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How is the use of AI perceived in a classroom environment?

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1. Introduction

We are living in an era defined by remarkable technological advances. Digital transformation and artificial intelligence (AI) have become the driver of the transformation of the economy and society, transforming our lives and our ways of communicating. Recent developments in technology in general and in AI, in particular, have also impacted education (Sekeroglu et al., 2019; Kumar, 2019). Applications of AI in the domain of education for predicting student performance, detecting undesirable student behaviour, or providing feedback for supporting instructors and students, are becoming more common (Baker et al., 2009).

This work is part of the evaluation proposal for the experimentation of the ClassMate Robot (CMR) project, promoted by the Protom Group (with Protom Robotics and Scuolab srl), in four Italian schools (junior high and high school level). The project includes the collaboration with the Projects of Intelligent Robotics and Advanced Cognitive System (PRISCA) Lab of the University of Naples Federico II for the development of the software infrastructure and the scientific support of the Department of Social Sciences (DiSS) of the same university. The idea behind CMR is to use AI, by introducing a social robot archetype, to bring upon the Italian school framework innovative teaching and learning processes. The experimentation consists in testing how a newly developed AI device for social education is received in a classroom environment. A post-experimental investigation was carried out to evaluate the performance of the CMR.

The work aims to develop an easy evaluation tool for the CMR that decision-makers can adopt. The work first implements an initial exploratory study of survey data and then investigates different dimensions that affect the students' evaluation analyzing how these dimensions impact this evaluation. The dimensions concern aspects relating to students' general perception of the CMR, their comfort level using the CMR, their perception of the CMR's impact on school results, and perception of platform likability. Structural equation modeling, and in particular Partial least squares - path modeling (PLS-PM), is used to examine the relationships between these dimensions. According to PLS-PM, student satisfaction may be defined as a multidimensional latent variable (LV) related to its manifest variables (MVs) and linked to other LVs, that represent the variables dimensions. The goal is to determine which aspects of this product need to be altered to boost student satisfaction.

2. Theoretical framework

PLS-PM is a framework for analyzing multiple relationships between blocks of observed and latent variables (Wold, 1974). This approach consists of two elements: the measurement model (also known as the outer model), which describes the relationships between each construct (LV) and its associated observed variables, also called indicators or items (MVs); and the structural model (also known as the inner model), which describes the causal-predictive relationships between the constructs.

According to Lauro et al. (2018) *the PLS-PM approach to SEM consists of an iterative algorithm that compute the estimation of the LVs and the relationships between them by means of an interdependent system of equations based on multiple and simple regression*. The aim is to determine the scores of the LVs through a process, that, iteratively, computes first an outer and then an inner estimation (Lauro et al., 2018), for making decisions and predictions.

The properties of this algorithm favor its application even when the number of observations is smaller than the number of the MVs. In recent years, the number of publications on PLS-PM has increased significantly. For a review of the PLS-PM approach and its advantages see Hair et al. (2021); Hair et al. (2019); Lauro et al. (2018); Latan and Noonan (2017); Esposito Vinzi et al. (2010).

One of the most important outputs of PLS-PM is the IPMA (Importance-Performance Matrix). It provides information on the relative importance of the dimensions in explaining other dimensions for conclusions. In this context, the IPMA can be considered as a valuable decision making tool (Ringle and Sarstedt, 2016) to identify the drivers to increase the student's satisfaction. It is based on a very intuitive scatter plot where each dimension is positioned according to its importance and performance with concerning the target construct: the vertical axis represents the performance of the attributes from poor performance to good performance, while the horizontal axis represents the perceived importance of the attributes from not very important to very important. In this kind of analysis, we have the possibility to analyze the strengths, weaknesses, opportunities, and threats of constructs, that are considered in the model in order to estimate a latent concept.

3. The model

The blocks relating to students' general perception of the CMR, their comfort level using the CMR, their perception of the CMR's impact on school results, and perception of platform likability are considered dimensions of the PLS-PM model. In this model, student satisfaction is conceived as a latent dimension linked to three dimensions of questionnaire (Figure 1).

