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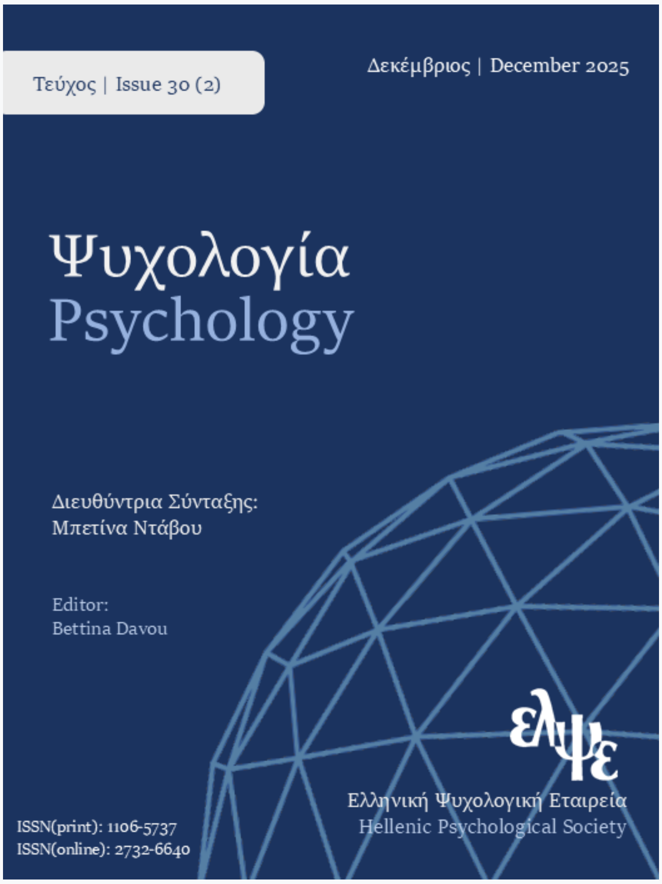

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Students' perceptions of the structure of the personality of a Socially Assistive Robot for Learning and Instruction

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KEYWORDS

Socially assistive robot
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ABSTRACT

Policymakers in the 21st century consider the application of Socially Assistive Robots (SARs) in the educational context essential to transform instruction and support students in achieving better learning results. However, several questions emerge regarding the conditions of SAR's application in education. The current study aimed to investigate students' perceptions regarding the personality of a SAR involved in learning and instruction, namely the dynamic and unique set of traits and characteristics that shape the SAR's behaviors and interactions with the students. An online questionnaire was administered to 1083 primary (N=390, M=11.23, SD=.72), lower secondary (N=378, M=14.10, SD=.85) and upper secondary (N=315, M=16.82, SD=.77) students from Greece and Finland. The exploratory factor analysis revealed two psychological factors that reflect two types of personality traits of a SAR for learning and instruction: the SAR as a "Regulator" and a "Facilitator" of learning. Then, a Confirmatory Factor Analysis showed that the model in which the two dimensions tap into the same factor that expresses the unity of a SAR's personality for learning and instruction had the best fit to the data. This structure was confirmed across both countries. Still, some age, gender and culture related differences in students' endorsements of the dimensions of the SAR's personality were identified. Capturing the dimensions of the personality of a SAR for learning and instruction can inform the design and development of more effective SARs tailored to specific cultural contexts and student preferences. Furthermore, these findings enhance our understanding of Human-Robot Interaction in education.

In the sci-fi film "Class of 1999", robot teachers restored order in schools, overtaken by violent gangs. The robot teachers were programmed to be strict and enforce discipline. Although this film was considered dystopian back in the '90s, policymakers in the 21st century consider the application of Socially Assistive Robots (SARs) in the educational context essential to transform instruction and support students in achieving better learning results (OECD, 2021; Vuorikari et al., 2020). Previous studies have shown that humans attribute human characteristics, cognitive, and emotional states to robots (Duffy, 2003; Wiese et al., 2017), as is the case with other entities (e.g., animals, gods) or inanimate objects (e.g., toys, the computer, smartphones or social media), a phenomenon known as anthropomorphism. Furthermore, researchers have concluded that using social features in SARs, such as personality (voice, gender, or movements), leads people to consider SARs to belong to the same ontological category as humans (Kim & Sundar, 2012).

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Given that humans often anthropomorphize robots and that social features in SARs lead to their categorization as human-like, designing effective robot personalities is essential for fostering meaningful and engaging Human-Robot Interactions (HRIs). Understanding the structure of SAR personality is crucial, as it influences how students perceive, interact with, and respond to these robots. A well-structured personality can enhance the robot's ability to motivate, engage, and support students, thereby improving educational outcomes. Additionally, a robot with a carefully designed personality can better adapt to the diverse needs of individual learners, creating a more personalized and effective learning experience. The aim of the current study was to investigate students' perceptions about the structure that the personality of a robot for learning and instruction should have.

Importance of Understanding SAR Personality

Understanding the structure of a SAR's personality is pivotal for designing effective interventions that resonate with students on a deeper level. Research indicates that students' learning outcomes significantly improve when interacting with robots exhibiting human-like behaviors. For example, Wijnen and colleagues (2019) used a social robot to examine the effect of the robot's personality on the explanatory behavior of children (aged 6-10) while working on an inquiry learning task. Specifically, the robot used human expressions (joy, surprise), provided feedback, and asked questions to the student population during the solution of the task. Results revealed that social robots, compared to a control group with a Computer Aided Learning system, were better at triggering students' explanatory behavior and improving the relevance of students' explanations. In another study, Jones and Castellano (2018) highlighted that when their social robot adjusted its feedback according to the needs of the students (10-12 years old), the student population showed increased self-regulation in their behavior compared to the control group, where the robot did not apply the same tactics. Ramachandran and colleagues (2018) showed similar results, finding that students who were encouraged to think aloud during problem-solving by a robot that followed this strategy had better learning outcomes, which they maintained for a more extended period while showing higher levels of engagement and compliance with the robot's instructions compared to the student population in the control group. Additionally, in other studies, the robot's behavior is adapted to the needs of the students in order to support personalized teaching. To illustrate, in the study carried out by Szafir and Mutlu (2012), robot personalized teaching was done using EEG to monitor student engagement in real time. It adapted behavior with immediacy cues like gestures and volume changes when attention dropped, improving recall by 43% and boosting female motivation and rapport, thereby enhancing overall learning outcomes.

