STUDENT ACCEPTANCE OF SOCIAL ROBOTS IN HIGHER EDUCATION – EVIDENCE FROM A VIGNETTE STUDY

Josef Guggemos[1], Stefan Sonderegger[2] and Sabine Seufert[2]
[1]University of Education Schwäbisch Gmünd, Hauberweg 48, 73525 Schwäbisch Gmünd, Germany
[2]University of St.Gallen, St. Jakob-Strasse 21, 9000 St. Gallen, Switzerland

ABSTRACT

Social robots have the potential to play a vital role in education. Student technology acceptance may be considered as a driver for their successful integration in educational processes. Based on the ICAP (Interactive, Constructive, Active, Passive) framework and research on social robot roles, we have developed eight vignettes describing scenarios for the use of social robots in higher education, e.g., teaching assistant. Students in an introductory university course completed the vignettes; they answered questions based on the unified theory of acceptance and use of technology (UTAUT), as well as on their ethical approval. Drawing from a sample of N = 361 students, we carried out confirmatory factor analysis. In line with the conceptual basis, eight scenarios can be described. Overall, students do not accept social robots as presenters; however, the assessment of other roles, such as teaching assistant, is positive. By means of a latent profile analysis, we were able to identify four profiles that may be meaningful from a conceptual point of view. One profile is particularly noteworthy. It comprises students who accept social robots not as a means of instruction, e.g., as a tutor, but as a tool, e.g., to promote computational thinking.

KEYWORDS

Social Robot, Higher Education, Technology Acceptance, Vignette, ICAP, Robot Roles

1. INTRODUCTION

Social robots have the potential to enrich educational processes (Belpaeme et al., 2018; Woo et al., 2021). A social robot can be defined as "an autonomous or semi-autonomous robot that interacts and communicates with humans by following the behavioral norms expected by the people with whom the robot is intended to interact" (Bartneck & Forlizzi, 2004, p. 592). Social robots can be used to teach about the robots themselves or as teaching aids (Mubin et al., 2013). When teaching about social robots, they are the actual content of instruction, for example, to teach computational thinking (Ching et al., 2018). Besides this, social robots (in collaboration with teachers) can carry out selected duties in the classroom or venue. Such roles are: teacher, teaching assistant, evaluator, tutor, and peer (Woo et al., 2021). If social robots should take over these roles, however, investigating technology acceptance may be an important consideration (Raffaghelli et al., 2022). Regardless of their actual value, social robots might only be useful if students are willing to use them.

The paper at hand focuses on the use of social robots in higher education, in particular, on academic writing. This domain is characterised by substantial student heterogeneity (Seufert & Spiroudis, 2017). Therefore, a general issue in higher education may be particularly problematic in this context: it is difficult to offer students sufficient guidance and support (Byrne et al., 2017; Cooney & Leister, 2019; Handke, 2018). Employing human lecturers for this purpose may be impossible, mainly due to budget restrictions. Social robots might be a viable option. Studies about the general acceptance of social robots by students for learning purposes are available in this context (Guggemos et al., 2020). However, these studies in general address the overall technology acceptance of students in higher education. This may not be satisfactory because the roles that a social robot can adopt are manifold (Belpaeme & Tanaka, 2021; Mubin et al., 2013; Woo et al., 2021). A first important question would be whether the roles of social robots as pointed out in the literature are meaningful, from a pedagogical point of view, and can they be empirically separated. Gauging student acceptance for specific robot roles may be beneficial for developing further use cases. If students, for instance, do not accept a social robot as a presenter but do so as a tutor, further developments might focus on the use of such robots in a tutor setting, instead of in a presenter setting. Besides this, there may not only be variance in the assessment of social robot roles; differences within specific roles may also be present. For instance, some students may accept social robots as a tutor whereas other students, for a variety of reasons, do not accept them for this purpose. Identifying the profiles of students with a similar acceptance of social robots allows for person-centered interventions (Hofmans et al., 2020). For example, the concerns of students who are overly skeptical about using social robots could be addressed. The paper at hand aims to contribute to a more detailed picture of technology acceptance by higher education students in comparison to the available studies on the subject.

2. THEORETICAL BACKGROUND

A first step is to classify meaningful pedagogical scenarios of social robot use. To this end, we rely on the ICAP framework (Chi & Wylie, 2014). It can be used to predict the level of learning outcomes of different activities. The acronym ICAP stands for the learning activities *Interactive*, *Constructive*, *Active*, and *Passive*. The authors argue and provide empirical evidence that in terms of learning outcomes it can be expected that: Interactive > Constructive > Active > Passive. In passive learning activities, learners absorb information from the material without engaging in learning-related activities, e.g., listening to a social robot without further activities. Active learning activities are characterized by activities that do not go beyond the information presented, e.g., making verbatim notes while listening to the robot. In constructive learning activities, learners generate output that goes beyond the information contained in the material, e.g., using the robot as a tool to perform computational thinking tasks. In interactive activities, learners perform the constructive activities with others (including a robot), e.g., solving a problem in collaboration with the social robot.

The interaction with a social robot can be one-to-one (human to robot) or between a robot and multiple humans (multi-party interaction) (e.g., Żarkowski, 2019). This classification is particularly relevant from a technical perspective. The requirements for a multi-party interaction involving the perception of various social cues and linguistic input from multiple individuals is substantially more complex than for a human-to-robot interaction (e.g., identifying who is the sender and who is the receiver of a speech input). Belpaeme et al. (2018) adopted this classification in their meta-analysis. In the studies under consideration, the robot is used to teach one learner in around two-thirds of the cases, and to teach many learners in around one-third of the cases. Woo et al. (2021), who address social robots in classroom settings, distinguish between whole-class instruction and one-to-one interactions.

