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Can MOOC be a medium of lifelong learning? Examining the role of Perceived Reputation and Self-efficacy on Continuous Use Intention of MOOC

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(submitted: 18/12/2022; accepted: 25/4/2024; published: 29/4/2024)

Abstract

Many Higher Education Institutions in India have started to include Massive Open Online Course (MOOC) as a part of their curriculum. Yet little research has been done to understand the factors that affect the users' sustained interest to recurrently enroll and complete MOOC courses throughout their lifetime. A sample of 316 students from Higher Education Institutes in India participated in this survey. Partial Least Square Structural Equation Modeling (PLS-SEM) using smartPLS was employed to assess the structural model. The structural model used is a combination of constructs from technology acceptance theories namely perceived usefulness, perceived ease of use, attitude, facilitating condition and continuous use intention of MOOCs, with perceived reputation and MOOCs self-efficacy as external variables. The results not only proved the applicability of basic TAM constructs in understanding the behavioral intention of MOOCs but also the significance of external variables, particularly the role of perceived reputation in influencing the perceived usefulness of MOOCs.

KEYWORDS: Moocs, Perceived Reputation, Self-Efficacy, Technology Acceptance Model.

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1. Introduction

Technology has penetrated the lives of many individuals because of the sudden eruption of the COVID-19 pandemic, as a result of which people started to experience significant lifestyle changes. With the Internet and smartphones/computers becoming an integral part of life, working from home and education from home have become new norms. During the times of strict lockdown in India to curb the spread of COVID-19 infection, people had no choice but to head online, even for a minimal need. Thus, access to Information and Communication Technology (ICT) has become necessary and is no longer a luxury. At this juncture, online learning started gaining momentum among educational institutions due to its prolonged closure. The sudden transition to online learning during the pandemic has made students and the educational fraternity realize the importance of online learning platforms (Sun et al., 2020). Many students started enrolling in Massive Open Online Courses (MOOC) during the pandemic, which is evident in the surge in the enrollment rate by 25-30% (Shah, 2020). MOOC has the potential to lessen educational inequity. It is a boon for developing countries like India in particular, as access to quality education remains a distant dream for many. With multi-disciplinary skill sets being sought after by industry, graduate and post-graduate students started opting for specialized courses that may or may not be directly linked to their core area. MOOC is a model for providing learning content online to anyone with almost no limit on attendance. The model started becoming more widely used as it served as a platform to equip the student with a relevant skill set at a time and duration convenient to the student (Ansari & Biswal, 2023). The pandemic has become a major driving force of MOOC acceptance and use (Shen et al,

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2024; Brauweiler & Yerismpasheva, 2021; Jones & Sharma, 2020) and there has been a wide acceptance of MOOC among students of higher education institutions due to pandemic (AL-Nuaimi et al., 2022; Rasli et al., 2022; Haryati et al., 2021). This study is pivotal amidst increasing awareness of digital learning post-pandemic, and many higher education institutions started to adopt the online mode of education including flipped learning.

While online learning was gaining momentum even before the onset of the pandemic, and MOOC, in particular, was seeing a surge in enrollments, particularly from the US, India and the UK during the pandemic and particularly, India saw a whooping 7 times increase in MOOC enrolment (Chris & Martin, 2021), there was no significant improvement in the completion rates (Blackwell & Wiltrout, 2021). A study done in India showed that despite a massive increase in MOOC usage by Indian students due to covid19 pandemic, the dropout rates remained significantly higher (Dang et al., 2022). One of the challenges still faced by MOOC providers is its poor completion rate (Rekha et al., 2023; Romero-Rodríguez et al., 2020; Pursel et al.,2016; Cisel, 2014; Khalil & Ebner, 2014). In developing countries like India, the nominal fee to earn a certificate is often considered a financial barrier to taking MOOC courses (Blackwell & Wiltrout, 2021). The study also highlighted that the initial surge in MOOC enrollments did not sustain because of low motivational levels, and learning boredom due to lifestyle changes, making the retention of MOOC learners all the more difficult. Kizilcec et al. (2013) studied the pattern of MOOC learners in four countries, namely the US, UK, India and Russia. They found that most of the learners from India watched a couple of videos at the beginning of the course and did not intend to complete any MOOC course. Therefore, it has become crucial for educators to provide an online learning environment that can retain the learners' interest for MOOC to be successful in the long run.

With most of the past MOOC research focused on MOOC adoption, there is an urgent need to understand the poor completion rate (Meet & Kala, 2021). There is a paucity of studies focusing on MOOC dropouts and retention, while available such studies were mainly from the USA, South Korea and China (Goopio & Cheung, 2021; Khan et al., 2021). The ultimate success of a MOOC course depends on the completion rate and not on the number of participants (Rekha et al., 2023) and there is a dearth of MOOC-related studies based out of India (Rekha et al., 2023; Rasheed et al., 2019). Also, many past studies on online learning that were conducted among students of Higher Education Institutions (HEI) were in a mandatory environment, wherein students had to enroll in an online course as a part of their academic requirement. This research addresses the gap in the existing literature by focusing on factors affecting the continuous use intention of MOOCs among students of HEI in India in the context of the voluntary environment. In a voluntary environment, students enroll in MOOC courses out of self-interest and thirst to gain knowledge in the subject of their choice.

To understand what influences an individual to adopt and use MOOC, a recent systematic literature review by Badali et al. (2022) stated that the Technology Acceptance Model (TAM) is the second most widely used model. The model explains how beliefs such as ease of use, the usefulness of technology, and attitude towards using it affect one's intention to use it (Davis et al., 1989). TAM model can be integrated with other external variables to yield better results (Tao et al., 2019). Though many researchers started incorporating external variables into TAM for better predictive power, few studies have had factors related to MOOC's characteristics (Kim & Song, 2021). This study addresses the gap by integrating two external variables, namely Perceived Reputation (PR) and Self-Efficacy (SE).

Perceived reputation, a factor related to MOOC, refers to a set of user beliefs placed on the institutions, platforms and faculty offering MOOC courses. Many studies have shown a significant influence of a website's reputation on consumers' trust, subsequently leading to a prolonged commitment to the online platform (Casalo et al., 2007). As MOOC platforms are mostly partnered with reputed institutions worldwide, it becomes a deciding factor when choosing and enrolling in a MOOC course (Alraimi et al., 2015). Most MOOC researchers have overlooked this factor of reputation, which is considered an intrinsic trait of MOOC (Tella et al., 2021). Thus adding the external variable PR to the model would help in understanding how reputation influences the behavioral intention of MOOC users.

The second external variable used in the context of MOOC is self-efficacy, a factor related to MOOC users that refers to an individual's skills and confidence in using MOOC effortlessly. SE is seen as an essential factor in the successful completion of online courses (Punjani & Mahadevan, 2021). It is a critical variable to be considered in a developing country like India, where both the first-level digital divide (inequity in owning ICT) and the second-level digital divide (inequity in the ability to use ICT) are more pronounced. According to a study based on National Sample Survey Office (NSSO) data, only 25% of currently enrolled students in India in the age group between 5 and 35 years have access to the Internet, of which only 9% have a computer with Internet connection (Reddy A et al., 2021). A similar study using NSSO data also reveals that the computer and internet literacy rate in India is low (Rajam et al., 2021). Hence, the self-efficacy to use MOOC could act as an essential factor for MOOC to become a medium of choice for lifelong learning, particularly in India.

Thus, this study's main aim is to understand the structural relationship between perceived reputation, self-efficacy, and constructs from technology Acceptance theories to understand the factors that affect users' continuous use intention of MOOC. By throwing light on the significant factors that affect the sustained interest of MOOC learners, this study will inform educational policymakers to develop and design MOOC courses so that MOOCs may become an ideal medium of choice for lifelong learning.

2. Literature review

Even though India has the second-largest MOOC users, and many MOOC platforms and courses are developed in India, implementing such online learning platforms does not necessarily translate into efficient usage. Even in the case of Indian home-based MOOC platforms, of the total enrolled students, less than 1% of students went on to complete the course (Bordoloi et al., 2020). The success and effectiveness of MOOC usage depend solely on the educators and students, who are in turn influenced by various factors of society, organization and culture. It is of utmost importance to evaluate learners' perception of the factors that influence them not just to enroll but also to complete MOOC courses, which is of interest to this study.

2.1 MOOC in HEI

Past studies have shown that course completion is not the only reason a student enrolls on a MOOC course (Goopio & Cheung, 2021). Most enrolled users used the course material selectively if they found it helpful (Jacobsen, 2019). However, the success of MOOCs depends on the number of those who complete the course (completion rate) than those who merely enroll (Khan et al., 2021; Yang et al., 2017). The initial push to enroll in a course is not sustained throughout the course leading to increased dropout rates in many MOOC courses.

In the past decade, there has been a surge of MOOC models being opted by universities. They started offering short courses with specific schedules with online exams and providing a vocational degree/certificate to the candidates who completed the program. With the Internet reaching most of the population, MOOCs became a significant channel to empower people across different geographies with relevant skill sets. For the last ten years, we have seen the emergence of not-for-profit and for-profit MOOC providers from private sectors like Khan Academy, edX, Coursera, etc. In India, students can now earn a bachelor's degree by completing 40% of the program online via SWAYAM, India's official MOOC. The increasing demand for higher education in Asia makes MOOCs a viable choice (Goopio, 2021). The National Education Policy 2020 by the Government of India has a particular emphasis on the online mode of education as it has the potential to reach the neediest and underprivileged segment of people in India (Government of India, 2020).

2.2 Technology Acceptance Theories

There are several frameworks or models to understand the factors that influence user acceptance of technology, which include Technology Acceptance Model (TAM) by Davis, Theory of Reasoned action (TRA), Theory of Planned Behavior (TPB), Innovation Diffusion Theory (IDT), Motivational model, Unified Theory of Acceptance and Use of Technology (UTAUT), Social Cognitive Theory and to name a few.

TPB, TAM and UTAUT are the most widely used models. Past studies suggested incorporating the relevant constructs with TPB, TAM and UTAUT to understand better MOOC user behavior (Song et al., 2017; Tawafak et al., 2020; Meet & Kala, 2021). TAM is an extension of TRA, which predicts user acceptance of technology through intention measures. TAM was designed to predict the acceptance of computer-based technology (Davis et al., 1989). TAM includes two important constructs that impact the user acceptance of a particular technology; Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). PU is defined as "the degree to which a person believes that using a particular system would increase his/her job performance", and PEOU is defined as "the degree to which a person believes that using a system would require little effort" (Davis et al., 1989). It is vital to examine the role of PEOU in using MOOCs in developing countries, as the HEI are bringing a paradigm shift in traditional classroom teaching (Khan et al., 2021). PEOU and PU will affect the individual's attitude towards using MOOC, which leads to intention towards using it. Attitude (ATT) is defined as "the individual's positive or negative feelings towards a technology" (Davis et al., 1989). UTAUT is a combination of critical factors from eight theories/ models related to technology use, proposed by Venkatesh et al. (2003). The model has been used in different studies on technology acceptance and usage. The essential constructs of UTAUT are effort expectancy similar to PEOU, performance expectancy similar to PU, Social Influence and Facilitating Condition (Taherdoost, 2018). This study incorporates the variable Facilitating Condition (FC) from the UTAUT2 (Venkatesh et al., 2012), an extension of the UTAUT model. FC is defined as "the consumers' perceptions of the resources and support available to perform a behaviour" (Venkatesh et al., 2003).

Studies in the past focused on the adoption of e-learning and factors affecting the adoption intention of e-learning among students of HEI (El-Masri & Tarhini, 2017; Decman, 2015; Mohammadi, 2015; Park, 2009). However, only a few past studies have used an integrated model to understand the students' continuous use intention of MOOCs (Tao et al., 2019; Yang et al., 2017). Particularly in India, such studies are sparse. Hence, the present study addresses the gap by integrating constructs from TAM and UTAUT to study the individual's intention to continue using MOOC in a voluntary environment.

2.3 Conceptual framework and hypothesis development

Figure 1 explains the proposed research model, in which Continuance Use Intention (CUI) is a dependent variable. Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and Attitude (ATT) from TAM are integrated with the Facilitating Condition (FC) of UTAUT2, with Perceived Reputation (PR) and Self-efficacy (SE) as external variables of TAM. The direction of influence of the constructs ATT, PU, PEOU AND FC on CUI is based on the theoretical models, namely TAM and UTAUT2. The direction of influence of external variables is explained in detail in the subsequent section.

2.4 Construct from TAM

A systematic literature review of MOOCs by Goopio and Cheung (2020) revealed that PEOU and PU positively affect continuance intention. Finally, ATT to Behavioral Intention (BI) is fundamental to TAM, which theorizes that the intention to use technology is based on an individual's positive attitude.

H1: Attitude towards using MOOCs positively influences an individual's continuous use intention of MOOCs.
H2: Perceived usefulness positively influences an individual's attitude toward using MOOCs.
H3: Perceived ease of use positively influences an individual's attitude toward using MOOCs.
H4: Perceived ease of use has a positive influence on perceived usefulness.

2.5 Constructs from UTAUT2

Access to digital infrastructure comes at the forefront of using digital learning tools seamlessly. In India, the digital divide is a pertinent issue, and access to the Internet is still meagre among a large population (Rajam et al., 2021). Given the prevailing status of ICT infrastructure in India, the construct facilitating condition plays a significant role in the continuous use intention of MOOCs by users. Thus, facilitating conditions plays a vital role in the practical usage of MOOCs by users.

H5: Facilitating condition positively influences an individual's continuous use intention of MOOC.

2.6 External Variables

The study uses two MOOC-related characteristics namely self-efficacy, which is a MOOC user factor and perceived reputation, a factor related to MOOC, to know how well they add as antecedents to TAM constructs in understanding users' continuous intention in using MOOCs.

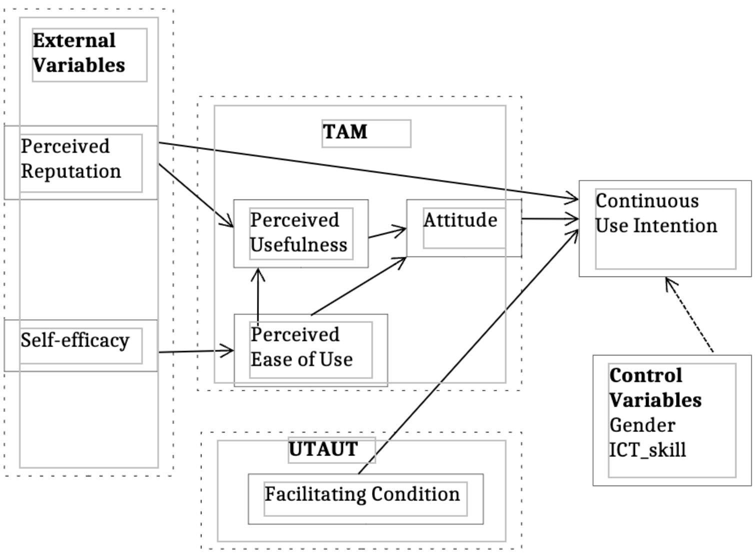

Figure 1 - Research Model. Integrating the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) with self-efficacy and perceived reputation as external variables.

Self-efficacy

Self-efficacy is drawn from Bandura's Social Cognitive Theory (Bandura, 1986). It is defined as an individual's ability to perform a specific task to yield the desired outcome. Prior studies showed that computer self-efficacy indirectly influenced behavioral intention to use technology via perceived ease of use (Roca et al., 2006; Venkatesh & Davis, 1996). Individuals having higher self-efficacy are often highly motivated, goal-oriented and self-regulated learners (Lee et al., 2020). In a voluntary environment, self-regulated learning is the key to successful online learning (Cho & Shen, 2013). Also, self-efficacy is the critical determinant of MOOC completers. Individuals exhibiting higher self-efficacy are more inclined to complete the MOOC course (Kuo et al., 2021; Barak et al., 2016). Hence, we postulate the following hypothesis:

H6: Self-efficacy positively influences an individual's perceived ease of use of MOOCs.

Perceived Reputation

An organization's reputation positively affects customer retention in service sectors (Milan et al., 2015). Reputation has been a variable of interest in many industries (Cioppi et al., 2019). In the context of MOOC, the reputation of the course provider is the key to retaining learners' interest (Khan et al., 2018). According to Fombrun and Van Riel (1997), reputation is defined as a "collective representation of a firm's past actions and results that describes the firm's ability to deliver valued outcomes to multiple stakeholders". Renowned and elite Western universities offer most MOOC courses hosted on platforms such as Coursera, edX, etc. (Rambe & Moeti, 2017). The fact that MOOC courses are being offered by reputed institutions worldwide is a significant reason for students from developing countries to enroll in such courses. Like in any other product/service sector where the reputation of a firm drives repeated purchases, in the context of MOOC, reputation could drive sustained usage among individuals. Also, there is a dearth of research looking at reputation as a MOOC feature in influencing the behavioral intention of learners, particularly in the Indian context. Studies by Wu and Chen (2017), Huanhuan and Xu (2015), and Alraimi et al. (2015) showed perceived reputation as a significant predictor of MOOC use intention. This study differs from the above studies in that reputation is used as an external variable in the integrated TAM model and is also hypothesized to influence CUI directly and indirectly via PU, particularly in the Indian context.

H7: Perceived reputation positively influences an individual's perceived usefulness of MOOC.

H8: Perceived reputation positively influences an individual's continuous use intention of MOOCs.

Control Variables

The control variables used in the research model are level of ICT skill and gender. Demographic variables, including gender and level of ICT skill, were examined in past studies to know how they impacted learners' MOOC behavior (Greene et al., 2015; Kaveri et al., 2015; Dillahunt et al.,2014). ICT skill is the extent to which an individual is good at using ICT and has four levels: elementary, limited, professional and expert.

3. Methods

The study uses a survey method to test the hypothesis developed. Questionnaire development and data collection are discussed subsequently.

3.1 Questionnaire development

We employed a questionnaire survey that has two sections. The first section is related to demographic profiles such as gender, place of study, etc. of the participants. The second section corresponds to items measuring constructs used in the research model. Each item is measured using a five-point Likert scale, with 1 being "strongly disagree" and 5 being "strongly agree". The appendix shows the items under each construct used in the research model.