Current approaches to the design of robot Personality

Human personality theories (e.g., the Five Factor Model), developed to study human behavior, emerged from the bottom-up, namely by observing the human and utilizing various psychometric instruments to assess human behavior and systematically categorize it into different types. In Human-Robot Interactions (HRIs), though, a design of the robotic personality from the bottom up seems misplaced, as the robot's personality needs to be designed and programmed by the researchers. Thus, researchers typically utilize a theoretical framework that corresponds to human personality in order to design the personality of the SAR by analogy, namely following a top-down approach. According to recent literature reviews, most researchers exploit the Five Factor Model to design the personality of SARs (Diefenbach et al., 2023; Mou et al., 2020; Robert Jr et al., 2020). Still, the exploitation of this framework is not universal and appears to have several limitations (Diefenbach et al., 2023; Mou et al., 2020; Robert Jr et al., 2020).

First, a literature review in the field of HRI reveals that although in the studies, the Five Factor Model for the design of a SAR's personality is exploited, there is no agreement among the researchers in the way the personality is expressed. The robotic personality can be expressed through different social cues attributed to the robot. For example, Andrist and colleagues (2015) implemented introverted and extroverted dimensions in their design of the robot's personality. In particular, they expressed these two dimensions through the robot's gaze and specifically through the frequency, duration and recipient of the gaze. In another study, Weiss and colleagues (2012) simulated introverted and extroverted personality by utilizing the robot's voice volume and speech rate. Additionally, Lohse and colleagues (2008) utilized the robot's nonverbal communication and movements to show introverted and extroverted behavior. In particular, the introverted robot spoke only when spoken to, used short sentences, and required direct user commands to move. In contrast, the extroverted robot spoke using longer, more complex sentences and moved autonomously without needing instructions from the user. The above examples indicate the discrepancy among researchers about the expression of the robot's personality, even if the same personality dimension (extroversion-introversion) is targeted in the design.

Second, researchers have extensively explored the impact of various sets of robot personality traits on user preference and interaction outcomes. For example, Meerbeek and colleagues (2008) showed that a robot in the role of a TV assistant with an extroverted and agreeable personality was preferred over a more introverted and formal robot. Furthermore, the study by Paetzel-Prüsmann and colleagues (2021) showed that a robot that scores high on agreeableness, emotional stability, and conscientiousness can attenuate strange and uncanny emotions when interacting with each other. Andrist et al. (2015) in a study with 40 participants, chose to test the effect of introverted and extraverted personality dimensions on enhancing the user's motivation to engage in repetitive tasks. The results showed that individuals were more motivated by the robot that displayed the same personality dimension as they did (introverted or extroverted). These results highlight that even the same set of personality traits can have varying consequences as well as that one personality type may have a different impact over another.

Third, the design of a SAR's personality is susceptible to the specific context and task for which it is intended. For example, Tay and colleagues (2014) found that a healthcare robot with an extroverted personality was more acceptable to the participants, while a security robot was preferred when exhibiting an introverted personality. In the healthcare domain, Goetz and Kiesler (2002) demonstrated that participants enjoyed interacting more with a 'playful' robot during strenuous exercise but were less willing to follow its prompts, indicating the need for a balance of traits to optimize task compliance. Similarly, Bartl et al. (2016) found that in adult care, a robot with a 'companion' personality was more likeable and perceived as more intelligent than a 'helper' personality. In a higher educational setting, Reich-Stiebert et al. (2020) highlighted that students preferred an assistant robot to exhibit conscientiousness and openness to experience. They also suggested that educational robots should be capable of motivating and adapting to individual needs. It is clear from the above that when designing robot personalities, it is crucial to consider the intended context and task of the robot.

Education stakeholders' perceptions about Socially Assistive Robots

Several literature reviews and empirical studies engaging stakeholders like teachers, school directors and students highlight that SARs are perceived in the context of education through their social role and the way they are being used in learning and instruction. The perceptions of social roles differ among various stakeholders, such as teachers and students, who assign different functions to robots in education based on their unique profiles and needs. For instance, teachers often see the robot as a "classmate" or "partner" in the learning process (Ahmad et al., 2016), while students view it as a "helper" for their studies (Shin & Kim, 2007). Moreover, the perceptions of the SAR's social roles may differ depending on the age group in which the robot will be used (e.g., primary education vs higher education). To illustrate, an "instructor/mentor" robot for elementary school students is perceived as capable of providing reinforcement instruction, while an "instructor/mentor" robot for the higher education student population is perceived as capable of providing personalized learning (Cheng et al., 2018). Distilling the results of these studies we underline three prominent social roles for a SAR for learning and instruction: (i) a "tool for learning and instruction" (e.g., Kennedy et al., 2016; Mubin et al., 2013; Pnevmatikos et al., 2022; Shin & Kim, 2007), (ii) a "learning assistant/peer/companion" (e.g., Ahmad et al., 2016; Belpaeme et al., 2018; Cheng et al., 2018; Kennedy et al., 2016; Mubin et al., 2013; Pnevmatikos et al., 2022; Shin & Kim, 2007) and (iii) a "mentor/tutor/instructor/teaching agent" (Belpaeme et al., 2018; Cheng et al., 2018; Kennedy et al., 2016; Mubin et al., 2013; Pnvematikos et al., 2022; Serholt et al., 2014). However, a gap in previous studies is that researchers have differing views on how the social roles assigned to SARs are defined, and they often avoid specifying the characteristics of each role. A previous study carried out by Christodoulou & Pnevmatikos (2022) followed a bottom-up participatory approach for designing a personality of a SAR for learning and instruction and particularly for STEM education, aimed at addressing this research gap. With this approach, the authors explored the perceptions of 24 education stakeholders (parents, school directors, students, and teachers) about the personality of a SAR for learning and instruction. The results highlighted that the stakeholders attributed to a SAR for learning and instruction for STEM education, the social roles of a teaching agent and an assistant for everyday tasks. Additionally, stakeholders projected on the robots more specific "traits" and behaviors that teachers usually display during learning and instruction as well as during in-class student-teacher interactions. These "traits" and behaviors projected on the robot two representations of teachers. In the first, the robot was perceived like a teacher who is facilitating learning and instruction, while in the second representation the SAR was perceived as a more authoritarian figure that evaluates students and provides them feedback without displaying any pedagogical tact (Christodoulou & Pnevmatikos, 2022).