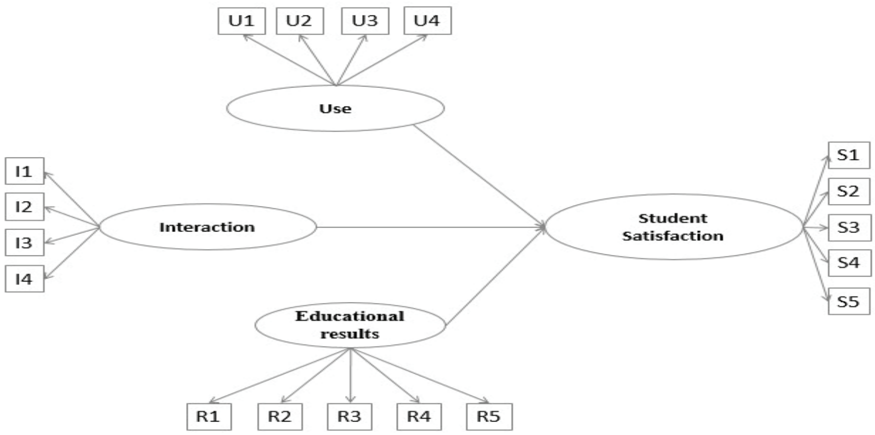

Figure 1: Student satisfaction model

The dimensions of interest were defined first from a qualitative perspective and then translated into survey items by also taking into consideration literature on satisfaction, perceived usefulness and perceived ease of use.

The study focuses on a reflective measurement model, assuming that each dimension is a common factor that reflects itself in its respective MVs, and formative structural model, in which the latent dimension is obtained as a linear combination of the three corresponding under dimensions. The *cSEM* package in the R programming language (Rademaker and Schuberth, 2021) was used to estimate the model.

4. The project and the data

The project experimental phase took place between October 2022 and May 2023 in four

Italian schools with a compatible profile (focus on technology and robotics) selected by the project coordinators. In detail, 21 students from a class in Carrù (2nd year Junior High), 29 from Dalmine (4th year High School), 19 from Rome (5th year High School) and 27 from Verona (5th year High School) were involved in the project, for a total of 96 individuals. The designated classes, which already actively participated in defining the educational framework and co-projecting software requirements, were provided with one of the few available CMR prototypes to test during school hours. The DiSS was responsible for carrying out a full assessment of this pilot study. Such assessment comprised both qualitative and quantitative tools, including a student questionnaire administered in classrooms by teachers at the end of the year.

Table 1: Survey questions, median and per cent distribution of answers

Dimension		Definition	Median	1	2	3	4
Use	U1	The CMR made lessons more fun	3	2	21	59	18
	U2	The CMR facilitates the study of difficult subjects	2	18	46	31	5
	U3	The CMR makes me feel more involved	2	14	42	35	13
	U4	Thanks to the CMR I can contribute to the definition of educational contents	3	8	22	57	13
Interaction	I1	I feel comfortable using the CMR	3	1	12	68	19
	I2	I am calm before a test or a question where I can use the CMR	3	23	17	44	16
	I3	I think the robot in the classroom can be a fun tool to use	3	2	14	51	32
	I4	I think interacting with CMR is simple	2	24	49	22	5
Educational results	R1	The ClassMate Robot motivates me to study	2	31	37	31	1
	R2	The CMR has increased my interest in the subjects studied	2	24	32	43	1
	R3	My academic results in educational activities where we used the CMR have improved	2	17	45	33	5
	R4	Teachers are happy with the results I have obtained in the teaching activities in which we have used the CMR	3	1	9	64	26
	R5	Parents are happy with the results I have achieved in the educational activities in which we have used the CMR	3	10	23	52	15
Satisfaction	S1	The experience with the CMR helped me feel more confident	2	32	45	20	3
	S2	The experience with the CMR has strengthened my skills in the use of digital technologies	2	14	43	33	10
	S3	The experience with the CMR has strengthened my interest in digital technologies	2	13	44	39	4
	S4	The experience with the CMR has improved my relationship with teachers	2	27	27	44	2
	S5	The experience with the CMR has improved my relationship with classmates	2	12	44	40	4

