting. It will be necessary to find out attitudes towards the proposed web application, cf. [34], and other educational elements within the accounting curriculum from them. These responses will need to be compared with the attitudes of teachers to refine the design for the development of a prototype web application to develop accounting thinking skills, to promote students' self-study and ability to learn, and to monitor their progress in accounting subjects. In accounting subjects, there is a high demand from schools for automated feedback to monitor learning progress, such that this quantitative research will be essential. This research also focused on the opinions of representatives of the application sphere on the availability of the proposed web application on the Czech market, and its benefits. A significant number of companies expressed positive opinions about the proposal. The future development of the web application will first be preceded by the selection of a suitable candidate from among the representatives of the application sphere who were contacted and who perceive the web application proposal to be in line with their goals and needs. Another limitation of the study is that the proposed web-based interactive application will be presented in the form of a description, rather than a prototype for pilot testing. This phase will be launched after the completion of the research oriented towards teachers' and students' attitudes towards the proposed web application.

5. Conclusions

The main motivation for this pilot qualitative study was to find out where accounting education at secondary and higher education institutions is currently heading, or is desirable to head, in the context of trends from the COVID-19 pandemic, through the preferences of these institutions in the Czech Republic and other countries. Based on the results, a methodology for the continuation of quantitative research will be proposed, which will focus not only on finding out the opinions of teachers and students on the given area but above all on the development of a prototype web-based learning application. Hence, the research was conducted in two basic levels of findings. First was how representatives of partner secondary schools and higher education institutions perceive the proposed web application to develop accounting thinking, in order to promote self-study and students' ability to learn and monitor their progress in accounting disciplines. Second was how the representatives of the Czech application sector perceive the availability of such a web application on the market. The results showed that the Czech market does not yet offer such a web application, and that the majority of relevant companies are interested in developing such a web-based interactive application. Representatives of partner secondary schools and higher education institutions evaluated it as necessary and beneficial. Its necessity appears mainly in its usability in distance learning with the visualization of account parameters (i.e., turnover, opening/ending balance, number of contra-accounts) and reconciliations (amount, impact of the operation on the statements) by means of the size, width and colour of the objects representing the accounts and reconciliations. The web application can be a useful didactic tool, especially in cases of distance or online learning. The usefulness of the web application appears further in distance learning and the interactive environment that the application offers for student self-study, and for providing information about their attitudes, current abilities, and learning progress in accounting disciplines. This study has practical implications not only for accounting education but also for other disciplines; the findings may be essential in order to advance the quality of student learning and teacher teaching. This study also has practical implications for the field of management. In order to implement such a form of education, teachers need to be trained and students also need to be introduced to the principles of Learning Analytics-based education. This would take time and money in terms of motivating secondary and higher education teachers. The results of the study also have theoretical implications in the field of quantitative research for further comparative research at the level of secondary and tertiary education, with overlap for other countries outside the Czech Republic, and in the field of the modification of the principles and methods of formative feedback based on Learning Analytics.

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Article

Student and Language Teacher Perceptions of Using a WeChat-Based MALL Program during the COVID-19 Pandemic at a Chinese University

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Abstract: The outbreak of COVID-19 has impacted conventional educational practice in universities worldwide. Chinese universities are no exception. WeChat, a social application widely used in China, has been considered a viable tool for language education. However, the perspectives of Chinese university students and English language teachers in terms of using WeChat for English vocabulary learning and teaching during the pandemic remain unclear. The aim of the present study was twofold: First, it explored Chinese university students' and language teachers' opinions of adopting a self-developed WeChat-assisted lexical-learning program (the WALL program) during COVID-19. Second, it gathered their evaluations of the WALL program. To achieve the aim, two sets of semi-structured interviews were used to gather qualitative data about five students' and three English language teachers' perceptions at a university in northern China. The results first revealed that the eight participants showed overwhelming opinions in support of adopting the program for vocabulary learning and teaching during the pandemic. In addition, it received mostly positive evaluations. However, the program had two main drawbacks: distracting learning environments and uncertain learning effects. The present study then made recommendations for future WeChat-based language learning and teaching programs. The findings are expected to provide pedagogical insights for tertiary educational institutions, practitioners, and students in the chosen context in order to deal with the future design and implementation of sound MALL-based approaches.

Keywords: mobile-assisted language learning (MALL); English vocabulary learning and teaching; WeChat; higher education (HE); mainland China

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1. Introduction

The COVID-19 pandemic has caused massive disruption to education worldwide. To contain the pandemic, China mandated nationwide school closure at the end of February 2020 [1]. An initiative in China, “Suspending Classes without Stopping Learning”, switched higher education (HE) online [2]. Learning using various mobile technologies outweighed conventional classroom-based learning in most Chinese universities during the pandemic [3,4]. The phenomenon that mobile devices, such as mobile phones or smartphones, are used to assist language learning in formal and/or informal environments is referred to as mobile-assisted language learning (MALL) [5]. MALL features ubiquity, social interactivity, authenticity, multimodality, and motivation enhancement [6–9].

MALL is increasingly prevalent in HE practices [10]. MALL pedagogies were adopted widely among Chinese students and language teachers as a preferred university English learning approach during the pandemic [11,12]. However, due to unexpected and sudden changes in learning environments and modes, Chinese university students and teachers faced numerous challenges in online educational infrastructure, IT-related skills and knowledge, and academic success [13]. These challenges led to a growing concern about the mobile technology-related educational experiences of Chinese university students and teachers during the pandemic [14]. These challenges thus called for the ways in which

students and teachers might perceive and evaluate MALL in Chinese HE sectors to be revealed. This was because MALL pedagogies remained problematic under such circumstances. Nonetheless, many positive findings have reported the advantages and affordances of implementing MALL pedagogies for university English educational practices in the chosen context [14,15]. Therefore, this study aimed to fill this gap by exploring Chinese university students' and language teachers' perceptions of using a WeChat-based MALL program for English vocabulary learning and teaching during COVID-19.

2. Literature Review

MALL studies were inadequate during the pandemic, despite them having been well-researched in past decades [16]. More explorations were required [17] because findings in normal times could arguably provide valid interpretations for relevant accounts under pandemic circumstances [18]. According to the wealth of literature, sociocultural theory was frequently adopted to scaffold MALL studies in this period [19]. However, the situated learning theory (SLT) [20], under the umbrella of sociocultural theory, remained overlooked. Nevertheless, different SLT elements have been discussed in MALL practices, such as collaboration [21]. The SLT propounds that learning is produced and developed by its embeddedness and situatedness in authentic activities and contexts by learners' constant engagement, as they are apprentices in the socially built contexts of practice [20]. The two most widely recognised SLT components are legitimate peripheral participation (LPP) and communities of practice (CoPs) [20]. By LPP, learners obtain knowledge and master skills in authentic practice, and they develop from novices into total participants gradually by interacting with other full participants [20]. In addition, CoPs refer to a context in which learners acquire knowledge and skills, strengthen sociocultural competence, and cultivate personality traits by jointly participating in interactivities with shared practical goals [20,22]. Therefore, echoed by the MALL features mentioned previously, the SLT was adopted as the theoretical framework of the present study in order to understand MALL practices during the pandemic.

Most extant empirical studies on MALL in the literature at tertiary levels during COVID-19 focused on discovering participant opinions and their experiences of adopting MALL pedagogies. For example, university students and teachers primarily held optimistic attitudes towards transitioning to mobile-assisted Russian learning [23]. Several Chinese studies also yielded positive results: one example is that most Chinese university students supported MALL as it enhanced their learning autonomy for university English courses [24]. In addition, university students accepted the affordances and use of mobile technologies for online English learning during the lockdown period [25], especially mobile phones and social applications [26]. Another study found that students were more compelled to use MALL-based pedagogies than conventional learning methods during the pandemic [14].

Most reviewed MALL empirical studies, however, did not consider the device and application types used when investigating participants' opinions. This variable is important because different mobile technologies have been used for language education in China [27]. In addition, factors, including user groups, academic contexts, and applications applied, can influence the understanding of MALL and the research findings greatly [28]. In this regard, the present study focused on using one particular application, WeChat, given its high popularity among Chinese university students [29]. One existing study has confirmed that some nationwide popular live platforms in China, especially WeChat, have significant affordances in supporting university English courses [30]. Some other studies that specifically focused on using WeChat for university English education found that WeChat-based tools have been well accepted by Chinese university students for English pronunciation learning during the pandemic [19]. Another study reported that participants favoured implementing WeChat for personal English-speaking tutoring [31]. However, as the most researched language-teaching area in MALL in pre-pandemic times, vocabulary was under-researched during COVID-19 [32]. Vocabulary acquisition is particularly challenging for Chinese English learners, and it receives more attention than other language teaching

areas [33]. Therefore, it calls for further explorations of how students and language teachers perceive WeChat-assisted English language vocabulary learning and teaching in Chinese HE contexts during COVID-19.