Cultural Impact of SAR's Personality Design

Understanding the structure of the personality of a SAR is essential not only for fostering meaningful interventions in education contexts but also for tailoring HRIs to the cultural context of the users. Cultural background profoundly impacts how individuals perceive and interact with robots (e.g., LeTendre et al., 2001; Mavridis et al., 2012), influencing their expectations, attitudes, and the interpretation of robots' behaviors and traits. Cultural norms and values shape the design and functionality of SARs, from their physical appearance and communication styles to their perceived personality traits. For instance, Lee et al. (2010) highlight how differences in cultural backgrounds (i.e., Korean vs US) can lead to varying interpretations of a robot's design, such as its shape, size, and gender. Moreover, cultural variations influence the attribution of personality traits to robots. Weiss et al. (2012) found that cultural background (i.e., Dutch vs. German) mediates how personality traits like extroversion or introversion are perceived in robots. This suggests that a robot designed to be perceived as extroverted in one cultural context might be interpreted differently in another.

The current study

So far, we have established that for educational interventions exploiting SARs to be effective, identifying the structure of the robots' personality is essential. However, the design of robot personalities according to human personality theories poses several limitations. These limitations concern the expression of personality traits on SAR's, the impact of personality traits on HRIs, the context-specificity of the robot personality design, and the lack of consensus on the specific traits attributed to the social role of SARs for learning and instruction. Moreover, previous literature reviews and empirical studies engaging education stakeholders underline that particular social roles are attributed to social robots. Some of them, like the social role of the teaching agent are relevant for learning and instruction. However, apart from the study by the main authors of this article (Christodoulou & Pnevmatikos, 2022), we have not identified studies suggesting specific "traits" for the design of the personality of a SAR as a teaching agent for learning and instruction in STEM education. This study proposed that the SAR could be perceived with two dimensions, as a facilitator and as a regulator, but there remains a gap in understanding how students, as key stakeholders, perceive such personality traits. Thus, the first research question of the study was to explore students' perceptions of the personality of a SAR involved in learning and instruction, focusing on how students conceptualize the personality traits of such robots. Due to the explorative nature of the first research question, no hypotheses were identified. Moreover, a second research question was formulated, namely what the structure of these perceptions is. In this case, the analysis could reveal that the two dimensions of the robot personality for learning and instruction could be independent resulting in two different robotic personalities (Hypothesis 1), the two dimensions could be related (Hypothesis 2) and the two dimensions could tap on a second order factor, indicating that the two dimensions are interpreted by a latent factor (Hypothesis 3). Further, previous research studies revealed that the perceptions of the robot's social role differed according to stakeholders' age (Cheng et al., 2018). Additionally, the impact that culture can have on the design of a SAR's Personality can be crucial (Weiss et al., 2012). So far, there are no studies investigating the role of students' or other education stakeholders' gender in the social role of a SAR. However, there are limited results in HRI studies indicating that factors like gender could influence perceptions about SARs. In particular, a study by Nomura and Suzuki (2023) revealed that individuals with stronger gender biases had more negative attitudes in regard to the social influence of robots and that expectations of social robots' gender appearances were influenced by individuals' gender. Therefore, the fourth research question of the current study was to explore how students' endorsements (preferences) of the two dimensions of the SAR's personality could vary based on individual factors, such as students' age, cultural background and gender. Our hypothesis (Hypothesis 4) was that students' age, cultural background and gender would differentiate their endorsements of the robot's personality. Still, due to a lack of more specific and relevant previous research data, more concrete hypotheses could not be articulated.

Method

Participants

Table 1. *Participants' descriptive information*

Country	Gender	Education Level			Total
		Primary Education	Lower Secondary Education	Upper Secondary Education	
Finland	Female	101	93	67	261
	Male	98	114	48	260
	Other	3	10	3	16
Greece	Female	90	77	106	273
	Male	98	84	91	273
Total		390	378	315	1083

A total of 1,083 students from Finland and Greece participated in the study, encompassing primary (N=390, M=11.23, SD=0.72), lower secondary (N=378, M=14.10, SD=0.85), and upper secondary (N=315, M=16.82, SD=0.77) education levels. Table 1 presents participants' descriptive information, also including information on participants' self-reported gender. A power analysis using GPower 3.1 indicated that to detect a small effect size (η_p^2 = 0.25) with a power (1−β) of 0.95, a correlation between repeated measures of r =0.5, and an alpha level of 0.05 (two-tailed), a sample size of 91 participants is required. This calculation is based on seven groups [gender (2), countries (2) and educational level (3)] and two measurements (2 personality dimensions) for conducting Repeated Measures Analysis of Variance (ANOVA). If the alpha level is adjusted to 0.01 (two-tailed), with all other variables remaining constant, the required sample size increases to 119 participants. Thus, the total number of students engaged in the study was deemed appropriate. The students who participated in the study were selected through convenience sampling.

Data collection

The data was collected as part of a HORIZON 2020 research and innovation program (grant agreement No. 709515) during 2017-2018. The data collection process was facilitated by a letter informing and inviting participants to take part in the study (Patton, 2002). Additionally, a consent form was prepared and distributed to the participants in advance. For underage students, parents and legal guardians signed the consent forms. These forms were collected promptly to ensure all participants could partake in the study. Data collection was in accordance with the ethical standards as laid down in the 1964 Declaration of Helsinki and its later amendments.

A self-administered questionnaire in electronic format was prepared for data collection. The questionnaire was designed based on topics identified in a previous study (Christodoulou & Pnevmatikos, 2022), creating a pool of potential variables to include. Specifically, these topics were the traits and behaviors attributed to the two personality aspects of a SAR as a teaching agent and were identified through bottom-up content analysis (Christodoulou & Pnevmatikos, 2022). Moreover, the potential variables included in the created pool were the wishes the education stakeholders expressed during the study. Table 2 presents the traits and behaviors that represented the two aspects of the social robot's personality for learning and instruction, namely the facilitator and the regulator, along with the attributed traits and behaviors as well as some of the potential variables included in the pool, while creating the data collection tool.

Table 2. *The traits and behaviors attributed to the two aspects of a SAR's personality (according to Christodoulou & Pnevmatikos (2022) and some examples of questions included in the data collection tool*

Personality aspect	Traits and Behaviors (example questions)
Facilitator in Learning and Instruction	- Motivation (e.g., I wished my robot could reward me if I managed to do something demanding) - Source of Information-Knowledge transfer (e.g., I wished my robot could find information in the internet when asked to) - Assistant in learning (e.g., I wished my robot helped me learn how to learn for problem solving.) - Guidance in STEM subject matters (e.g., I wished my robot could facilitate me understand what I do not understand in STEM related courses.)
Regulator in feedback and students' evaluation	- Monitoring students' progress (e.g., I wished my robot could evaluate me according to my school performance.) - Judge (e.g., I wished my robot could tell me when my behavior made it sad.) - Reminding of rules (e.g., I wished my robot could remind me how should I behave according to class rules.)