The questionnaire was developed by a multidisciplinary team of experts with the purpose of measuring the end-user satisfaction and provide insights on how to improve performance. In detail, questions were specifically developed to measure: students' general perception of the use of the CMR (4 items on usability and likability), students' comfort level in interacting with the CMR (4 items), students' perception of CMR impact on school results (5 items), students' overall satisfaction (5 items). All Likert scale items are on a 4-point system where the options were "1 = Not at all", "2 = A little", "3 = Enough", "4 = A lot". A 4-point Likert scale was preferred to discern between positive/negative aspects without a neutral choice. Being an experimental project, the participation of the schools was on a voluntary basis. Only 78 viable questionnaires were returned to the DiSS by the schools.

Table 1 summarizes the questions, median, and distribution of answers for each item. In general, students are quite satisfied their experiences of CMR because the median is 2 and 3 out of 4 for most answers. If we look at the distribution of answers, we notice that the highest frequency of responses is concentrated around 2 and 3.

5. Evaluation of the model

The evaluation of the PLS-PM results begins with an assessment of the reflective measurement models. Table 2 shows the results and evaluation criteria outcomes.

Table 2: Assessment results of reflective measurement model

		Convergent Validity	Internal consistency reliability	
LVs	**AVE**	**Cronbach Alpha**	**Reliability ρ_A**	**Composite reliability ρ_C**
Threshold	*>0.50*	*0.70-0.90*	*>0.70*	*>0.70*
Use	0.54	0.720	0.824	0.824
Interaction	0.51	0.709	0.762	0.762
Educational results	0.49	0.736	0.824	0.824
Satisfaction	0.53	0.786	0.852	0.852

All four reflective measurement blocks meet the relevant assessment criteria. More specifically, all AVE values are above 0.50, providing support for the measures' convergent validity. The composite reliability ρ_C is clearly above the expected minimum level of 0.70. Moreover, the Cronbach's alpha values range between 0.709 and 0.786, which is acceptable. Finally, all composite reliability ρ_A values meet the 0.70 threshold. These results show that the outer model is well specified and that the LVs are well measured by the MVs, their synthesis being good.

We can proceed with the assessment of the structural model, starting to check the VIF values of all predictor constructs in the model. All VIF values are below the conservative threshold of 3, concluding that collinearity among the predictor constructs is not a critical issue in the structural model.

Analyzing the path coefficient estimates of the structural model (Table 3), it is possible to note that not all dimensions are important in order to estimate student satisfaction.

It mainly depends on educational results (path coefficient of 0.366) and, subsequently, on interaction (path coefficient of 0.253); Use is not relevant with a path coefficient of 0.189 and with not significant effect at the 5% probability of error level.

Table 3: The inner estimation

LVs	Estimate	Std.Error	t-value	Pr(>|t|)	CI 95\% percentile
Use	0.189	0.1184	1.6016	0.1092	[-0.0303; 0.4196]
Interaction	0.253	0.1085	2.3350	0.0195	[0.0558; 0.4764]
Educational results	0.366	0.1127	3.2514	0.0011	[0.1464; 0.5707]

6. Analysis – IPMA

The IPMA was considered to identify which aspects can be considered as drivers to increase the student's satisfaction. It is important to focus attention in the lower right quadrant because there are all important aspects that need to be improved. According to the IPMA matrix (Figure

2), the block of educational results is in the critical area because it represents an essential aspect of student satisfaction but has a low performance. This aspect is a critical driver to increasing the CMR evaluation. If we look the IPMA of educational results block we note that three out five aspects are in the critical area, aspects related to motivation to study, interest in study subjects and better educational results. So the analysis found that the educational results dimension is a key factor in increasing the student's evaluation of CMR but has low performance, suggesting that developers need to focus more on this component to improve CMR evaluation.

