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ServeSmart: Bridging Theory and Practice in Customer Service Education through AI-Supported Experiential Learning

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Abstract: Artificial Intelligence (AI) is increasingly used in higher education to support experiential learning in customer service training, where applying theoretical frameworks such as the SERVQUAL model can be challenging. Students frequently struggle with emotional recognition, immediate decision-making, and applying SERVQUAL dimensions during role-play. To address these gaps, this study introduces ServeSmart, an AI-supported learning system that provides real-time guidance during customer service scenario role-play. Using a preliminary exploratory quantitative survey design, this study evaluated students' perceived learning experiences and the platform's usability. Using a non-probability purposive sampling strategy, 30 undergraduate students participated in individual scenario-based simulations followed by a validated post-evaluation questionnaire. Baseline findings indicated that a majority of participants had difficulty with emotional recognition and lacked immediate instructional feedback during simulations. Post-simulation results revealed that all participants reported higher perceived confidence in executing customer service tasks, a clearer perceived understanding of SERVQUAL concepts, and strong interest in future platform utilization. Overall, the findings demonstrate positive student perceptions of ServeSmart as a supportive experiential learning tool, highlighting its potential to offer an immediate instructional platform in service management education.

Keywords: *Artificial Intelligence, Experiential Learning, Customer Service Education, Decision Support System, SERVQUAL, Higher Education*

1. Introduction and Background

Intelligent tutoring systems, adaptive learning platforms, and generative artificial intelligence are being increasingly introduced into teaching and learning. Instead of remaining merely digital tools, these technologies are able to offer extra support in areas such as student engagement, personalized learning, and problem-solving. The employment of such technologies is especially relevant in professional education, since students are expected not only to understand concepts but also to show how they can be applied in work situations. Examples of subjects include customer service and hospitality management, since it is difficult to make the shift from knowledge to practice. Providing effective customer service requires more than just technical knowledge; students also need emotional awareness, good communication skills, and the ability to make decisions when situations change rapidly. Because of this, role-play, case studies, and simulations are frequently used to give students the chance to develop these skills in a controlled learning environment (Humpherys et al., 2022). Yet students may still find these activities difficult, especially when they have to deal with different customer behaviors within a short time frame.

The problem becomes more apparent when students are doing their practical training, as they come across customers who have different expectations, emotions, and problems requiring service. In such situations, they have to make use of their theoretical knowledge while at the same time managing their emotions, communicating in the right way, and deciding on their next move. A difficult interaction can therefore impose a number of demands on a student at one and the same time. For certain students, this kind of pressure makes it hard for them to apply frameworks like SERVQUAL consistently and can have an effect on their confidence when dealing with customers.

The same sorts of problems can arise in classroom role-plays. Even if students know the principles of good service, they may find it difficult to apply them when facing an emotionally demanding situation. A second limitation concerns the timing of the feedback. In a great many role-plays, the instructor gives their comments only after the activity has finished. As a result, students do not realize until after the interaction has taken place

that they have missed a cue or given an ineffective response. This means that they lose the chance to make an immediate adjustment and attempt a different approach while the situation is still going on (Tosterud et al., 2020).

AI-supported learning represents one way to address this gap. It is able to examine a situation, propose possible responses, and give instant feedback as students are engaged in practice (Coskun & Er, 2026). In the context of customer service education, this kind of assistance could help students work with the SERVQUAL dimensions—such as empathy, responsiveness, reliability, assurance, and tangibles—in various service situations (Lyu et al., 2020). ServeSmart was designed with that aim in mind. Rather than delaying guidance until the simulation has finished, the system gives advice as the interaction takes place and adjusts its assistance according to the customer's behavior and the context of the situation. Students are therefore able to apply service concepts as they respond, review their decisions, and keep on practicing in the same activity. In this respect, the system is meant to supplement classroom teaching rather than take the place of the lecturer. The study, which is exploratory in nature, looks at how students see their learning experience and the usability of ServeSmart in the context of customer service education. The study is based on two questions: first, what are the students' views regarding the way in which the SERVQUAL dimensions are used through ServeSmart? Second, in what way does ServeSmart help to promote students' engagement in hands-on learning?

2. Literature Review

Artificial Intelligence in Higher Education

The use of artificial intelligence in higher education has developed a great deal, extending from routine administrative tasks to more interactive kinds of learning support (Hoogers et al., 2025). AI applications nowadays can work with teachers by giving them extra aid instead of taking the place of the relationship between student and teacher. By means of natural language processing and adaptive recommendations, AI systems are able to respond to a student's progress, modify the learning activities, and offer support that is more in line with individual needs (Tan et al., 2022). Moreover, some AI agents are also capable of maintaining conversations and imitating real-world personalities, so that students can interact with customer-like scenarios in a relevant context (Lewandowski et al., 2023).

At the same time, there are significant concerns regarding the use of AI in education. Things like student data privacy, possible algorithmic bias in assessments, and an overreliance on automated assistance should all be taken into account. If students place too much trust in AI-generated advice, they will have fewer chances to build up their ability to make independent judgements and to develop critical decision-making skills (Townsend, 2026). Because of this, AI-based learning support is more suitable when it supplements rather than replaces the judgement of both students and educators.

Learning analytics can further enhance learning supported by AI by offering data on student performance, the way they respond, and the decisions they make. This kind of information can enable teachers to detect the areas in which students need extra support and allow classroom simulations to become more purposeful and structured.