The questionnaire consisted of two parts. The first part collected demographic data of the participants (e.g., gender, age, education level), while the second part included 18 questions regarding the personality of a SAR for learning and instruction and particularly for the context of STEM education. The questionnaire utilized a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Participants completed the questionnaire individually using a computer or tablet online in a classroom. Teachers along with the researchers had oversight of the data collection process. Data collection took less than half a class period (20-25 minutes).

Results

To examine students' perceptions regarding the personality of a SAR involved in learning and instruction we conducted an exploratory factor analysis (EFA). The goal of the EFA is to identify latent variables that form the basis of a set of observed variables when there are no a priori assumptions about these variables (Fabrigar et al., 1999). Given the lack of prior research that could lead to formulating hypotheses for factor extraction, we used the Principal Component Analysis (PCA) approach to study the entire variance in the data and detect potential patterns.

Initially, we examined whether the variables showed significant correlation and shared sufficient variance to justify factor extraction by checking the results of Bartlett's Test of Sphericity (p<0.001) and the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy (KMO=0.892). These criteria justified factor extraction, leading us to perform PCA with varimax rotation (Kaiser Normalization).

For factor extraction, we considered the agreement between the eigenvalue criterion and the scree plot (Cattell, 1966). We retained factors with eigenvalues greater than 1. Additionally, the adequacy of the extracted factors was determined by three criteria: (1) loadings on the primary factor should be at least 0,30, ensuring a high degree of correlation between a variable and a factor (Tabachnick & Fidell, 2007); (2) there should be at least a 0,30 difference between loadings on the primary factor and other factors to ensure each variable is prominent in one factor (Di Fabio & Gorri, 2016); and (3) there should be at least three variables per factor to ensure stable and interpretable factors (Tabachnick & Fidell, 2007). The analysis revealed three components with eigenvalues greater than 1. The total variance explained was 56.06%. The analysis revealed that the first component included ten variables with loadings above 0.431, an eigenvalue of 7.38, and explained 41.02% of the total variance. The second component had eleven variables with loadings above 0.392, an eigenvalue of 1.58, and explained 8.08% of the variance. The third component had five variables with loadings above 0.302, an eigenvalue of 1.12, and explained 6.24% of the variance. Three variables out of the five showed parallel loadings violating the second adequacy criterion (parallel loading difference <0.30) (Di Fabio & Gorri, 2016) and two variables, loaded only on the third component, namely these variables were “I wished my robot could reward me even if I do not manage to do something challenging” and “I wished my robot could reward me when I do something challenging”. We excluded these two variables from further analysis as they violated the third criterion (at least three variables per factor) (Tabachnick & Fidell, 2007).

Then, we repeated the EFA with varimax rotation, including sixteen variables. Two components were revealed with eigenvalues greater than 1. The total variance explained was 52.75%. The analysis revealed that the first component included eleven variables with loadings above 0.312, an eigenvalue of 6.86, and explained 42.89% of the total variance. The second component included eleven variables with loadings higher than 0.403, an eigenvalue of 1.58 and explained 9.86% of the total variance. Six variables were loading in parallel components violating two of the adequacy criteria (loadings on the primary factor >0.30 and 0.30 difference between parallel loadings) (Di Fabio & Gorri, 2016; Tabachnick & Fidell, 2007) and were excluded from further analysis. These variables were a)“I wished my robot could remind me what I have to do in accomplishing my aims”, b)“I wished my robot could show me that it is proud that I try to solve a problem”, c)“I wished my robot could correct me when I am not thinking in the right way”, d)“I wished my robot could encourage me to do something difficult”, e)“I wished my robot could evaluate me according to my performance in school”, and f)“I wished my robot could tell me whether it is happy from the way I thought to solve a problem”.

The EFA was repeated for the third time with varimax rotation, including ten variables. The analysis revealed two components explaining 56.88% of the total variance. In particular, five variables were loaded on each component with loadings above 0.681 and 0.618 respectively. The eigenvalues were 4.16 for the first component and 1.52 for the second component explaining 41.64% and 15.24% of the variance respectively.

Table 3. *Loadings from the principal component analysis for Finland (FIN) and Greece (GR)*

Items	FN_Component		Items	GR_Component	
	1 *	2 **		1 **	2 *
I wished my robot could help me in doing my homework.	0.824		I wished my robot could tell me that it feels disappointed that I do not try hard enough.	0.818	
I wished my robot could facilitate me in studying for exams by providing me also tests.	0.803		I wished my robot could tell me that my behavior made it angry.	0.726	
I wished my robot could facilitate me understand what I do not understand in STEM related courses.	0.770		I wished my robot could tell me when my behavior made it sad.	0.713	
I wished my robot could find information on the internet when asked to.	0.759		I wished my robot could tell me that it is worried because the other students were better than me.	0.618	
I wished my robot could tell me that my behavior made it angry.		0.835	I wished my robot could facilitate me in studying for exams by providing me also tests.		0.754
I wished my robot could tell me that it feels disappointed that I do not try hard enough.		0.832	I wished my robot could facilitate me understand what I do not understand in STEM related courses.		0.719
I wished my robot could tell me when my behavior made it sad.		0.744	I wished my robot could help me in doing my homework.		0.716
I wished my robot could tell me that it is worried because the other students were better than me.		0.701	I wished my robot could find information on the internet when asked to.		0.674
Explained Variance (66.93%)	51.20%	15.73%	Explained Variance (52.71%)	32.86%	19.85%

**Note. Facilitator*

***Note. Regulator*

However, when controlling per country, we identified that in the case of the Finish data, two variables were loading in both components violating two of the adequacy criteria (loadings on the primary factor >0.30 and 0.30 difference between parallel loadings) (Di Fabio & Gorri, 2016; Tabachnick & Fidell, 2007). Thus, we decided to exclude them from further analysis. These items were “I wished my robot could tell me whether it is satisfied with my behavior” and “I wished my robot could help me learn how to learn in order to solve problems”.

Finally, the EFA was repeated for the fourth time with varimax rotation, including eight variables that loaded on two components explaining 60.31% of the total variance. Specifically, four variables were loaded on the first and four variables were loaded on the second component. The loadings on the first component were above 0.720 and 0.661 for the second component. Additionally, the eigenvalues were 3.41 and 1.41 explaining 42.72% and 17.59% of the variance respectively. In Table 3, we present the components per country, particularly the loadings of the variables per component and the total variance explained for the Finnish and

Greek data. The two components emerging from the final EFA have interpretable psychological and pedagogical value. The first factor, "Facilitator in Teaching and Learning," emphasizes the robot's support during exercises, exam preparation, problem-solving strategies, understanding challenging concepts in STEM, and information provision. The second factor, "Regulator in Emotional Feedback," highlights the importance of the robot's direct emotional feedback based on school performance.