3. Research Aim and Questions

The present study aimed to explore Chinese university students' and language teachers' perceptions of using WeChat for English vocabulary learning and teaching during the pandemic. To achieve this aim, a WeChat-assisted lexical-learning program (the WALL program) was developed by the researcher. Five students and three English language teachers at a university in northern China were interviewed about their opinions of the program after the approximately one-month program delivery, from 24 May to 21 June 2020. The following questions were to be addressed:

- (1) What were Chinese university students' and language teachers' opinions of using the self-developed WALL program for university English vocabulary learning and teaching during the pandemic?
- (2) What were Chinese university students' and language teachers' evaluations of the WALL program?

4. Research Methods

4.1. Research Design

The research design underpinning the present study was a qualitative case study. This study, under a larger-scope mixed-methods research project, reported qualitative data about five students' and three language teachers' perceptions of using the WALL program for vocabulary learning and teaching during the pandemic. The qualitative data were gathered using two sets of semi-structured interviews in the qualitative phase of the project. The quantitative findings in the quantitative phase have been published in a separate paper [34]. A qualitative approach was adopted because it allowed the researcher to explore and understand the meaning the participants attributed to the research problem via emerging questions, collecting data in participant settings, analysing data inductively, building general themes, and interpreting data [35]. In addition, a case study helped the researcher to explore a real-life contemporary bounded system, or multiple bounded systems over time, through the collection of detailed, in-depth information and report themes, and descriptions of the case [36].

4.2. Participants and Sampling Techniques

As mentioned above, this case study involved the participation of five students and three English language teachers in two sets of semi-structured interviews. The duration of the three language teachers' working experiences in higher-education contexts varied from 10 to 15 years. Initially, the teachers nominated the intact classes they were assigned to. All students ($N = 133$) and the teachers trialled the WALL program for around one month. Of the students, five consented to participate in the semi-structured interviews. They contacted the researcher via email after the program delivery. Table 1 below presents the details of the eight interview participants: five students and three language teachers. This sample size was acceptable because case studies generally include about four to five cases [35]. In addition, sample sizes for qualitative research are not generally justified, as long as they are large enough to sufficiently describe the phenomenon of interest and address the research questions [37,38].

University students were purposively chosen as the sample group because learning at tertiary levels is more independent [39]. Another reason was that the WALL program was to be delivered on mobile phones, and China has a large population of mobile-phone users in universities [40]. In addition, only the students in Year One and Year Two were purposively recruited. This was because non-English majors in most Chinese universities usually complete English courses at the end of their second year. This student group was thus considered the most suitable for this study.

Table 1. Detailed information about the eight interview participants.

Academic Faculties/Disciplines/Schools	Students ($n = 5$)			Teachers ($n = 3$)	
Architecture	No. 1	F	Y1	No. 1	F
Chemistry	No. 2	M	Y1	No. 2	M
Information Technology	No. 3	M	Y1	No. 3	F
Media and Communication	No. 4	F	Y2		
	No. 5	F	Y2	N/A	

M = Male; F = Female; Y1 = Year One; Y2 = Year Two.

4.3. Research Instruments

4.3.1. The WeChat-Assisted Language Learning Program (the WALL Program)

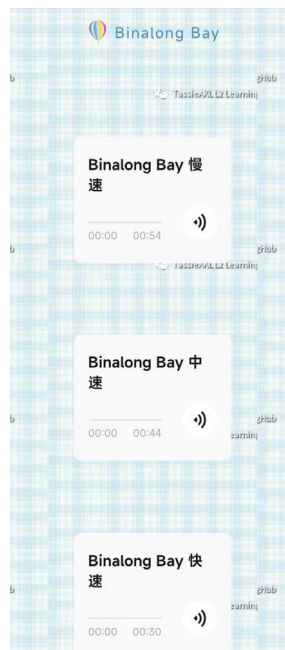
The WALL program was designed for university English vocabulary learning. Learning materials, practice and drills, and additional learning resources were delivered on a self-designed WeChat public account. The students and teachers received notification messages at around one o'clock in the afternoon every day during the program delivery period. The learning resources covered a wide variety of knowledge about Tasmania, Australia, including natural scenery, wild animals, daily life, and local cultures. Learning materials were presented in forms of texts (with graphics), audio, and video clips (as shown in Figure 1). The program also provided daily practice and drills in the form of tests (as shown in Figure 2). The length of the intervention duration was around one month. This was determined because an intervention or treatment that is less than one month benefits participant improvement [41]. Longer program lengths could cause fatigue [42] if the novelty effect of the WALL program wore off among the participants over time [43].



A 2-minute Guide to Tasmania



(a)



(b)



(c)

Figure 1. Examples of vocabulary-learning resources. (a) Video-formatted learning resources with English and Chinese subtitles (b) Audio-formatted learning resources at the different speeds (c) Text-formatted learning resources with English and Chinese transcripts.

1. On some entertaining occasions in Tasmania, people could enjoy themselves with few restraints. In other words, people could _____.
A. kick up heels B. wander around C. commit crimes D. quit working
2. Which one of the following has an OPPOSITE meaning to "kick back"?
A. Work hard. B. Chill out. C. Take breaks. D. Catch one's breath.
3. The question that what Tasmania is like is quite _ _____.
A. tricky B. certain C. simple D. direct
4. What kind of building is the one that was titled as "Lonely Plant's Best New Places to Stay" in 2018?
A. A castle. B. A lodge. C. An apartment. D. A cave.

Figure 2. An example of daily practice and drills in the form of tests.

4.3.2. Semi-Structured Interviews

Two sets of ten semi-structured interview questions were used to explore both students' and language teachers' perceptions of using the WALL program for English vocabulary learning and teaching during the pandemic (as shown in Table 2). The interview questions were devised based on the research aim and informed by the relevant literature [44]. Interviews, as a qualitative research approach, helped the researcher analyse the data naturally by eliciting information that was difficult to obtain using other data collection techniques, such as the observation of feelings, thoughts, and intentions [45,46]. In addition, compared to unstructured and structured interviews, semi-structured interviews allowed the interviewer to receive guidance and take in interaction, and interviewees had more freedom to express their views on their own terms [47]. The reason for this was that semi-structured interview questions are generally prepared and given to respondents in a random order or without a predetermined wording [46].

Table 2. Overview of the interview questions.

Q1. What is your opinion of using WeChat for vocabulary learning/teaching?
Q2. How is mobile-based vocabulary learning different from the learning/teaching method(s) you have used before? Apart from what has been offered in the WALL program, is there anything else you would expect?
Q3. How would you evaluate the WALL program?
Q4. Did you like using the WALL program? Why or why not?
Q5. How do you like the vocabulary-learning activities you participated in?
Q6. What is your opinion of the delivered learning resources?
Q7. Could you comment on the three forms of the delivered learning resources (namely texts, audio, and video clips)?
Q8. Is there anything you would like to suggest for the WALL program?
Q9. How do you think the WALL program has influenced your vocabulary learning/teaching?
Q10. How do you think the WALL program has influenced your/students' motivation for vocabulary learning?

5. Data Analysis

In this study, the following qualitative data were gathered from the eight participants: five students' and three language teachers' answers to the two sets of ten semi-structured interview questions. The interview questions collected their perceptions of using the

WALL program for vocabulary learning and teaching based on their understanding and experiences. The participants were offered an outline of the interview questions in advance so that they could better prepare for the interviews. The process of analysing qualitative data allowed the researcher to have an insider's view of the field via a close association with both the participants and activities in the natural setting [48]. The qualitative data collected from the semi-structured interviews were in a textual format. The interview data were first audio-taped and then transcribed into text. After transcribing the raw data, the researcher read through the interview transcripts carefully. Thematic analysis was then adopted to interpret the qualitative data. This helped the researcher to identify, analyse, and report the emerging themes regarding the students' and language teachers' perceptions of the WALL program [49]. The NVivo software version 14.0 was used to transcribe the responses because of its effectiveness in transcribing, organising, interpreting, and analysing qualitative data in various formats, such as documents, texts, and audiotapes [39]. In addition, it categorised the data systematically [50].

6. Results

As mentioned above, the qualitative data were gathered from the two sets of ten interview questions. The data were used to address the research aim concerning the students' and language teachers' perceptions of the WALL program. In total, there were eight participants: five students and three language teachers participated in the semi-structured interviews. The lengths of the interviews ranged from 15 min to 25 min. After the interviews, the interview data were transcribed into texts for data analysis. Table 3 below presents the themes and sub-themes that emerged from the data. It also shows the numbers of comments, which indicate the frequencies of the themes mentioned by the participants.

Table 3. Overview of the identified themes, sub-themes, and number of comments.

Themes	Sub-Themes	Comments
Theme 1: Students' and language teachers' evaluations of the WALL program	• Program design	76
	• Delivered learning resources	
	○ Audio	
	○ Video clips	
	○ Texts	
	• Designed learning activities	
Theme 2: Advantages of WeChat-based learning approaches	○ Daily drills and practice	49
	○ Bonus resources	
	• Learner-friendliness	
Theme 3: Problems of the WALL program	• Motivation enhancement	14
	• Support for collaborative learning	
	• Distracting learning environments	
	• Uncertain learning effects	

6.1. Theme 1: Students' and Language Teachers' Evaluations of the WALL Program

The most important theme that emerged from the students' and language teachers' responses was their evaluation of the WALL program, which had 76 comments. The theme showed that they held overwhelming positive attitudes towards the WALL program. It specifically focused on the program design and the designed vocabulary-learning activities, followed by the delivered vocabulary-learning resources.