An established theory to evaluate student acceptance of social robots is the unified theory of acceptance and use of technology (UTAUT) (Fridin & Belokopytov, 2014). The UTAUT (Venkatesh et al., 2003) implies that the use intention can be predicted with performance expectancy, effort expectancy, and social influence. Performance and effort expectancy could be classified as internal beliefs, and social influence as external beliefs (Scherer et al., 2020). Adapted to our context, these constructs are defined as: the degree to which students believe that using social robots in a specific role will benefit them (performance expectancy), the degree of ease associated with the use of social robots in a specific role (effort expectancy), the degree to which students believe others want them to use social robots in a specific role (social influence), and the intention to use the social robot in a specific role (behavioral intention) (Venkatesh et al., 2003). Besides these generic constructs, technology, such as social robots, also brings with it (new) moral challenges (Serholt et al., 2017; Sharkey, 2016; Smakman et al., 2021). Hence, it may also be important to consider student ethical approval about the use of social robots in order to obtain a full picture of technology acceptance. Ethical approval could be defined as the degree to which students regard the use of social robots in a specific role as morally correct.

3. THE PRESENT STUDY

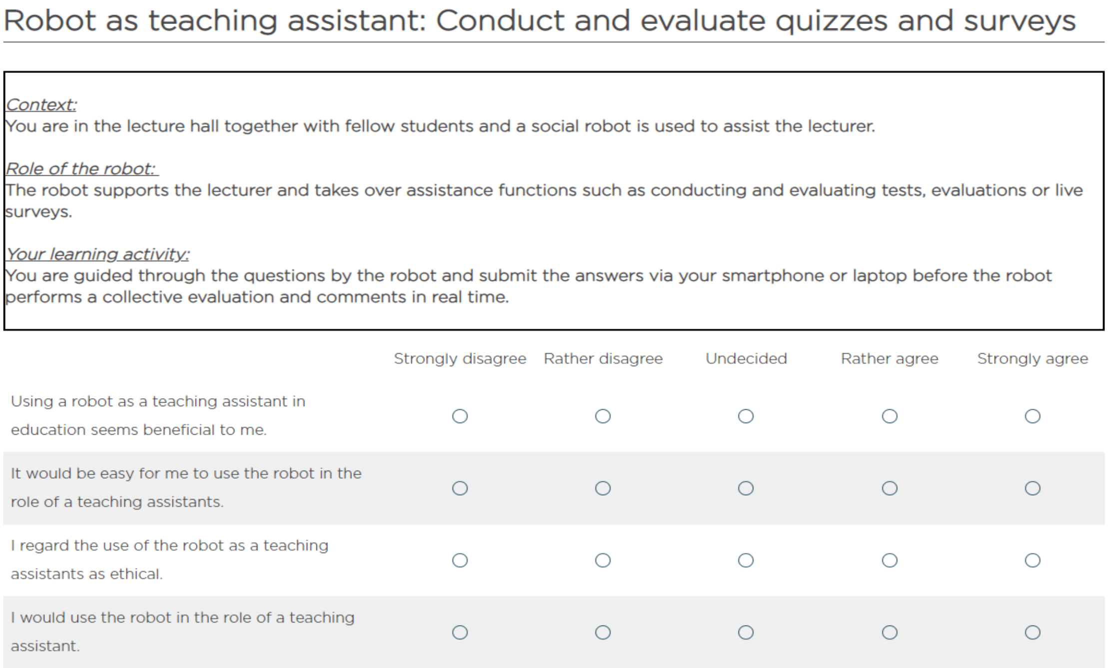
Social robots are a novel technology for higher education students, especially in the social sciences (Guggemos et al., 2020). Hence, it might be difficult for such students to assess the various roles social robots can play. A viable option to tackle this issue may be vignettes (Sailer et al., 2021). Vignettes are stimuli that present realistic scenarios in order to evoke a reaction from the study participants (Skilling & Stylianides, 2020). It may be advantageous to combine both text and videos. Hence, before performing the vignettes, all students watched a video demonstrating the capabilities of social robots, capabilities relevant for all the vignettes (https://youtu.be/GTyKb8c2b6w). The social robot in the video is a Pepper model from Softbank robotics. As previously demonstrated, Pepper may be suitable for educational purposes (Alnajjar et al., 2021) and the robot has been increasingly used in education in recent years (Woo et al., 2021). Drawing from the theoretical background, we developed four vignettes according to the ICAP framework where the robot acts in a robot-to-class setting, and four vignettes in a one-student setting. Following Skilling and Stylianides (2020), the written part of each vignette ranges between 50 and 200 words. Table 1 provides an overview of the eight vignettes.

We validated the eight vignettes in an expert interview with Prof. Handke, a renowned researcher in the realm of social robots in higher education (e.g., Alnajjar et al., 2021), and we revised the eight vignettes based on his feedback. By means of this, we may have obtained a fair representation of social robots' capabilities in higher education (see Table 1).

Table 1. Summary of eight vignettes presenting robot scenarios in higher education