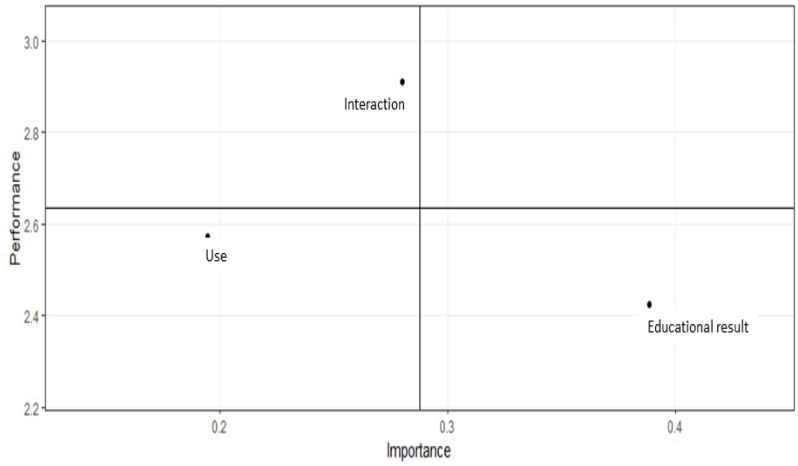

Figure 2: Importance performance analysis on student satisfaction

Figure 3 reports the aspects for each dimension. If we look the IPMA of educational results block we note that three out five aspects are in the critical area, aspects related to motivation to study, interest in study subjects and better educational results. So the analysis found that the educational results dimension is a key factor in increasing the student's evaluation of CMR but has low performance, suggesting that developers need to focus more on this component to improve CMR evaluation.

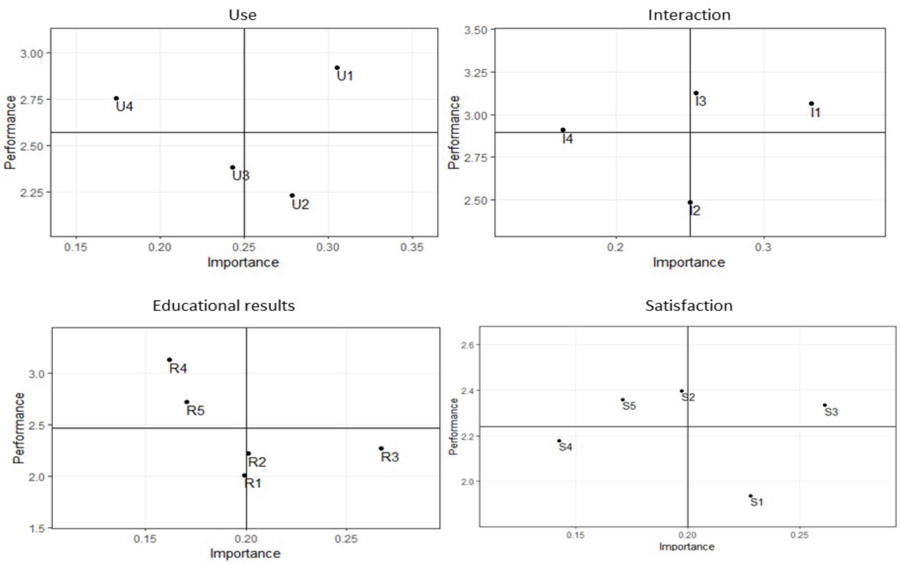

Figure 3: Importance performance analysis of dimensions

7. Remarks

This study, applying PLS-PM and IPMA, investigates the dimensions that affect the students' evaluation of CMR. The analysis shows that the relevant dimensions are related to between-student interaction and to educational results. The study also found that the educational results dimension is a key factor in increasing the student's evaluation of CMR but has low performance, suggesting that developers need to focus more on this component to improve CMR evaluation.

It may be underlined that the results of this paper should be interpreted in light of the small non-representative sample, a consequence of the cost and complexity of the prototype, which did not allow for mass production. This work should thus be considered as a pilot study which can be improved only after the adoption of CMRs by other schools.

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