3.2 Data collection

The target participants of this study are undergraduate and postgraduate students of Higher education Institutions from Chennai (Metro) and Coimbatore (semi-metro) cities in India. Chennai and Coimbatore are cities located in the state of Tamil Nadu, India. According to the AISHE 2019-20 report, Tamil Nadu is one of the top 5 states with the highest number of student enrollment in higher education. A purposive sampling method was employed, and the interested participants were given the questionnaire. Participants were briefed about the survey, and data was collected only from those who had either enrolled or completed a MOOC course in a voluntary environment. With a 95% confidence interval and a 5% margin of error, the sample size estimated was 384. However, out of 466 responses received, only 316 were complete responses and considered for further analysis.

3.3 Data analysis

Data analysis involves two components: Confirmatory Factor Analysis (CFA) explained in the section confirmatory factor analysis and Structural Equation Modeling (SEM) explained in the section structural model and hypothesis testing. Partial Least Square Structural Equation Modeling (PLS-SEM), a widely used tool in Information System (IS) literature, is used to analyze data. PLS-SEM is best suited for performing both exploratory and confirmatory factor analysis as it does not have any assumptions about the data distribution and works well even with a small sample size (Hair et al., 2017). However, we used the recently introduced Consistent Partial Least Square (PLSc) estimation using SmartPLS due to the following reasons: (1) It is more robust than the traditional PLS-SEM; (2) The estimations of PLSc are almost similar to CB-SEM result; (3) Constructs are reflective (Dash and Paul, 2021; Cheah et al., 2018).

Reliability, convergent, and discriminant validity are assessed for CFA with the PLSc method. According to Hair et al. (2017), construct reliability and convergent validity: CR >=0.70, Average Variance Extracted (AVE) for CV >=0.50 and item factor loading >0.70. Discriminant Validity (DV) is assessed using the consistent PLS-based Heterotrait-Monotrait (HTMT) method proposed by Henseler et al. (2015). According to this method, the correlation of items is measured simultaneously within the same construct and across the constructs. A predefined threshold of 0.85, as Kline suggested, and the HTMT values should be lower than the threshold value (HTMT 0.85) to achieve discriminant validity (Kline, 2011). The hypothesis and relationship between the constructs in the study are tested using PLS-SEM. The metric for validating the proposed model includes the R^2 value.

4. Results

4.1 Descriptive summary

Table 1 shows the descriptive summary. About 45% of the respondents were female, and 55% were male students. Those studying in the metro region comprise 29%, and those from the semi-metro constitute about 71%. ICT skills are limited for 49% of the total respondents, 39% were professional, 6% exhibited elementary-level ICT skills, and 5% were ICT experts.

4.2 Confirmatory Factor Analysis

Reliability and Convergent validity

Table 2 shows Cronbach's Alpha score to measure reliability. As mentioned earlier, the score should be greater than 0.70. Convergent validity is measured using three criteria put forward by Fornell and Larcker: item loading, Composite Reliability (CR) and Average Variance Extracted (AVE), as shown in Table 2. Cronbach's alpha and Convergent Validity of all the constructs met the required criteria and were deemed adequate.

Discriminant Validity

Discriminant validity refers to the extent to which a given construct differs from another. Prior researches show that the HTMT method is preferable to the Fornell-Larcker method (Ramayah et al., 2017; Henseler et al., 2015) due to the bias effect suffered by the consistent PLS-based Fornell-Larcker method (Afthanorhan et al., 2021). Hence, this study uses HTMT to assess DV. Table 3 presents the HTMT values of each construct, which is less than HTMT0.85, thus satisfying the Discriminant Validity criterion.

4.3 Structural model and hypothesis testing

The consistent PLS technique is used to assess the structural model and estimate the path coefficient and significance of the proposed hypothesis. Figure 2 shows the path coefficients and corresponding level of significance. The variance of the dependent variable is also shown in Figure 2. The R square value quantifies the amount of variance in the dependent variable as explained by the independent variables. The R-square value of the dependent variable, CUI, is 68.5%, which is highly acceptable and 50.3% for the construct attitude. Perceived ease of use and Perceived reputation together account for 59.4% variance in Perceived Usefulness, while self-efficacy accounts for 46.1% variance in PEOU.

Table 4 shows the proposed hypothesis's indirect, direct, and total effects. The results show that attitude is the strongest predictor (β = 0.718) of continuous use intention of MOOC, which implies that students who have a positive attitude towards using MOOC tend to use it persistently. In turn, attitude is affected directly by perceived usefulness (β = 0.448) and perceived ease of use (β = 0.309). Thus, hypotheses 1-4 related to TAM constructs are all supported. Facilitating condition, a construct from UTAUT added to the model does not affect the continuous use intention of MOOCs, rejecting hypothesis H5. The facilitating condition talks about available resources and support in using MOOCs.

Table 1 - Descriptive summary.

Variables		*Frequency*	*%*
Gender	Female	141	44.62
	Male	175	55.38
Place of Study	Metro	91	28.80
	Semi-Metro	225	71.20
ICT_Skill	Elementary	20	6.33
	Limited	156	49.37
	Professional	124	39.24
	Expert	16	5.06

Table 2 - Reliability and convergent validity.

Construct	*Item code*	*Item loading*	*AVE*	*CR*	*Cronbach's α*
Perceived Usefulness	PU1	0.843	0.633	0.873	0.874
	PU2	0.779			
	PU3	0.769			
	PU4	0.792			
Perceived Ease of Use	PEOU1	0.780	0.689	0.869	0.869
	PEOU2	0.845			
	PEOU3	0.865			
Attitude	ATT1	0.805	0.655	0.850	0.850
	ATT2	0.783			
	ATT3	0.838			
Continuous Use Intention	CUI1	0.731	0.520	0.812	0.812
	CUI2	0.744			
	CUI3	0.707			
	CUI4	0.703			
Facilitating Condition	FC1	0.755	0.526	0.769	0.770
	FC2	0.682			
	FC3	0.738			
Perceived Reputation	PR1	0.749	0.588	0.851	0.851
	PR2	0.797			
	PR3	0.740			
	PR4	0.781			
Self-efficacy	SE1	0.734	0.532	0.773	0.773
	SE2	0.723			
	SE3	0.731			

Table 3 - Discriminant validity (HTMT ratio).

	ATT	CUI	FC	PEOU	PR	PU	SE
ATT							
CUI	0.824						
FC	0.794	0.682					
PEOU	0.647	0.623	0.579				
PR	0.654	0.586	0.522	0.559			
PU	0.681	0.644	0.600	0.759	0.540		
SE	0.782	0.691	0.779	0.680	0.654	0.627	

Table 4 - Summary of the direct and indirect effects of the proposed hypothesis.

H#	*Proposed relationship*	*Indirect effect*	*Direct effect*	*Total effect*	*Results*
H1	ATT (+) -> CUI	-	0.718^{***}	0.718	Supported
H2	PU (+) -> ATT	-	0.448^{***}	0.448	Supported
H3	PEOU (+) -> ATT	0.298^{***}	0.309^{**}	0.607	Supported
H4	PEOU (+) -> PU	-	0.667^{***}	0.667	Supported
H5	FC (+) -> CUI	-	0.062	0.062	Not Supported
H6	SE (+) -> PEOU	-	0.680^{***}	0.680	Supported
H7	PR (+) -> PU	-	0.167^{*}	0.167	Supported
H8	PR (+) -> CUI	0.054	0.077	0.131	Not Supported

The external variables added to the TAM model are self-efficacy and perceived reputation. Self-efficacy directly affects perceived ease of use (β = 0.680) and indirectly affects attitude (β = 0.413) positively. Those who perceive that they are capable of using MOOCs tend to feel comfortable in using MOOCs and also show a positive attitude towards using them, supporting hypotheses 6 and 7. Perceived reputation positively affects perceived usefulness (β = 0.167). However, its relationship with continuous use intention is insignificant, supporting H8 (β = 0.131) and rejecting hypothesis H9, respectively. Students who think that MOOC courses are offered by prestigious universities and taught by well-qualified professors from such universities tend to perceive MOOCs to be very useful, but the same does not lead to continuous use intention. The control variables used in the model, namely gender and ICT skill, came out to be insignificant.

5. Discussions and Conclusion

Students' continuous use intention of MOOC is the main emphasis of this study. The study uses TAM as the underlying theoretical model with two external variables, namely perceived reputation and self-efficacy and includes constructs from the UTAUT model to understand the factors that affect the continuous use intention of MOOCs.

The study also includes two control variables, namely gender and ICT skills.

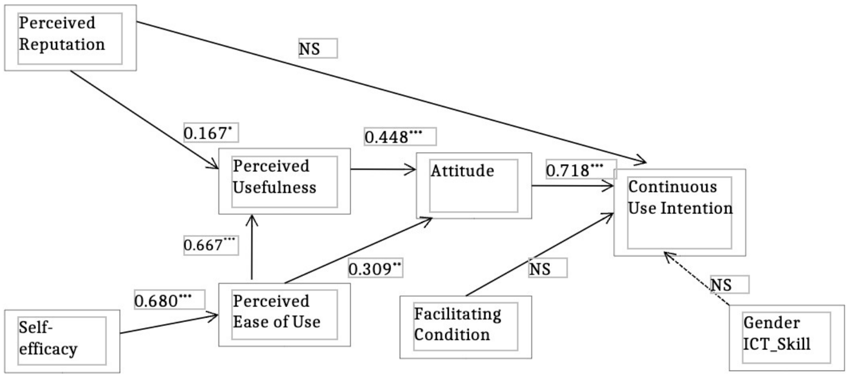

Figure 2 - Structural model analysis.
Note: path coefficient and T-test are significant at: *P<0.05, **P<0.01, ***P<0.001, NS-Not Significant

The model could explain 69% of the variance in explaining the continuous use intention of MOOCs with the attitude of MOOC users being the strongest predictor of continuous MOOC usage and is consistent with past studies (Wang et al., 2022; Cheon et al.,2012; Park, 2009). This is in line with similar researches done in India to study the adoption intention using the TAM model, which showed the positive effect of attitude on intention to adopt MOOCs (Virani et al., 2023; Singh, A. et al., 2021).

As with many prior studies, perceived usefulness and perceived ease of use are the strongest determinants of attitude, and perceived ease of use affects attitude through perceived usefulness (Saleh et al., 2022; Decman, 2015; Cheon et al., 2012; Park, 2009), reinforcing the applicability of the basic TAM model in understanding the factors affecting continued use intention of MOOC in a voluntary environment, among students of HEI in India. In a cross-country study between India and Italy, Indians rely more on the perceived usefulness of a technology which in turn affects its continuous use intention (Chauhan et al., 2021). The results prove that if the users believe that using MOOCs would add value to building their careers, they will develop a positive attitude towards using it persistently. MOOC designers should not overlook the factor "user-friendliness" and its role in MOOC usage. The course modules' design should allow MOOC users to use its features with little effort. The facilitating condition, a construct from UTAUT2 added to the model, does not affect the continuous use intention of MOOCs. The facilitating condition is found to be insignificant in affecting MOOC usage. A possible reason could be the nature of respondents, who are HEI students and it is presumed that they have adequate supporting resources to access MOOC courses. As Venkatesh et al. (2012) described, facilitating condition and its relationship with behavioral intention to use technology is greatly influenced by the environment where the individual uses it.

The study reveals the importance of the external variables integrated with the model in affecting the continuous use intention of MOOCs. Self-efficacy, an intrinsic motivational factor, directly affects perceived ease of use, and attitude indirectly through PEOU and is consistent with a study by Chahal & Rani (2022) on e-learning acceptance by students of higher education institutions in India. This result is also in line with a study by Badali et al. (2022) that showed motivation is one of the most critical factors affecting MOOC retention, and self-efficacy is considered an intrinsic motivational factor (Park, 2009). Those who feel skilled at using MOOC use it with little effort, which in turn influences them to be lifelong users of MOOC.

Perceived reputation affects perceived usefulness positively, aligning with the studies by Huanhuan and Xu (2015) and Wu and Chen (2017). MOOC users are more influenced by reputed institutions and faculty offering MOOC courses. In other words, students from developing countries are particularly attracted to MOOCs because reputed institutions offer the vast majority of courses on MOOCs. The caveat here is that although perceived reputation affects perceived usefulness, it does not significantly impact the continuous use intention of MOOCs. Hence, perceived reputation could initially be a critical factor for attracting first-time users to register for MOOC courses (Gupta & Maurya, 2020); it may not be enough to drive them through course completion and sustained usage.

Implications

The inference from the study provides some valuable suggestions for policymakers in the field of education and MOOC content providers to shape the professional lives of students. In addition to providing the best quality content, MOOC providers should form tie-ups with reputed companies for course content creation, similar to what many universities do. This activity will put continuous positive pressure on MOOCs to provide content relevant to the industry and help enhance perceived reputation among prospective students. As given in the study model, this will positively affect the perceived usefulness of MOOCs, which will be mutually beneficial to both students and content providers. Students get rewarded significantly in their place of work because of acquiring the required skill set, and the MOOC will increase the perceived reputation quotient, which will increase enrollment.

The major thrust will be on the education policy. Self-efficacy, perceived ease of use and overall attitude towards MOOC can be influenced from the high school/college level by providing essential knowledge for all students. This can make them feel at ease when using information technology platforms. Additionally, some of the courses can be taught in a hybrid manner with explanations in the school/college and follow-up activities based on online content. This intervention will help boost the attitude toward completing MOOCs, as students may not feel different when enrolling for MOOCs where everything is online. Also, the habituation to this hybrid environment from the school level will have a system-driven positive influence on the self-efficacy of students, as group activities are known to motivate team members to rise to the occasion.

To corroborate the implications given in this study, policymakers can carry out research (data from other geographies also) to understand the influence of the hybrid model of curriculum (part offline and party online) on the self-efficacy of the students and, in addition, on the attitude of those who had enrolled in MOOC in those geographies. MOOC content providers can also engage in peer research surveys to understand the proportion of users who complete vs who enrol among peer groups, the strategies that are being followed by successful content providers (based on the response from students), etc. This will make the industry more competitive, resulting in developing better quality content and devising strategies that make the content more engaging. Also, the results help the content providers understand the gaps between perceived use and reputation among peers and may help them act upon these to enhance them.

Limitations and Future Research

The inference from this study is from a state with relatively higher enrollment in education. Similar surveys have to be conducted in different geographies with different precedence w.r.t education like north, west, east and northeastern part of India to include the demographic and cultural factors. Also, the place of study can be extended to rural to get the complete demography. The result may further strengthen the hypothesis and open up new areas regarding control factors that must be considered.

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Appendix - Survey items

Constructs	*Items*	*Measures*	*References*
Attitude	ATT1	Learning through MOOC is a good idea	Park (2009)
	ATT2	Learning through MOOC is a wise idea	
	ATT3	I am positive towards using MOOC	
Facilitating Condition	FC1	I have adequate resources to use MOOC	Venkatesh et al.(2003)
	FC2	I can get help from others when I have difficulties using MOOC	
	FC3	I have knowledge necessary to use MOOC	
Perceived Usefulness	PU1	MOOC helps me to be self-reliable	Chiu & Wang (2008)
	PU2	MOOC improves my learning performance	Bhattacherjee (2001)
	PU3	MOOC improves my learning effectiveness	Bhattacherjee (2001)
	PU4	I find MOOCs to be useful to me	Roca, Chiu, & Martínez (2006)
Perceived Ease of Use	PEOU1	MOOC is easy to use	DeLone & McLean (2003)
	PEOU2	It is easy to become skillful in using MOOC	Wu and Zhang (2014)
	PEOU3	Interaction with MOOC is clear and understandable	Wu and Zhang (2014)
Perceived Reputation	PR1	MOOC courses are offered by reputed universities	Munisamy, Jaafar, & Nagaraj (2014); Wu & Chen (2017)
	PR2	MOOC partners (Coursera, edX, etc) - universities have good reputation	
	PR3	Professors from reputed universities teach MOOC courses	
	PR4	Good reputation of MOOCs platform offers courses I am interested in.	
Self-efficacy	SE1	I am confident in using MOOC	Liaw (2008)
	SE2	I feel confident in operating MOOC functionalities	
	SE3	I am confident using MOOC course contents	
Continuous Use Intention	CUI1	I intend to continue using MOOC in the future	Alraimi et al.(2015)
	CUI2	I will continue using MOOC in future	
	CUI3	I will strongly recommend MOOC for others to use it	
	CUI4	I will keep using MOOC as regularly as I do now	

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From learning machines to teaching robots. Interaction for educational purposes between the Social Robot NAO and children: a systematic review

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Abstract

Interaction between social robots and children occurs today in a variety of environments, including schools, hospitals, and homes. This review aims to highlight studies that delve into this interaction in the educational settings, exploring the characteristics of the social robot NAO and how its features influence its relationship with children. A search was conducted on July 1st, 2023 in Scopus and PsychInfo. Inclusion criteria pertained to (1) typical development; (2) age range 4-12 years; (3) educational setting; (4) type of robot (NAO); (5) type of publication: peer-reviewed journal; (6) language: English; (7) research studies. Of the 116 results that emerged from the search, 92 were excluded, yielding 24 valid results. We classified the records into two categories, namely 17 results were included in the "NAO as an informational and educational tool" category and 7 in the "NAO as a relational agent" category. The first category considers all studies where social robots were used as tools for educational and informational support; these studies delve into topics related to the teaching of school subjects and personalized learning, with a specific focus on emotional education. In the second category, we encounter studies that explore the relationships between children and robots, with a primary emphasis on the phenomenon of anthropomorphism, the attribution of mental states, touch interaction, and the robot's caregiving abilities. Based on the present review, social robots like NAO emerge as potential resources to implement new forms of teaching and interaction within the educational context; however, more research is needed to design developmentally-tailored programs and child-friendly features.

KEYWORDS: NAO, Children, Interaction, Education, Learning.