Vignette	Summary of scenario	Added value of the robot	Conceptual basis
Robot-to-class scenarios (1-many)			
1. Presenter (pre) *(passive learning)*	The robot assumes the role of a content presenter in the classical teaching format for knowledge transfer, while the students have a passive role.	Relief for lecturers; variety for students; efficiency benefits; monitoring functions (e.g., attention, volume, air)	~Role of presenter (Handke, 2020, p. 111)
2. Teaching assistant (tas) *(active learning)*	The robot supports the lecturer in a teaching assistant role by conducting and evaluating quizzes or live surveys that students submit.	Support for lecturers; activation of students; evaluations in real time through connection to cloud-based survey tools or LMS	~Role of assistant (Handke, 2020, p. 122)
3. Formative assessor (fas) *(constructive learning)*	The robot, in the role of an examiner, conducts and analyzes competence-oriented assessment tasks, which are solved individually before evaluation and discussion in a plenum.	Relief for lecturers in conducting assessments; consistent and fair exam preparation across courses or years; AI can review text-based answers faster than humans	~Role of examiner (Handke, 2020, p. 127)
4. Moderator (mod) *(interactive learning)*	The robot takes over the moderation and organization of discussions, debates, or group work. Students discuss ideas and lines of argumentation under the robot's guidance.	A robot moderator can store, summarize, and analyze discussion content with AI-based services (e.g., cluster analysis, subjectivity, fact check)	~Role of moderator (e.g., Short et al., 2016)
Robot-to-student scenarios (1-1)			
5. Tutor (tut) *(passive learning)*	The robot adopts the role of a personal tutor offering adaptive repetition and tutoring of content during and after courses to students.	Individual support for students; content is visually/auditorily enhanced and patiently repeated on demand (efficiency)	~Role of tutor (Handke, 2020, p. 106)
6. Advisor (adv) *(active learning)*	The robot, as a learning advisor, answers questions, conducts self-assessments, and provides learning guidance based on learning data.	Recurring admin. questions answered by robot to relieve staff; robot advisory functions based on learning analytics (LMS data)	~Role of advisor (Handke, 2020, p. 118)
7. Tool (tol) *(constructive learning)*	The robot is used as a hands-on learning tool to promote problem solving skills, programming, and computational thinking.	Hands-on orientation provides higher forms of engagement (constructive learning); project-based learning	~Robot as a tool (Handke, 2020, p. 141)
8. Conversation partner (cov) *(interactive learning)*	The robot, as a conversation partner, holds and simulates conversations with students and gives feedback (e.g., simulation of job interview).	Scalable solution to simulate human conversation and learning partners; 'learning by teaching' effect for students	~Conversation practice (e.g., Engwall et al., 2021)

Figure 1 depicts one of the eight vignettes. As can be seen, four questions are embedded in each vignette (in English). Three of these questions are based on the key technology acceptance variables of performance expectancy, effort expectancy, and use intention. We have omitted social influence as it is an external belief. The self-determination theory indicates that such external beliefs could be problematic (Deci et al., 2017); if prompted by others, students may use social robots but with low engagement. We complemented these technology acceptance questions with one question concerning the ethical use of robots.



Robot as teaching assistant: Conduct and evaluate quizzes and surveys

Context:
You are in the lecture hall together with fellow students and a social robot is used to assist the lecturer.

Role of the robot:
The robot supports the lecturer and takes over assistance functions such as conducting and evaluating tests, evaluations or live surveys.

Your learning activity:
You are guided through the questions by the robot and submit the answers via your smartphone or laptop before the robot performs a collective evaluation and comments in real time.

	Strongly disagree	Rather disagree	Undecided	Rather agree	Strongly agree
Using a robot as a teaching assistant in education seems beneficial to me.	○	○	○	○	○
It would be easy for me to use the robot in the role of a teaching assistants.	○	○	○	○	○
I regard the use of the robot as a teaching assistants as ethical.	○	○	○	○	○
I would use the robot in the role of a teaching assistant.	○	○	○	○	○

Figure 1. Vignette example – Robot as teaching assistant

Based on the student assessment of the eight scenarios, we aim to answer two research questions:
RQ1: What is the factor structure of the eight scenarios of social robot use in higher education?
RQ2: What latent profiles of social robot acceptance exist among students in higher education?

4. METHOD

4.1 Sample

First-year students from the course 'Introduction to Academic Writing' (about 1,500 participants) at the University of St.Gallen in Switzerland were asked to perform the eight vignettes in November 2021. Of this group, 371 students voluntarily participated. We checked for multivariate outliers by means of Mahalanobis distances. We excluded ten students with significant ($\alpha = .01$) Mahalanobis distances, which yields a sample of 361 students. Of the data, 0.3% is missing; we inspected the data and concluded it was missing completely at random. Of the students, 36.7% are female and 63.3% male. Their intended study subjects are business administration (43.4%), economics (15.0%), international affairs (11.4%), law (6.1%), and law and economics (8.3%); 15.8% of the students are undecided. On average, the students are 19.71 years old (SD = 1.52 years), min = 17 years, max = 27 years, median = 20 years. The German language track was selected by 63.2% of the students, and the remainder (36.8%) chose the English language track.

4.2 Confirmatory Factor Analysis, Model Assessment, Factor Extraction (RQ1)

To answer RQ1, we carry out confirmatory factor analysis using the 'lavaan 0.6-11' package in R (Rosseel, 2012). Since all the items are measured on a five-point scale of rating, we utilize a robust maximum likelihood estimator (MLR) (Robitzsch, 2020). Missing data are handled using full information maximum likelihood estimation. According to Hu and Bentler (1999), a CFI and TLI > 0.95, as well as a RMSEA < 0.06 and SRMR < 0.08, may indicate a good fit of a model. In addition to demonstrating a sufficient fit of a hypothesized model, it is necessary to compare competing models (Sarstedt et al., 2022). Lin et al. (2017) demonstrated in a simulation study that for this purpose the information criteria *Scaled unit information prior BIC* (SPBIC) and *Haughton's BIC* (HBIC) may be most suitable. To assess the quality of the measurement, we rely on different measures. A McDonald's ω greater than .7 points to a sufficient internal consistency reliability; an average variance extracted (AVE) greater than .5 might indicate convergent validity, and a heterotrait–monotrait ratio smaller than 0.85 discriminant validity (Sarstedt et al., 2022). After having identified the optimal model, we extract factor scores for the subsequent latent profile analysis (Scherer et al., 2021). Factor scores are superior to sum scores (McNeish & Wolf, 2020). We opt for Bartlett factor scores as they yield unbiased estimates for the true scores (DiStefano et al., 2009). The disadvantage of factor scores is the lack of a meaningful zero point. They are standardized in a way that the sum of all students' factor scores of a construct is zero. However, this zero point does not correspond with the neutral scale mean of the five-point scale of rating (= 3). Therefore, we recalibrate the factor scores: a factor score of zero in our study means that a student is undecided concerning all the questions. Hence, we can answer whether student acceptance of a specific scenario, e.g., social robots as presenters, is positive or negative.