The reliability of each component in terms of internal consistency was calculated using Cronbach's alpha per country and per component ($\alpha_{Finland\_Regulator}$=0.84, $\alpha_{Finland\_Facilitator}$=0.82, $\alpha_{Greece\_Regulator}$=0.70, $\alpha_{Greece\_Facilitator}$=0.70) and was deemed acceptable (Taber, 2017; Van Griethuijsen et al., 2015). The overall internal consistency of the questionnaire per country was acceptable ($\alpha_{Finalnd}$=0.86, α_{Greece}=0.70). The overall internal consistency of the questionnaire per component was acceptable ($\alpha_{Regulator}$=0.77, $\alpha_{Facilitator}$=0.78) and for both components was good (α=0.80).

To investigate the structure of the two SAR personality components derived from EFA, we conducted a Confirmatory Factor Analysis (CFA) using EQS software (Bentler & Wu, 2003). Confirmatory factor analysis (CFA) is a subset of structural equation modeling focused on measurement models. It examines the relationships between observed indicators, such as test items, scores, or behavioral ratings, and latent variables or factors (Brown & Moore, 2012). Due to multivariate non-normality, indicated by Mardia's multivariate kurtosis normalized estimate exceeding 5.0, the ML robust estimation method was utilized (Byrne, 2013). Therefore, robust estimates, including the Satorra-Bentler (SeB) chi-square, CFI, RMSEA, and its 90% confidence interval (CI), were utilized, with values approaching 1.00, indicating an excellent fit.

Three models were tested with the CFA. The first model assumed that the two components identified in the EFA are two uncorrelated factors representing separate constructs. The second model assumed a correlation between the two factors. The third model introduced a higher-order factor, indicating that the two components essentially tap the same underlying construct. The analysis was conducted on the entire data and for each country separately. The first model with the two uncorrelated factors had a weak fit to the data. The second model with the two correlated factors demonstrated an adequate fit. In contrast, the third model with the second-order factor had the best fit for the data, deeming this solution as the most appropriate (Table 4). This model assumes that the two components measure the same underlying construct. This construct suggests that facilitating teaching and learning, along with providing emotional feedback are two dimensions of the SAR's personality for education.

Table 4. *Structural Equation Models examined the structure of the SAR's personality for education*

Model	**S-B χ^2**	**df**	**sig**	**CFI**	**ΔCFI**	**RMSEA**	**90% CI**
Model 1	232.539	20	<.001	.893	-	.099	[.088, .111]
Model 2	84.429	19	<.001	.967	.074	.056	[.044, .069]
Model 3	40.575	17	<.001	.988	.021	.036	[.022, .050]

Further, we tested the confirmed model (Model 3) for invariance using a Multi-Group Confirmatory Factor Analysis (MGCFA) with EQS software (Bentler & Wu, 2003). This approach would allow us to evaluate the responses of the two cultural groups (FN & GR) to the questionnaire. Invariance refers to a condition where differences in the key statistical properties of group responses to a questionnaire are so minor that they can be attributed to chance rather than to inherent group characteristics (Vandenberg & Lance, 2000). To compare mean scores between groups, multiple levels of equivalence must be established. First, the pattern of fixed and free factor loadings between items and factors must be consistent across groups (known as configural invariance) (Vandenberg and Lance 2000; Wicherts & Dolan, 2010). A good indicator of configural invariance is an RMSEA value of less than .05 (Brown et al., 2015). Second, the regression weights from factors to items should only vary due to chance, with metric invariance indicated by a small change in CFI (i.e., ΔCFI ≤ .01, i.e., metric invariance) (Cheung & Rensvold, 2002). Third, the intercepts of items on factors should also only vary by chance, with scalar invariance confirmed if ΔCFI ≤ .01. Under measurement invariance, all measurement parameters should remain consistent across groups (i.e., strict invariance). Configural, metric, scalar and strict invariance are necessary to confirm measurement invariance and allow group comparisons (Vandenberg & Lance, 2000). A joint model (2 groups) for all participants was tested for invariance using MGCFA. Table 5 presents the results of the invariance measurement, indicating that the differences between the two cultural groups can be due to chance and not group characteristics.

Table 5 *Multi-group Confirmatory Analysis examined invariance between Finland and Greece*

Model	χ^2	df	sig	$\Delta\chi^2$ (Δdf)	CFI	ΔCFI	RMSEA [90%CI]	Δ RMSEA	AIC
Configural Invariance	111.310	32	<.001	-	.976	-	.034 [.027,.041]	-	47.31
Metric Invariance	126.629	40	<.001	-15.31(-8)	.973	-.003	.032 [.025, 0.038]	-.002	46.63
Scalar Invariance	113.551	32	<.001	13.08(8)	.975	+.002	.034 [.028, .041]	+.002	49.55
Strict Invariance	117.470	42	<.001	-3.92 (-10)	.977	+.002	.029 [.023, .035]	-.005	33.47

Table 6: *Means and Standard Deviations of Personality Dimensions by Education Level, Gender, and Country*

Subgroup	Facilitator (Ms, *SDs*)	Regulator (Ms, *SDs*)
	4.22 (*0.78*)	3.32 (*0.98*)
Education Level		
Primary	4.37 *(0.73)*	3.61 *(0.95)*
Lower Secondary	4.13 *(0.88)*	3.10 *(1.01)*
Upper Secondary	4.14 *(0.70)*	3.24 *(0.89)*
Country - Education Level		
Finland - Primary	4.41 *(0.77)*	3.72 *(1.00)*
Finland - Lower Secondary	4.11 *(0.97)*	3.15 *(1.09)*
Finland - Upper Secondary	4.09 *(0.74)*	3.02 *(0.92)*
Greece - Primary	4.32 *(0.68)*	3.50 *(0.89)*
Greece - Lower Secondary	4.16 *(0.75)*	3.03 *(0.88)*
Greece - Upper Secondary	4.17 *(0.68)*	3.36 *(0.85)*
Gender - Education Level		
Female - Primary	4.34 *(0.73)*	3.72 *(0.88)*
Female - Lower Secondary	4.22 *(0.78)*	3.31 *(0.92)*
Female - Upper Secondary	4.20 *(0.67)*	3.21 *(0.93)*
Male - Primary	4.39 *(0.72)*	3.51 *(1.01)*
Male - Lower Secondary	4.06 *(0.95)*	2.92 *(1.05)*
Male - Upper Secondary	4.06 *(0.74)*	3.26 *(0.84)*
Gender - Country		
Female-Finland	4.33 *(0.74)*	3.43 *(1.01)*
Female-Greece	4.19*(0.72)*	3.41 *(0.85)*

In order to examine the value of these components among the students, we conducted a Repeated Measures ANOVA. Finish participants representing the gender “other” (N=16) were excluded from further analysis. Thus, the number of participants was 1067 (N_{female}=534). The mean scores of the personality dimensions (Facilitator vs Regulator) were used as within-subject factors, while education level, country and gender were used as between-subject factors. The analysis showed a significant main effect of the within-subject factor revealing a higher preference for the "Facilitator" dimension. See Table 6 for means and standard deviations across all subgroups, and Table 7 for repeated measures ANOVA results.