6.1.1. Program Design

Most participants commented on the design of the WALL program. Examples are provided by three students and one language teacher who showed their approval:

The research team made the right decision because we use WeChat and public accounts every day. They are a part of my life. So, it's natural to use WeChat, even for learning purposes. (Student No.4)

WeChat and public accounts empower us with instant messaging, including voice and video calls, with lovely widgets and GIFs. Also, public accounts provide us with information in different forms, like texts, graphics, audio, and videos. (Student No.2)

The topics in the bonus resources were entertaining to read. They were about different aspects of the introduced place, such as traffic rules. These greatly raised my motivation in reading the posts because I had rarely heard about or known these things before. I was attracted to find out more about the topics and to use the program in the long term. (Student No.3)

I saw most students were fascinated by the topics. They were able to know about a particular location overseas, ranging from its local cultures, social life, and natural scenery. As the teacher, I was also intrigued by these contents because I felt curious about the contents. (Lecturer No.3)

6.1.2. Delivered Learning Resources

The sub-theme that had the second most comments was the students' and language teachers' supportive comments about the delivered vocabulary-learning resources. They showed a primary focus on the multimodal ways of delivering the content, namely audio, video clips, and texts. Supportive examples for this were provided by two students and two language teachers by saying the following:

The audio materials were an effective tool for the students with different language-proficiency levels because they were able to select the speeds that suited them the best, namely slow, medium, and fast. For me, I often selected the slow speed for intensive vocabulary learning, writing down each word as I could. I practiced my listening skills using the medium speed. The fast speed helped me improve my speaking and fluency. These three speeds were used differently for personalised learning purposes. (Student No. 5)

The audio-formatted resources helped the students learn vocabulary and benefited their different language skills, such as listening and speaking. They were able to read after the audio or scripts. It was also like a level-up game that motivated the students in achieving the learning tasks due to the different speeds. They could move up to the next level, which was more challenging, after they had managed the current difficulty level. (Lecturer No. 1)

The videos improved my different language skills, such as listening, speaking, and translating. This was because videos combined textual, audio, and visual information together for vocabulary learning. Also, lexical knowledge became more vivid than the content presented in plain texts in my textbooks. Sometimes, the videos were a good way of entertainment after study. (Student No. 1)

Memorising new words in the conventional way, such as rote learning, copying wordlists, and doing dictations, remains a pervasive approach for vocabulary learning in most Chinese universities. I believe there are some teachers and students who still prefer text-formatted materials. As well, remembering the word form was the most direct and regular approach for the students to learn vocabulary. It was particularly true for non-English major students, like those recruited in this research project. (Lecturer No. 2)

6.1.3. Designed Learning Activities

Apart from the two sub-themes above, the students and language teachers showed positive attitudes towards the designed vocabulary-learning activities. They mainly praised the daily lexical practice, drills and the bonus resources. Examples were provided by one student and one teacher by claiming the following:

The daily practice successfully enhanced my vocabulary-learning outcomes. Because doing follow-up practice helped me have a deeper impression of and a better memory of the lexical knowledge and items I learned. Also, the daily practice pushed me to review the lexical items every day after learning the delivered learning content. (Student No. 3)

The daily practice, as spaced repetitions of the target lexical knowledge, strengthened lexical-learning effects through frequent reviewing of the learning materials. As well, the students were able to examine their learning achievements or performances. (Lecturer No. 1)

6.2. Theme 2: Advantages of WeChat-Based Learning Approaches

The second most mentioned theme was the advantages of the WeChat-based learning approaches (N = 49). This theme indicated that the students and language teachers believed that WeChat-based learning approaches had the advantages of learner friendliness, motivation enhancement, and support for collaborative learning.

6.2.1. Learner Friendliness

Within this theme, the learner friendliness of the WeChat-based learning approaches received the most comments. Two students provided further explanations by stating the following:

WeChat-based learning approaches made vocabulary learning easy for me. Because learning was more convenient, compared to the traditional methods I used to apply, such as reciting target lexical items in my English textbook. I mean, I didn't have to bring learning materials to learn vocabulary. All I needed was WeChat on my mobile phone. (Student No. 4)

I was able to learn vocabulary anytime and anywhere. For example, when I was on the go, such as heading to classrooms or for the next classes, I was able to listen to the audio materials. Also, when I was on the shuttle bus to the apartment and lining up in the cafeteria, I was able to see the short videos on the program. I didn't need to sit in the classroom or library to learn. More importantly, I was able to take notes using my phone. (Student No. 5)

6.2.2. Motivation Enhancement

The sub-theme that had the second most comments was the enhancement of learning motivation. Two language teachers supported this idea by claiming the following:

Most students in my class tended to have a stronger interest in learning the target lexical items delivered on the program. For instance, some watched the videos before classes and during class breaks. Some discussed the content they had problems with partners and in groups. Also, some students asked me for help. They were fascinated with the learning content and topics and would like to learn more about the target vocabulary actively, compared to their old learning behaviours. (Lecturer No. 3)

Most students showed stronger learning motivation because they found WeChat-based learning approaches interesting to use. They engaged in learning the target lexical items and using the WeChat-based program because of the sense of novelty. As a language teacher, I found it fun to use WeChat for vocabulary teaching myself, as well. (Lecturer No. 2)

6.2.3. Support for Collaborative Learning

Another sub-theme was the collaborative vocabulary-learning activities supported by the WeChat-based learning approaches. Examples from two students are shown below:

WeChat-based learning approaches supported my vocabulary learning with my fellows. I often learned the target lexical items delivered by the program with my best friends or room-mates. As well, we quizzed each other on some important lexical content. Additionally, if I had some problems with the delivered lexical-learning content, I was able to leave messages

to or have instant communication with the straight—A students in my class. If they couldn't figure out the answers, I would turn to my teacher for learning assistance and guidance on WeChat. (Student No. 3)

We recited the target lexical items together after class. We also did the vocabulary quizzes on the program in groups to check how well we had learned. We often quizzed each other. WeChat provided instant communication and prompt learning assistance. We were able to get help from our fellow students and teachers. (Student No. 1)

6.3. Theme 3: Problems of the WALL Program

The last theme was about the problems of the WALL program. This received only 14 comments. The students and language teachers argued that the WALL program had distracting learning environments and uncertain learning effects.

6.3.1. Distracting Learning Environments

Within this theme, the distracting learning environments of the WALL program received more comments than the other sub-theme. Two students and one teacher mentioned this by clarifying as follows:

It was hard to stay focused due to the inevitable distractions. I mean, there were unexpected messages on WeChat when I was learning vocabulary or watching the videos using the program. There was not much I could do about it, since WeChat is a social app. (Student No. 4)

It was hard to focus on learning vocabulary using the program because of the disturbances on WeChat and mobile phones. Unlike in classrooms where teachers are always around, I found it challenging to ensure my learning efficiency and outcomes. (Student No. 5)

6.3.2. Uncertain Learning Effects

The other sub-theme included the uncertain learning effects of the WALL program. An example of this was provided by one language teacher:

The students could not have satisfactory learning outcomes when using the program for vocabulary learning. It was less likely to make sure their learning engagement, learning attitudes, and learning behaviours in the program-based learning setting. (Lecturer No. 2)

This section presented the textually formatted qualitative data gathered from the five students' and three language teachers' semi-structured interview transcripts. The data were analysed using thematic analysis with NVivo software. Three themes emerged from the raw data: *Evaluations of the WALL program*, *Advantages of WeChat-based approaches*, and *Problems of the WALL program*. The next section will discuss the findings aligned with the existing literature through the lens of the SLT.

7. Discussion

This section will discuss the findings based on the qualitative results following the SLT. The findings were examined in light of the relevant literature to observe to what extent the findings of the present study supported or were opposed to other existing studies. The findings indicated that all the participants held positive opinions about the use of the WALL program for vocabulary learning and teaching during the pandemic. However, they also stated that the program had drawbacks. Following this, recommendations were further provided for future WeChat-based language learning and teaching programs in the chosen context.

7.1. Students' and Language Teachers' Perceptions of the WALL Program

The present study reported that the five students and three language teachers overwhelmingly supported using the self-designed WALL program for vocabulary learning and teaching during the pandemic. This finding is consistent with previous studies that

found that social applications such as WeChat were considered viable tools for Chinese university English learning and teaching during COVID-19 [26,51]. In addition, aligned with another existing study, most of the recruited participants revealed positive attitudes to MALL approaches and experiences during the pandemic [25]. The reason for this was that WeChat had been increasingly adopted for foreign language education in China before the pandemic [10]. Most of the students and language teachers in the present study were familiar with WeChat and used it for different purposes in their daily lives. Thus, it was unlikely that they would find it challenging to use WeChat for academic purposes.