4.3 Latent Profile Analysis (RQ2)

The approach of the latent profile analysis follows Guggemos et al. (2022). We use the 'tidyLPA 1.1.0' R-package in combination with MPlus 8 to identify profiles of social robot acceptance by means of a latent profile analysis (LPA) (Hallquist & Wiley, 2018; Rosenberg et al., 2018). We have to restrict variances to be equal across profiles and the covariance among the variables to be zero in order to avoid convergence problems (Meyer & Morin, 2016). Missing data are not present due to the use of full information maximum likelihood. The critical step in the LPA is to identify an appropriate number of profiles. This decision might be based on information criteria and likelihood ratio tests, as well as on conceptual deliberations (Scherer et al., 2021). Against this backdrop, we first assessed different class solutions. Following Morin and Marsh (2015) and Hofmans et al. (2020), we report the information criteria AIC, CAIC, BIC, and aBIC, as well as the bootstrap likelihood ratio test (BLRT). Since these criteria may point to a different number of optimal profiles, we also utilize the approach of Akogul and Erisoglu (2017) where information criteria are weighted to determine the optimal number of latent profiles (from an empirical point of view). The identified solution should have a sufficiently high precision of classification, indicated by an entropy greater than 0.7. To demonstrate the robustness of the findings we conduct a replication of the LPA with 100 random samples of 150 students from our overall sample of 361 students (Vanslambrouck et al., 2019). Besides this, the profiles should be substantially different from each other, which can be checked by means of a MANOVA (Tondeur et al., 2019). Afterwards, we evaluate if this approach yields a meaningful solution. The profiles should be of reasonable size and show substantial shape differences, i.e., differences that not only differ in levels but also in their pattern (Morin & Marsh, 2015).

5. RESULTS

5.1 Confirmatory Factor Analysis, Model Assessment, Factor Extraction (RQ1)

The fit of the tested models is reported in Table 2. First, we tested a basic model (model 1) where the eight scenarios of robot use are operationalized with four items (see Figure 1) addressing *use intention* (use), *performance expectancy* (pe), *effort expectancy* (ee), and *ethical approval* (eth). The fit is poor: TLI = 0.858, RMSEA = 0.087. The modification indices pointed to an additional factor for ethical approval. In model 2 (see Figure 2), we added the factor *ethical approval* where, in addition to model 1, the factor ethical approval is operationalized with the ethical approval items of the eight scenarios; the fit is good: TLI = 0.954, RMSEA = 0.049. Model 3 includes, in addition to model 2, two higher order factors to consider the role of the robot, i.e., robot to class (vignettes 1–4) and robot to student (vignettes 5–8). The fit of model 3 is good: TLI = 0.954, RMSEA = 0.050. Model 4, in addition to model 2, considers the four ICAP dimensions as higher order factors: I (vignettes 4 and 8), C (vignettes 3 and 7), A (vignettes 2 and 6), and P (vignettes 1 and 5). The fit of model 4 is good: TLI = 0.953, RMSEA = 0.050. Model 5 is a combination of models 3 and 4, and considers the two roles of the robot and the four ICAP dimensions as higher order factors. The fit of model 5 is good: TLI = 0.955, RMSEA = 0.049. Based on the fit values, model 1 can be rejected. SPBIC and HBIC both point to model 2 as the best trade-off between model complexity and accuracy. Hence, we use model 2 for all our further analyses.

Table 2. Comparison of competing models

Model	Considered factors	YB–χ^2 (df)	TLI	RMSEA	SPBIC	HBIC
1	8 scenarios	1461 (436)	0.858	0.087	27,583	27,271
2	8 scenarios, 1 ethical approval	744 (420)	0.954	0.049	26,747	26,409
3	8 scenarios, 1 ethical approval, 2 1:class vs. 1:1 setting	793 (445)	0.953	0.050	26,813	26,514
4	8 scenarios, 1 ethical approval, 4 ICAP dimensions	777 (438)	0.953	0.050	26,790	26,483
5	8 scenarios, 1 ethical approval, 2 1:class vs. 1:1 setting, 4 ICAP	750 (427)	0.955	0.049	26,759	26,428

YB–χ^2 = Yuan Bentler χ^2, df = degrees of freedom, TLI = Tucker-Lewis index, RMSEA = root mean square error of approximation, SPBIC = scaled unit information prior BIC, HBIC = Haughton's BIC.

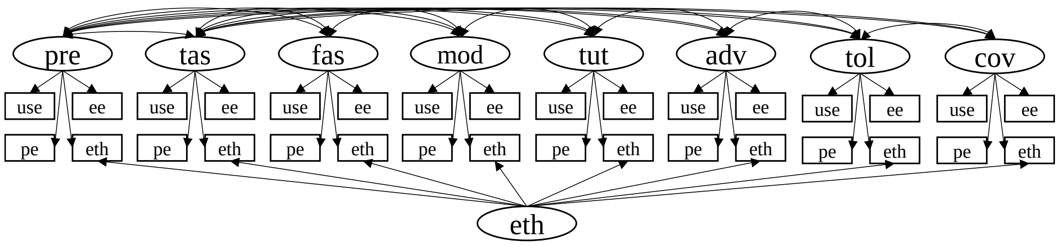


Figure 2. Preferred model (see Table 2). Note: For reasons of clarity, the correlations between the eight roles (pre – cov) with eth are not depicted. All correlations among constructs are reported in Table 3

Model 2 yields overall decent properties: YB-χ^2 (420) = 744; CFI = 0.961; TLI = 0.954; RMSEA = 0.049, 90% CI [0.041, 0.055]; SRMR = 0.029. The internal consistency reliabilities are greater than .85. The AVE is greater than .65 with one exception: the factor ethical approval shows a low AVE (.23). However, this is an auxiliary factor to consider the residual correlations among the ethical approval questions. The highest heterotrait–monotrait ratio (between *tutor* and *advisor*) equals 0.60, which is well below the cut-off value of 0.85. Table 3 also indicates moderate correlations in technology acceptance within the eight scenarios. Hence, indeed, they may capture different constructs.