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1. Introduction

Anthropomorphic robots are an increasingly widespread technology in educational settings, such as classrooms. They have evolved into a facilitating tool with significant results in promoting the learning process, due to their ability to motivate children and increase their curiosity (Goh et al., 2007). Human-like robots have been used to examine social interaction (Tanaka et al., 2007), develop language knowledge, motivate learning and goal achievement, reduce anxiety (Alemi et al., 2015), enrich pedagogical scenarios (Park et al., 2016), improve problem solving during lessons (Brown et al., 2013), and capture children's attention (Ioannou et al., 2015). However, considering the speed of technological development in the field of education, academic knowledge and understanding of how young children use and learn with these robots are still very limited. Despite the current relevance of the topic, there

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is still a limited body of research that has examined the effects of this educational interaction on children.
In this sense, the National Association for the Education of Young Children (NAEYC) has recognized the potential of technology and has also called for increased research to better understand the use of technology in educational contexts (NAEYC, 2012). To respond to this request, many authors explored the possibilities offered by humanoid robots, including NAO. In research focused on education, NAO is often used because of its features, such as its advanced multimedia system, including four microphones, two speakers, and two cameras, which make it highly engaging for children. Moreover, this allows the robot to perform various operations, including voice and facial recognition. Secondly, despite its advanced technology, it does not require extensive programming experience from the user. This is an added value for its use in educational contexts, where the robot might be used by operators without specific programming competencies. Finally, previous research has shown that children feel comfortable interacting with NAO and perceive it more as a peer than as a toy (Ioannou et al., 2015). Other findings highlight that children are more attracted to robots than books or CDs, which leads, in turn, to better learning outcomes (Woods et al., 2004). This result was mainly observed in language learning contexts (e.g., Georgieva -Tsaneva et al., 2023). The recent developments in social robots' design had a relevant impact in terms of the learning possibilities that help develop a close and personalized connection with the user (Feil-Seifer & Mataric, 2005). For instance, the newest robots can integrate instructional structures and establish unique relationships with individual students (Ramachandran et al., 2017). Moreover, each student can independently determine their level of education and communicate their learning needs to the robot (Chen et al., 2020).
However, the cognitive aspect of learning is not the only one. Studies concerning motivational strategies underline the importance of the affective dimension of learning; among these, Riggs et al. (2016) state that emotional development precedes cognitive development. Therefore, when programming social robots, especially those that interact with young children, aspects of emotional recognition should always be integrated with the specific language and cognitive skills of that age group. Indeed, social robots are capable of developing additional interactive features, including recognizing emotional responses, thus generating a differentiated motivational strategies and catering to the preferences, requirements, and needs of each child (Obaid et al., 2018).
In sum, within the developmental and educational contexts, the use of social robots may vary from offering a technological support to teaching to stimulating engagement and motivation in children. We, therefore, conducted a systematic literature review to provide an overview of the state of the art regarding its interaction with children, both in the instructional and in the psychological fields. The purpose of this systematic review is to provide an overview of studies conducted in the field of education that have explored various types of interaction while simultaneously offering a map of activities within an educational context involving NAO and children. To do so, we included studies that examined the child-NAO relationship from a learning and/or engagement perspective. The following section presents all the steps that led to the final results included in this review.

2. Materials and Methods

Based on the criteria provided by the PRISMA guidelines for systematic reviews (Moher, Liberati, Tetzlaff, Altman, & The PRISMA Group, 2009), a search was conducted on July 1st, 2023, in two databases, namely Scopus and PsycInfo, using the following keywords strings, "robot nao" AND "child*" AND "educ*" OR "interact*". One hundred and sixteen documents were identified in the databases. After removing duplicate records, the studies were screened based on seven inclusion criteria: (1) typical development; (2) age range 4-12 years; (3) educational setting; (4) type of robot (NAO); (5) type of publication: peer-reviewed journal; (6) language: English; (7) research studies. The inconsistencies were discussed by the team of authors. After this process, 62 records were excluded; the second exclusion phase was defined by a single criterion: 1) out of scope. In this phase, 1 record was excluded because it presents the development of a collaborative behavior controller for social robots without taking into account the children-robot interaction.
Therefore, the full-text of N = 24 eligible articles was accessed. After reading the full-text, all documents were deemed eligible for the current review (Figure 1).
The included articles described the functionalities exhibited by NAO and, consequently, the perceptions and reactions of children during learning activities, games, and explorations of these new technologies by tutors and researchers. To better understand the functionality of NAO in the educational context and its required features, as well as the issued related to it, we divided the included studies into two categories, namely 1) "NAO as an informational and educational tool", and 2) "NAO as a relational agent". The first category includes all research in which NAO was utilized as an educational and informational assistance aid; the second category includes studies in which it was employed as relational agent to be known through multimodal experiences.

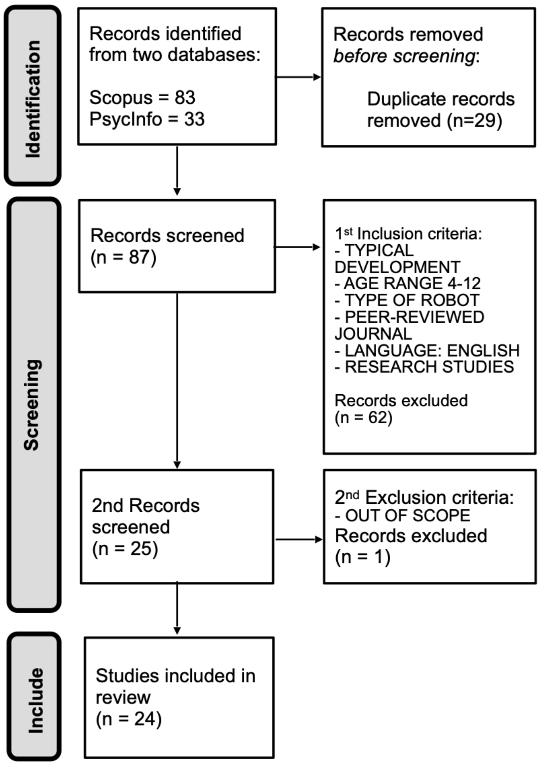

Figure 1 - PRISMA 2020 flow diagram for new systematic reviews which included searches of databases.

3. Results

Regarding the "NAO as an informational and educational tool" category (Table 1), 17 results have been included.

The implementation of a NAO tutor with a personalization policy, conducted by Almousa and Alghowinem (2022), was measured on three behavioral outcomes of children: (1) academic knowledge (answer correctness), (2) attentional orientation and gaze direction, and (3) hesitation (time lag before answering). The results showed that children exhibit different behaviors and follow multiple learning paths during the interaction. Facial recognition, which allows the robot to learn and remember the child's name, has been highlighted as a central mechanism for attention and engagement. Indeed, the robot could detect if and when the child lost attention, assessing gaze and engagement zone, providing personalized feedback (e.g., calling the child by name) and repeating the question to regain attention. The authors underline personalization features, such as the ability of social robots to modify their expressiveness based on the perceived difficulty level for the child, as key to the child's greater engagement in educational tasks. Further research in this sense is recommended; for example, the social robot would gain a better understanding of where the child is facing difficulties and adapt accordingly, for example, by adjusting speech speed to that of natural human speech (Rossi et al., 2019)

So and Lee (2023) implemented a study in which NAO was used to create a playful and enjoyable interaction while teaching mathematics. The teaching of mathematical concepts related to lengths and their measurement was conducted through the social robot's presentation of slides, worksheets, and playing cards.

The results showed a greater effectiveness in learning when the interaction is perceived as friendly. NAO piqued the children's interest while delivering a concise mathematics lesson in the absence of a human instructor. Children exhibited a range of engagement cues, including head movements, facial expressions, bodily gestures, and verbal prompts. They identified the robot as a friendly learning companion and actively participated in the activities. However, integrating NAO into a formal setting proved to be challenging in the absence of trained personnel due to unexpected technical issues and constraints within the learning environment.

In the domain of math teaching, Alhashmi et al. (2021) studied the relational and learning outcomes of a robot teacher. Students expressed that they enjoyed the session with the robot and would have liked to dedicate more time to it. In terms of the learning experience, they reported better understanding of decimal numbers. The students thought the robot could not make mistakes because «he is electronic and knows many things» compared to the teacher. Teachers found that the robot lacked of empathy and would likely be unable to assist with tasks requiring social or emotional competence such as counseling, hugging a child, or promoting children's well-being.

Ponce et al. (2022) conducted a study aiming to explore the professional integration between educators and social robots in order to enhance students' attention capacity through a richer and diversified learning dynamic in different areas of the Mexican curriculum. Four different approaches were implemented: three in elementary schools and one in higher education. These approaches included the LEGO® robotics kit and the NAO robot for STEM (science, technology, engineering, and mathematics) teaching, the NAO robot for physical education (PE), and the PhantomX Hexapod. Participants were divided into two groups, with only one group interacting with the social robot to examine the difference in learning and exercise resolution in the following topics: sound propagation, the metric system, and fractions with whole numbers. The results demonstrated that students who interacted with NAO showed better outcomes in terms of attention retention, thus enhancing their overall performance during the lesson. Similarly, students preferred a robotic educational environment that reinforced the theoretical concepts previously taught in class (Ponce et al., 2022).

Levinson et al. (2021) demonstrated that social robots can be integrated into summer camps but also highlighted some critical issues. For instance, some children lost interest in the activities because of the robot's repetitive behavior. Moreover, the interaction with the social robot was not always smooth, and the authors found that its maximum and duration was close to seven minutes; they also considered the construction of mixed indoor and outdoor activities to be crucial.

Similarly, Crompton et al. (2018), while underling the new and extensive pedagogical possibilities and innovations in students' engagement provided by robots, noted that integrating them is often challenging due to teachers' lack of experience and knowledge on how to use them. Moreover, sometimes the social robot itself has limitations that inhibit its functionalities, which depend on unexpected events, resulting in failure to respond to a command given by a child or a teacher (Crompton et al., 2018).

Molenaar et al. (2021) conducted an experimental study investigating the effect of speech dragging in in Robot-assisted language learning (RALL). Specifically, the study aimed to delve into the convergence of voice pitch between NAO and children to examine potential differences in language learning. They found no interaction between the test phase (pre-test or post-test) and group (control or entrainment). Therefore, there is no evidence that entrainment in the robot can lead to a larger learning effect than otherwise.

In the field of music education, de Souza Jeronimo et al. (2022) compared two different robots, namely NAO and Zembo, in terms of children's preference after a guitar lesson delivered by the robot itself. Most children preferred Zenbo's cute appearance, facial expressions, and ability to express joy and sadness. NAO relies on voice pitch, body movements, and discreet lights in its eyes to express emotion. These lights may however make it difficult for users to recognize emotions and for robot designers to model them. In this sense, from a developer's perspective, NAO's emotional expressivity does not offer room for improvement, while Zenbo offers different facial expressions and the possibility of displaying animation (de Souza Jeronimo et al., 2022).

Still in the field of artistic activities, Neumann et al. (2022) studied the possibility of children developing a relationship with NAO during a drawing activity, in which the robot instructed the children. Some children talked to NAO but did not attempt the drawing task, while others performed the drawing tasks without verbally interacting. 83% of the children followed the robot's instructions and attempted to reproduce what was asked of them. The authors, in line with previous works (Baxter & Belpaeme, 2016; Baxter et al., 2017; Verhagen et al., 2019; Johal, 2020), point out the need to explore some individual variables that could affect children's interaction with social robots, such as personality traits. For instance, Baxter and Belpaeme (2016), based on a study investigating the extroversion/introversion continuum in primary school children, suggest that the application of personality assessments in a child-robot interaction should be conducted by also taking into account context-related variables.

Lopez-Caudana et al. (2022) conducted a study aimed at demonstrating NAO's ability to capture children's attention (being followed in the instructions and rules it provides) during a theoretical and practical physical education (PE) session. The study took place in primary school classes, where the levels of attention and motivation were analyzed. NAO was able to foster concentration, consequently leading to higher motivation and ultimately positively impacting PE participation and the adoption of a healthy lifestyle.

Rosi et al. (2016) explored the possibility of using NAO as an instructor and motivator in nutrition education at school. The presence of NAO in this intervention study did not increase knowledge of nutrition compared to "traditional" lessons. However, commitment and motivation of the child towards healthier food choices have been encouraged through the use of the robot.

Bono et al. (2020) studied the interaction between a child and three storytelling robots depicting a bullying scenario. The narrator was portrayed by NAO, while a Pepper robot played the bully, and another robot played the protagonist, i.e., the victim. The narrator, calling the children by name, invited them to give advice to the victim, in order to establish affiliation between the child and the robot. Children showed appreciation for storytelling through humanoid robots, even more so because they were programmed to express the internal states of the characters. Interestingly, users showed empathy also towards the bully (Bono et al., 2020). Some critical issues concerned the construction of the story dynamics and its duration, the number of scenes, and the (sometimes sparse) interaction among the characters.

With the aim of contributing to the growing field of affective robot tutors, Imbernón Cuadrado et al. (2016), developed ARTIE (Affective Robot Tutor Integrated Environment), a platform useful to identify emotional states. The authors integrated an educational software for primary school children with a component that identifies the emotional state of students interacting with the software and the driver of a tutor robot that provides personalized emotional pedagogical support. Despite the simplicity of the prototype and the involvement of only two children, the authors concluded that the humor of the robot is a motivating factor and the correct parameterization of the pedagogical intervention is essential. Moreover, it is necessary to understand what in the intervention sequence can increase the participant's difficulty; another element that can cause much frustration to the students is the misidentification of cognitive-affective states (Imbernón Cuadrado et al., 2016).

Regarding the “NAO as a relational agent” category (Table 2), seven results have been included.

Manzi et al. (2020) investigated the attribution of mental states to two humanoid robots, NAO and Robovie, differing in degree of anthropomorphism. 5-, 7-, and 9-year-old children attributed mental states to the first robot because it exhibited human-like characteristics, while the second robot was perceived as having more mechanical features. The research group's findings demonstrate that 5-year-old children have a greater tendency to anthropomorphize robots compared to older children, regardless of the type of robot, thus supporting previous findings (Manzi et al., 2017; Di Dio et al., 2018; 2019; 2020a; 2020b). Additionally, while this result may seem counterintuitive to what was mentioned earlier, the authors observed a difference in emotional attribution toward NAO, noting that younger children attributed fewer negative emotions to the robot compared to older children (Manzi et al., 2020).

About the establishment of a children-robot relationship, and specifically considering dimensions of trust, closeness, cognitive and affective perspective-taking, and social presence, Van Straten et al. (2022) aimed to experimentally investigate self-disclosure and question-asking by a social robot toward children. The authors discovered that, for example, asking questions increased children’s trust in the robot and influenced their perception of the robot as being more capable of perspective-taking. Neither question-asking nor self-disclosure affected children's feelings of closeness toward the robot or their experience of its social presence. Furthermore, it was found that children's experience of the robot as an actor that they could befriend remained unaffected (Van Straten et al., 2022).

Van Straten et al. (2020) experimentally investigated the effects of transparency regarding a robot’s lack of human psychological capabilities (intelligence, self-awareness, emotions, identity construction, social cognition) on children's perceptions of the robot itself and their relationship with it. Transparency (i.e., providing children with detailed information on NAO’s lack of human qualities) negatively affected the child-robot relationship in terms of decreased trust but it did not influence feelings of closeness toward the robot. In the absence of transparent information, children tended to be ambivalent in perceiving the animated state of the robot. Conversely, ratings of social presence were particularly high in the transparency condition (Van Straten, 2020). According to the authors, this indicates that children's experience of social presence decreases but does not disappear when information about a robot's lack of human psychological capabilities is provided.

Stower et al. (2022) analyzed children’s social attitudes when interacting with NAO to complete a task in which they programmed Cozmo (a truck robot) to navigate on a physical map. There were two conditions: one in which NAO provided correct information, while the other in which the robot provided incorrect information. The authors’ findings demonstrate that a robot error had no significant effect on children’s social attitudes, behavior, or task performance. The authors suggested two possible explanations for this: the first possibility is that no child noticed the error due to the numerous elements within the research environment (NAO, Cozmo, the map and the tablet); the second possibility is that some children perceived the error but did not consider it relevant to the interaction and the task. In this case, children might have decided not to consider NAO’s mistake because the robot would have admitted its mistake, thus preserving children’s trust.

In several studies, NAO acts as a mediator between the child and the environment or more specifically another digital or robotic technological object. In the study by Flanagan et al. (2023), the central theme is perceived agency. The authors studied the beliefs of children aged 4 to 11 about two familiar technologies: Roomba and Amazon Alexa, compared to beliefs about a humanoid robot like NAO. Using feature clustering, they figured out that children’s beliefs about the characteristics of technological agents are organized into three distinct groups: having experiences, having minds, and ability to act in moral scenarios. They also found that older children tended to view the functionality of technologies as tightly bound by their programming. The results of the study show that young children don’t seem to lose sight of the fact that they are interacting with artifacts designed for a particular function. Also, with this awareness, younger children attribute action to technologies more than older children.

Okanda and Taniguchi (2022) investigated whether preschool-age children exhibit a tendency towards “yes” responses to yes-no questions asked by a humanoid robot. Their hypothesis was that the responses would be similar to those given in the presence of familiar humans, with younger children, specifically three-year-olds, showing a “yes” bias regardless of the conditions compared to older children. The hypothesis was only partially supported. Younger children did indeed exhibit a “yes” bias, as an automatic or impulsive response (Okanda & Itakura, 2010, 2011); however, the older children showed a “no” bias. According to the authors, these results can be explained by stating that the robot used in the study did not exert a high level of social pressure, and the older children did not feel obligated to respond obediently.

Table 1 - NAO as an informational and educational tool” (n = 17 studies).