The analysis revealed that the four-way interaction was not significant. Still, some lower-order three-way and two-way interactions were identified. Regarding the three-way interactions, a significant interaction between personality dimensions, education level and country was found with a small effect size (see Table 7 for the results). One-way ANOVAs further revealed significant differences across education levels for the Finnish students regarding both the "Regulator" and "Facilitator" dimensions (see Table 8 for full details of one-way ANOVA results). Specifically, elementary students had a higher preference for both personality dimensions compared to lower and upper secondary students, but only in the "Regulator" dimension the effect size was medium. However, for the Greek students, only one difference for the "Regulator" dimension was revealed (see Table 8 for full details of one-way ANOVA results). Elementary students had a higher preference with a small effect size compared to lower and upper secondary students as well as upper secondary students compared to lower secondary students.

Another three-way significant interaction was between personality dimensions, education level and gender with a small effect size (see Table 7 for results). One-way ANOVAs revealed significant differences in the "Regulator" dimension among female students across education levels (see Table 8 for full details). Specifically, female primary education students showed a higher preference with a medium effect size for the "Regulator" dimension compared to both lower and upper secondary students. For the male students, significant differences were found for both the "Regulator" and "Facilitator" dimensions (see Table 8). Male primary education students demonstrated a higher preference for the "Regulator" dimension compared to lower secondary students, while upper secondary students showed a higher preference compared to lower secondary students. The effect size was medium. For the "Facilitator" dimension, primary education students exhibited a stronger preference compared to both lower and upper secondary students with a small effect size.

Table 7. *Repeated Measures ANOVA Results for Main Effects and Interactions*

Effect	*F*	df	*p*	η_p^2
Main Effects				
Personality Dimension (Facilitator vs Regulator)	*899.304*	1, 1000	<*.001*	.460
Three-Way Interactions				
Education Level × Country × Personality Dimension	*3.520*	2, 2000	<*.05*	.007
Education Level × Gender × Personality Dimension	*6.666*	2, 2000	<*.005*	.012
Country × Gender × Personality Dimension	*8.125*	1, 1000	<*.005*	.008
Two-Way Interactions				
Education Level × Personality Dimension	*8.553*	2, 2000	<*.001*	.016

Further, a significant interaction between personality dimensions, country and gender was found (See Table 7). The independent sample t-tests revealed a significant difference ($t_{(532)}$=2.112, p=.05) only between the female Finnish and Greek students regarding the "Facilitator" dimension (see Table 6) with a medium effect size (Cohen's d=.182).

Finally, a significant two-way interaction was found between education level and personality dimensions, with a small effect size (see Table 7 for results). One-way ANOVAs revealed significant differences across education levels for both the "Regulator" and "Facilitator" dimensions (see Table 8 for full details). Specifically, elementary students showed a higher preference for the "Regulator" dimension compared to both lower and upper secondary students with a medium effect size. Similarly, elementary students demonstrated a stronger preference for the "Facilitator" dimension compared to lower and upper secondary students, but the effect size was small.

Table 8. *One-Way ANOVA Results for Education Level, Gender, and Country*

Dependent Variable	Subgroup	*F*	df	*p*	η_p^2	Post-Hoc Comparisons
Regulator (Finland)	Education Level	*23.154*	2, 520	<.*001*	.082	Primary > Lower Secondary* Primary > Upper Secondary*
Facilitator (Finland)	Education Level	*8.125*	2, 1066	<.*001*	.030	Primary > Lower Secondary** Primary > Upper Secondary**
Regulator (Greece)	Education Level	*12.754*	2, 545	<.*001*	.045	Primary > Lower Secondary* Upper Secondary>Lower Secondary**
Regulator (Female)	Education Level	*16.141*	2, 533	<.*001*	.057	Primary > Lower Secondary* Primary > Upper Secondary *
Regulator (Male)	Education Level	*17.800*	2, 532	<.*001*	.063	Primary > Lower Secondary * Upper Secondary > Lower Secondary***
Facilitator (Male)	Education Level	*9.802*	2, 532	<.*001*	.036	Primary > Lower Secondary * Primary > Upper Secondary **
Regulator	Education Level	*29.417*	2, 1066	<.*001*	.052	Primary > Lower Secondary* Primary > Upper Secondary*
Facilitator	Education Level	*10.792*	2, 1066	<.*001*	.020	Primary > Lower Secondary* Primary > Upper Secondary*

*.001, **.005, ***.01

Discussion

The aim of the current study was to investigate students' perceptions of the personality of SAR used in learning and instruction. In particular, we were interested in investigating the structure of the personality of SAR for learning and instruction assuming that the two dimensions of the robot personality for learning and instruction could be independent (H1), be related (H2), or they could tap on a second order factor, indicating that the two dimensions are interpreted by a latent factor (H3). To meet this aim, we conducted an EFA to investigate the structure of students' wishes regarding the personality of a SAR for education in a cross-cultural setting, namely the education context of Greece and Finland. Then, we verified the structure from the EFA with a CFA and conducted invariance measurements to identify potential cross-cultural differences. The results of the analysis revealed that the two dimensions of the SAR personality for learning and instruction tap on a second order factor. Moreover, since invariance was established, we can argue that the structure of the personality of a SAR for learning and instruction has the same meaning across different cultural groups. Further, we explored students' preferences between the personality dimensions revealed by the CFA, as we assumed that students' age, cultural background and gender would differentiate their endorsements of the robot's personality (H4). For this purpose, we conducted a repeated measures ANOVA identifying some cross-group differences with small and medium effect sizes.