As LPP indicated, learning should be embedded in authentic situations in which relevant practices occur [52]. For instance, the WALL program empowered the students with multimedia-based vocabulary-learning resources, namely texts, audio, and video clips. These learning resources created authentic language-related environments mirroring real-life settings involving different language skills, such as listening and speaking. In addition, learning, as a social practice, has social features, and it occurs in a setting that is socially built [20]. The program, based on WeChat, an instant messaging application, allowed for both synchronous and asynchronous social activities between students and between students and teachers. Additionally, learners realised learning through a changing process in which they participated as apprentices [53]. The program helped the students achieve learning vocabulary through learning with and from more advantaged fellow students.

According to CoPs, the goal of obtaining knowledge is to use it for practical purposes [54]. For example, the designed vocabulary-learning activities were associated with the students' practical needs in terms of exam-oriented university English learning, especially when taking tests. The delivered vocabulary-learning resources also suited the students' personal needs and preferences by entitling them to different forms, namely texts, audio, and video clips. In addition, learners are interconnected due to their same learning goals [55]. The program supported vocabulary learning interactivities centred on the same learning and teaching objective. Moreover, learners could change their mindsets and behaviours when engaging in community-based activities [56]. The students showed improved interest and increased engagement in learning vocabulary due to their participation in the learning interactivities and communities supported by the program.

7.2. Problems of the WALL Program

Some students and language teachers in the present study argued that using WeChat for university vocabulary learning and teaching under the pandemic circumstances remained problematic. They argued that the program had the following drawbacks: distracting learning environments and uncertain learning effects. This is congruent with the findings of several previous studies, which found that MALL-based approaches generally have several issues; these include external distractions and disturbances and uneven effectiveness [28,34,57]. Supported by other existing research, Chinese university students have experienced challenges in terms of obtaining satisfactory learning performances in online learning settings during the pandemic, owing to concentration difficulties and distractions [58]. These defects deterred the participants in the present study from providing satisfactory evaluations on WeChat-based learning and teaching approaches. Supported by a recent study, some surveyed participants held neutral attitudes towards using WeChat for language educational practices, due to its adverse effects [59].

7.3. Recommendations for Future WeChat-Based Language Learning and Teaching Programs

In light of the abovementioned problems, this study makes several recommendations for future WeChat-based language learning and teaching programs. First, WeChat-based language learning and teaching programs should provide learning environments involving the participation and support of learning instructors. This is because instructors are conducive to learners' learning outcomes and engagement in mobile-based learning environments [60]. In other words, teachers potentially play a vital role in mediating students' learning performances by providing learning supervision and guidance in WeChat-based

learning environments. Another recommendation is that WeChat-based language learning and teaching programs should focus on the development of learners' various academic abilities in WeChat-based learning contexts to ensure their learning outcomes. For instance, such programs can provide different learning activities, such as group learning activities, where students can cultivate self-regulated learning abilities. This is because mobile-assisted learning is more like a self-paced learning style than a teacher-led instruction [61]. The third recommendation is that instructors be required to update their technical skills to ensure the quality of teaching when adopting WeChat-based programs for language education. The reason for this is that teachers might grapple with unfamiliar technologies due to their lack of information technology literacy for mobile-assisted teaching purposes [62].

8. Limitations and Suggestions

The present study has several limitations. First, the sample size ($N = 8$) in this qualitative case study was small. Consequently, the findings might not be able to interpret and present the situations at other universities in different regions of China. Further studies should have a larger sample size and if feasible, cover a wider geographical range to provide a larger picture of relevant accounts. Second, the selected topics and program design might be attributed to students' less satisfactory participation intentions and willingness to participate in this study. As [58] mentioned, issues regarding the design and quality of the delivered learning materials could largely influence learners' learning motivation and outcomes. Future studies are expected to involve diverse topics for language learning. Third, since MALL-based approaches have been used for different language teaching areas [63], apart from vocabulary, other language skills or a combination of different language teaching areas should be investigated in future studies. Fourth, the interview questions only slightly touched on factors such as learning motivation and learner autonomy. Future studies are suggested to probe into these factors under the relevant researched topics of MALL. Lastly, longer intervention duration length is recommended if possible.

9. Conclusions

This study explored Chinese university students' and language teachers' perceptions of using WeChat for English vocabulary learning and teaching during the pandemic. According to the qualitative results, the students and language teachers primarily favoured using the WALL program for university vocabulary learning during the pandemic. In addition, they evidenced that WeChat-based approaches empowered learner friendliness, enhanced learning motivation, and supported collaborative learning. This was because the program created authentic learning environments, was associated with practical learning needs, provided social interaction, supported learning interactivities, and impacted learning behaviours. However, some participants argued that WeChat-based approaches had the following pronounced drawbacks: distracting learning environments and uncertain learning effects. In light of the disadvantages, the present study then made recommendations for future WeChat-based language learning and teaching programs, including the involvement of instructors, the development of learner academic abilities, and the improvement of instructor IT-related knowledge and skills.

At the microscale level, the present study was anticipated to troubleshoot potential issues in regard to adopting WeChat for English language education in Chinese HE contexts during COVID-19 and post-COVID-19 periods. From the macro-level perspective, the results of this study may provide a valuable reference point for future studies that aim to design and develop MALL-based pedagogically sound approaches to ensure efficient and effective learning and teaching.

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Review

Retention Factors in STEM Education Identified Using Learning Analytics: A Systematic Review

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Abstract: Student persistence and retention in STEM disciplines is an important yet complex and multi-dimensional issue confronting universities. Considering the rapid evolution of online pedagogy and virtual learning environments, we must rethink the factors that impact students' decisions to stay or leave the current course. Learning analytics has demonstrated positive outcomes in higher education contexts and shows promise in enhancing academic success and retention. However, the retention factors in learning analytics practice for STEM education have not been fully reviewed and revealed. The purpose of this systematic review is to contribute to this research gap by reviewing the empirical evidence on factors affecting student persistence and retention in STEM disciplines in higher education and how these factors are measured and quantified in learning analytics practice. By analysing 59 key publications, seven factors and associated features contributing to STEM retention using learning analytics were comprehensively categorised and discussed. This study will guide future research to critically evaluate the influence of each factor and evaluate relationships among factors and the feature selection process to enrich STEM retention studies using learning analytics.

Keywords: student retention; student success; learning analytics; STEM; higher education

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1. Introduction

Science, Technology, Engineering, and Mathematics (STEM) education has become a global discussion topic in the last decade. The change in the global economy and the needs of the workforce indicate that STEM-prepared graduates will be in short supply around the world [1]. However, STEM disciplines in higher education institutions continue to face significant challenges due to high attrition and low retention rates. Many STEM entrants perform poorly in comparison to their peers, end up changing to non-STEM disciplines, or leave without earning any educational qualifications [2]. A student's early withdrawal from a degree program has detrimental effects on the well-being of students, institutions as well as a society [3]. This problem demands that institutions take measures to encourage students' persistence during their participation in STEM programs, increase retention rates, and assist students with academic success.

The retention analysis challenge arises as a result of the development of digital transformation in higher education institutions [4,5]. The rapid evolution of online pedagogy has resulted in the expansion of computer-supported learning environments, such as the Learning Management System (LMS) and Massive Open Online Courses (MOOCs), to improve the learning process of students. The COVID-19 outbreak in 2020 accelerated the pace of transition to online pedagogy, both nationally and internationally. Since COVID-19, there is a tendency to continue to offer online courses and/or blended learning courses [6]. This rapid transition has resulted in a tremendous amount of data being generated by the LMS and Student Information System (SIS) [7] which can be used to continuously track the online learning process. In this context, the need for high-tech data-driven solutions is becoming increasingly apparent in many institutions.

Learning Analytics (LA) has grown in popularity as a result of the use of big data analysis and the premise of optimising learning environments and improving retention

in STEM disciplines [8]. LA has emerged since 2011, and is commonly defined as the “measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs” [9] (p. 305). It allows objective information on students’ learning progress to be tracked by using data obtained automatically from students’ interactive activity with the online learning platform. Improving the retention rate is a multi-dimensional process involving many levels of relationship [10], and many factors contribute to a students’ decision to persist in their current course, or switch discipline or even leave university without gaining an academic qualification [2,11,12]. In dynamic learning environments, it enables researchers to capture and analyse a variety of data with the assistance of new tools and techniques [13]. LA uses digital traces, such as clickstream, assessment participation, etc., to provide insights into a student’s learning progress within a learning environment, which can be used to identify retention factors.

It should be noted that the “one size fits all” in LA may be counterproductive to student persistence and retention [14], and overgeneralising should be avoided in the practice of learning analytics across different disciplines [15]. The retention factors for STEM education explored in LA studies have yet to be systematically reviewed. Therefore, the purpose of this study is to contribute to this research gap by reviewing the empirical evidence on factors affecting student retention in STEM disciplines in higher education and what features can be used to measure and quantify those factors in learning analytics practice.