Authors (year)	*Sample*	*Outcomes investigated*	*Main results*
Ahmad, M.I., Mubin, O., & Orlando, J. (2017)	23 children aged 10-12	NAO performed 1) game-based adaptations, 2) emotion-based adaptations, and 3) memory-based adaptation	Emotion-based adaptations of NAO were found to be the most effective, even more than memory-based adaptations.
Ahmad, M.I., Mubin, O., Shahid, S., & Orlando, J. (2019)	24 children aged 10-12	Emotion and memory model for a social robot	Interaction with NAO presenting positive emotional feedback facilitates vocabulary learning.
Alhashmi, M., Mubin, O., & Baroud, R. (2021)	20 fourth grade students	NAO Co-teacher	NAO’s role as co-teacher has been appreciated by students, while teachers express some concerns.
Almousa, O., & Alghowinem, S. (2023)	5 preschool children aged 3-5; 2 preschool teachers	Personalized learning	The personalized interaction with NAO showed a positive potential in increasing the children's learning.
Basori, A.H. (2020)	Children, number and age unknown	Body touch and character recognition	The robot was able to achieve a high 75% recognition rate for kid's manuscripts.
Bono, A., Augello, A., Pilato, G., Vella, F., & Gaglio, S.(2020)	1 child aged unknown	Interactive storytelling	NAO’s role as a storyteller increases credibility if it communicates the internal states of the characters.
Crompton, H., Gregory, K., & Burke, D. (2018)	3 teaching assistants and 50 children aged 3-5	Student development in all learning domains	Interaction with NAO has made a greater respect for turns in cooperation.
Cuadrado, L.-E.I., Riesco, Á.M., & De La Paz López, F. (2016)	20 children aged 10-11 (scratch use experience) 2 children aged 8 and 11 (interaction with NAO)	Personalized emotional pedagogical support	Interacting with NAO must be dynamic enough not to frustrate or bore.
De Souza Jeronimo, B., de Albuquerque Wheler, A.P., de Oliveira, J.P.G., Melo, R., Bastos-Filho, C.J.A., & Kelner, J. (2022)	20 children aged 9-11	Musical education	NAO emotional expressivity does not offer room for improvement, while Zenbo offers alternative skins for facial expressions.
Levinson, L., Gvirsman, O., Gorodesky, I.M., Perez, A., Gonen, E., & Gordon G. (2021)	46 children aged 6.7 ± 0.9	STEM teaching	Interaction with NAO at a summer camp is effective but needs to be made more dynamic.
Lopez-Caudana, E., Ponce, P., Mazon, N., & Baltazar, G. (2022)	26 third grade students and 25 fourth grade students	Physical education	Interaction with NAO improves children’s attention span and motivation.
Molenaar, B., Fernández, B.S., Polimeno, A., Barakova, E., & Chen, A. (2021)	32 children aged 8-11	Robot-assisted language learning	Tone of voice convergence between NAO and student has no significant effect on language learning.
Neumann, M.M., Neumann, D.L., & Koch, L.-C. (2023)	40 preschoolers aged 4.58	Drawing activity	In the drawing activity together with NAO, 83% of the children followed the instructions and 60% interacted verbally.

Authors (year)	Sample	Outcomes investigated	Main results
Peretti, G., Manzi, F., Di Dio, C., Cangelosi, A., Harris, P.L., Massaro, D., & Marchetti A. (2023)	112 children aged 5-6	Recognize, and morally evaluate, lies and mistakes produced by a human as compared to a NAO robot	When children interact with NAO they understand mistakes better than lies.
Ponce, P., López-Orozco, C.F., Reyes, G.E.B., Lopez-Caudana, E., Parra, N.M., & Molina, A. (2022)	186 4th, 5th, and 6th grades of elementary schools	STEM Teaching and physical education	Students prefer a robotic teaching environment to reinforce theoretical concepts seen in the classroom.
Rosi, A., Dall'Asta, M., Brighenti, F., Del Rio, D., Volta, E., Baroni, I., Nalin, M., Coti Zelati, M., Sanna, A., Scazzina, F. (2016)	112 fourth grade students	Nutritional aspects	Game-based educational interaction with NAO increased children's nutritional knowledge.
So, S., & Lee, N. (2023)	20 children aged 9-12; 15 guardians aged 26-46	Teach a mathematical concept of measurement	Children's impressions of NAO focused on involvement and curiosity.

Table 2 - NAO as a relational agent (n= 7 studies).

Authors (year)	*Sample*	*Outcomes investigated*	*Main results*
Flanagan, T., Wong, G., & Kushnir, T. (2023)	127 children aged 4-11	Beliefs about familiar technologies and NAO	Young children attribute agency to technologies more than older children.
Ioannou, A., Andreou, E., & Christofi, M. (2015)	4 preschoolers aged 3-5	Thoughtful and caring attitudes	Preschoolers demonstrate caring behaviors such as hug to NAO.
Manzi, F., Peretti, G., Di Dio, C., Cangelosi, A., Itakura, S., Kanda, T., Ishiguro, H., Massaro, D., & Marchetti A. (2020)	189 children aged 5-9	Anthropomorphism	Children tend to anthropomorphize humanoid robots that also have some mechanical characteristics.
Okanda, M., & Taniguchi, K. (2022)	45 children aged 3-5	Yes-no answers to questions about familiar and unfamiliar objects	The 3-years-old children, unlike older preschoolers, showed yes bias with NAO.
Stower, R., Abdelghani, R., Tschopp, M., Evangelista, K., Chetouani, M., & Kappas, A. (2022)	72 children aged 7-10	Perceived agency	The authors found no quantitative effects robot error on children's self-reported attitudes, behavior, or task performance. Age was also not significantly correlated.
Van Straten, C.L., Peter, J., Kühne, R., & Barco, A. (2020)	144 children aged 8-9	Transparency about robots' machine nature	Transparency reduced children's perception of the robot in terms of animation, anthropomorphism, social presence, and perceived similarity.
Van Straten, C.L., Peter, J., Kühne, R., & Barco, A. (2022)	293 children aged 7-10	Self-disclosure	Children's consideration of the robot as social actor and a potential friend did not differ across conditions.

Furthermore, four-year-old children, who are known to say “no” to adults (Okanda et al., 2012), did not do so with NAO. It seems that four-year-old children may perceive NAO as an artifact that falls somewhere between an unknown-authoritative figure and a familiar-friendly one.

The study by Ioannou et al. (2015) showed that children aged 3-5 tend to interact with NAO as if it were one of them. Furthermore, the study demonstrated that children pay particular attention to NAO when it needs help (e.g., when it falls), displaying caring and friendly behaviors. This finding is consistent with the research by Tanaka, Cicourel, and Movellan (2007), who argued that children between 8 and 24 months old exhibit a variety of social behaviors around a robot, including treating it as a peer. This finding suggests that humanoid robots evoke feelings and may facilitate the acquisition and awareness of the importance of care behaviors.

4. Discussion and Conclusions

The aim of this systematic review was to identify the characteristics of the interaction between the social robot NAO and children in educational and relational contexts. From an initial total of 116 studies, we obtained a total of 24 studies through two rounds of exclusion. For the sake of clarity, we divided the results into two main categories: 1) “NAO as an informational and educational tool”, and 2) “NAO as a relational agent”. This division allowed us to capture the structural and operational characteristics that these studies share more effectively.

Regarding studies in the field of education and learning, the authors agree on the identification of the main emotions that influence children’s immediate perception of robots, such as recognizing them as friendly, fun, curious, and positive (Ponce et al., 2022; So & Lee, 2023). Positive emotional feedback is specifically highlighted for enhanced lexical learning, fostering children’s appreciation of NAO as a co-teacher. Additionally, programming NAO to respect turn-taking in question-answer dynamics and cooperative activities is found to be significant, promoting dynamic responses, actions, and gestures that facilitate learning and cultivate curiosity. It is essential to continue studying this phenomenon to improve our understanding of children’s actual learning, especially on the long-term (Baddeley, 2007; Sherwood, 2015). This result can only be achieved through longitudinal studies.

In studies within the realm of relationship, it is noteworthy that research by various authors aligns with the understanding that children, particularly those under the age of 6, tend to attribute consciousness to objects, a phenomenon known as animism (Di Dio et al., 2020b). This tendency tends to diminish significantly around the age of 9.

Anthropomorphization is a noteworthy phenomenon to be taken into account during the robot programming phase, due to its potential influence on the structural aspect of the robot as well as paraverbal and tone of voice aspects.

It is also important to acknowledge that, despite the anthropomorphization tendency, children can generally distinguish between a human being and a robot, especially based on the attribution of human psychological states, such as intelligence, self-awareness, emotionality, identity construction, and social cognition. The exploration of transparency (i.e., directly informing children that robots do not experience those psychological states) and its impact on children's perception during interactions with social robots contributes to a nuanced understanding of mental state attribution (AMS) and the formation of relationships with humanoid robots.

Moreover, this line of research sheds light on children's expectations, perceptions of robotic design, and imaginative features influencing the development of the animism phenomenon. The theoretical insights gained from these studies may offer valuable guidance for the future development of humanoid robots, aiming to promote richer and more respectful coexistence and conviviality.

Overall, the research analyzed in the present review highlights key practical aspects for the utilization of social robots, particularly NAO, in educational and relational contexts with children. Practical considerations encompass the recognition of positive emotional feedback to facilitate lexical learning and the endorsement of NAO as a co-teacher. The programming of NAO to adhere to turn-taking in interactions is also emphasized. Furthermore, attention is directed towards anthropomorphization during NAO programming, emphasizing the influence of structural, paraverbal, and tonal aspects. Transparency emerges as a pivotal element shaping interactions, diminishing children's perception and altering the spontaneous nature of engagements. Lastly, some studies propose that theoretical and practical insights provided by the research can guide the future development of social robots, aiming to foster a more enriched and respectful coexistence.

In conclusion, this review aimed at capturing both the potential uses of social robots in the fields of education and relationship-learning, as well as key aspects to keep in mind when programming NAO for such purposes. Among these, we highlight the positive effects of personalized learning, closely linked to the ability of robots to assume various social roles; the playful experience that these technologies can provide during the transmission of educational content, which can be connected to studies on transparency and control, where relevant issues regarding the operation of biases in interaction with social robots have emerged. Another important research direction for both fields is related to aspects of mutual care: from the child to the robot and vice versa. This latter line of research raises new ethical and developmental psychology questions. Lastly, we emphasize the significance of studies on anthropomorphism, which raise new research questions concerning design and, therefore, the perception of differences and similarities between humans and robots in terms of action and aesthetics.

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Factors Influencing 360-Degree Video Adoption in e-Learning: a UTAUT2 Case Study with Pre-service Primary Education Teachers in Spain

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Abstract

This study analyses the acceptance of immersive virtual reality (iVR) videos among e-learning students (N=198) enrolled in a Primary Education Degree English course at the University of Las Palmas de Gran Canaria. iVR, with its ability to create realistic and interactive virtual environments, has emerged as a transformative tool in enhancing learning experiences. Its application extends to higher education, proving invaluable for pre-service teacher training through an authentic simulation of classroom dynamics. Acknowledging the pivotal role of student acceptance and comfort with this technology, this research aims to understand the factors influencing its efficacy.

To measure acceptance, students actively engaged in a competency activity, immersing themselves in the analysis of a 360-degree-recorded classroom practice within a Primary Education setting. Subsequently, a structured questionnaire, based on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), was administered. This questionnaire assessed the factors influencing the acceptance of this educational technology across eight dimensions and their behavioral intentions to use it.

Results from this investigation underscore that the factors Hedonic Motivation, Performance Expectancy and Effort Expectancy received the highest ratings among participants. Conversely, lower ratings were observed for Habit and Price Value. Confirmatory factor analysis demonstrated that the UTAUT2 model effectively captured preservice teachers' perceptions of iVR across all dimensions (Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, Habit and Behavioural Intention).

KEYWORDS: UTAUT2 Model, Immersive Virtual Reality, e-Learning, Pre-Service Teacher Training.

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1. Introduction

Virtual reality (VR) is gaining momentum in education, as evidenced by initiatives such as the European Horizon program on eXtended Reality Learning (European Commission, 2021). This technology is being regarded as a highly effective educational tool (Li et al., 2022), particularly within the landscape of higher education where extended reality (XR) technologies, including VR and 360-degree videos (immersive virtual reality (iVR) videos), are undergoing active exploration (Brown et al., 2020). Despite diverse applications of 360-degree videos in education, with a noticeable focus on Medicine and Healthcare (c.f., Bernard et al., 2019; Chang et al., 2019; Zulkiewicz et al., 2020, to name a few), studies on their use in teacher education are scarce (Theelen et al., 2019; Theelen et al. 2020; Walshe & Driver, 2019; Ye et al., 2021), indicating a need for more exploration, a gap this study seeks to address.

The versatility of 360-degree videos, recorded in immersive reality with spherical cameras, offers users a

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unique ability to navigate and control their viewing experience. Their immersive nature, sense of presence, and interactivity are key attributes that contribute to their effectiveness (Walsh & Pawlowski, 2002). In the field of education, the realism of 360-degree videos, their affordability and mobility provide an immersive experience that enhances content understanding (Shadiev et al., 2022), and can encourage the development of educational inclusion through the use of technologies (Guerra-Santana et al., 2022). Yet, for iVR benefits to materialize, it is crucial for students to accept and feel comfortable with the technology.

To investigate the factors influencing on the acceptance and intention to use iVR within the context of teacher training, our study adopts the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) (Venkatesh et al., 2012) as its research framework. UTAUT2 is a widely used model in educational settings, and it provides a robust foundation for understanding technology perceptions (Abdekhoda & Dehnad, 2023; Bower et al., 2020; Tamilmani et al., 2021). Its versatility is evident in applications across diverse educational contexts, including studies on mobile phone usage, PowerPoint, Google Classroom, the metaverse, and virtual reality games (Chávez Herting et al., 2020; Jakkaew & Hemrungrote, 2017; Nikolopoulou et al., 2020; Udeozor et al., 2021; Yang et al., 2022). The absence of similar investigations in Spain underscores the distinctive value of our research, especially considering that studies on iVR acceptance using UTAUT2 have been conducted in various other countries such as China (Li et al., 2022), Australia (Bower et al., 2020), Belgium (Boel et al., 2023), and South Africa (Mbonye, 2022).

UTATU2 builds upon the foundation of the original UTAUT model (Venkatesh et al. 2003), which identifies four key factors shaping an individual's intention to use and actual usage behavior of a technology: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions. UTAUT2 introduces three additional constructs: Hedonic Motivation, Price Value, and Habit (Venkatesh et al., 2012). Compared to the original UTAUT model, this extended framework is better equipped to explain and analyze individuals' technology acceptance behaviors (Tamilmani et al., 2021). Given the explanatory power of UTAUT2 in anticipating behavioral intention, particularly in contexts where educators have more freedom to choose teaching tools (Wong et al., 2013), it is deemed more appropriate for our study. Below is a brief overview of the constructs of UTAUT2 that influence and predict the intention and usage of iVR, adapted to the purpose of this study.

Performance Expectancy: the extent to which pre-service teachers believe that using 360-degree videos will enhance their teaching performance and contribute to improved learning outcomes in their future classrooms.

Effort Expectancy: prospective teachers' perceptions of the ease of use (mental and physical effort) associated with integrating iVR videos into their teaching practices.

Social Influence: the influence of various stakeholders, such as colleagues and educational authorities, on trainee teachers' decisions to adopt 360-degree videos in their teaching.

Facilitating Conditions: pre-service teachers' perceptions of the availability of organisational and technical support systems necessary to facilitate the integration of 360-degree videos into their future teaching practice.

Hedonic Motivation: the intrinsic pleasure, enjoyment, and satisfaction that student teachers derive from using iVR videos in their teaching.

Price Value: the future teachers' perceptions of the cost-effectiveness and value proposition of using 360-degree videos in their teaching practice.

Habit: the degree to which pre-service teachers' use of 360-degree videos becomes habitual and automatic over time, based on their prior experiences and reinforcement.

Behavioural Intention: the individuals' intentions and willingness to incorporate 360-degree videos into their future teaching practices.

Figure 1 presents the UTAUT2 model, providing a visual guide to the eight constructs under investigation.

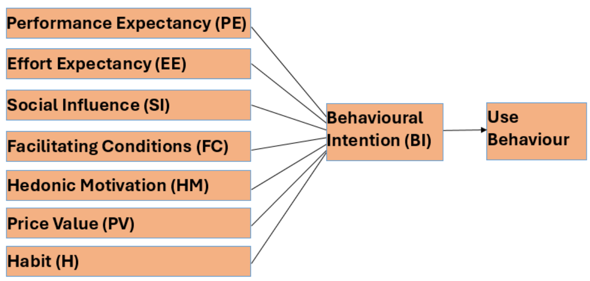

Figure 1 - UTAUT2 model (based on Venkatesh et al., 2012).

The object of study in this research is to quantitatively measure pre-service teachers' perceptions of iVR videos in each dimension of the UTAUT2 model. Specifically, the study explored the following research questions:

RQ1. What factors influence e-learning pre-service teachers in adopting immersive virtual reality in their future teaching practice?

RQ2. To what extent are e-learning pre-service teachers inclined to use immersive virtual reality in their future teaching practice?

The subsequent sections delve into the methodology, results, and discussion, offering a comprehensive analysis of the factors influencing pre-service teachers' perceptions of immersive virtual reality use in education.

2. Methods

2.1 Participants

The research encompassed a total of 198 (N=198) undergraduate pre-service teachers enrolled in the bachelor's degree program in Primary Education, which was delivered in an e-learning format at the University of Las Palmas de Gran Canaria. Table 1 summarizes information about participant profiles.

Table 1 - Demographic overview of participants.

Variable	Value	n	%
Gender	Male Female	43 155	22.0 78.0
Age	18-24 25-34 Over 35	90 77 31	45.5 38.9 15.7
Experience with iVR	No experience Very little experience Some experience A lot of experience Extensive experience	52 69 54 20 3	26.3 24.8 27.3 10.1 1.5

2.2. Measure and procedure

As part of the e-learning course, students engaged in a competency-based activity, viewing a 6:21-minute recording of a 4th-grade English class in Primary Education captured using a 360-degree camera (Insta360 ONE X2), recorded by the researcher. They analyzed the video based on dimensions aligned with the course content (teaching aims, teaching steps, grouping, classroom management). Afterward, students completed an online questionnaire via Google Forms, expressing their intentions regarding future iVR use in teaching.

The survey, based on the UTAUT2 instrument (Venkatesh et al., 2012), adapted for iVR by Bower et al. (2020), consisted of 28 items on a 7-point Likert scale (1=strongly disagree to 7=strongly agree), measuring eight UTAUT2 dimensions: Performance Expectancy (PE, 4 items), Effort Expectancy (EE, 4 items), Social Influence (SI, 3 items), Facilitating Conditions (FC, 4 items), Hedonic Motivation (HM, 3 items), Price Value (PV, 3 items), Habit (H, 4 items), and Behavioural Intention (BI, 3 items).