Specifically, the findings of the exploratory analysis highlighted that the personality of a SAR for education has two dimensions: the "Facilitator" in learning and instruction and the "Regulator" of emotional feedback. Eight variables are loaded under these two components. In the first case, the dimension is conceptually more straightforward, portraying the behavior of a teacher facilitating students in learning and instruction. Four variables loaded under this component reflect the robot's instructional and learning guidance during homework of STEM-related concepts, along with support in exam preparation and provision of information to students. The robot's role as a "Facilitator" in teaching and learning aligns with psychological and pedagogical theories related to constructivist and student-centered approaches. According to Rogers, who redefined the teacher's role as a "Facilitator" rather than an authoritative figure, educators should focus on the student's personal development through autonomous learning, empathy and acceptance (Rogers & Freiberg, 1994). Contemporary research also emphasizes balancing information provision and student support, which can be challenging for educators (Strømme & Furberg, 2015). This aspect emerged in the robot's "Facilitator" personality dimension. Although balancing information provision and support may seem contradictory for the "Facilitator" role, we view these elements as complementary, not contradictory. This aligns with Robertson's (2005) "Generative Paradox" in student-centered teaching, where seemingly contradictory elements, like facilitation and information provision, complement each other, ensuring student autonomy and content knowledge are not compromised during learning experiences. Yew and Yong (2014) revealed in their study that students value teachers reflecting the role of a Facilitator when they have strong content knowledge (deep understanding and effective communication).

The second component that emerged was the "Regulator" of emotional feedback. Four variables are loaded under this component. This dimension suggests that the robot functions as an agent that provides emotional feedback to students based on their behavior or school performance. Teachers' emotional feedback to students can manifest in teachers' verbal praise or criticism towards students' behavior (Brophy, 1981). The impact of praise and criticism on students is mixed. On the one hand, research shows that both verbal praise (e.g., Droe 2013) and criticism (e.g., Guo et al., 2019) can enhance student motivation in specific contexts (criticism was effective in low-performing students). On the other hand, findings indicate that verbal praise may be ineffective in motivating students (e.g., Benson-Goldberg & Erickson, 2021; Maclellan, 2005), and criticism can undermine student motivation and effectiveness (e.g., Atlas et al., 2004). Notably, the variables that loaded under this component were associated with the robot's criticism towards students. This behavior could pose the SAR as an inflexible, straightforward and unempathetic agent. Pedagogically, this lack of empathy and flexibility might relate to a teacher lacking "pedagogical tact" (van Manen, 2015). However, previous research has highlighted that people perceive robots as having a low capacity for empathy (Gray et al., 2007), which could explain the perception of the SAR as lacking pedagogical tact.

The EFA revealed differences between the two countries in terms of the variance that each component explained per country as well as differences in the variables' loadings on each component per country. The analysis revealed that the Finnish data were better explained by the "Facilitator" component (51.20%) compared to the "Regulator" component (15.73%), while Greek data presented a more balanced variance, with the "Regulator" component (32.86%) explaining slightly more than the "Facilitator" component (19.85%).

Loadings on each component also differed. For example, in the “Facilitator” component, variables related to practical support, like homework and STEM understanding, had a higher ranking for Finnish students. In contrast, for Greek students in the “Regulator” component, higher loadings exhibited the items that related to emotional feedback, such as disappointment and anger.

The CFA verified the structure of the SAR’s personality, indicating that the two personality dimensions of the SAR constitute two aspects of an underlying construct. This construct comprises the “Facilitator” and the “Regulator” dimensions and has psychological and pedagogical value. First, both dimensions reflect teachers’ associated behaviors in learning and instruction. Second, this higher-order factor represents a "pedagogical" latent factor essential for the design of a SAR’s personality for education. We define this latent factor as the pedagogical personality of a SAR for education. The pedagogical personality of a SAR for education consists of a set of behaviors that eventually could influence students’ learning outcomes. This study extends prior research on students' and stakeholders' perceptions of SAR in learning and instruction (e.g., Ahmad et al., 2016; Belpaeme et al., 2018; Cheng et al., 2018; Kennedy et al., 2016; Mubin et al., 2013; Pnevmatikos et al., 2022; Serholt et al., 2014; Shin & Kim, 2007) by moving beyond the mere mapping of perceptions to a deeper investigation of their underlying structure.

Despite the differences identified in the EFA between Finnish and Greek students, the analysis established invariance for cross-cultural comparisons. Specifically, the questionnaire exhibited configural, metric, scalar, and strict invariance across the Finnish and Greek groups. This indicates that the measurement tool operates similarly across these cultural contexts, and the observed differences in the latent construct of "social robot personality" could be attributed to actual differences between the two groups rather than measurement bias. Still, as the repeated measures ANOVA revealed the effect sizes regarding these differences were in their majority small and only in a few cases medium. Therefore, the differences likely stem from the varying approaches and values of the two educational systems, which may shape how students in each country perceive the role of a SAR in education. On the one hand, Finland is known for its student-centered model, characterized by a high level of trust in teachers and a minimal focus on standardized testing. These factors might lead Finnish students to view the SAR mainly as a facilitator in their learning process. On the other hand, the Greek educational system is more teacher-centered and emphasizes exam preparation, which may influence students to regard the SAR as an authority figure who provides emotional feedback rather than just a facilitator. Further, cultural norms may further highlight these distinctions, though it’s important to consider that these cultural influences may be subtle, especially given that most of the effect sizes are small. Finnish culture tends to prioritize autonomy and self-regulation, possibly leading to a greater emphasis on components related to learning facilitation and support. In contrast, Greek culture emphasizes authority and adherence to rules, which may result in a stronger preference for the SAR’s regulatory and feedback-oriented behaviors. Additionally, in the "Regulator" component, variables such as expressions of anger, disappointment, sadness, or worry—as well as comparisons among students—might be viewed less favorably in the Finnish educational context, which values constructive and personalized feedback. However, it is essential to highlight again that these cultural differences do not necessarily imply drastic differences between the two groups.

Moreover, in this study, we examined students’ preferences between the dimensions of the SAR’s personality as verified by the CFA. Repeated Measures ANOVA revealed a main effect concerning students’ higher preference for the SAR’s “Facilitator” personality dimension over the “Regulator” dimension. This difference may be attributed to the guidance and support associated with the “Facilitator” dimension. Previous studies suggest that when teachers adopt teaching methods that support student autonomy, engagement and motivation increase (Hospel & Galand, 2016; Reeve, 2012; Reeve & Jang, 2006). Additionally, the preference for the robot as a Facilitator may reflect a preference for the positive student-teacher relationship developed when teachers adopt student-centered teaching practices (Cornelius-White et al., 2020).