1.1. The Scope of This Study

Student persistence and retention in STEM disciplines is a critical challenge confronting higher education institutions. The existing reviews of retention learning analytics have primarily focused on the overall disciplines for higher education institutions [16], MOOCs [17], and online learning [18]. Therefore, this research is intended to present a comprehensive review of empirical studies that use LA to identify retention factors of higher STEM education in computer-supported learning environments. Through a systematic literature review, our contribution can be summarised as follows:

- A summary of factors, sub-factors, and features contributing to retention learning analytics in STEM education is presented. It provides researchers with guidance regarding which factors and features have been explored using learning analytics in the context of the digital transformation in the higher education sector.
- The features measured for each of the retention factors are evaluated and discussed. In the review of LA studies, it demonstrates how each factor can be quantified based on available datasets from systems (e.g., LMS and SIS) to predict student likelihood of persisting.
- This review also highlights the features that significantly contributed to STEM retention. This will facilitate the feature selection process and improve exploratory modelling efficiency in LA studies.

1.1.1. Research Questions

To carry out the systematic review, two research questions were formulated:

Research Question 1 (RQ 1): *What factors have been identified that impact retention in STEM education?*

Research Question 2 (RQ 2): *In STEM retention studies, how are retention factors quantified and measured in learning analytics practice?*

2. Methodology

This systematic review was conducted based on guidelines established in the Preferred Reporting Items for Systematic Reviews and Meta-analysis Protocols PRISMA [19]. The entire review process of studies selection is detailed in a flow chart (see Figure 1).

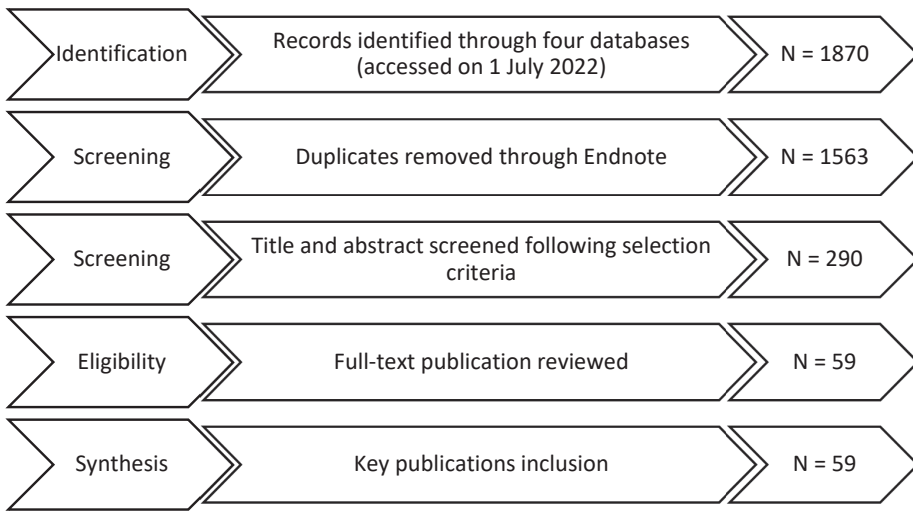


Figure 1. Flow diagram of PRISMA article selection process.

2.1. Search Strategy

Four academic databases, including Scopus, ScienceDirect, ACM Digital Library and IEEE Xplore, were chosen to search for empirical studies related to using learning analytics for student retention in STEM education. We began the search by establishing search terms according to the research questions. All of STEM subjects were taken into consideration in this review. To avoid accidentally excluding studies representing STEM, we decided to leave specific subject qualifiers out of the search terms, e.g., chemistry, biology, and agricultural science. Studies that relate to non-STEM fields were filtered during the screening and eligibility review process. Therefore, the relevant papers were extracted based on two different types of search terms, as shown in Table 1. Filters were used to identify papers written in English between 2014 and 2022 as studies in this nine-year duration would be sufficient evidence of the recent developments of using learning analytics for STEM retention studies.

Table 1. Search terms and search query.

Type	Search Terms	Search Query Example
Purpose	retention OR attrition OR completion OR dropout OR success	Scopus: TITLE-ABS-KEY ("learning analytics" OR "academic analytics" OR "educational analytics") AND TITLE-ABS-KEY (retention OR attrition OR completion OR dropout OR success)
Technique	"learning analytics" OR "academic analytics" OR "educational analytics"	

2.2. Selection Criteria

The main purpose of this study was to summarise and synthesise evidence from empirical studies utilising learning analytics demonstrating the features and variables that impact STEM retention in a computer-supported learning environment among higher education institutions. In this systematic review, eligibility criteria were identified to determine the publications to be considered to answer research questions.

2.2.1. Inclusion Criteria

- The articles were published in a peer-reviewed journal or conference;
- The study employed learning analytics techniques with empirical evidence;

- The study explored an online learning environment and examined data collected from a LMS or a similar online learning platform;
- The study subjects' major should be within STEM field;
- The sample population should be from higher education institutions.

2.2.2. Exclusion Criteria

- The articles did not fulfil the eligibility criteria;
- The study did not contribute to the research questions.

2.3. Selection of Publications

As shown in Figure 1, the initial search from four electronic databases yielded 1870 articles. Of these results, three hundred and seven (307) duplicates were automatically screened and eliminated by Endnote. In the screening phase, all articles that did not match the selection criteria were excluded, leading to two hundred and ninety (290) articles remaining for full-text eligibility check. At the end of this phase, fifty-nine (59) key publications that contribute to the research questions were selected for the systematic review, as listed in Table 2.

Table 2. Summary of fifty-nine (59) publications.

Reference	Key Purpose	Data Source	Data Collection Methods *	Sample (N)	Subjects **	Commencing Students
[20]	Identifying at-risk student	For-credit institution	AD	99	M	N
[21]	Predicting performance	For-credit institution	AD	134	T	Y
[22]	Predicting dropout	For-credit institution	AD	492	T	Y
[23]	Predicting performance	For-credit institution	AD	1100	T	N
[24]	Predicting performance	For-credit institution	AD, Q	310	S	N
[25]	Predicting dropout	For-credit institution	AD	362	M	Y
[26]	Predicting performance	MOOC	AD	597,692	T	N
[27]	Predicting performance	For-credit institution	AD	239	T	Y
[28]	Predicting performance	For-credit institution	AD, Q	784	E	Y
[29]	Predicting performance	For-credit institution	AD	140	T	N
[30]	Predicting performance	MOOC	AD	2794	S	N
[31]	Predicting performance	For-credit institution	AD	136	M	Y
[32]	Predicting performance	For-credit institution	AD	12,836	E	N
[33]	Identifying at-risk student	For-credit institution	AD	224	T, E, M	N
[34]	Identifying at-risk student	For-credit institution	AD	57	M	N
[35]	Predicting dropout	For-credit institution	AD	N/A	T	N
[36]	Identifying struggle student	For-credit institution	AD	312	T	N
[37]	Predicting performance	For-credit institution	AD	802	S, T	N
[38]	Predicting dropout	For-credit institution	AD	31,071	E	N
[39]	Predicting performance	MOOC	AD	6272	S, T, E, M	N
[40]	Predicting performance	For-credit institution	AD, Q	2864	S	Y
[41]	Predicting dropout	For-credit institution	AD	1421	T	N
[42]	Predicting dropout	For-credit institution	AD	429	E	Y
[43]	Predicting performance	For-credit institution	AD	2056	T	Y
[44]	Predicting performance	For-credit institution	AD	695	E	Y
[45]	Predicting performance	For-credit institution	AD	197	T	Y
[46]	Predicting performance	For-credit institution	AD	400	E	Y
[47]	Identifying at-risk student	For-credit institution	Q	164	T	Y
[48]	Predicting performance	For-credit institution	AD	419	E	N
[49]	Identifying at-risk student	For-credit institution	AD	130,170	T	N
[50]	Predicting dropout	For-credit institution	AD	383	T	N
[51]	Identifying at-risk student	For-credit institution	AD	400	T	Y
[52]	Predicting performance	For-credit institution	AD, Q	954	S	N
[53]	Predicting dropout	For-credit institution	AD	2713	T	N
[54]	Identifying at-risk student	MOOC	AD	4064	T	N
[55]	Predicting dropout	For-credit institution	AD	274	T	N
[56]	Identifying at-risk student	For-credit institution	AD	163	T	Y
[57]	Predicting performance	For-credit institution	AD	1232	E	N
[58]	Identifying at-risk student	For-credit institution	AD	3063	E	Y
[59]	Predicting performance	For-credit institution	AD	57	T	Y
[60]	Identifying at-risk student	For-credit institution	AD	8762	S	Y

Table 2. Cont.

Reference	Key Purpose	Data Source	Data Collection Methods *	Sample (N)	Subjects **	Commencing Students
[61]	Predicting performance	For-credit institution	AD	53	T	N
[62]	Predicting performance	For-credit institution	AD	251	T	N
[63]	Identifying at-risk student	For-credit institution	AD	5000	S, T, M	Y
[64]	Predicting dropout	MOOC	AD	10,554	T	N
[65]	Predicting performance	MOOC	AD	6455	S, T, E, M	N
[66]	Identifying at-risk student	MOOC	AD	7409	M	N
[67]	Identifying at-risk student	For-credit institution	AD	260	T	N
[68]	Predicting performance	MOOC	AD	32,621	T	N
[69]	Predicting performance	For-credit institution	AD	2472	S	N
[70]	Predicting dropout	MOOC	AD	3617	T	N
[71]	Predicting performance	For-credit institution	AD	3225	S	N
[72]	Predicting dropout	MOOC	AD	20,142	T	N
[73]	Identifying at-risk student	For-credit institution	AD	76	T	N
[74]	Predicting dropout	For-credit institution	AD	83	S, M	N
[75]	Predicting performance	For-credit institution	AD	85	T	Y
[76]	Predicting dropout	For-credit institution	AD	728	M	N
[77]	Identifying at-risk student	For-credit institution	AD	111	T	N
[78]	Predicting performance	For-credit institution	AD	753	M	Y

* AD: available data source, Q: questionnaires/surveys. ** S: science, T: technology, E: engineering, M: mathematics.