2.3. Data analysis

Statistical analysis was conducted using IBM SPSS (Statistical Package for the Social Sciences) version 25.0. The analysis focused on examining participants' Likert scale ratings based on the UTAUT2 factors to assess the factors influencing the acceptance and intention to use iVR in the context of teacher training. Descriptive analysis was performed to explore the distribution of participant responses across different UTAUT2 constructs, thereby providing insights into the perceptions of iVR use in education. Additionally, correlation analysis investigated the relationships among key UTAUT2 constructs. Linear regression analysis was utilized to assess the predictive capability of the UTAUT2 model for pre-service teachers' perceptions of iVR use in education.

3. Results

3.1 Model Fit, reliability, and descriptive analysis

The examination of participants' Likert scale ratings based on UTAUT2 factors revealed an adequate model fit: χ^2=495.320, df=271, χ^2/df=1.83, p<0.0001. The Tucker-Lewis Index (TLI) and Comparative Fit Index (CFI) surpassed the threshold of 0.9, with values of 0.928 and 0.940, respectively (Hair et al., 2014). Consistent with assessment criteria (Hair et al., 2014), the standardised root mean square residual (SRMR) and root mean square error of approximation (RMSEA) fell within acceptable ranges at 0.07 and in the 90% confidence interval of 0.06 to 0.07. Standardised estimates for all items exceeded 0.50, ranging from 0.6 to 0.9, affirming the structural equation model's alignment with observed data.

Reliability assessment using Cronbach's Alpha (Table 2) revealed values exceeding 0.80 in seven constructs and 0.732 in one, indicating good internal consistency. This attests to the high reliability of the measurement instrument (Taber, 2017). The results of the Confirmatory Factor Analysis (CFA) confirmed the UTAUT2 model's suitability in explaining participant perceptions of iVR use in education.

Table 2 displays a detailed breakdown of the descriptive statistics for participant responses to Likert scale questions across different constructs within the UTAUT2 model. Mean scores, ranging from 1.69 to 5.45 indicate diverse ratings, reflect a spectrum of perceptions across UTAUT2 dimensions. Hedonic Motivation emerges with the highest mean score of 5.36, indicating a strong inclination towards intrinsic enjoyment and satisfaction derived from using iVR. Following closely are Performance Expectancy and Effort Expectancy, with mean scores of 4.99 and 4.81 respectively. This suggests a significant belief in the technology's capability to enhance performance and ease of use. Conversely, Habit exhibits the lowest mean score of 2.77, underscoring a relatively weaker habitual tendency towards iVR adoption. Price Value and Social Influence also demonstrate lower mean scores of 3.19 and 3.92 respectively, which showing less emphasis on the perceived affordability and external influence in shaping participants' intentions towards iVR use.

The standard deviations, ranging from 0.23 to 0.93, highlight the variability in participant responses across various constructs. Habit shows a remarkably low standard deviation ranging from 0.23 to 0.70, which points to a more consistent and less varied response pattern among participants regarding the habitual nature of using iVR. In contrast, Social Influence stands out with a higher standard deviation, ranging from 0.80 to 0.93. This indicates a greater diversity of opinions among participants regarding the influence of important individuals on their decision to use iVR. Overall, the variability in participant responses captures nuanced attitudes towards the adoption of iVR in education.

3.2 Statistical analysis: Correlation and Regression

Table 3 illustrates the Pearson correlation coefficients, revealing significant relationships among key constructs within the UTAUT2 model with Behavioural Intention. A notably strong positive correlation ($r=0.737$, $p<0.001$) is observed between Habit and Behavioural Intention, indicating the substantial impact of habitual use on the intention to use iVR among pre-service teachers. Additionally, Hedonic Motivation exhibits a robust positive correlation with Behavioural Intention ($r=0.565$, $p<0.001$), which emphasizes the influence of enjoyment and pleasure associated with iVR on the intention to use it. Similarly, Performance Expectancy and Social Influence demonstrate a moderately strong positive correlation with Behavioural Intention ($r=0.545$, $p<0.001$; $r=0.518$, $p<0.001$, respectively), highlighting the importance of perceived performance benefits and the impact of peer and social factors in shaping the intention to use iVR. In contrast, Facilitating Conditions, Price Value, and Effort Expectancy exhibit comparatively lower correlations with Behavioural Intention, with coefficients of $r=0.376$ ($p<0.001$), $r=0.342$ ($p<0.001$), and $r=0.337$ ($p<0.001$) respectively. This implies a weaker influence on participants' intention to use iVR compared to other UTAUT2 constructs.

In Table 4, the linear regression analysis offers insights into the UTAUT2 model's predictive capability for preservice teachers' perceptions of immersive virtual reality use in education. With a significant correlation coefficient ($R=0.828$), the model accounts for approximately 66.7% (adjusted $R^2=0.667$) of the variance in preservice teachers' intention to use virtual reality. The standard error of the estimate (0.719) indicates precise estimation.

Statistical change metrics reveal the model's impact, with a change in R squared of 0.686, denoting improved predictive accuracy, supported by a change in F statistic (36.897, df1=11, df2=186, $p<0.000$). The Durbin-Watson statistic (2.214) suggests no significant autocorrelation in residuals, affirming the model's reliability. Expanding on these findings, multiple regression analysis offers further insights into the predictive factors. Among the scrutinized predictors, Habit emerges as the most influential (Sig.=.000; $t=9.142$), followed by Hedonic Motivation (Sig.=.000; $t=5.313$), and Age (Sig.=.003; $t=2.961$), albeit with a somewhat lesser influence. Additionally, two other variables, Social Influence (Sig.=.049; $t=1.981$) and Performance Expectancy (Sig.=.023; $t=2.299$), also surface as significant moderators of Behavioural Intention regarding the use of iVR.

4. Discussion and Conclusions

This study delves into the behavioral intentions of e-learning pre-service Primary Education teachers in Spain concerning the adoption and use of iVR technology in online learning, employing the UTAUT2 model. This represents a novel exploration within the Spanish context and contributes to the broader international discourse on the integration of immersive technologies in education. Understanding the behavioral intentions of future teachers towards incorporation of such innovative technologies hinges on the acceptance and intention of users (Bower et al., 2020). The findings gleaned from this investigation offer valuable insights for educators, researchers, and policymakers involved in shaping the landscape of technology-enhanced education. Furthermore, the outcomes of this study serve as a benchmark for future research endeavors using the UTAUT2 model in the domain of iVR in education.

From a methodological standpoint, this study underlines the effectiveness of the UTAUT2 model in delineating the factors that influence the behavioral intentions of e-learning trainee teachers in Spain towards the adoption of iVR. The Confirmatory Factor Analysis (CFA) indicates favorable model fit indices, affirming the applicability of the UTAUT2 model in the unique context of iVR integration in education.

This validation aligns with previous research that has successfully employed the UTAUT2 model in diverse educational technology contexts (e.g., Chávez Herting et al., 2020; Jakkaew & Hemrungrote, 2017; Nikolopoulou et al., 2020).

Table 2 - Descriptive statistics for each item of the UTAUT2 model.

Constructs	*Means*	*Standard deviation*	*Cronbach's alpha*
Performance Expectancy (PE)	**4.99**	**0.78**	0.825
I think Virtual Reality is useful for teaching in schools. (PE1)	5.20	0.86	
Using Virtual Reality increases my chances of achieving my teaching goals. (PE2)	4.88	0.79	
Using Virtual Reality is helpful for accomplishing things more quickly in teaching. (PE3)	5.01	0.80	
Using Virtual Reality helps increase my teaching productivity. (PE4)	4.88	0.74	
Effort Expectancy (EE)	**4.81**	**0.77**	0.861
Learning how to use Virtual Reality is easy for me. (EE1)	4.82	0.76	
My interaction with Virtual Reality technology is clear and understandable. (EE2)	4.66	0.73	
I find Virtual Reality easy to use. (EE3)	4.73	0.75	
It is easy for me to become skillful at using Virtual Reality. (EE4)	5.01	0.85	
Social Influence (SI)	**3.92**	**0.88**	**0.**945
People who are important to me think that I should use Virtual Reality. (SI1)	3.90	0.93	
People who influence my behavior think that I should use Virtual Reality. (SI2)	3.84	0.91	
People whose opinions that I value suggest that I use Virtual Reality. (SI3)	4.01	0.80	
Facilitating Conditions (FC)	**4.45**	**0.55**	0.732
I have the resources necessary to use Virtual Reality. (FC1)	4.09	0.43	
I have the knowledge necessary to use Virtual Reality. (FC2)	4.07	0.43	
Virtual Reality is compatible with other technologies I use. (FC3)	5.02	0.78	
I can get help from others when I have difficulties using Virtual Reality. (FC4)	4.62	0.61	
Hedonic Motivation (HM)	**5.36**	**0.77**	0.950
Using Virtual Reality is fun. (HM1)	5.37	0.77	
Using Virtual Reality is enjoyable. (HM2)	5.25	0.75	
Using Virtual Reality is very entertaining. (HM3)	5.45	0.81	
Price Value (PV)	**3.19**	**0.52**	0.925
Virtual Reality is reasonably priced. (PV1)	3.01	0.48	
Virtual Reality is a good value for the money. (PV2)	3.27	0.50	
At the current price, Virtual Reality provides good value. (PV3)	3.29	0.58	
Habit (H)	**2.77**	**0.27**	0.812
The use of Virtual Reality has become a habit for me (H1)	2.57	0.27	
I am addicted to using Virtual Reality. (H2)	1.69	0.23	
I must use Virtual Reality. (H3)	4.20	0.70	
Using Virtual Reality has become natural to me. (H4)	2.62	0.24	
Behavioural Intention (BI)	**4.15**	**0.65**	0.863
I intend to continue using Virtual Reality in the future. (BI1)	4.14	0.67	
I will always try to use Virtual Reality in my teaching. (BI2)	4.30	0.66	
I plan to continue to use Virtual Reality frequently. (BI3)	4.02	0.68	

Table 3 - Pearson Correlation coefficients among UTAUT2 constructs.

		Performance Expectancy (PE)	**Effort Expectancy (EE)**	**Social Influence (SI)**	**Facilitating Conditions (FC)**	**Hedonic Motivation (HM)**	**Price Value (PV)**	**Habit (H)**
Performance Expectancy (PE)	Pearson correlation							
	Sig. (bilateral)							
Effort Expectancy (EE)	Pearson correlation	0,306**						
	Sig. (bilateral)	<0,001						
Social Influence (SI)	Pearson correlation	0,393**	0,181*					
	Sig. (bilateral)	<0,001	0,011					
Facilitating Conditions (FC)	Pearson correlation	0,309**	0,531**	0,370**				
	Sig. (bilateral)	<0,001	<0,001	<0,001				
Hedonic Motivation (HM)	Pearson correlation	0,489**	0,446**	0,303**	0,241**			
	Sig. (bilateral)	<0,001	<0,001	<0,001	<0,001			
Price Value (PV)	Pearson correlation	0,279**	0,193**	0,296**	0,252**	0,322**		
	Sig. (bilateral)	<0,001	0,006	<0,001	<0,001	<0,001		
Habit (H)	Pearson correlation	0,459**	0,387**	0,541**	0,504**	0,391**	0,376**	
	Sig. (bilateral)	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	
Behavioural Intention (BI)	Pearson correlation	0,545**	0,337**	0,518**	0,376**	0,565**	0,342**	0,737**
	Sig. (bilateral)	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001

* Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Table 4 - Linear Regression model[b] summary of preservice teachers' perceptions of iVR use in education.

Model	**R**	**R squared**	**Adjusted R squared**	**Standard error of the estimate**	**Change Statistics**					**Durbin-Watson**
					R square changed	F Change	df1	df2	Sig. Change in F	
1	0.828[a]	0.686	0.667	0.719	0.686	36.897	11	186	< 0.0000	2.214

a Predictors: (Constant), Gender, Age, Experience with iVR, Hedonic Motivation, Price Value, Social Influence, Effort Expectancy, Performance Expectancy, Facilitating Conditions, Habit

b Dependent Variable: Behavioral Intention

RQ1. What factors influence e-learning pre-service teachers in adopting immersive virtual reality in their future teaching practice?

The analysis of descriptive statistics reveals that participants prioritize, in this order, Hedonic Motivation, Performance Expectancy and Effort Expectancy as the most influential factors shaping their willingness to accept iVR use. This pattern is consistent with similar findings from previous UTAUT2 studies on iVR acceptance for prospective educators (Boel et al., 2023; Bower et al., 2020; Li et al., 2022), though in the latter study, Performance Expectancy is ranked fifth, which might be attributed to the focus on both teachers and students as designers of iVR. However, it diverges from studies on the acceptance of different educational technologies. For instance, in studies related to Google Classrooms (Jakkaew & Hemrungrote, 2017), PowerPoint (Chávez Herting et al., 2020), mobile phones (Nikolopoulou et al., 2020), the metaverse (Yang et al., 2022), and e-learning systems (El-Masri & Tarhini, 2017). Hedonic Motivation and Performance Expectancy complement each other. Whereas the former is closely linked to intrinsic motivation, reflecting users' internal drive and perceptions of enjoyment and pleasure associated with a specific technology, the latter relates to extrinsic motivation, instilling a sense of purpose as users believe that a technology can enhance their task performance or productivity (Venkatesh et al., 2012). As for Effort Expectancy, participating prospective teachers seem to have generally found learning to use iVR technology straightforward and comprehensible, indicating a favorable view of its usability and accessibility. This implies that participants likely perceive iVR technology as user-friendly, potentially enhancing their willingness to adopt it in educational settings. Thus, the findings results of this study highlight the significance of harnessing both the enjoyment derived from iVR use in educational settings and its perceived utility. By emphasizing the intrinsic enjoyment and practical benefits of iVR technology, teacher education programs and educational systems can effectively maximize its potential benefits in schools. Effort Expectancy complements these factors by emphasizing the practical aspect of technology adoption, highlighting the ease and convenience of integrating iVR into teaching practices.

The dimensions that moderately influence the prediction of participants' adherence to iVR in this study are Facilitating Conditions and Social Influence. In similar studies, the ranking fluctuates between 4 to 6 positions for these factors (Boel et al., 2023; Li et al., 2022), but is not the case with Bower et al. (2020), where Social Influence was rated seventh, possibly due to aspects related to context. While participants showed moderate agreement with statements related to Social Influence, the mean scores suggest that the influence of important individuals and opinions on iVR adoption may vary among participants. This highlights the importance of considering individual differences in social influence when promoting iVR use in education. Participants reported favorable perceptions regarding the availability of resources and knowledge necessary for using iVR, as well as the compatibility of iVR with other technologies. However, the mean score for the item related to seeking help from others indicates a slightly lower perception of support available when encountering difficulties with iVR. One implication of these moderate influencing factors is the need for targeted interventions to address perceived barriers and enhance supportive conditions for iVR adoption in educational settings. Educators and policymakers could focus on providing comprehensive training and resources to support teachers in effectively integrating iVR into their teaching practices. Additionally, efforts to cultivate a supportive social environment, where colleagues and administrators encourage and assist each other in using iVR, can bolster its acceptance and use. Moreover, initiatives aimed at improving the compatibility of iVR with existing educational technologies can further facilitate its seamless integration into teaching and learning activities.

In our study, participants consistently rated Habit as the least important factor influencing their willingness to accept iVR use, in consonance with the outcomes of prior research conducted on the use of iVR by Bower et al. (2020) and Li et al. (2022), as well as with results from studies on the acceptance of the use of other technologies such as Google Classroom (Jakkaew & Hemrungrote, 2017) and PowerPoint (Chávez Herting et al., 2020). Yet, it deviates from findings in studies on mobile phone usage (Nikolopoulou et al., 2020), the metaverse (Yang et al., 2022), and e-learning systems (El-Masri & Tarhini, 2017). Our study also found that the second factor with less weight is Price Value, contrasting with previous findings results (Bower et al., 2020; Li et al., 2022). This discrepancy may arise from previous studies often using mounted-head or similar devices for iVR, incurring additional expenses if implemented in a classroom setting, whereas our study allowed students to engage with iVR content using their own devices (PC, laptop, mobile, tablet), eliminating any perceived extra cost. Notably, similar results were found in studies on e-learning systems and mobile phone usage (El-Masri & Tarhini, 2017; Nikolopoulou et al., 2020), and in research on the metaverse (Yang et al., 2022), which even discarded Price Value as one of the influencing factors for its use. In the context of this study, the findings suggest that leveraging readily available devices could be pivotal for the scalability of iVR adoption in educational settings.

According to the multiple regression analysis, Habit, Hedonic Motivation, Age, Social Influence, and

Performance Expectancy have significant positive effects on pre-service teachers' Behavioral Intention. However, our results diverge from those of Boel et al. (2023), whose analysis found that the interaction effects of gender, age, and experience with iVR were not significant predictors, and Li et al. (2022), who observed that while age initially had a significant positive effect on behavioral intention towards iVR use, this effect disappeared when additional factors were included in the regression model. Similarly, gender, year of study, and previous experience with iVR did not significantly influence behavioral intention in their study. These discrepancies highlight the variability in findings across studies in the field of technology adoption and education and underscore the importance of considering contextual factors and methodological differences when interpreting results in the field of technology adoption and education. All in all, by fostering a conducive environment for the effective integration of iVR technology into teaching practices, educational institutions can promote the widespread acceptance and usage of iVR in educational contexts.

RQ2. To what extent are e-learning pre-service teachers inclined to use immersive virtual reality in their future teaching practice?

In line with UTAUT2's propositions, the results point out that all seven dependent variables significantly influence students' intention to use iVR in their future teaching practice, exhibiting a robust positive correlation among them. Hence, the UTAUT2 model proves to be effective in elucidating the factors shaping the acceptance of iVR by future teachers, aligning with previous studies on iVR by Bower et al. (2020) and Li et al. (2022). This study, distinct from the aforementioned articles, tests the applicability of UTAUT2 in a new context (e-learning) and a different cultural environment (Spain), representing a valuable step in theory advancement as advocated by Alvesson and Kärreman (2007, in El-Masri and Tarhini, 2017).

Regarding methodological implications, two crucial points emerge. Firstly, the substantial correlation between Habit and Behavioural Intention holds significant implications for teaching and learning. Given that participants in this study are prospective teachers, an increase in the use and training on iVR during their university studies could heighten the likelihood of their intention to persistently use it in their future classroom practices, benefiting their potential students. Additionally, among all factors, the variables of Hedonic Motivation and Performance Expectancy secured the second and third highest ratings, respectively. This suggests that trainee teachers are cognizant of the utility of virtual reality as an educational tool and recognize its potential as a source of motivation.

