SOCIALLY ASSISTIVE ROBOTS IN HIGHER EDUCATION: STUDENTS' PERCEPTIONS AND EXPECTATIONS VIA THE UTAUT MODEL

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Abstract - The integration of robots in education is becoming increasingly dynamic. A particularly relevant topic is the use of socially assistive robots (SAR) in higher education institutions. This study presents students' attitudes towards the use of SAR in the educational process. A total of 199 students from various specialties at "Paisii Hilendarski" University of Plovdiv, Bulgaria, participated in the survey. A structural equation model (SEM) was used in the context of the Unified Theory of Acceptance and Use of Technology (UTAUT), which includes factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions. The results indicate that the model is largely good and reliable for assessing students' attitudes towards the use of socially assistive robots in the educational process, as all major UTAUT factors provide insight into students' understanding and acceptance of these technologies.

Keywords -Human-Robot Interaction, Socially Assistive Robots, Acceptance, Higher Education, UTAUT Model

I. INTRODUCTION

Education is undergoing a revolution as digital technologies penetrate deeper into the learning process. The digitization of educational content, the use of online platforms, and interactive tools transform the way teachers teach and students acquire knowledge (Johnson 2021). These new technologies are complex, and there is an element of uncertainty associated with their use in people's minds. Therefore, they form certain attitudes and intentions related to their efforts to learn to use the new technology even before they begin to exert effort. Attitudes and intentions to use may be unclear, lack confidence, or confidence may appear only after some experience with the technology (Bagozzi et al. 1992).

Education has always been integral to human development, and computers have been incorporated into training systems for many years. The integration of robots into education appears to be a logical progression from using static computers. Human-Robot Interaction (HRI) has become a broad and varied field of research and design, with the body of literature growing quickly and producing hundreds of publications annually (Sheridan, 2016). Most studies related to the use of robots in education have used educational robots like Cellbot, LEGO Mindstorms, etc. (Cruz-Martín et al. 2012; Aroca et al. 2013) or telepresence robots (Double Robotics) based on artificial intelligence (Corsby & Bryant 2020). Very few studies are related to the use of socially assistive (or humanoid) robots in higher education such as NAO robot, Humanoid robot, SIMROID, Pepper robot (Buchem 2023; Abe et al. 2018), and Furhat (Kulathunga & Universit 2024). Regardless of their actual effectiveness and roles, social robots can be beneficial only if students are willing to use them. In general, attitudes related to social robots used in education appear to be positive (Guggemos et al., 2022).

Objectives of The Study

This study aims to fill this gap and explore students' attitudes towards the use of social robots in higher education, as well as to examine whether socio-demographic factors such as gender, age, and specialty influence these attitudes. We adopted the Unified Theory of Acceptance and Use of Technology (UTAUT) as the theoretical framework. UTAUT is an integrated causal model developed to describe and predict the acceptance and use of technology in various fields and has been empirically tested for validity and reliability in previous studies (Tarhini et al. 2014; Venkatesh & Davis, 2000, etc.). In our study, the research model shown in Fig. 1 includes determining factors Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) that are likely to affect Behavioral Intention (BI). These factors help form a positive or negative judgment of the individual when interacting with new technology.