3. Results

In this section, the results of the surveyed key publications are reported from three dimensions, including general information, characteristics of selected studies, and summarised retention factors, sub-factors and features.

3.1. Type of Publication

The 59 key articles include thirty-three journal articles and twenty-six conference papers. Figure 2 presents the distribution of journal articles and conference papers over the selected publication years. Although the number of included articles in 2022 is seven, this is the search results for only the first half of the year. LA is addressing retention challenges in STEM education, and more studies in the future will enhance learning environments by employing LA.

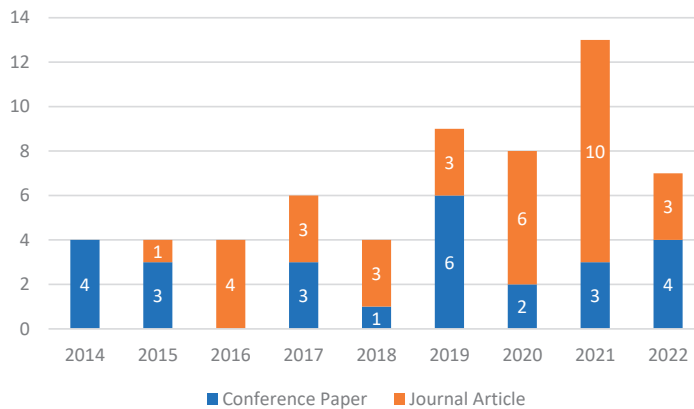


Figure 2. Number of studies in terms of types from year January 2014 to June 2022.

3.2. Characteristics of Selected Studies

Table 2 provides a summary of characteristics of the selected studies that focus on learning analytics for STEM retention and identifies the key purpose of each study, data source, data collection methods, sample size, and students' enrolment courses and commencing student status.

Of the 59 articles included, the common key purposes were predicting student performance (grade) (29), identifying at-risk students (fail/pass, engagement/disengagement) (15), and predicting dropout (14). For the dataset, 49 collected corpus data from for-credit institutions and 10 used available datasets from MOOCs to conduct learning analytics practice. Student information and digital footprints in the virtual learning environment are easily accessible. There were five studies that implemented questionnaires/surveys aiming to collect basic data [47], measure self-efficacy and motivation [24], learning approaches and skills [28,40], and self-regulation levels [52]. Figure 3 illustrates the frequency of the key publications based on the size of sample dataset. Nearly half of the studies (28) employed a dataset of less than 500 student records for learning analytics. It was observed that only 19 studies used a dataset with more than 2500 students’ data, and the data source for 10 of these articles was from different MOOCs.

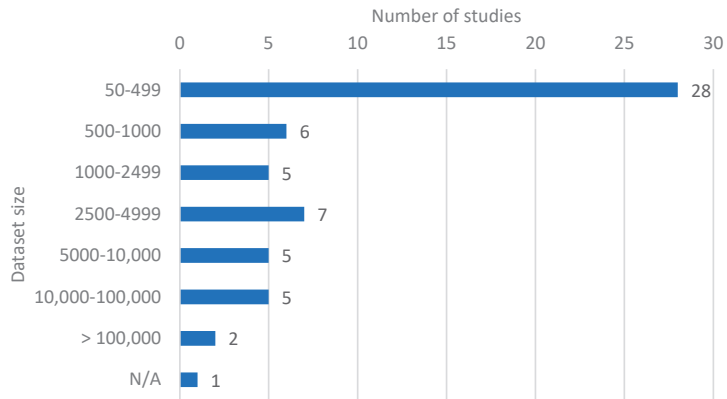


Figure 3. The frequency of articles according to the size of sample dataset.

3.3. STEM Retention Factors, Sub-Factors and Features

The purpose of this paper is to provide a comprehensive review that concentrates on the categorisation of retention factors and the quantified features used in learning analytics in higher STEM education. As presented in Table 3, the retention factors used in the selected studies can be grouped into seven categories. Six of them are student-focused factors, including *student personal characteristics, enrolment features, prior academic performance, current academic performance, behavioural engagement, and academic engagement*. One factor is *course design*, data extracted from the subject/unit level. The review found that students’ current academic performance (56%), student behavioural engagement (58%), and academic engagement (78%) have been studied in most of the key publications. Only six (10%) articles examined the course design factor.

Table 3. List of retention factors and studies.

Retention Factors	References	Number of Studies	Percentage of Studies
Student personal characteristics	[21,22,26,28,31,37,38,40,42,44,47,50,52,55,62,64,68,71,76]	19	32%
Student enrolment properties	[23,26,28,31,40,42,46,47,50,55,71,73]	12	20%
Prior academic performance	[21,23,26,28,32,38,40,42,44,47,50,52,55,56,63,68,71,76]	18	31%
Current academic performance	[20,22–25,27–29,31–34,37,38,40,42,45,47,49,52,54,58–60,62,66,67,70–73,76,78]	33	56%
Behavioural engagement	[20–22,24,26–28,30,35,37,39,41–43,46,48,49,52,53,56,57,59–61,63,65,67–71,73,74,77]	34	58%
Academic engagement	[20–22,24,26,27,29–31,33–37,39,41–44,46,48,49,51–53,56,57,59–70,72,73,75,77,78]	46	78%
Course design	[25,34,37,41,49,54]	6	10%

In a virtual learning environment, static and dynamic data are readily accessible from an institution’s systems and contribute to the quantification of retention factors. The

following sections identify how retention factors are quantified and measured in learning analytics. Each factor with sub-factors and features is detailed below.

3.3.1. Student Personal Characteristics

Regarding student personal information, basic demographic features and socioeconomic features are normally considered in retention studies. The analysed features and the number of studies are listed in Table 4. It can be observed that a host of studies have investigated basic demographic features, such as students' gender (18) and age (10), which are the two most selected features. Students' family income level (5) and his/her parental education information (4) are two commonly examined features for understanding a students' socioeconomic level.

Table 4. Student personal characteristics and features with numbers of times occurred.

Factor	Sub-Factors	Features		
Student Personal Characteristics	Basic demographic features	Gender (18) Race/Ethnicity (7) City of residence (4)	Age/DOB (10) Citizenship (7) First generation university student (4)	Disability (1) Working status (2)
	Socioeconomic features	Family structure (1) # siblings (1)	Family income (5) Parental occupation (1)	Parental education (4) Socioeconomic level (1)

denotes the shorthand for frequency.

3.3.2. Student Enrolment Properties

Student enrolment properties were studied in relatively low numbers (Table 5). The features encompass the administrative data recorded in SIS, such as whether the student studies full-time or part-time (2), whether the current STEM degree is the student's initial intended degree (4), etc. Other financial support data (financial aid, scholarship) is also taken into account. Financial assistance may contribute to dropout decisions [79] and enhance student persistence in certain majors [80].

Table 5. Student enrolment properties and features with numbers of times occurred.

Factor	Sub-Factors	Features		
Student Enrolment Properties	Administrative	Adm. Type (3) Enrolment date (1) Internship (1)	Study load (3) Intended degree (4) Dormitory (1) Scholarship (2)	International student (1) Distance from campus (1) # course enrolled (3) Award (1)
	Financial	Financial aid (1)		

denotes the shorthand for frequency.

3.3.3. Student Prior Academic Performance

Student prior knowledge can be reflected by data from a students' educational background and admission tests for entering the university (Table 6). Features of educational background include students' academic background level (6), grade point average (GPA) of high school, and GPA of prior university. Admission test data covers admission test overall scores (11) and STEM-related scores such as mathematics (8) and science (3) scores.

Table 6. Student prior academic performance and features with numbers of times occurred.

Factor	Sub-Factors	Features		
Prior Academic Performance	Educational background	Educational level (6) No. of credits (2)	High school (4) GPA prior Uni (2)	GPA high school (9)
	Admission test	Score of admission test (SAT, ACT, PSU, GTA) (11) Maths score (8)	English score (2)	Science score (3)

3.3.4. Student Current Academic Performance

Students' current academic performance and achievements play a vital role in students' persistence in continuing their current degree and courses participation and enrolment. In Table 7, it shows that this retention factor can be split into two sub-factors: overall, academic performance regards the achievement at course level, such as GPA each semester (8), overall GPA ranking (1), course(s) score (7), etc.; assessment performance which includes assessments (11), quiz/test (5) or lab (1) score, and final examination grades (3).

Table 7. Student current academic performance and features with numbers of times occurred.