In light of these findings, the beliefs and intentions of pre-service teachers regarding emerging technologies, such as iVR, seem to wield a substantial influence on the adoption and effective use of these tools within educational settings. Therefore, a profound understanding of the factors shaping their behavioral intentions becomes imperative. This study employed the UTAUT2 model to scrutinize the factors influencing the behavioral intention of undergraduate students pursuing a bachelor's degree in Primary Education at ULPGC, specifically in the context of e-learning.

The obtained results highlight the significance of the correlations between dependent variables, all of which are not only significant but also positive. This implies that, to enhance individuals' behavioral intention, a strategic focus on improving these variables is crucial. Such a conclusion underlines the crucial need for targeted interventions aimed at cultivating positive attitudes toward iVR technology among pre-service teachers, thereby paving the way for its extensive adoption and integration in educational contexts.

Overall, The UTAUT2 model was chosen for this study with the aim of investigating the variables that affect the acceptance of iVR among pre-service teachers pursuing a bachelor's degree in Primary Education in the online modality. Binomial correlation reveals that factors such as Hedonic Motivation and Performance Expectancy emerge as pivotal considerations in the acceptance of educational technologies like iVR, whereas Habit and Price Value do not seem to have a great impact on their adherence to iVR in their future teaching practice in the context of this research. Furthermore, the data yielded from the multiple regression analysis underscore the importance of factors such as Age and Social Influence in shaping preservice teachers' attitudes and intentions towards the integration of iVR technology. These results highlight the multifaceted nature of the variables influencing acceptance and usage of iVR technology among preservice teachers, bearing significant implications for the development of effective training programs in higher education and strategies in online education.

While this study provides valuable insights, it is not without limitations. Constraints related to time and scope necessitate further research encompassing diverse cohorts and employing longitudinal approaches. Qualitative interviews offer a promising avenue for deeper exploration of participants' motivations, offering richer insights into their perspectives. These collective efforts will undoubtedly contribute to a more comprehensive understanding of the intricate interplay between emerging technologies and education, facilitating the development of informed strategies for their effective integration.

In conclusion, this study emphasizes the pivotal role of Hedonic Motivation in shaping the acceptance of iVR among e-learning pre-service teachers. The robust positive correlations observed between Habit and Behavioural Intention underline the importance of habitual tendencies in predicting the intention to use iVR, despite its lower mean score compared to other constructs. These findings emphasize the complex nature of iVR adoption and the need to consider various factors, including both intrinsic motivations and habitual behaviors, when planning the integration of iVR in educational settings.

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Experiences in higher education in times of pandemic: a systematic review of the literature

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Abstract

This paper aims to review the literature related to the experience of students and teachers in Higher Education in times of the COVID-19 pandemic. A Systematic Literature Review was conducted using the scientific databases Scopus and Web of Science, following the Preferred Reporting Items for Systematic Reviews and Meta Analyses (PRISMA) guidelines, structured in three stages of the experience: Pre-Core, Core and Post-Core. The results provided by the 105 studies selected for the review are heterogeneous and diverse in terms of the positive and negative factors and elements of the Higher Education Experience in the global health crisis. The method with the highest presence in the selected studies was quantitative with 51.4% and its main instrument was the questionnaire. Likewise, social interaction in the context of Higher Education is one of the most negatively impacted dimensions of the transition to distance education, with important implications for the mental health of students and teachers.

KEYWORDS: Experience, Higher Education, Pandemic, Review.

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1. Introduction

According to Langegård et al. (2021), after the COVID-19 pandemic, the use of Distance Education through digital tools supported on the Internet in different universities and higher education institutions has expanded exponentially. An exceptional situation unprecedented in the history of humanity, in educational systems and in teaching and learning activities around the world following the outbreak and the obligation to close university campuses (Ali, 2020; Alsoud & Harasis, 2021).

Educational institutions implemented learning technology platforms and tools with different capabilities, approaches, and strategies to address pedagogical processes (Carter et al., 2020, Silva García & Rodríguez Pérez, 2023). In this sense, the moderating effect of the expansive outbreak implies the acceleration of digitalization in higher education, significant experiential changes in academic communities and their ways of interacting, within an emerging transformation of society.

For Durmaz et al. (2012), Distance Education is defined as the use of technology to deliver, support and develop learning and teaching through digital tools, and involves communication and interaction between students and teachers using online content and tools. For students at the higher education level, the new landscape required adapting to the demands and learning needs in the midst of the health emergency and entering online study environments supported by dynamic, open and pragmatic learning (Marinoni et al., 2020; Rodríguez, 2023). Consequently, the emerging forms implemented in crisis require a reflection on the very experience of the architects involved in the educational processes and their iterations, complex phenomena that map and exchange relationships based on a changing reality, thus Distance Education renews

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non-shelf learning is not free of problems due to its nature and its technological base added to a state of global isolation. In this order of ideas, technology as an essential factor in this context transforms and conditions social relations from the environment in which they are executed.

In the context of higher education, institutions applied different means in the search for solutions to cope with the impacts of the pandemic and enable students to achieve real learning outcomes (Petchamé et al., 2021; Guerra et al., 2023). In response to the crisis, universities have been challenged at all levels, and teachers faced the need to apply technological tools to provide distance learning (Zapata-Garibay et al., 2021). For Laher et al. (2021), the transition to emergency distance learning impacted students' mental health, in addition to the anxiety and fear ascribed to the crisis; the pandemic has added a new dimension to students' experiences and mental health.

To stop the pandemic, the measures adopted began to generate negative and harmful effects on the health of students in terms of anxiety, decreased physical activity, depression, interpersonal interactions, proliferation of sedentary behaviors, and stress (Petchamé et al., 2021; Montoya-Restrepo et al., 2022). These restrictions have affected students' learning and the way they relate to their professors and peers; consequently, there has been a notable decrease in the social aspects of university life (Laher, et al, 2021).

Widespread digitization establishes the need for new approaches to higher education in the context of continuous scientific and technological development: reconfiguring educational processes, redesigning the role of the teacher and transforming the management approaches of educational organizations (Kobysheva et al., 2021).

The disruptions of the health crisis were not limited to the functioning of the educational system, they also directly impacted the learning experience of students in the access to elements and materials necessary for training and research, in addition to presenting disadvantages related to greater possibilities of distraction, technological limitations and absence of social interaction with professors and the university community in general (Alsoud & Harasis, 2021). Additionally, according to Hebebci et al. (2020), students in the middle of distance learning presented difficulties in conducting group projects and activities because of the lack of socialization and interaction on campus.

On the other hand, according to Sadeghi (2019) the advantages of distance learning lie in studying from anywhere at any time, saving a significant amount of money by avoiding commuting, flexibility in selecting courses, and overall time savings. Consequently, the impacts on higher education since the crisis have configured alternative scenarios of interaction in the development of training programs based on disruptive experiential transformations around the changes implied by the transition to distance learning. On the other hand, for Robayo-Pinzon et al. (2023) although the transformative capacity of artificial intelligence (AI) in different sectors is advancing rapidly, one of the sectors in which there has been an increase in these developments is the educational sector; the role of students as possible co-creators of these developments has not yet been considered.

In this sense, the objective of this article was to carry out a Systematic Literature Review of the publications that explore, describe, and analyze the experiences and factors that affect the teaching processes in Higher Education in times of pandemic.

1.1 The experience and the consumption process

In educational environments, the focus of the processes is centered on the student, on his or her development and on the generation of skills and competencies that will enable future opportunities, either to continue studying or to find a job market that will enable him or her to satisfy his or her economic and personal development needs. In this context, the student can be seen as the main consumer of education and the one who is directly affected by all the actions determined in this field (Grinard, 2023).

In this scenario, the relationship with students and their families is understood through the understanding of a wide range of stimuli that influence the multiple experiential responses they experience in relation to the needs that motivate them to carry out the selection process of the program they wish to study (Becker & Jaakkola, 2020; Lemon & Verhoef, 2016; Sabogal Russi & Rojas-Berrio, 2019; Schmitt, 1999; Verhoef et al., 2009). The above implies the involvement of rational and emotional judgment within the consumption situation, which is an outcome of a value co-creation process from encounters with it (Lusch & Vargo, 2006; Pang, 2013; Sabogal Russi & Rojas-Berrio, 2019; Vargo & Lusch, 2008).

Thus, higher education can be analysed from the perspective of service marketing, since service is understood as: "the application of specialized competences (knowledge and skills) through acts, processes and actions for the benefit of another entity or of the entity itself" (Lusch & Vargo, 2006, p. 2); in this case, of the population that benefits from training in this type of knowledge; it focuses on the exchange of intangible goods seen as specialized knowledge that is delivered to the consumer. However, this raises the need to understand the interaction between the customer and the organization, so that the consumer lives a consumption process (before, during and after) around the experience itself (Lusch & Vargo, 2006).

From this perspective, the student-customer is conceived as a co-creator of value, since his experience starts from the pre-consumption (Pre-Core) moment in which he establishes a series of encounters prior to the provision and effective enjoyment of the service, experiences the consumption process (Core) of the intangible associated with the training in knowledge and skills provided by higher education, and ends continuously in the post-consumption (Post-Core) situations (Becker & Jaakkola, 2020; Lusch & Vargo, 2006).

In this sense, non-deliberate and spontaneous responses and reactions to certain stimuli correspond to the definition of Customer Experience, starting from the ordinary to the extraordinary in accordance with the customer's responses to them, which are contextualized in three consumption processes, Pre-Core, Core and Post-Core (Becker & Jaakkola, 2020; Jain et al., 2017; Vasconcelos et al., 2015). Daily experiences that will be evaluated by each actor involved in the service logic and will allow the metaphorical construction of the journey map, describing that consumption process (Pre-Core, Core and Post-Core), anticipating unsatisfactory encounters, and improving the experience from the organization's initiative and value offer (De Keyser et al., 2020; Edelman & Singer, 2015; Hamilton and Price, 2019; Lemon & Verhoef, 2016).

Encounters that, from the physical realm, Bitner et al. (1990), are going to describe as satisfactory or unsatisfactory in the face of possible service failures and dissatisfaction of needs, which within the logic of experience marketing. Verhoef et al. (2009), Lemon and Verhoef (2016), Becker and Jaakkola (2020), De Keyser et al. (2020), and Rincon-Novoa et al. (2021), will raise under the concept of touch points, to subsequently integrate them into the experience journey map, in order to be able to describe the interconnection of these encounters through a sequential map that will allow to see in aggregate form the achievement of the Pre-Core, Core and Post-Core process in the provision of the service.

2. Materials and Methods

To carry out the research objective, a pragmatic (Dewey, 1927; 1948) and abductive (Saunders et al., 2007) exercise was contemplated with a documentary analysis strategy from a Systematic Literature Review with the methods suggested by the literature for the field of Administration (Chicaiza-Becerra et al., 2017; Kitchenham et al., 2010; Paul and Criado 2020; Pérez Rave et al., 2012), whose purpose was to explore the experience of students and teachers in higher education in times of pandemic, and was conducted using the scientific databases: Scopus and Web of Science (WoS), following the checklist of the Reporting Items for Systematic Reviews and Meta Analysis (PRISMA) guidelines.

The pandemic experience was structured in a three-moment process: Pre-Core, Core and Post-Core, in relation to each moment of the experience: pre-pandemic, pandemic and post-pandemic, to apply to the educational context a perspective from a consumer point of view.

2.1 Search strategy

Table 1 below presents the search strings applied at each moment of the pandemic experience. Information analysis window from August 2019 to August 2022, based on the publication dates of the articles. The search strategy was developed using the Patient, Intervention, Comparison, Outcome (PICO) methodology. The population was limited to students and professors in higher education in the context of the pandemic generated by COVID-19. Based on keywords selected and validated as descriptors, a combination of terms was structured to construct the search string.

Table 1 - Search strings applied in pre-pandemia Pre-Core (Pre-pandemic), Core (Pandemic) and Post-Core (Post-pandemic).

Experience moment	String	Time window of observation	Quantity in WoS	Quantity in Scopus
Pre-Core Pre-pandemic	Higher Education OR Research OR Third Mission AND Educational Experience OR Student Experience OR Learning Experience OR User experience OR Customer Experience	2018-2019	32	91
Core Pandemic	Higher Education OR Research OR Third Mission AND Educational Experience OR Student Experience OR Learning Experience OR User experience OR Customer Experience AND Pandemic OR Coronavirus OR SARS-CoV-2 OR COVID-19	2020-2021	35	85
Post-Core Post-pandemic		2022	369	272

2.2 Selection criteria

Studies eligible for review met the following selection criteria:

1. Contains information regarding the higher education-only experience of students and faculty in the context of the pandemic.
2. Contains information related to the teaching, research, and outreach domains of higher education in the context of the pandemic.
3. It is empirical research.
4. It is an investigation limited to one of the following modalities of higher education: face-to-face, virtual, or mixed.

Figure 1 presents the flow chart of the literature review studies through four stages: identification, selection, eligibility, and inclusion.

3. Results

A total of 884 records were obtained from the search of scientific databases. After elimination of duplicate records, the titles and abstracts of the articles were examined according to the inclusion and exclusion criteria. Next, 130 articles were selected for full reading and 25 were excluded for lack of empirical evidence. Finally, 105 relevant studies were selected for the final analysis.

The predominant method in the selected studies was quantitative with 51.4%, these investigations constitute non-experimental research, and are located within the survey research strategy. Their main instrument was the questionnaire.

On the other hand, the qualitative method represents the second position (35.2%); these investigations are based on different research strategies: phenomenological (59.1%); case study (27.3%), action research (9.1%) and grounded theory (4.5%). For the qualitative method: interviews (58.3%), questionnaire (33.3%), focus group (4.2%) and life histories (4.2%), were the main instruments. Finally, in the case of mixed methods with 11.4%, the research strategies used were: concurrent (66.7%), sequential exploratory (22.2%) and sequential explanatory (11.1%). The main instruments in the mixed methods were questionnaire (61.5%), interviews (23.1%) and focus group (14.4%). The overview of the methods and their strategies is presented in Figure 2. In this sense, the search for understanding the phenomenon of experience involves multiple strategies adapted to each study in the midst of changes in higher education, a scenario in which institutions were not prepared for an emergency and has represented a challenge at the methodological level in research where it is required to make use of technologies supported mainly on the Internet.

The main dimensions for which findings were found were Student Support, Learning Experience, Flexibility, FE-HE (further education-higher education) Transition, Technology in Education, Mental Health and Motivation, Communication, Change Management and Digital Inequality, which are described sections: Pre-Core, A pre-pandemic approach to experience; Core, Application of online learning and experience in higher education; and Post-Core, More recent approaches to experience, indicating at what point in the experience they are most involved.

3.1. Pre-Core: A pre-pandemic approach to experience

For Oktavia et al. (2018), social networks allow students to interact more intensively through a range of tools, including in support of their learning process, connect within a dynamic and rich social environment, rather than learning individually.

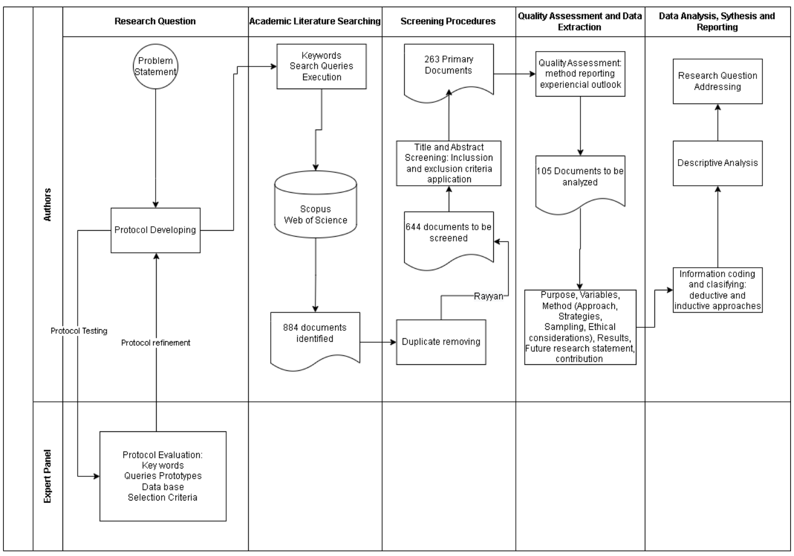

Figure 1 - PRISMA flow chart of study selection.

Moreover, according to Baik (2018), educational institutions should seek to balance their efforts and actions from developing strategies to attract international students to finding ways to address shared challenges and improve the quality of the international student experience internally and externally to universities.

According to Power and Handley (2019), a best practice model for seeking to integrate interdisciplinarity into the higher education Student Experience involves six enablers of interdisciplinarity from a synthesis of literature and data from an expert panel they developed: positioning, personas, environment, reward, behavioral factors, and communication.

For Bunn et al. (2019), temporal fragmentation and accelerating spatiotemporal individualization, including in terms of online communication, learning, and disposition, are described as generating new forms of inequality for students; spatiotemporal equity in higher education must recognize the complex histories and difficulties faced by students from less favorable backgrounds in accessing higher education.

Additionally, according to Young et al. (2020), students who identify as generally anxious and those who do not identify as generally anxious experience negative emotions at some points, within the first semester; therefore, to support toward a positive transition to higher education, universities require consideration of support toward students for the development of emotional intelligence skills and strategies that strengthen abilities to process and resolve negative experiences, develop resilience, and promote honesty about challenges, inconveniences, fears, and anxieties about the educational experience.

On the other hand, for Sandu and Gide (2019), the integration of AI-Chatbots in the education sector facilitates the achievement of student-centered learning; however, there are negative effects of using the technology, such as addiction; moreover, their introduction means that students will interact with Chatbots more frequently than with teachers.

According to Chiu and Lee (2019), to facilitate students' experiential learning, firstly, experiential learning should be transformed and empowered to be beneficial to all, and secondly, bridge the gap to extend experiential learning from inside to outside the classroom environment; in other words, transform experiential learning into a mutually beneficial nature by extending its boundaries beyond the personal level.

Additionally, according to Parusheva et al. (2018), the use of social networking tools in learning and education, should no longer be considered as innovation, it should be a daily practice for HEIs, which aims to improve the quality of the learning process and the interactive nature of learning, the great interest of students in the educational service.