As can be seen from Table 3, the overall acceptance of social robots as teaching assistants, tutors, advisors, and tools is significantly positive; the overall evaluation of robots as presenters and formative assessors is significantly negative.

Table 3. Mean, standard deviation, reliability, average variance extracted, and correlations among constructs (N = 361)

Variable	*M*	*SD*	ω	AVE	1	2	3	4	5	6	7	8
1. presenter	**-0.32**	1.08	.91	.67								
2. teaching assistant	**0.31**	1.01	.92	.67	**.41**							
3. formative assessor	**-0.12**	1.11	.92	.69	**.29**	**.47**						
4. moderator	0.01	1.10	.91	.66	**.40**	**.41**	**.25**					
5. tutor	**0.13**	1.14	.91	.71	**.24**	**.44**	**.37**	**.38**				
6. advisor	**0.26**	1.04	.91	.71	**.32**	**.44**	**.36**	**.41**	**.54**			
7. tool	**0.53**	0.90	.89	.66	**.36**	**.47**	**.30**	**.44**	**.43**	**.46**		
8. conversation partner	-0.04	1.17	.90	.71	**.33**	**.34**	**.25**	**.45**	**.38**	**.48**	**.39**	
9. ethical approval	**0.14**	0.61	.86	.23	.03	**.18**	**.12**	.03	.05	.05	.06	-.02

Note. Figures in bold indicate significance (two-sided) at the 5% level. Constructs are based on Bartlett factor scores. The factor scores are standardized such that zero equals the neutral scale mean of the five-point scale of rating.

5.2 Latent Profile Analysis (RQ2)

Table 4 shows the results of the latent profile analysis; the information criteria point to different class solutions. The algorithm of Akogul and Erisoglu (2017) suggests four profiles as the optimum. Moreover, the entropy for this solution is sufficiently high (0.813). A replication of the latent profile analysis with 100 samples of 150 students points to three profiles. In 1% of the cases, two profiles are optimal (criterion: Akogul & Erisoglu, 2017); in 57% of the cases, three profiles; in 30% of the cases, four profiles; in 12% of the cases, five or six profiles. The MANOVA yielded significant different means among the four profiles: $F(24, 1015.7) = 50.16$, Wilk's $\Lambda = 0.104$, $p < .001$, $\eta^2 = .400$. In other words, 40.0% of the variance can be explained by profile membership. These findings and Figure 3 point to sufficiently distinct profiles.

Table 4. Information criteria, entropies, and BLRT results for the seven latent profiles

No. profiles	-LL	No. Par.	AIC	CAIC	BIC	aBIC	Entropy	p(BLRT)
1	4,276	16	8,584	8,585	8,646	8,595	1.000	-
2	3,971	25	7,991	7,995	8,089	8,009	0.812	.000
3	3,886	34	7,841	7,848	7,973	7,865	0.790	.000
4	3,860	43	7,807	7,819	7,974	7,838	0.813	.000
5	3,841	52	7,786	7,804	7,988	7,823	0.786	.000
6	3,823	61	7,768	7,794	8,006	7,812	0.793	.000
7	3,804	70	7,749	7,783	8,021	7,799	0.780	.158

Note: -LL = - Log-likelihood, No. Par. = number of estimated parameters, AIC = Akaike's information criterion, CAIC = Consistent AIC, BIC = Bayesian information criterion, aBIC = adjusted BIC, BLRT = bootstrap likelihood ratio test.

The four latent profiles can be described as follows:

- Profile 1: Students in this profile are skeptical about social robots in general. They do not accept any of the eight social robot roles. Profile 1 comprises 45 students (12.5%).
- Profile 2: Students are skeptical about social robots as a means of instruction (scenarios 1–6 and 8). However, they assess the use of social robots as the instruction content as positive, e.g., to learn computational thinking. Profile 2 is the smallest one with 26 students (7.2%).
- Profile 3: Students have a differentiated view. They show a significant negative acceptance for social robots as presenter and formative assessor, a neutral assessment towards social robots as moderator, tutor, and conversational agent, and a significant positive assessment towards social robots as teaching assistant, advisor, and tool. Profile 3 is the largest one with 169 students (46.8%).
- Profile 4: Students have a positive acceptance towards all eight roles of social robots. This profile is also substantial in size with 121 students (33.5%).

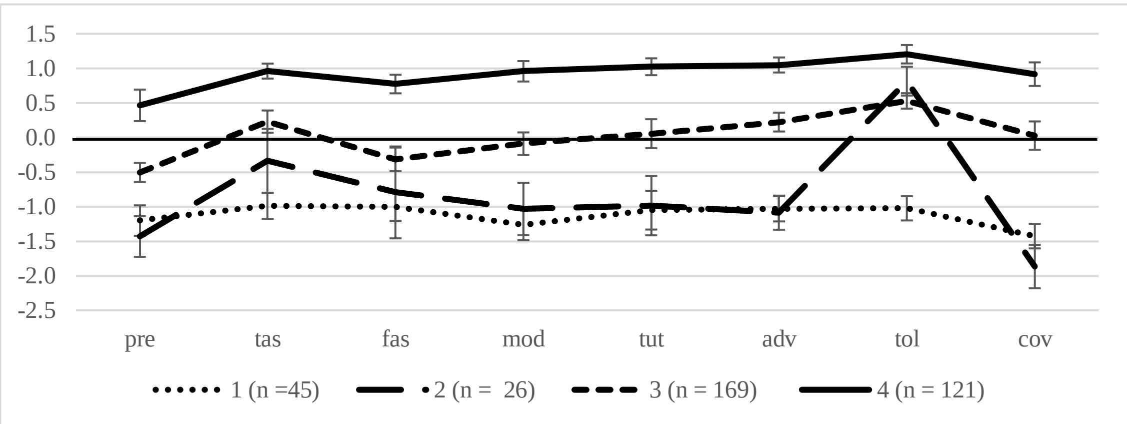


Figure 3. Latent profiles of social robot acceptance among higher education students (N = 361). Recalibrated factor scores (zero = neutral scale mean) and corresponding 95% confidence intervals