Factor	Sub-Factors	Features		
Current Academic Performance	Overall academic performance	GPA (8) Score course(s) (7)	GPA ranking (1) Credit earned semester(s) (1)	GPA semester(s) (9)
	Assessment performance	Assignment score (11) Quiz/Test score (5)	Assignment pass/fail (1) Lab score (1)	Final exam score (3)

3.3.5. Student Behavioural Engagement

Student behavioural engagement refers to the actions that are indirectly related to the learning process. As shown in Table 8, the most common examined features can be categorised as clickstream data, such as the number of student logins to the virtual learning system (20), the total number of clicks (2), the frequency students visit course pages (11), announcement content viewed (3), notification messages read (2), and glossary views (2). Other features are also representative of students' behavioural engagement, for example, the total time students spend on the learning system (10), the number of days students login into the system, and students' attendance for the enrolled subject (4).

Table 8. Student behavioural engagement and features with numbers of times occurred.

Factor	Sub-Factors	Features		
Behavioural Engagement	Clickstream	# login (20) # days login (3) # clicks (2)	# notification view (2) # announcement view (3) Online time (10)	# course page view (11) # glossaries view (2) First day login (2)
	Class participation	Attendance (4)		

denotes the shorthand for frequency.

3.3.6. Student Academic Engagement

Student academic engagement is one of the most examined factors in both online and hybrid learning environments for dropout prediction and at-risk student identification. The literature reviewed revealed three sub-factors, including engagement with learning material, assessment participation, and interactive activities with peers and instructors (Table 9).

Student engagement data with learning material is recorded on an ongoing basis to reflect student learning habits, processes, and strategies. The features include the frequency of students' exposure to learning resources (25), lectures viewed (6), videos watched (8) and video solutions reviewed (1), the number of unique days students viewed the resources (3), and the number of resources downloaded by the students (3). In addition to the commonly applied data on engagement with learning management systems, [35,43,76] collected data on programming behaviours from students in the Technology discipline, such as the number of logical lines, number of test cases, and number of commands students generated during programming exercises.

Table 9. Student academic engagement and features with numbers of times occurred.

Factor	Sub-Factors	Features		
Academic Engagement	Learning material	# resources view (25)	# unique days visit (3)	# weekly content click (1)
		# back jump (1)	# lecture viewed (6)	# resources downloaded (3)
		Hyperlink click (5)	Time spent per module (2)	Specific course activity (3)
		Content complete percentage (1)	Video content (8)	Video solution (1)
	Assessment participation	# instruction view (2)	# task finished (16)	Quiz review (2)
		# quiz (8)	Quiz on time (1)	Exam reflection (2)
# submission file (2)		Extracurricular quiz (2)	Exam preparation (2)	
# attempt (8)		Days assignment submitted in advance (1)		
	Grade view (2)	Time spent on assessments (4)		
Interactivity	Discussion/Forum viewed (17)	Discussion/Forum posted/commented (21)	Post about learning concept (1)	
	Collaborative communication (3)	Messages send to instructor (2)	Messages received from instructor (1)	
	Peer assessment (1)	Consultation attend (4)		

denotes the shorthand for frequency.

In terms of assessment participation factors, the following features were considered: the number of completed assignment task (16), quiz (8), extracurricular quiz (2) and mock exam (2), the number of times students attempt to complete the assessments (8), the frequency with which students view their grades (2).

Another set of important features is considered as students' interactive activities with their peers and instructors. Those analysed features are number of visits (17) by students to the discussion/forum and participation in posts or comments (21), times of involvement in collaboration with their peers (3), the times that students interacted with instructors through consultation time (4), and email (2).

3.3.7. Course Design

Course design is another factor that was examined in retention studies, although there are only six studies (see Table 3) covering this factor among the 59 key publications in this systematic review. The listed features (Table 10) cover the information about pedagogical materials, for example, how many content pieces have been introduced to student for certain subject (1) and how many assessments have been presented to students (3). The course outcome is composed of students' online activity and performance, the features include assignment submission rate (1) and course pass rate (1). Features that measure student LMS usage at course level are taken into consideration. For example, total/average number of clickstream records for all students (1) and average student online activity days (2).

Table 10. Course design factor and features with numbers of times occurred.

Factor	Features		
Course Design	# assignment/quiz (3)	Content pieces (1)	Pass rate (1)
	# distinct assignments (1)	Assessments completion rate (1)	
	# clickstream (1)	Average activity days (2)	

denotes the shorthand for frequency.

4. Findings and Discussion

In this section, the reviewed articles will be further analysed. The answers to the *Research Questions* in Section 1.1.1 are provided and discussed here structured according to each of the retention factors, followed by recommendations for future learning analytics research for improving STEM retention.

4.1. Retention Factors and Quantified Features Explored by LA in STEM Education

Seven factors employed in LA studies were summarised to be associated with student retention in STEM disciplines, answering RQ 1: *What factors have been identified that impact retention in STEM education?* To address RQ 2: *In STEM retention studies, how are factors quantified and measured in learning analytics practice?*, each factor has been examined and corresponding measurable features have been identified. A summary of factors and features that have been identified as having a significant impact on retention are presented in Table 11.

Table 11. Summary of factors and significant features.

Factor	Sub-Factors	Significant Features		
Student Personal Characteristics	Basic demographic features	Age/DOB	City of residence	Gender
Student Enrolment Properties	Administrative	Intended degree		
	Financial	Financial aid		
Prior Academic Performance	Educational background	Educational level	GPA prior Uni	GPA high school
	Admission test	Score of admission test (SAT, ACT, PSU, GTA)	Maths score	Science score
Current Academic Performance	Overall academic performance	GPA	GPA semester(s)	Credit earned semester(s)
	Assessment performance	Assignment score	Quiz/Test score	Lab score
Behavioural Engagement	Clickstream	# login	# days login	# course page view
		# notification view		
Academic Engagement	Class participation	Attendance		
		# resources view	# unique days visit	# lecture viewed
	Learning material	# resources downloaded	Video content	
		Assessment participation	# task finished	Time spent on assessments
Interactivity	Discussion/Forum viewed	Discussion/Forum posted/commented		
Course Design		# assignment/quiz		

denotes the shorthand for frequency.

4.1.1. Student Personal Characteristics

The finding of this study revealed that individual characteristics and family background have a relevant influence on students' motivation and persistence in completing the course. The most often measured features for this factor were student gender, age, and race/ethnicity. Seventeen of the nineteen articles included this factor in the prediction studies. In the STEM discipline, demographic factors seem to be significant features that impact retention rate [81], particularly in the first half of the academic year [63]. It has been evidenced using LA that older students showed more likelihood of persistence in STEM online courses [82], and gender has been shown to be a significant predictor of student success in computing curricula [83]. Despite this there is some evidence that shows such static features (age, gender, ethnicity) [16,21,42], and socio-economic factors [42,84] are irrelevant to a student's performance and dropout decision.

4.1.2. Student Enrolment Properties

It is observed that the student enrolment data recorded in the Student Information System contains useful information that has not yet been fully explored. Only a handful of LA articles (12) considered this factor. Features of enrolment are often omitted from the analysis of LA due to its static data nature.

The proxy features of student intended degree and financial support data have been found to correlate with student dropout decision. When using LA to predict student dropout for 429 first-year engineering students, a student's intended degree has been identified as the second ranking feature of 17 total features from six factors [42]. To some extent, it reflects a student's interest and motivation in accessing and continuing in STEM subjects. This feature has also been included in the LA studies for identifying at-risk students of subject failure or dropping out of Technology [47,50,55]. Financial support features, such as financial aid [71] and scholarship [49,71], help predict the student likelihood of continuing the current STEM subjects as finances may contribute to dropout decisions [79] or enhance student persistence in their course [80]. Though finances may not be accurate in identifying at-risk students without considering other factors impacting a student's learning progress and academic status.

4.1.3. Student Prior Academic Performance

Our findings reveal that a student's prior knowledge is an important factor in both dropout prediction and performance prediction. It is possible to represent this factor using features, such as high school GPA, scores on entrance examination, and maths scores on an admission test. It has been proven to be significantly correlated by predictive learning analytics because these features reflect student interest and capability to continue their study in STEM disciplines.

This retention factor is found to significantly affect student success in both for-credit institutions [42,63] and MOOCs [66], especially for entrance examinations [50]. The analysis indicates that students who have good marks in previous degrees and admission tests have significantly better achievements [47] and are less inclined to drop out or switch to another degree [76]. This review also highlighted the influence of prior academic performance in STEM subjects in dropout prediction. Generally, secondary school graduates are not equally ready for STEM courses due to differences in school types and maths curricula [85]. Students' prior knowledge has been found repeatedly in the selected articles to be related to academic success in STEM subjects [55,56]. Particularly for mathematic proficiency, students with basic mathematics deficiencies have a higher chance of failure or dropping out of STEM-related subjects [86]. Commencing students with a mathematical background are more likely to overcome any obstacles during learning and continue studying successfully [87]. Retention studies that involved the features such as high school score, maths score, or science score in an admission test demonstrated promise in measuring student STEM preparation level and forecasting struggling students at an early stage.