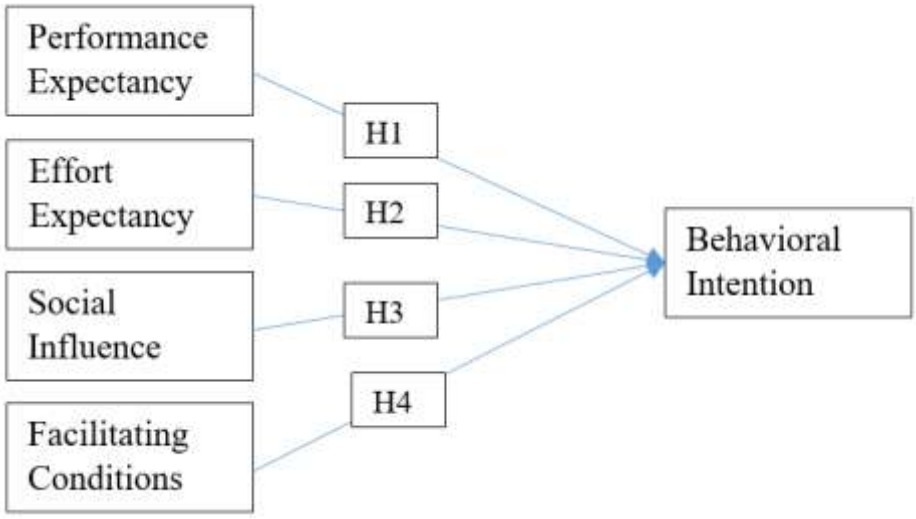


Figure 1. UTAUT conceptual framework

Hypotheses

Performance Expectancy (PE) is the perceived usefulness of adopting a technology and the belief that its use will help in work (Venkatesh et al. 2003). In the context of this study, PE will be examined in relation to socially assistive robots and their introduction into higher education. H1: Performance Expectancy (PE) will have a significant positive effect on Behavioral Intention (BI).

Effort Expectancy (EE) is defined by Venkatesh et al. (2003) as the ease with which the new system is accepted. H2: Effort Expectancy (EE) will also have a significant positive effect on Behavioral Intention (BI).

Social Influence (SI) is a concept described by Venkatesh et al. (2003) as the individual‘s perception of the degree to which important people to them (e.g., colleagues, friends, family) believe they should accept and use a new system. H3: Social Influence (SI) will have a significant positive effect on Behavioral Intention (BI).

Facilitating Conditions (FC) is a concept that describes the degree to which individuals believe that organizational and technical infrastructures exist that support the use of a new system or technology. According to Venkatesh et al. (2003), Facilitating Conditions include the availability of resources, knowledge, and support that facilitate the adoption and effective use of a technology. H4: Facilitating Conditions (FC) will have a significant negative effect on Behavioral Intention (BI).

II. MATERIALS AND METHODS

A pilot study on students‘ attitudes towards the use of socially assistive robots in the educational process was conducted. The empirical basis of the study is based on the results of an online survey (using Google Forms) involving students from various specialties at „Paisii Hilendarski“ University of Plovdiv, Bulgaria. The survey was built around the adapted and revised UTAUT model, with factors and formulations modified to better reflect the uniqueness of the technology under study. It contains 16 questions with a Likert scale for assessment (see Appendix A). The reliability of the questionnaire was measured using Cronbach‘s alpha coefficient $\alpha = 0.805$ and is considered reliable. The results of the empirical study were processed and summarized, leading to scientifically grounded conclusions relevant to the aim and objectives of the study. Data were processed using IBM SPSS 21 and Smart PLS 4.

2.1 Method

Data collection was conducted in May 2024. A total of 204 responses were collected, but 5 were eliminated as participants did not complete the survey, making their responses incompatible with our analysis. This resulted in a final database of 199 responses from participants with an average age of 26 years. The demographic profile of the sample was outlined by grouping the studied individuals by gender, age, and specialty (Table 1).

Demographic Feature	Categories	%
Age	up to 20 years	23%
	21 - 30 years	59%
	31 - 40 years	10%
	41 - 50 years	8%

Demographic Feature	Categories	%
	over 50 years	-
Specialty	Pedagogy	7%
	Philology	22%
	Economics and Finance	21%
	Law and Public Administration	12%
	Mathematics and Informatics	4%
	History and Philosophy	13%
	Biology	13%
	Chemistry	4%
	Physics	6%
Gender	Male	15%
	Female	85%
	Prefer not to answer	-

Table 1. Demographic Characteristics

The initial measurement model was partially determined using exploratory factor analysis in SPSS, employing principal axis factoring and Varimax rotation. The KMO test for data suitability was 0.852 with $p < 0.001$, indicating high suitability. To prove the main hypotheses, a structural equation model was created (Fig. 2).