Although the effect sizes were small, age-related, cultural-related, and gender-related differences were evident with respect to the students' endorsements' regarding the two SAR's personality dimensions. As far as the age-related differences in preferences for the two pedagogical personality dimensions are concerned, elementary students showed significant preference for the "Regulator" and the "Facilitator" dimensions compared to middle and upper school students. Interestingly, this preference was evident only for the "Regulator" when the effect was controlled across the two countries. In both countries, primary education students preferred the "Regulator" dimension of the SAR's pedagogical personality, while the "Facilitator" was endorsed by Finnish primary education students. Studies have shown that younger children aged 6-11 benefit from direct, authoritative guidance that provides reassurance and explicit direction (Martínez-Miranda et al., 2018). Moreover, the consistency of preferences for the "Regulator" dimension across different cultural contexts, such as Finland and Greece, most likely underscores a universal aspect of early childhood, namely that regardless of the educational system, younger students benefit from an authoritative teaching agent that recognizes achievements, and correct mistakes. As students mature and become more independent in middle and upper school, they are more likely to value the "Facilitator" dimension, which supports autonomy and self-regulated learning. This shift in preferences reflects the developmental changes in students' needs, where older students require less external regulation and more opportunities for autonomous learning (Bardach et al., 2023). Still, students' endorsement of the "Facilitator" dimension, which supports autonomy and learning, is stronger among Finnish primary education students than older or Greek students. This finding is most likely interpreted culturally, as the Finnish educational system emphasizes student-centric instruction and supports students in constructing self-regulation and autonomy skills.

Some gender differences in preferences of the SAR's personality dimensions were revealed. In particular, female primary education students preferred the "Regulator" personality dimension. This could be interpreted by the fact that female elementary students score higher in conscientiousness and agreeableness traits, which implies that they could be more diligent and tend to conform to classroom norms compared to boys (Herrera et al., 2020). For male primary education students, the significant preference for both SAR's personality dimensions indicates that boys value not only the emotional feedback guidance but also the supportive role of the SAR in their learning, showing a balanced need for both types of interaction. Previous studies have shown that boys are not affected negatively by teachers' criticism in comparison to girls (Guo & Zhou, 2021), which implies that boys may be more receptive to feedback, whether it is positive or negative. This interpretation would justify boys' preference for emotional feedback from the SAR. Moreover, Madill and colleagues (2014) revealed in their previous study that supportive teacher-child interactions can foster a positive classroom environment, particularly for boys, which could justify why boys highly endorsed the "Facilitator" dimension. Finally, results revealed a higher mean score of Finnish female students compared to Greek female students towards the "Facilitator" dimension. This finding could be interpreted by the strong emphasis given to the promotion of gender equality in the Finnish educational system (see e.g., Brunila & Kallioniemi, 2018), where girls might feel more empowered and value more teaching styles that reflect the "Facilitator" teaching behavior, in comparison to Greek society, where cultural expectations and gender stereotypes still permeate Greek education (Kitta & Cardona-Moltó, 2022).

The present study introduces a novel investigation of the culturally validated structure of the personality of a SAR for education, revealing significant implications for educational practice and SAR design. By identifying the latent factor of pedagogical personality with the dual dimensions of "Facilitator" and "Regulator" within the SAR's personality, this research underscores the potential of SARs to enhance student learning and emotional engagement through tailored, culturally sensitive interactions. The findings highlight the importance of considering cultural, age-related, and gender-related differences when integrating SARs into educational settings. The preference for the "Facilitator" dimension, particularly among Finnish students, emphasizes the value of student-centered approaches and the need for autonomy-supportive educational tools. Conversely, the significance of the "Regulator" dimension for younger students suggests a crucial role for structured emotional feedback in early education. This study offers a foundational framework for developing SARs that align with pedagogical principles and diverse student needs, advancing educational technology.

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ΕΜΠΕΙΡΙΚΗ ΕΡΓΑΣΙΑ | RESEARCH PAPER

Αντιλήψεις μαθητών για τη δομή της προσωπικότητας ενός Ρομπότ Κοινωνικής Αρωγής για την εκπαίδευση

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ABSTRACT IN GREEK

Οι υπεύθυνοι χάραξης πολιτικής θεωρούν, ότι η εφαρμογή των Ρομπότ Κοινωνικής Αρωγής (ΡΚΑ) στην εκπαίδευση είναι απαραίτητη για τον μετασχηματισμό της διδασκαλίας και την υποστήριξη των μαθητών στην επίτευξη καλύτερων μαθησιακών αποτελεσμάτων. Ωστόσο, ανακύπτουν διάφορα ερωτήματα σχετικά με τις προϋποθέσεις εφαρμογής των ΡΚΑ στην εκπαίδευση. Η παρούσα μελέτη είχε ως στόχο να διερευνήσει τις αντιλήψεις μαθητών και μαθητριών σχετικά με την προσωπικότητα ενός ΡΚΑ για την εκπαίδευση. Ένα διαδικτυακό ερωτηματολόγιο χορηγήθηκε σε 1083 μαθητές δημοτικού (N=390, M=11.23, SD=.72), γυμνασίου (N=378, M=14.10, SD=.85) και λυκείου (N=315, M=16.82, SD=.77) στην Ελλάδα και τη Φινλανδία. Η διερευνητική παραγοντική ανάλυση αποκάλυψε δύο παράγοντες με ψυχολογική σημασία που αντικατοπτρίζουν δύο τύπους της προσωπικότητας ενός ΡΚΑ για την εκπαίδευση: Το ΡΚΑ ως "ρυθμιστής" και ως "διευκολυντής". Στη συνέχεια, μια επιβεβαιωτική παραγοντική ανάλυση έδειξε, ότι την καλύτερη προσαρμογή στα δεδομένα είχε το μοντέλο στο οποίο οι δύο διαστάσεις της προσωπικότητας του ΡΚΑ ερμηνεύονταν από έναν δεύτερης τάξης παράγοντα. Η δομή της προσωπικότητας επιβεβαιώθηκε και στις δύο χώρες. Εντούτοις, εντοπίστηκαν κάποιες διαφορές που σχετίζονται με την ηλικία, το φύλο και το πολιτισμικό πλαίσιο των μαθητών και μαθητριών ως προς τις διαστάσεις της προσωπικότητας του ΡΚΑ. Η επιβεβαίωση της δομής της προσωπικότητας ενός ΡΚΑ για την εκπαίδευση μπορεί να ενημερώσει το σχεδιασμό και την ανάπτυξη πιο αποτελεσματικών ΡΚΑ προσαρμοσμένων σε συγκεκριμένα πολιτισμικά πλαίσια και στις προτιμήσεις των μαθητών και των μαθητριών. Επιπλέον, τα ευρήματα αυτά ενισχύουν την κατανόηση της Αλληλεπίδρασης Ανθρώπου-Ρομπότ στην εκπαίδευση.

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