4.1.4. Student Current Academic Performance

The analysis found that a student's current academic performance measured by both subject overall performance and assessment performance are appropriate data for predicting dropout/retention/performance.

Overall academic performance was widely evaluated as a predictor using various forms of grades, such as overall GPA, semester GPA, credit students earned in first semester [23,25,27–29,32,37,40,42,47,49,52,60,66,67,71,73,76]. The impact of performance on attrition for first and second year students has also been verified in predicting student performance and dropping out [32,76]. In addition, the credits student obtained in the first semester [38] and early academic success [38] in STEM disciplines are found to be two of the most important predictors of student dropout risk.

Assessment performance is another sub-factor in predicting student performance. Continuous data from assessment features (quiz, assignment, and/or test) proved predictors for students' academic status in computer-supported learning. For example, there has been evidence to suggest that assignment scores affect discrimination student performance [20]; the test scores obtained for each chapter exercise among 20,142 MOOC learners in Technology study have been examined and validated as the most discriminating variable in dropout

prediction [72]. Low-achieving students are more likely to lose confidence and motivation to continue their studies, consequently leading to a decrease in their participation [50].

4.1.5. Student Behavioural Engagement

How students engage with LMS has sparked considerable interest among researchers in LA. To evaluate behavioural engagement, a set of features derived from the learning system's log data were identified in predictive learning analytics, such as login numbers, online time, and attendance.

In the virtual learning environment, behavioural engagement is a key precondition for effective learning, and students at risk of failure or dropout are linked to a lack of engagement [88]. Meanwhile, disengagement is a persisting issue in STEM subjects [54]. The traditional use of log data, such as the number of logins/clicks and attendance, has been criticised in a few studies. It has been argued that the login data were not related to learning outcomes [61] and clickstream activity failed to pinpoint students with high-risk [24]. While it has been well-documented that clickstream in LMS has positive correlations with student final marks [26,39,48,67], these features would reflect student self-motivation and self-efficacy in the blended learning environment [49]. The possible reason may be due to the different forms of data transformation used in the analysis. Data segments appear to be more accurate at recognising student dropouts when behavioural data are split into phases, such as weekly [22,70], every three weeks [71], and specified phases [73]. The transformation of features over time is an area of future research for exploring the potential of using data from a LMS for more accurate prediction results.

There are also concerns about the influence of class attendance in retention analysis, as it might be influenced by causes that are out of students' control [16]. Class attendance demonstrates an essential role in enhancing academic performance among 239 commencing students in the Technology discipline [27]. Overall, the evidence of this review study indicates students who take a more active role and spend more time on the learning platform show a willingness to make a commitment to the course and tend to achieve higher grades.

4.1.6. Student Academic Engagement

Our findings reveal that student academic engagement contains features reflecting the dynamic learning behaviour within the learning environment and measures their perceived usefulness and direct effects on student learning performance. Most of the studies (78%) developed predictive LA using data generated from student engagement with online learning material and assessment as well as interaction with peers and instructors. Features, such as frequency of resources viewed, number of assessments finished, and discussion/forum commented, are significant indicators to be included in LA to address STEM retention problem.

Engagement with learning material. This sub-factor consists of the behavioural and cognitive dimensions of the learning process in a dynamic way and is tightly linked to academic performance [89]. The information regarding the changes in student activity, such as resource viewing frequency [42,48,51,58], content completed percentage [90], and time spent on each module [53,57], which may be measured to recognise struggling students at an early stage. The usage of subject material and lecture resources [60] and student effort over time [68] indicate positive correlations with subject outcomes over a semester. In addition, combining these types of data allows us to gain an insight into how personal characteristics of individual students and their educational trajectories are connected [91]. In particular, the results revealed features that are used in the context of programming education. Such data differs considerably, for example, keystroke latency, number of test cases and number of error message received [35,36,43,75]. This kind of feature shows promise in identifying students that struggle with programming subjects and provides insights into where and when students may struggle.

Assessment participation. Not only is the outcome of the assessment a predictor of student subject performance, but the footprint activities from the completion process of assessment also provide effective predictors to identify at-risk students [34]. For example, the average date between assignment deadlines and student's work submissions can imply a student's difficulty with deadlines, and this feature has been confirmed as an important indicator of dropout tendency [41]. Students' behaviour in completing assessments (time spend on assessment, number of attempts, exam preparation) is an expression of self-efficacy that influences how the learner addresses goals, tasks, and challenges [92]. High self-efficacious students are more likely to get involved in a task more readily, committing more time and perseverance to its completion [93].

Interactivity. Student interaction with their peers and instructors through discussion/forums, collaborative work, email and consultation provide meaningful data to examine the impact on student learning progress and retention. The importance of engagement with peers and instructors has been identified [21]. Forum communication (frequency of discussion/forums viewed/posted/commented) was commonly analysed for dropout study in the online learning environment. Successful students show a higher frequency of discussion or forum page views and spend more time reviewing content [59,65,94]. The interactivities, to some extent, may mirror the sense of belonging in the academic realm, and the willingness to interact with others contributes to students' persistence [92].

4.1.7. Course Design

The importance of the course design factor was identified in this systematic review, although this factor and features were underexplored among the 59 key articles. The pedagogical material and assessment design are linked with student performance and dropout decisions. For example, the number of content pieces and number of assignments/quizzes have an important impact on student engagement in the learning process [95] and partially contribute to the engagement level with the learning platform [31,65,96]. It is possible to represent this factor with the data related to the overall learning activity. These features are composed of students' online activity and performance. With the consideration of the variation in behavioural data over the learning process at the level of activity across the subject, it is possible to detect the dropout probably of a subject or a course in LA [25].

4.2. Recommendations for Future Research

Several limitations and underexplored retention factors and proxy features were identified which help understand students and their behaviours in STEM disciplines.

- Seven retention factors and their sub-factors and features have been summarised. The power of each feature associated with each factor should be critically examined in future learning analytics studies. In addition, relationships between factors should be further evaluated.
- Features from static factors (student personal characteristics, student enrolment properties, and prior academic performance) demonstrated promising results in early detection of at-risk students. Learning analytics currently tends to explore dynamic data on the learning process leading to a snapshot of student learning patterns and predictions of learning outcomes for the purpose of providing intervention. However, these static factors and features are under explored in retention learning analytics studies; therefore, there is a need to further explore the potential of this data in LA for early prediction and/or even assist institutions in the phase of applicant selection to address the STEM retention challenge.
- The limited consideration towards the course design factor has been identified after reviewing the key publications. Most studies are student-focused, and the results emphasise that more attention and further research could be aimed at the pedagogical design of assessment, such as problem-based and cooperative learning to improve students' interactions and maintain interest in STEM courses.

- Factor and feature selection and the data form denoted should direct studies in retention towards learning analytics. Combining features from different factors may yield better prediction results, though different data selection can result in varying predictive performance in identifying at-risk students [33]. Predictive model development should carefully select features and should avoid choosing purely one kind of retention factor. The results from one factor in learning analytics are far less accurate. [34]. A better performance model might be developed by combining other, even individually less effective, factors or features.
- The analysis may not be generalisable for all subjects in STEM disciplines, as the assessment and marking of each subject varies. Additionally, prediction models can also be affected by the pedagogical circumstances in the subject [15]. Future researchers could employ data from subjects in the same discipline that share similar pedagogy design and assessment format.

4.3. Limitations

The systematic review is an appropriate method for synthesising findings from research on the topic of STEM retention in learning analytics, but the tools, analysis techniques, algorithms, and methods employed in the selected studies have not yet been analysed. The effectiveness of retention factors should be read in the context of the methodology applied. Therefore, this limitation can be addressed by expanding this review with an examination of learning analytics approaches. This will facilitate the identification of important research trends and concerns in the literature on the learning analysis of STEM retention at a method level.

5. Conclusions

STEM retention is a critical challenge confronting higher education institutions. In the context of transformation of computer-supported learning environments, the effectiveness of learning analytics in identifying retention factors has been demonstrated by conducting a systematic literature review. This review brought together and synthesised the latest evidence on retention LA in STEM disciplines while categorising and highlighting the factors and their quantified features that are significantly discriminative in learning analytics practice. The influential factors impacting student persistence and retention were summarised into seven categories: (1) student personal characteristics, (2) student enrolment properties, (3) prior academic performance, (4) current academic performance, (5) behavioural engagement, (6) academic engagement, and (7) course design. Deliberate consideration of the selection and combination of these factors and features can be advisable in the implementation of learning analytics in STEM education, which can support establishing the profile of at-risk students who show a likelihood to discontinue studying in STEM courses and facilitate the prediction of students who need support.

The contribution of this review study is twofold: (1) The comprehensively reviewed retention factors and proxy features enriches LA studies in STEM disciplines. The findings of this paper can be used as a guide for data selection for use with LA to improve predictive model accuracy. (2) The categorisation presented in this systematic review can assist researchers in investigating the influence of factors and examining the relationship between factors/features in STEM retention studies. Having knowledge of the retention factors and possible measurable features, it is possible for subject designers and instructors to gain a deeper insight into the digital footprint of students' learning process.

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