6. DISCUSSION, LIMITATIONS, AND CONCLUSION

We have developed and validated eight vignettes for social robot use in higher education. These vignettes may offer the students a fair representation of the capabilities of social robots at the current state of the art. Based on confirmatory factor analyses, there is evidence for the model structure with eight robot-use scenarios. The students regard the scenarios in substantially different and unique ways. However, when considering the four ICAP dimensions as higher order factors, this reduces the fit of the model in such a way that does not compensate the increased degrees of freedoms. The same holds true when considering the setting: robot to class vs. robot to student. From an empirical point of view, the ICAP and setting of robot use may not be a suitable structure for the vignettes. Nevertheless, they may be important from a conceptual point of view. The ICAP is a suitable framework to classify the quality of educational technology use (Sailer et al., 2021). The setting is important from a technical point of view as a robot-to-class setting is (except for the role of presenter) more difficult to implement than a robot-to-student setting.

An additional factor, *ethical approval*, is necessary in the confirmatory factor analysis in order to achieve a good model fit. The explanation for this may be due to the fact that ethical approval is a construct outside the UTAUT framework and, therefore, of a different nature. However, ethical approval may be an important facet of social robot acceptance in higher education: the AVE is greater than 0.5 for all eight scenarios; the standardized loadings of the ethical approval items on the factors exceed in all cases 0.613 ($p < .001$).

The latent profile analysis pointed to four profiles. These profiles can be interpreted in a meaningful way. However, three profiles rather than four may also be acceptable. Our replication with 100 random samples of 150 students pointed to three profiles. Moreover, the BIC—a suitable criterion to identify the optimal number of classes in mixture modeling (Nylund et al., 2007)—indicates three profiles. In the case of opting for three profiles, profiles 1 and 2 collapse. Profile 2 is small; however, it may be revealing from a conceptual point of view. Social robots can be used as a means of instruction or as the content matter in education. Students in profile 2 distinguish between these two kinds of use. We also tested models with five or more classes; however, they yield profiles that are very small and/or difficult to interpret. As a limitation, due to convergence problems, we had to assume equal variances across the profiles and covariances of zero. These assumptions are restrictive (Scherer et al., 2021). Against this backdrop, it would be beneficial to replicate our four-class solution with another sample.

Overall, the roles with the highest acceptance are social robots used as a tool and as teaching assistant. Social robots as a presenter are rated most negatively; the acceptance of social robots as a formative assessor is also negative. The vignettes may help students to obtain a more realistic picture about the capabilities of social robots in specific roles; however, they present scenarios where everything works well, i.e., no breakdowns or malfunctions of the robot occur. When social robots are used as a means of instruction (scenarios 1–6 and 8), malfunction may decrease acceptance for all roles at the same rate. Hence, the patterns of the latent classes might be unchanged but at an overall lower level. The acceptance reported in the study at hand could be regarded as the upper band. It allows conclusions about the acceptance of social robot roles that are, even in an error-free scenario, not positive. Further research could shed light on the latent profiles of students with varying degrees of acceptance toward the malfunctioning of robots.

We followed the suggestion of Skilling and Stylianides (2020) and aimed to have a vignette word count of between 50 and 200. For social robots, which are a novel and complex technology, this may not be enough to present a fair picture. On the other hand, however, more elaborate descriptions could yield higher rates of missing values and a decreasing number of participants. Overall, we regard qualitative research, which allows the study participants an in-depth interaction, as a promising way to complement quantitative studies (Sonderegger et al., 2022). In particular, the concept of ethical approval should be investigated more elaborately than has been done in our study.

Our contributions to the literature are: 1) We have developed theoretically based (ICAP framework) vignettes that fairly portray the use scenarios of social robots in higher education at the current technical state of the art. 2) We considered ethical approval as a facet of social robot acceptance, which goes beyond the classical technology acceptance variables. 3) We offer a detailed picture of student social robot acceptance by considering variance within social robot use, i.e., eight scenarios, and within students, i.e., four latent profiles.

Our work has also implications for practice. There is a considerable proportion of students (in our case, profiles 1 and 2, comprising 20% of our sample) who are skeptical about social robots. Technology acceptance should not be taken for granted among students within the social sciences. Our findings can help developers in the trade-off between technology acceptance and pedagogical and technical aspects. If the pedagogically desirable (ICAP framework) scenarios of 4 and 8 were introduced, students may be neutral towards them. It may be beneficial to accompany the introduction to such scenarios with a description about the benefits of social robot use in these roles, with a special focus on students from profiles 1 and 2.