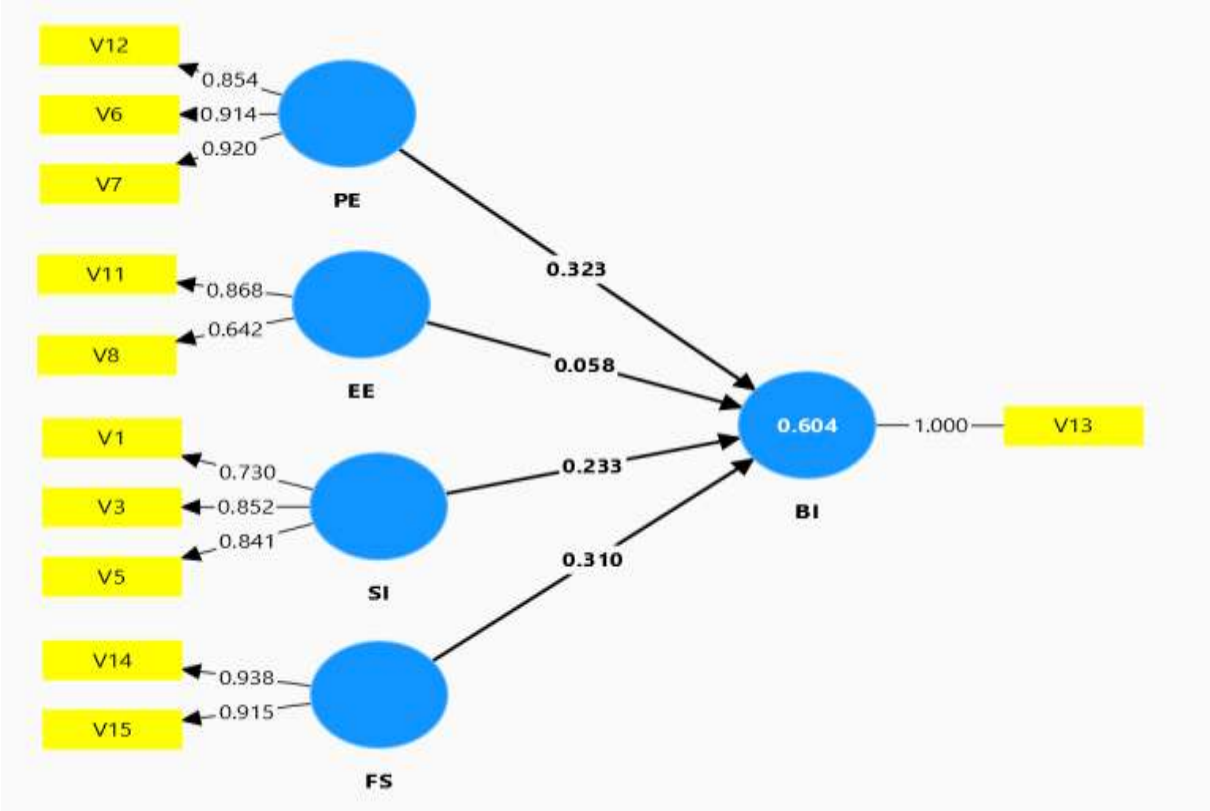


Figure 2. Structural Equation Model

The first step in measuring the reflex is the internal consistency of the latent variable. Table 2 shows the reliability and validity of the constructs. Hair et al. (2016) recommend using composite reliability (CR), which includes both ρa (total reliability) and ρc (composite reliability), as a better measure of internal consistency compared to traditional Cronbach's Alpha. They highlight that CR provides a more accurate estimate, especially in the context of confirmatory factor analysis (CFA). They also propose using convergent validity (average variance extracted, AVE) to assess the commonality among the constructs and ensure that each latent construct accounts for most of its indicators.

Constructs	Items	ρa	ρc	AVE
Performance Expectancy	PE1 - PE3	0.819	0.876	0.705
Effort Expectancy	EE1 - EE3	0.771	0.852	0.661
Social Influence	SI1 - SI4	0.723	0.819	0.602
Facilitating Conditions	FC1 - FC4	0.825	0.892	0.676
Behavioral Intention	BI1 - BI4	0.812	0.881	0.678

Table 2. Constructs Reliability and Validity

The second step is to evaluate the discriminant validity of the constructs by applying the Fornell-Larcker criterion. According to Fornell and Larcker (1981), a latent construct should explain more variance in its own indicators than in the indicators of other constructs in the model. Therefore, the AVE for each construct should be greater than the shared variance with other constructs. In Table 3, the square root of the AVE for each construct is compared with the correlations between the constructs.

Constructs	PE	EE	SI	FC	BI
Performance Expectancy	0.840	0.486	0.425	0.375	0.611
Effort Expectancy	0.486	0.813	0.470	0.422	0.608
Social Influence	0.425	0.470	0.776	0.387	0.481
Facilitating Conditions	0.375	0.422	0.387	0.822	0.462
Behavioral Intention	0.611	0.608	0.481	0.462	0.823

Table 3. Discriminant Validity

III. RESULTS AND DISCUSSION

Hypothesis testing was conducted using SEM in Smart PLS 4. The results indicate a positive effect of Performance Expectancy, Effort Expectancy, and Social Influence on Behavioral Intention, while Facilitating Conditions do not significantly influence Behavioral Intention (Table 4).