3.2 Core: Application of online learning and experience in higher education

For Sailer et al. (2021), a fundamental factor affecting students' academic experiences and, consequently, the satisfaction of psychological needs within learning processes is the way in which teachers implement digitally mediated learning.

From the students' perspective, the type of online learning, the academic load, and the assignment of activities, acquire special relevance for them and the continuity of their training (Eberle & Hobrecht, 2021). Therefore, the implications in higher education from the application of distance learning have repercussions not only at the academic level, but also at the social level in relation to access to higher education and the continuity of training processes.

Amid the pandemic, Higher Education Institutions have been faced with various issues in relation to their readiness for teaching and learning with digital technology; teachers and students require an infrastructural, institutional, and organizational environment, conducive to online teaching and learning (Liu et al., 2020).

Live videoconferencing represents the most noted and valued online learning opportunity for university students according to Aristovnik et al. (2020). On the contrary, the majority of students consider the Asynchronous Online Learning facilities, supported by presentations, video recordings and written communication through forums and chats on different learning platforms, to be functional (Eberle & Hobrecht, 2021).

For Liu et al. (2020) adoption and implementation are a complex process in which learning technologies, academia, context and educational strategies influence and interact. Therefore, the application of online learning by teachers constitutes a significant element in the adaptation in the face of the crisis and the transformation of the experience in higher education from distance learning and the implications for students from the contextual emergence.

For Feldman (2020), implicit in understanding student experiences is always the question of what caring practices teachers should employ in the future to better support student learning; therefore, within an educational institution what has emerged in relation to an ethic of care is the need for connectivity and interaction that goes beyond the systemic organization of the institution.

On the other hand, according to Gaikwad and Kulkarni (2021), students find online learning more convenient than physical classrooms and allows regularity in class attendance with significant challenges and technical difficulties; students perceive that online learning generates physical stress, at the same time, learning is hindered by more distractions.

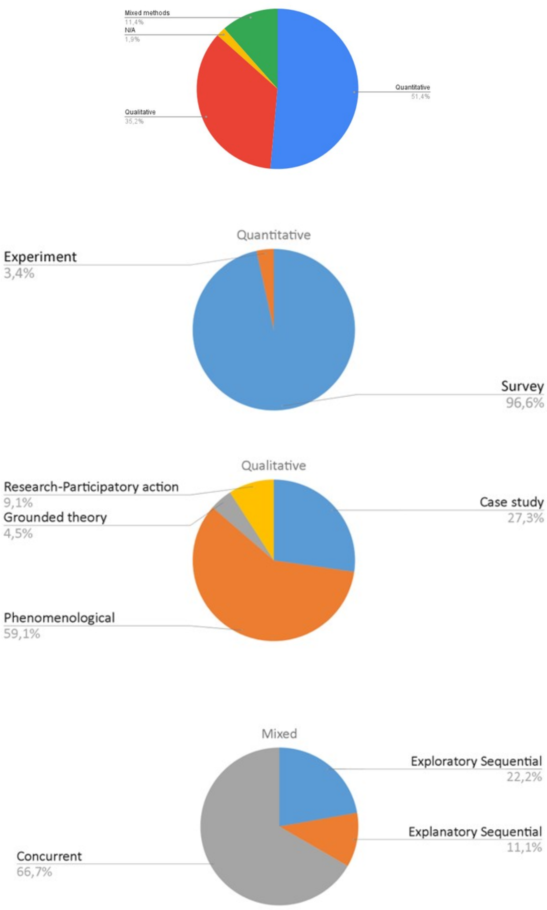

Figure 2 - Results of the methods and research strategies of the selected studies.

For Laher et al. (2021), strategies to manage COVID-19, including confinement, have caused disruption to students' learning and to the ways in which they interact with staff and peers; the situation involved sudden changes in daily life and limited opportunities for social interaction; responses to online learning were emotionally charged with the following words that reflect the difficulty experienced by students: stressful, tense, numbing, frustrating, heart-breaking, exhausting and so on.

In that vein, according to Maqableh and Alia (2021), there are large numbers of students dissatisfied with the online learning experience, learning materials, interactions with peers and professors, exams and quizzes; they recommend that each educational institution create an Academic Continuity Planning Committee (ACPC) to review and evaluate online learning, adopt new technologies, monitor the learning process, and adopt flexible and appropriate methodologies to facilitate learning.

According to Katz et al. (2021), the essential elements inscribed to student competence and aptitude in Distance Learning are (1) continuous high-speed Internet connectivity and devices to connect, and (2) the ability to relate and communicate with teachers and instructors; however, students' challenges with Internet connectivity and digital devices during remote learning were associated with lower remote learning proficiency.

3.3 Post-Core: More recent approaches to experience

For Banda (2022), by conceptualizing learning as a means of making use of retained and acquired knowledge, attitudes, and skills over time, COVID-19 became an obstacle to accessing such learning; the threat to students' basic needs, including safety and social needs, not only hindered their self-realization through the achievement of Higher Education, but also affected other psychological dimensions of their lives.

According to Kalmar et al. (2022), when changing from face-to-face education to online teaching, neither teachers nor students were prepared for the consequences of the changes; on the one hand, teachers suddenly had to become experts in recording videos, navigating digital tools they had not used before, redesigning some of their course content: learning objectives, materials and assessment methods, to be aligned with these new digital tools and students were affected, especially in courses where teamwork is essential.

Similarly, for Bartolic et al. (2022) students in more difficult study situations, with no space to study, high noise, and poorer health, reported greater disruption to their learning than their peers who lived in less difficult conditions; student learning was impaired in courses that moved to distance learning and student vulnerabilities may have been exacerbated by public health responses to Sars-CoV-2.

According to Nguyen et al. (2022), there is an interrelationship between university support, student experience, and university brand image; student experience is one of the factors that positively and significantly affect university brand image.

Finally, according to Smith et al. (2022), the exploration of self-identification in an academic role through the COVID-19 pandemic was organized into three broad themes: (1) a disturbed academic identity; (2) sense-making and resources for identity work; (3) nostalgia for what was lost; thus, the teaching team devoted additional time to online activity, to the detriment of personal time and the fulfillment of other expectations of assigned roles; In that sense, the COVID-19 pandemic has materialized the importance and the risk of not having talented academics motivated by research, science and the advancement of knowledge, who adapt their teaching to provide students with an excellent, quality education, regardless of the vicissitudes and challenges facing humanity.

4. Discussion and Conclusions

The analysis of the selected studies indicates that the impact of the COVID-19 pandemic on higher education experiences has profound implications on educational processes from change and adaptation to emergency distance learning with mixed results. The perception and satisfaction in relation to distance learning by students is heterogeneous in terms of positive and negative aspects. However, social interaction in a university context is one of the most affected and deteriorated dimensions from the transition to distance learning with implications on the mental health of students and teachers.

In addition, the research showed that the main approach to address experiences in higher education in times of pandemic is based on primary sources. The use of quantitative methods through the questionnaire survey research strategy predominates. However, mixed, and qualitative approaches are showing increasing interest.

In terms of limitations, most studies indicate that the analysis conducted corresponds to specific cases and particular contexts. Therefore, more research is needed to generalize repetitive behaviors to any type of educational institution. On the other hand, the unpredictability of the pandemic does not allow the evaluation of a previous distance education scenario, so only the experience of the service as a response to the health crisis is evaluated.

Additionally, there are multiple variables that have been modified due to the management performed to face the pandemic, such as qualification methodologies, network connection problems, connectivity devices and others. Finally, from the managerial implications and in future research, there will be a concern for blended learning and hybrid models in the midst of changes and interactions mediated by technology and the implications and privacy risks that this implies in higher education, especially its impact on learning. Thus, there is a need to continue the search by institutions for strategies and dynamic balance points amidst the lessons left by the pandemic and experiential risks. Also, the need for connectivity, hardware and specialized software to accompany teachers in training; in addition, studies related to the timely training of teachers to provide this type of training will be developed.

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Trends in the use of Multivariate Analysis in Educational Research: a review of methods and applications in 2018-2022

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Abstract

Multivariate analysis is a statistical solution effectively used to investigate educational phenomena. It operates simultaneously on many variables and data and allows the development of classifications and models by returning data-driven understandings.

How does the international educational research community make use of multivariate analysis techniques?

We conducted a methodological review to identify trends in applying these methods in education. We extracted only papers written in English, indexed in Scopus, and published from 2018 to 2022 in journals in the Education category. Our review included bibliometrics such as years of publications, leading journals, and most cited articles.

We detected an increase in papers using multivariate analysis in the educational research in Scopus publications over the past five years, particularly in journals in quartiles Q1 and Q2. MANOVA represents the main method used for the analysis along with regression methods; the former may be overestimated due to the overlap of names with terms searched in the string. University students represent the preferred experimental subjects for investigation; the administration of surveys and questionnaires is the most practiced way to collect data; preferred analysis tools among those declared are non-free. Based on the topics, some research categories emerged: Teaching, Medical Education, STEM, Digital Education, Professional Development, Inclusion, Wellbeing.

However, the number of citations is low (less than 8) for three-quarters of the articles in our selection.

To increase the effective use, confidence, and understanding of multivariate analysis processes, appropriate skills in education, statistical analysis, and interpretation of results need to be strengthened.

KEYWORDS: Multivariate Analysis, Educational Research, Methodological Review, DIKW Hierarchy.

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1. Introduction

Multivariate analysis is a collection of statistical techniques that analyze multiple variables that simultaneously change and whose effects cannot be understood separately (Hair et al., 2014). These methods allow to develop models (i.e., regressions), classifications, and groupings (i.e., cluster analysis) and to reduce dimensionality and identify factors and latent traits (i.e., factorial analysis) by returning data-driven understandings of phenomena also in social sciences (Bartholomew et al., 2008; Hair et al., 2014; de Lillo et al., 2007; De Santis, 2022).

In education research, scholars use multivariate analysis to investigate students' opinions, perceptions and assessments, teachers' training and skills, efficacy of teaching methods and digital tools, educational poverties, organization of training institutions, and more just like: flipped class (Sointu et al., 2023) or university climate (Felini & Zobbi, 2022) through factorial analysis; serious games (Iten & Petko, 2016) using linear regression; teachers' role (León-Jariego et al., 2020) through cluster analysis and multidimensional scaling; students' activities in blended courses (Stites et al., 2019) using cluster

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analysis; disabilities and ethnic disparities (Morgan et al., 2017) or lifelong learning (Narushima et al., 2016) using logistic regression.

A large amount of data is stored in platforms and contexts related to the educational sector and can represent a relevant source to deepen the procedures related to learning and teaching and the management of education systems. Data are produced in digital learning environments that host large numbers of learners in online learning (Reich, 2022) but also in physical environments where online surveys or assessments and mobile apps are commonly used (Sannicandro, 2023).

However, storing data is not enough to obtain new understandings. Looking at information philosophy and knowledge management, in the well-known DIKW pyramid (also called "information hierarchy", "knowledge hierarchy", or "wisdom hierarchy"), data are defined as symbols, objective observations, basic elements that have no meaning or value until processed. Classification, selection, sorting, and calculation procedures allow data transformation into information with meaning and significance; the combination of information, experiences, human understandings, skills, and values generates knowledge (Ackoff, 1989; Rowley, 2007).

The transformation of data into useful information and knowledge, therefore, requires operations of analysis and interpretation. To do this, the following are necessary at least:

- *an interdisciplinary set of skills*: educational knowledge should be developed/combined alongside statistical and computing skills;
- *rigorous practices*: multivariate analysis can represent one of the solutions to work on multiple variables and plenty of data;
- *proper tools*: statistical softwares simplify the mathematical and computing procedures behind statistical techniques.

Our study aims to identify trends in applying multivariate analysis methods in the education field over the past five years, showing common uses and areas of application that can expand.

We realized a review of analysis methods used in the papers published between 2018-2022 and indexed on Scopus in journals in Education category.

Section 2 describes the method used for the investigation; Section 3 contains the results achieved. The last Section presents conclusions and future developments of the research.

2. Materials and Methods

Based on the previous considerations, the analysis in this paper starts from the research question: how does the international educational research community make use of multivariate analysis techniques?

We carried out a review of methods to reply to our question.

Methodological reviews, also found under other nomenclature in scientific literature (e.g. "methodological survey", "systematic review", "meta-research", "research-on-research"), increased over the last few years. They examine the methodological issues and choices related to design, conduct, analysis, or reporting adopted in research, describing and comparing research practices and appropriate structured procedures. The aim is to detect and enhance the quality, accuracy, and consistency of research, showing, in some cases, gaps and needs to improve the investigation methodology (Mbuagbaw et al., 2020; Aguinis et al., 2023).

The research was structured as a *descriptive review* (Paré et al., 2015) that aims to summarize a topic of interest and provide a comprehensive scenario of an area of study. By proposing a replicable process of selecting the papers through structured search methods, in descriptive review, researchers collect the features of the analyzed studies and provide quantitative results about frequency of themes, methods, authors, and so on. The main goal is to identify trends and patterns and draw conclusions on the investigation topic.

We have conducted a review that delves into the application of multivariate analysis techniques in the educational field. By investigating the most recent scientific literature, we can gain awareness of how multivariate analysis techniques are being used in educational research, the topics for which the use of such techniques is well established, and the areas in which further actions are needed.

The review covers five years between 2018-2022 and consists of two phases. In the first one, we conducted a more general investigation by inserting the term "multivariate analysis" in the search string. In the second phase, aware that multivariate analysis includes numerous techniques, we'll refine our search based on the results of the first phase, replacing the most popular multivariate analysis techniques in the strings.

This paper presents the results of the first phase of our study.

We used as search strings: "multivariate analysis" AND education; "multivariate analysis" AND learning; "multivariate analysis" AND teaching. We decided to set the search string without using boolean operators because we were interested in how the single terms combined with the others.

We defined the following eligibility criteria for the papers:

1) Period: 2018-2022
2) Category Journal on Scopus: Education (1470)
3) Language: English
4) Document type: article
5) Source type: journal
6) Publication stage: final
7) Distribution: open access
8) Topic: compliant with the themes

The research focus is not on the quality of the studies or their results but on how the techniques were used.

In the analysis, we provided the topics, kinds of methods, data features, sample sizes, analysis tools, and the countries where the studies were conducted. Our analysis included bibliometrics such as years of publications, leading journals, and most cited articles.

3. Results

Figure 1 contains the selection process for the identification of the papers to include in the review.

	"multivariate analysis" AND education	"multivariate analysis" AND learning	"multivariate analysis" AND teaching
IDENTIFICATION	20,007 doc	6,000 doc	3,715 doc
APPLYING THE ELIGIBILITY CRITERIA			
SCREENING	111 doc	82 doc	42 doc
ELIMINATING DUPLICATION			
INCLUDED	157 doc		

Figure 1 - Process of identification of the papers to include in the review.

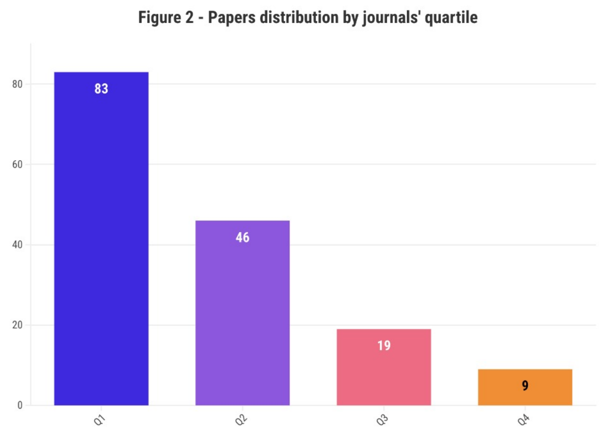
We obtained the highest number of papers using the term "education" in the search string and the lowest using the term "teaching". This result brings forward the findings on the topics focused on by the studies we present in the next.

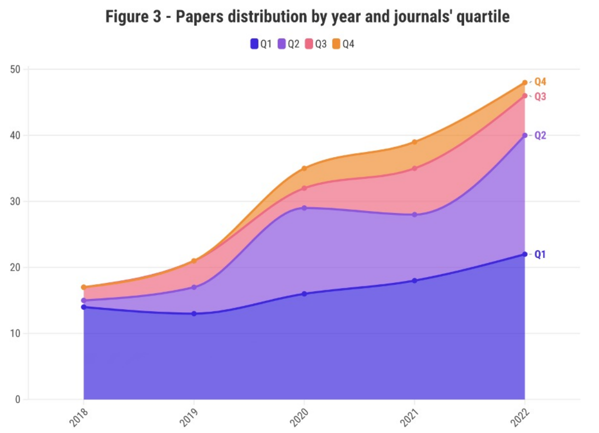
The described process yielded 157 documents.

Figures 2 and 3 describe the distribution of papers among journals by journals' quartile and year.

Around half of the selected papers (83) belong to Q1 journals.

In the last five years, the number of papers in Q1 published every year went from 14 to 22, delivering a relevant increase. However, the quartile where the changes are more important is the second one, where the papers published every year went from 1 to 18 over the five years, reaching almost the amount for Q1 journals.





Figures 2 and 3 - Paper distribution by year and journals' quartile.

The papers published in Q1 belong to 39 journals. 41 of them (49%) are published in journals of the medical field. The Q1 journals that host the higher number of papers that deal with education and multivariate analysis are not surprisingly related to the health sector: "BMC Medical Education" (22); "Academic Medicine" (4); "Nurse Education Today" (4); "Medical Education Online" (3).

The number of papers belonging to the medical field in the journals of other quartiles is smaller: 5/46 in Q2, 2/19 in Q3, 2/9 in Q4.

Table 1 contains the four papers with the highest citations on Scopus. We also report the citation number on Scholar as a confirmation. These papers cover a comprehensive range of topics: the role of parents in school education and the life quality of university students during the COVID-19 pandemic, the skills of nurses and midwives, and teaching in science courses.

The article with the highest number of citations is not in the health field but is published in a strictly educational journal and, as we shall see below, it involves parents who are an unusual type of statistical unit with respect to the mainly implemented practices.

50% of papers in our selection have less than three citations on Scopus, and 75% less than 8, indicating that they have little impact on the scientific discussion.

Figures 4 and 5 represent the countries in which the studies were conducted (from now on, the sum can be higher than the number of papers because more techniques, statistical units, software, and tools can be used in each research).