REFERENCES

Akogul, S., & Erisoglu, M. (2017). An approach for determining the number of clusters in a model-based cluster analysis. *Entropy*, *19*(9), 452. https://doi.org/10.3390/e19090452

Alnajjar, F., Barntneck, C., Baxter, P., Belpaeme, T., Cappuccio, M., Di Dio, Cinzia, Eyssel, F., Handke, J., Mubin, O., Obaid, M., & Reich-Stiebert, N. (2021). *Robots in education: An introduction to high-tech social agents, intelligent tutors, and curricular tools*. Routledge. https://doi.org/10.4324/9781003142706

Bartneck, C., & Forlizzi, J. (2004). A design-centred framework for social human-robot interaction. In *Proceedings / RO-MAN 2004, 13th IEEE International Workshop on Robot and Human Interactive Communication: September 20 - 22, 2004, Kurashiki, Okayama, Japan* (pp. 591–594). IEEE Operations Center. https://doi.org/10.1109/ROMAN.2004.1374827

Belpaeme, T., Kennedy, J., Ramachandran, A., Scassellati, B., & Tanaka, F. (2018). Social robots for education: A review. *Science Robotics*, *3*(21), 1-9. https://doi.org/10.1126/scirobotics.aat5954

Belpaeme, T., & Tanaka, F. (2021). Social robots as educators. In OECD (Ed.), *Digital Education Outlook 2021* (pp. 143–157). OECD. https://doi.org/10.1787/7fbfff45-en

Byrne, B. M., Rossi, A., & Doolan, M. (2017). Humanoid robots attending lectures. In *Proceedings of the 9th International Conference on Education Technology and Computers, ICETC*, Barcelona, Spain.

Chi, M. T. H., & Wylie, R. (2014). The ICAP Framework: Linking Cognitive Engagement to Active Learning Outcomes. *Educational Psychologist*, *49*(4), 219–243. https://doi.org/10.1080/00461520.2014.965823

Ching, Y.-H., Hsu, Y.-C., & Baldwin, S. (2018). Developing computational thinking with educational technologies for young learners. *TechTrends*, *62*(6), 563–573. https://doi.org/10.1007/s11528-018-0292-7

Cooney, M., & Leister, W. (2019). Using the Engagement Profile to design an engaging robotic teaching assistant for students. *Robotics*, *8*(1), 1–26. https://doi.org/10.3390/robotics8010021

Deci, E. L., Olafsen, A. H., & Ryan, R. M. (2017). Self-Determination Theory in Work Organizations: The State of a Science. *Annual Review of Organizational Psychology and Organizational Behavior*, *4*(1), 19–43. https://doi.org/10.1146/annurev-orgpsych-032516-113108

DiStefano, C., Zhu, M., & Mîndrilã, D. (2009). Understanding and using factor scores: considerations for the applied researcher. *Practical Assessment, Research, and Evaluation*, *14*(20), 1–11. https://doi.org/10.7275/DA8T-4G52

Engwall, O., Lopes, J., & Åhlund, A. (2021). Robot Interaction Styles for Conversation Practice in Second Language Learning. *International Journal of Social Robotics*, *13*(2), 251–276. https://doi.org/10.1007/s12369-020-00635-y

Fridin, M., & Belokopytov, M. (2014). Acceptance of socially assistive humanoid robot by preschool and elementary school teachers. *Computers in Human Behavior*, *33*, 23–31. https://doi.org/10.1016/j.chb.2013.12.016

Guggemos, J., Seufert, S., & Román-González, M. (2022). Computational Thinking Assessment – Towards More Vivid Interpretations. *Technology, Knowledge and Learning*. Advance online publication. https://doi.org/10.1007/s10758-021-09587-2

Guggemos, J., Seufert, S., & Sonderegger, S. (2020). Humanoid robots in higher education: Evaluating the acceptance of Pepper in the context of an academic writing course using the UTAUT. *British Journal of Educational Technology*, *51*(5), 1864–1883. https://doi.org/10.1111/bjet.13006

Hallquist, M. N., & Wiley, J. F. (2018). Mplusautomation: An R package for facilitating large-scale latent variable analyses in Mplus. *Structural Equation Modeling: A Multidisciplinary Journal*, *25*(4), 621–638. https://doi.org/10.1080/10705511.2017.1402334

Handke, J. (2018). Digitale Hochschullehre – Vom einfachen Integrationsmodell zur Künstlichen Intelligenz. In U. Dittler & C. Kreidl (Eds.), *Hochschule der Zukunft* (pp. 249–263). Springer Fachmedien Wiesbaden. https://doi.org/10.1007/978-3-658-20403-7_15

Handke, J. (2020). *Humanoide Roboter: Showcase, Partner und Werkzeug.* Tectum Wissenschaftsverlag.

Hofmans, J., Wille, B., & Schreurs, B. (2020). Person-centered methods in vocational research. *Journal of Vocational Behavior*, *118*, 103398. https://doi.org/10.1016/j.jvb.2020.103398

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Lin, L.-C., Huang, P.-H., & Weng, L.-J. (2017). Selecting Path Models in SEM: A Comparison of Model Selection Criteria. *Structural Equation Modeling: A Multidisciplinary Journal*, *24*(6), 855–869. https://doi.org/10.1080/10705511.2017.1363652

McNeish, D., & Wolf, M. G. (2020). Thinking twice about sum scores. *Behavior Research Methods*, *52*(6), 2287–2305. https://doi.org/10.3758/s13428-020-01398-0

Meyer, J. P., & Morin, A. J. (2016). A person-centered approach to commitment research: Theory, research, and methodology. *Journal of Organizational Behavior*, *37*(4), 584–612. https://doi.org/10.1002/job.2085

Morin, A. J. S., & Marsh, H. W. (2015). Disentangling shape from level effects in person-centered analyses: An illustration based on university teachers' multidimensional profiles of effectiveness. *Structural Equation Modeling: A Multidisciplinary Journal*, *22*(1), 39–59. https://doi.org/10.1080/10705511.2014.919825

Mubin, O., Stevens, C. J., Shahid, S., Mahmud, A. A., & Dong, J.-J. (2013). A Review of the applicability of robots in education. *Technology for Education and Learning*, *1*(1), 1–7. https://doi.org/10.2316/Journal.209.2013.1.209-0015

Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the Number of Classes in Latent Class Analysis and Growth Mixture Modeling: A Monte Carlo Simulation Study. *Structural Equation Modeling: A Multidisciplinary Journal*, *14*(4), 535–569. https://doi.org/10.1080/10705510701575396

Raffaghelli, J. E., Rodríguez, M. E., Guerrero-Roldán, A.-E., & Bañeres, D. (2022). Applying the UTAUT model to explain the students' acceptance of an early warning system in Higher Education. *Computers & Education*, *182*, 104468. https://doi.org/10.1016/j.compedu.2022.104468

Robitzsch, A. (2020). Why Ordinal Variables Can (Almost) Always Be Treated as Continuous Variables: Clarifying Assumptions of Robust Continuous and Ordinal Factor Analysis Estimation Methods. *Frontiers in Education*, *5*, Article 589965. https://doi.org/10.3389/feduc.2020.589965

Rosenberg, J., Beymer, P., Anderson, D., van Lissa, C., & Schmidt, J. (2018). tidyLPA: An R package to easily carry out latent profile analysis (LPA) using open-source or commercial software. *Journal of Open Source Software*, *3*(30), 978. https://doi.org/10.21105/joss.00978

Rosseel, Y. (2012). lavaan: An R package for structural equation modeling. *Journal of Statistical Software*, *48*(2), 1–36. https://doi.org/10.18637/jss.v048.i02

Sailer, M., Stadler, M., Schultz-Pernice, F., Franke, U., Schöffmann, C., Paniotova, V., Husagic, L., & Fischer, F. (2021). Technology-related teaching skills and attitudes: Validation of a scenario-based self-assessment instrument for teachers. *Computers in Human Behavior*, *115*, 106625. https://doi.org/10.1016/j.chb.2020.106625

Sarstedt, M., Hair, J. F., Pick, M., Liengaard, B. D., Radomir, L., & Ringle, C. M. (2022). Progress in partial least squares structural equation modeling use in marketing research in the last decade. *Psychology & Marketing*, *39*(5), 1035–1064. https://doi.org/10.1002/mar.21640

Scherer, R., Howard, S. K., Tondeur, J., & Siddiq, F. (2021). Profiling teachers' readiness for online teaching and learning in higher education: Who's ready? *Computers in Human Behavior*, *118*, 106675. https://doi.org/10.1016/j.chb.2020.106675

Scherer, R., Siddiq, F., & Tondeur, J. (2020). All the same or different? Revisiting measures of teachers' technology acceptance. *Computers & Education*, *143*, 103656. https://doi.org/10.1016/j.compedu.2019.103656

Serholt, S., Barendregt, W., Vasalou, A., Alves-Oliveira, P., Jones, A., Petisca, S., & Paiva, A. (2017). The case of classroom robots: teachers' deliberations on the ethical tensions. *AI & SOCIETY*, *32*(4), 613–631. https://doi.org/10.1007/s00146-016-0667-2

Seufert, S., & Spiroudis, E. (2017). Wissenschaftliche Schreibkompetenz in der Studien-eingangsphase fördern: Erfahrungen mit einem Rückmelde- und Bewertungsraster (Rubric). *Zeitschrift Schreiben*, *15*, 1–9.

Sharkey, A. J. C. (2016). Should we welcome robot teachers? *Ethics and Information Technology*, *18*(4), 283–297. https://doi.org/10.1007/s10676-016-9387-z

Short, E., Sittig-Boyd, K., & Mataric, M. J. (2016). Modeling moderation for multi-party socially assistive robotics. In *IEEE Int. Symp. Robot Hum. Interact. Commun.(RO-MAN 2016)*. IEEE.

Skilling, K., & Stylianides, G. J. (2020). Using vignettes in educational research: a framework for vignette construction. *International Journal of Research & Method in Education*, *43*(5), 541–556. https://doi.org/10.1080/1743727X.2019.1704243

Smakman, M. H. J., Konijn, E. A., Vogt, P., & Pankowska, P. (2021). Attitudes towards social robots in education: Enthusiast, practical, troubled, sceptic, and mindfully positive. *Robotics*, *10*(1), 24. https://doi.org/10.3390/robotics10010024

Sonderegger, S., Guggemos, J., & Seufert, S. (2022). How Social Robots Can Facilitate Teaching Quality – Findings from an Explorative Interview Study. In W. Lepuschitz, M. Merdan, G. Koppensteiner, R. Balogh, & D. Obdržálek (Eds.), *Lecture Notes in Networks and Systems. Robotics in Education* (Vol. 515, pp. 99–112). Springer International Publishing. https://doi.org/10.1007/978-3-031-12848-6_10

Tondeur, J., Scherer, R., Baran, E., Siddiq, F., Valtonen, T., & Sointu, E. (2019). Teacher educators as gatekeepers: Preparing the next generation of teachers for technology integration in education. *British Journal of Educational Technology*, *50*(3), 1189–1209. https://doi.org/10.1111/bjet.12748

Vanslambrouck, S., Zhu, C., Pynoo, B., Lombaerts, K., Tondeur, J., & Scherer, R. (2019). A latent profile analysis of adult students' online self-regulation in blended learning environments. *Computers in Human Behavior*, *99*, 126–136. https://doi.org/10.1016/j.chb.2019.05.021

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425–478. https://doi.org/10.2307/30036540

Woo, H., LeTendre, G. K., Pham-Shouse, T., & Xiong, Y. (2021). The use of social robots in classrooms: A review of field-based studies. *Educational Research Review*, *33*, 100388. https://doi.org/10.1016/j.edurev.2021.100388

Żarkowski, M. (2019). Multi-party turn-taking in repeated human–robot interactions: An interdisciplinary evaluation. *International Journal of Social Robotics*, *11*(5), 693–707. https://doi.org/10.1007/s12369-019-00603-1