Path	Coefficient	t-value	p-value
PE → BI	0.352	4.425	0.001
EE → BI	0.328	4.007	0.001
SI → BI	0.210	2.547	0.012
FC → BI	0.124	1.651	0.105

Table 4. Path Coefficients

Influence of Performance Expectancy (PE) on Behavioral Intention (BI)

The analysis results show that Performance Expectancy (PE) has a significantly positive influence on Behavioral Intention (BI) with $\beta = 0.392$ and $p < 0.001$. According to Cohen (1988), the effect size is from medium to large, closer to large. This result confirms hypothesis H1, indicating that performance expectations significantly influence users' intention to adopt the new technology.

Lack of Influence of Effort Expectancy (EE) on Behavioral Intention (BI)

The structural equation model shows that Effort Expectancy (EE) has no significant influence on Behavioral Intention (BI) with $\beta = -0.036$ and $p = 0.478$, which does not confirm hypothesis H2. This means that for the sample, the expected effort required to use the technology is not a significant factor in the decision to adopt the technology.

Influence of Social Influence (SI) on Behavioral Intention (BI)

Hypothesis H3 is confirmed with $\beta = 0.340$ and $p < 0.001$.

Influence of Social Influence (SI) on Behavioral Intention (BI)

Hypothesis H3 is confirmed with $\beta = 0.340$ and $p < 0.001$, indicating a medium to large effect size according to Cohen (1988). This result demonstrates that social influence significantly impacts the behavioral intention to adopt the new technology.

Influence of Facilitating Conditions (FC) on Behavioral Intention (BI)

Hypothesis H4 is also confirmed with $\beta = 0.179$ and $p < 0.001$, showing a small to medium effect size as per

Cohen (1988). This finding indicates that facilitating conditions positively influence the intention to use the technology, though the effect is less pronounced compared to other factors.

IV. DISCUSSION AND CONCLUSION

This study utilized the UTAUT theoretical framework, adapted to explore students' general perceptions regarding the intention to use socially assistive robots in higher education. The UTAUT framework helped design and test a structural equation model (SEM) based on survey data collected from students of various majors at Plovdiv University "Paisii Hilendarski." The findings validate the model and clarify several important conclusions.

The results confirm that UTAUT can partially predict the likelihood of technology adoption intentions, highlighting the influence of Performance Expectancy (PE), Social Influence (SI), and Facilitating Conditions (FC) as factors likely to affect Behavioral Intention (BI). This finding is consistent with other studies (Venkatesh et al., 2003; Zainab et al., 2018).Additionally, Effort Expectancy (EE) did not show an impact on the intention to adopt these technologies. There are studies suggesting that EE lacks significance entirely (Andrews et al., 2021). As Andrews et al. (2021) mention, one possibility lies in the ambiguity regarding what artificial intelligence entails, which underpins socially assistive robots. Another possibility is reflected in some student responses, where they mentioned that the primary difficulty in using the robot is the age of university lecturers, who might not be able to manage the new technology. Lastly, the high cost of these robots is also a significant factor.Moreover, it is permissible that the questions related to the EE construct require additional attention and possible revision.

This study provides significant theoretical and practical insights into students' perceptions regarding the use of socially assistive robots in higher education. By applying the UTAUT model and structural equation modeling (SEM), we identified key factors influencing the intention to adopt these technologies.Overall, the results indicate that performance expectations, social influence, and the availability of appropriate conditions are key factors influencing users' intention to adopt the new technology. The effort required to use the technology is not a significant factor. This highlights the necessity of creating an environment that supports and facilitates the use of socially assistive robots in education.The study is among the first to explore students' attitudes toward using socially assistive robots in higher education. The UTAUT model reliably evaluates these attitudes. Our findings indicate that Performance Expectancy, Effort Expectancy, and Social Influence significantly predict Behavioral Intention, while Facilitating Conditions do not. Future research should investigate other factors influencing the acceptance and use of socially assistive robots in higher education.The novelty of the research lies in its focus on socially assistive robots and their role in higher education, which is a relatively new area of study. It provides valuable empirical data on students' attitudes and extends the theoretical framework of the UTAUT model in the context of education.

LIMITATIONS

Since the study is a pilot, it has some limitations. First, although the sample of 190 participants is significant, it is below the ideal size of 384 participants, calculated for a 95% confidence level and a 5% margin of error. This may affect the representativeness of the results.Another limitation is the fact that the survey was distributed only among students from Plovdiv University "Paisii Hilendarski."

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