There is a distribution throughout the world.

A third of the studies analyzed were conducted in the United States (28) and Indonesia (25). Other countries that more consistently are the setting for the research on education through the use of multivariate analysis techniques are Spain (11), Germany (8), Turkey (7), Australia (6), and France (5).

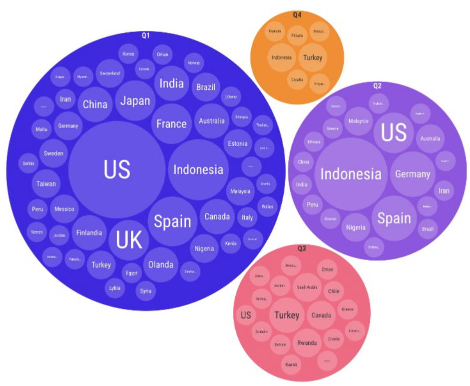
In the distribution by journals' quartile, we can observe that in the first one, US (23), Indonesia (9), Spain (6) are the most productive countries. In the second one, Indonesia (13), Spain (5) and Germany (5). In the third and fourth, Turkey (respectively 3 and 2 papers) rises up.

Table 1 - Most cited papers in journals of the education category.

Q	*Paper title*	*Scopus citations*	*Scholar citations*
Q1	Lee, S. J., Ward, K. P., Chang, O. D., & Downing, K. M. (2021). Parenting activities and the transition to home-based education during the COVID-19 pandemic. *Children and Youth Services Review*, *122*, 105585.	197	420
Q1	Ross, L., McSherry, W., Giske, T., van Leeuwen, R., Schep-Akkerman, A., Koslander, T., Hall, J., Steenfeldt, V.Ø., & Jarvis, P. (2018). Nursing and midwifery students' perceptions of spirituality, spiritual care, and spiritual care competency: A prospective, longitudinal, correlational European study. *Nurse education today*, *67*, 64-71.	77	139
Q1	Cavanagh, A. J., Chen, X., Bathgate, M., Frederick, J., Hanauer, D. I., & Graham, M. J. (2018). Trust, growth mindset, and student commitment to active learning in a college science course. *CBE - Life Sciences Education*, *17*(1), ar10.	68	168
Q2	Silva, P.G.D.B., de Oliveira, C.A.L., Borges, M.M.F., Moreira, D.M., Alencar, P.N.B., Avelar, R.L., Sousa, R.M.R.B., & Sousa, F.B. (2021). Distance learning during social seclusion by COVID-19: improving the quality of life of undergraduate dentistry students. *European Journal of Dental Education*, *25*(1), 124-134.	45	107

Figure 4 - Paper distribution by country

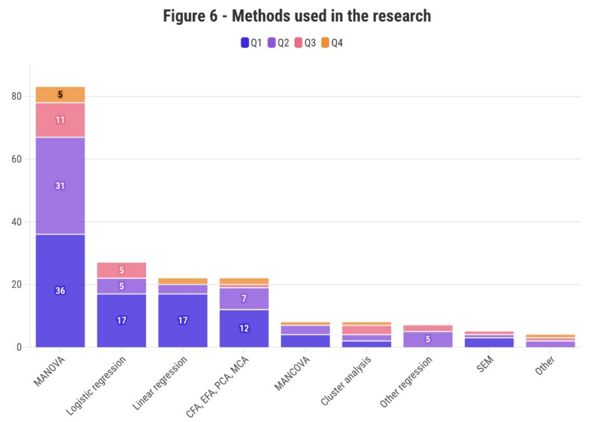
Figure 5 - Paper distribution by country and journals' quartile

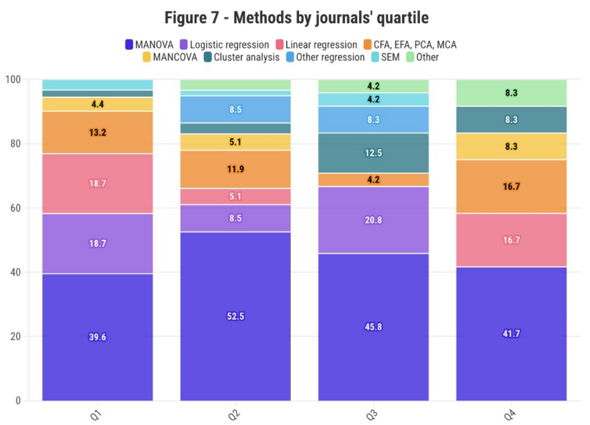


Figures 4 and 5 - Paper distribution by country and journals' quartile.

Figures 6 and 7 represent more elements related to the methods used. In particular, around half of the research used multivariate analysis methods such as MANOVA (multivariate analysis of variance) followed by regression, data reduction, and classification techniques. MANOVA is used to compare group differences in metric dependent variables simultaneously so that it can be instrumental in experimental designs but also in non-experimental designs to assess the statistical significance of differences among groups built based on particular features (Hair et al., 2010). However, we are aware that the results can be distorted because the full name of the technique MANOVA contains the words in the search string.

Overall, MANOVA and MANCOVA cover 48.9% (92 papers) of the research; regression methods 30.1% (56 papers), data reduction 11.8% (22 papers) and cluster analysis 4.3% (8 papers).





Figures 6 and 7 - Paper distribution by methods and journals' quartile.

This odd is about similar also within each quartile.

However, in papers in Q1 journals, there is a higher percentage of logistic and linear regression techniques equally. In Q2, on the contrary, there is a greater representation of MANOVA and MANCOVA at the expense of regressions. Although the number of papers is lower in Q3 and Q4 journals, we observe that in Q3, 5 researches use logistic regression and none the linear one; in contrast, in Q4, the regression is used only in 2 papers as linear.

One third of the papers do not state the statistical analysis software used (54, 34.4%); SPSS is used in half of the papers (80, 51.0%). STATA, SAS, R, and Jamovi are chosen in the remaining papers, mainly from Q1 journals (Figure 8).

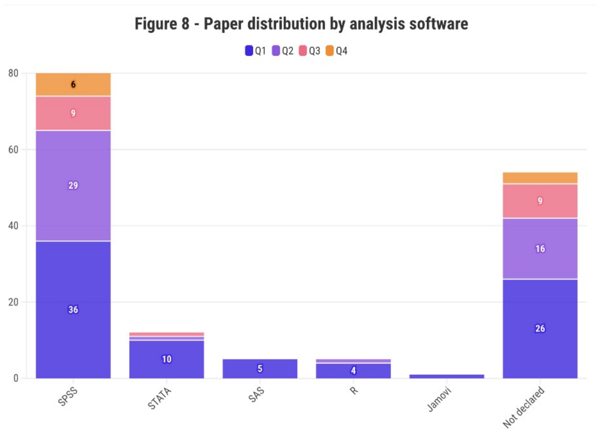


Figure 8 - Paper distribution by analysis software.

Three-quarters of the articles analyzed have a sample/ population size below 500 units. Papers with larger samples were published in Q1 and Q2 journals (Figures 9 and 10).

This result should be read in conjunction with the data collection techniques used and the statistical units chosen.

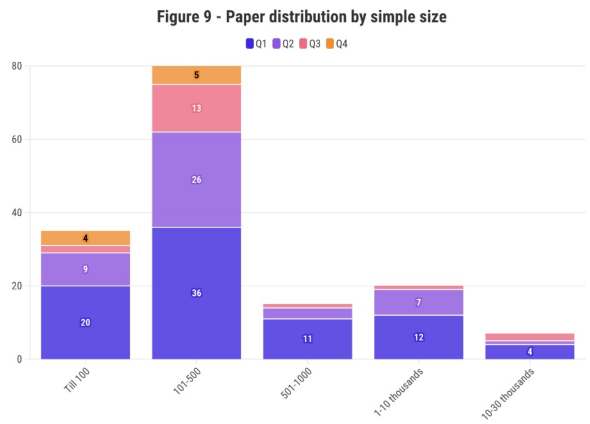
In almost all cases (87.6%), the techniques for detecting data are questionnaires, scales, inventories, and assessments. In only 10 cases, the analyses originate from national or regional datasets, and a few others involve the analysis of audio, documents, computer metrics, and medical records.

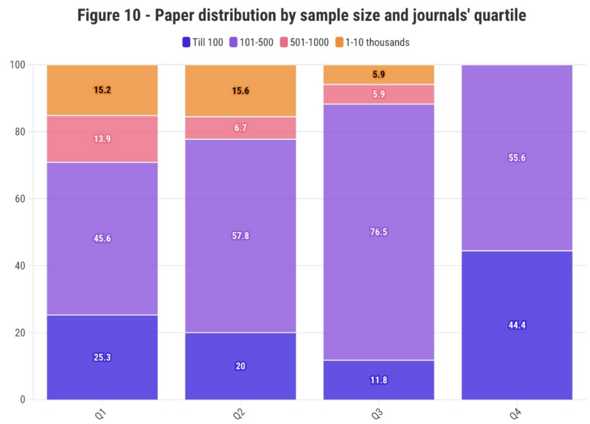
The main statistical units considered are students, teachers, and other professionals.

In details:

- 35.4%, university students;
- 24.4%, students from kindergarten, primary and secondary schools;
- 15.9%, preservice teachers, teachers, and professors;
- 10.9%, residents and health professionals.

The choice of statistical units "other than humans" is more unusual: schools, lessons, and courses, together with objects such as metrics, books, claims, hymns, and so on, represent the statistical units of 8.5% of papers.





Figures 9 and 10 - Paper distribution by sample size and journals' quartile.

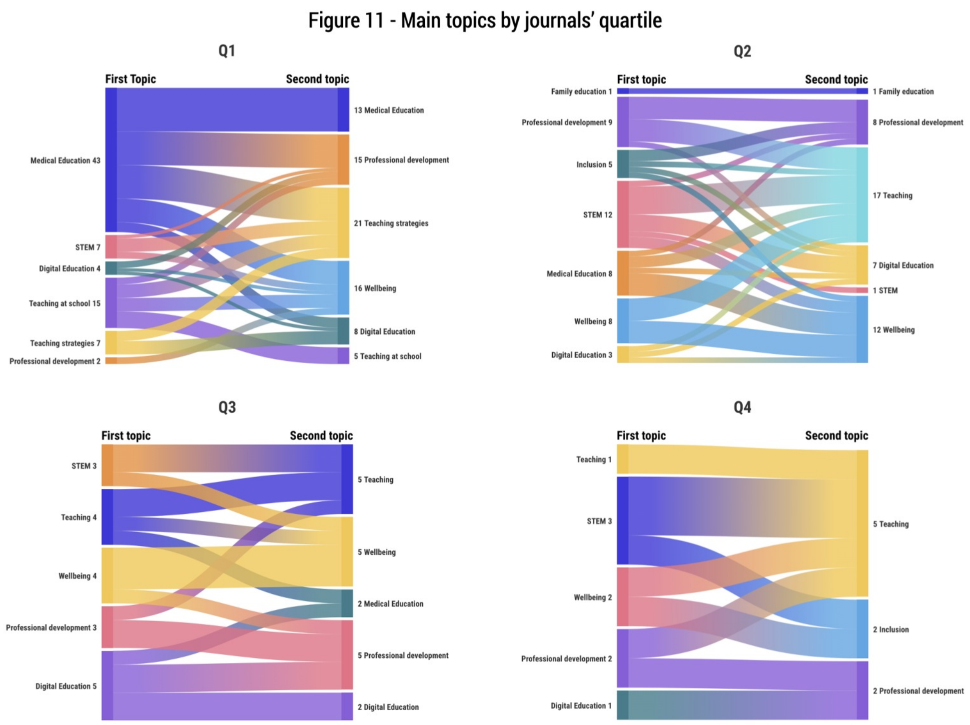
We identified one or more main investigation fields for each paper and connected them to the kinds of statistical units.

Figure 11 shows the main topics explored in the papers distinguished for journals' quartile.

Medical Education occupies a significant role in papers from Q1 journals; the topics of Medical Education are intertwined with Professional development (including faculty development, teachers' training, and career skills), Teaching strategies, Wellbeing, and Digital Education. Teaching strategies are also a theme related to schools, STEM, and Digital Education. Wellbeing, considered as a macro-area including motivation, anxiety, stress, and mental health, connects with all the previously mentioned themes. Papers dealing with Medical Education are in the same number as those dealing with Teaching strategies in general and in schools.

In the papers belonging to Q2, Q3, and Q4 journals, the number of journals dealing with health and the number of papers dealing with Medical Education decreases, leaving room mainly for topics related to Teaching, Professional development, and Wellbeing. Papers dealing with STEM and Digital Education are in a good number in the Q2 papers.

For papers in the Q2 and Q4 journals, it seemed important to add the topic of Inclusion for research focused on pre-service teachers' opinions on it, reasons for dropout, and EFL students' skills.



Figures 11 and 12 - Main topics and statistical units by journals' quartile.

Finally, Figure 12 highlights the relationship between the main topics and the statistical units selected by the researchers.

University students represent the preferred experimental subjects for investigation together with secondary school students, teachers and pre-service teachers, and children in all journal quartiles.

Considering all the quartiles and only one main topic for the papers, we observed that residentials/ practitioners and health professionals are more frequently the units in papers in the Q1 sector focused on Medical Education; studies on Digital Education and Professional development more frequently involved teachers and pre-service teachers; research on Teaching and Wellbeing focus on children and secondary school students; the use of statistical units different from students or professionals is diffused among papers on Medical Education and Teaching.

4. Conclusions

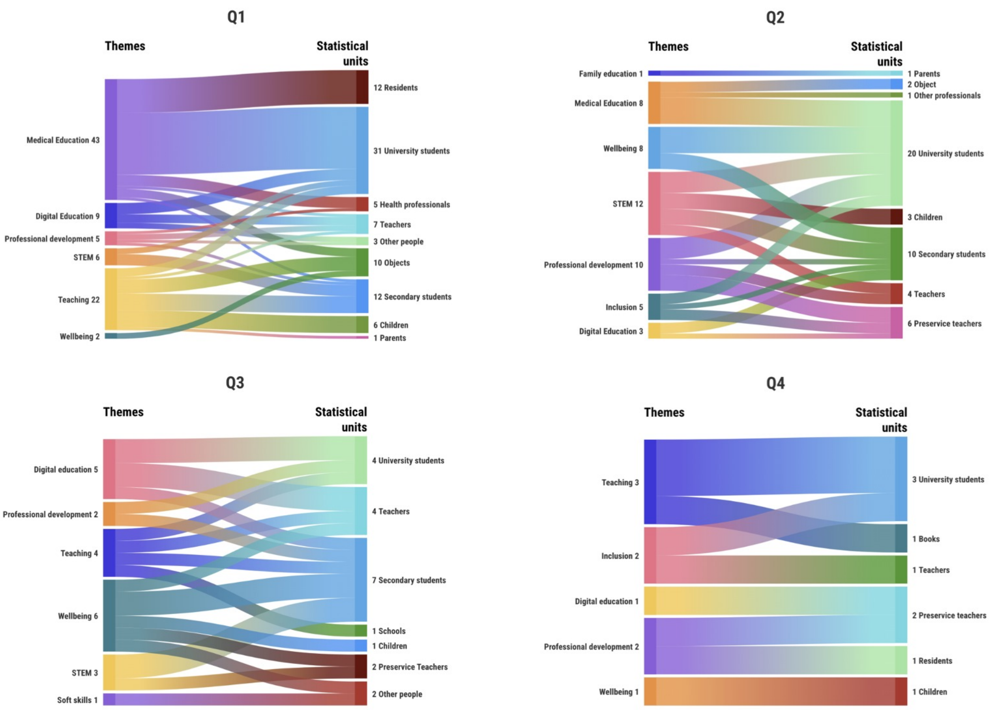
This first stage of review analysis leads to some considerations.

Our analysis shows that there has been an increase in papers using multivariate analysis in the educational field in Scopus publications over the past five years, particularly in Q1 and Q2 journals ranked in the Education category.

Synthesizing the main results of our analysis, we can say that:

- the number of citations is low (less than 8) for three-quarters of the articles in our selection;
- a large number of countries produced studies using these methods; however, one third took place in the United States and Indonesia;
- MANOVA is among the most commonly used multivariate analysis techniques, along with regression methods. The former may be overestimated due to the overlap of names with terms searched in the string;
- samples/populations less than 500 is the most commonly recorded choice;
- administration of surveys and questionnaires is the most practiced way to collect data;
- in about one-third of the papers, the tools used are not stated. Preferred analysis tools among those declared are non-free. SPSS is used in half of the studies, and few studies state the use of open source software;
- Teaching, Medical Education, STEM, Digital Education, Professional Development, Inclusion, and Wellbeing are among the many topics investigated using multivariate analysis;
- researches mainly use (university) students as statistical units.

Figure 12 - Main topics and statistical units by journals' quartile



Figures 11 and 12 - Main topics and statistical units by journals' quartile.

Our research returns a scenario in which, as a hypothesis, poor citations could show a need for more confidence and understanding of multivariate analysis processes or, on the contrary, they could be a symptom of low relevance of results, which was not an element analyzed in our study.

Many other applications of multivariate analysis, using varying statistical units, topics, methods, and data collection tools, could be considered.

Databases in online learning environments or data from digital devices can replace those collected by surveys or similar methods, which represent the most frequent choice in the paper analyzed and could be affected by the perceptions of subjects involved in detection.

Data collection and analysis could be extended to other unrepresented fields of study by also addressing subjects not necessarily involved in formal training.

Additionally, the use of open source software could broaden the application of the techniques.

In general, as we have sustained from the beginning of this paper, appropriate skills in both education and statistical analysis and interpretation of results need to be strengthened.

Future studies may analyze papers belonging to other academic databases. The second phase of the research will involve using some of the most common multivariate analysis techniques in education and teaching in the search string.

Authors' contribution

According to CRedit system, Annamaria De Santis: Conceptualization, Methodology, Investigation, Data Curation, Writing - Original Draft, Visualization. Katia Sannicandro: Methodology, Resources. Claudia Bellini: Resources. Tommaso Minerva: Supervision.

Note

This paper describes the whole research partially introduced in the conference abstract "Trends in the use of multivariate analysis in educational research: a review of methods and applications in 2018-2022" presented at the Italian SYmposium on Digital Education (ISYDE) held in Reggio Emilia (Italy) on September 13-15th, 2023.

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