Customer Service Competencies and the SERVQUAL Framework

To prepare students for jobs in the field of services, it is necessary to carry out learning activities that link up the existing concepts of service quality with real-life customer interactions. A framework that is among the most widely recognized is SERVQUAL, which was developed by Parasuraman, Zeithaml, and Berry. This framework specifies five dimensions of service quality: tangibles, reliability, responsiveness, assurance, and empathy (Parasuraman et al., 1988). Even though these dimensions are easy to describe, putting them into practice when dealing with a difficult customer situation can be a great deal more challenging.

For students whose customer-handling abilities are still being developed, an annoyed customer might require them to show empathy and assurance at the same time as identifying the service problem and then deciding on a suitable solution. Although traditional role-play can be of some use in this regard, it does not always manage to replicate the emotional pressure and complexity found in real service situations (Schaefer & Palanski, 2014). It is therefore necessary for learning activities to include opportunities for students to practice these behaviors

in scenarios that mirror the demands of working in the workplace.

Even though there has been growing attention given to AI-supported learning, relatively little research has looked at how it can be specifically incorporated into customer service role-play. Most simulation exercises still depend mainly on instructor supervision, with feedback being given only after the exercise is completed. As a result, students often receive very little instructional support at the moment when they are making decisions during a customer interaction (Chernikova et al., 2020). This situation offers a good opportunity to investigate whether AI-assisted tools could provide timely and adaptive guidance within experiential learning. To deal with this problem, ServeSmart provides support to students as they deal with various customer situations. The system is intended to help learners identify service needs, apply the SERVQUAL principles, and build up more confidence in their communication and problem-solving during the simulation.

SERVQUAL Operationalization in ServeSmart

ServeSmart converts the five SERVQUAL dimensions into components that can be used in its scenarios, evaluation procedures, and feedback systems (Parasuraman et al., 1988), the aim being to link the existing service quality framework and the students' real responses in the simulated customer interactions more apparent. The physical, visual, and digital elements of the service environment—such as cleanliness, the professional appearance, the design of the digital interface, and other types of physical evidence—are all included within the concept of tangibles. When developing a service response, ServeSmart takes into account the way students perceive and react to these cues (Parasuraman et al., 1988; Bitner, 1992).

Concerns about reliability pertain to whether the student's suggested solution is accurate, consistent, and dependable; the system examines if the student has identified the fundamental service problem, suggests a realistic remedy, and sticks to the commitment made to the simulated customer (Parasuraman et al., 1988; Ladhari, 2009). Responsiveness refers to the speed and willingness with which a student responds to a customer's request or complaint. In the interactive situation, ServeSmart takes into account both how quickly the response is given and the degree to which the student shows that they are ready to help (Parasuraman et al., 1988; Johnston, 1995).

Assurance is connected with knowledge, courtesy, competence, and the capacity to earn customer trust. ServeSmart employs language-related clues to determine if students display the right level of politeness, confidence, and credibility, especially in situations involving anxious or dissatisfied customers (Parasuraman et al., 1988; Bowen & Lawler, 1995). Empathy means recognizing the customer's feelings and giving them individual attention. By using cues from natural language processing, the system looks at the ways in which students show that they are frustrated, indicate that they understand, and then proposes an appropriate response for service recovery (Parasuraman et al., 1988; Stock & Hoyer, 2005).

When combined, these functions enable ServeSmart to link each dimension of the SERVQUAL model with observable indicators in a customer situation and with feedback that students can use during their learning process. Hence, the system goes beyond a purely theoretical discussion by providing students with opportunities to think about how the dimensions manifest themselves in real service communication.

3. Research Methodology

ServeSmart integrates the five SERVQUAL dimensions—tangibles, reliability, responsiveness, assurance, and empathy—into its customer service simulation exercises. The platform analyses customer communications and provides immediate suggestions, step-by-step advice, and feedback on communication and emotional management. These features are designed to enable students to apply the SERVQUAL concepts in a variety of simulated service scenarios. This study employed a non-probability purposive sampling strategy involving 30 upper-level students enrolled in the Bachelor of Business in Service Management (Honours) program. This background was seen as relevant since the participants had already come across customer service situations and could thus make a judgment about the usefulness of ServeSmart in relation to their previous learning experience. The evaluation was conducted individually over a single 45-minute session. After an initial orientation, participants interacted with ServeSmart as an instructional assistant while navigating standardized service-recovery scenarios. Immediately post-simulation, students completed a validated,

structured evaluation questionnaire assessing their baseline learning challenges, system usability, SERVQUAL dimension alignment, and perceived educational benefits. Questionnaire items were adapted from established literature on educational technology and service quality, were based on previous research, and employed a five-point Likert scale going from 1 (Strongly Disagree) to 5 (Strongly Agree). The responses were analyzed with the help of descriptive statistics and agreement percentages in order to look at the students' views following their use of the system.

4. Results

The initial assessment included 30 undergraduate students who were studying the Bachelor of Business in Service Management. The survey was filled out by the students after they had used ServeSmart in connection with customer service activities. The results cover the participants' backgrounds, the difficulties they encountered when dealing with customers, their perception of the usefulness of the system, the features they preferred, their intention to continue using the system, and the learning benefits they felt. Table 1 shows the participants' background.

Table 1: Participants' background

Variables	Category	Frequency (n)	Percentage (%)
Gender	Female	22	73.3
	Male	8	26.7
Program	Bachelor of Business in Service Management	30	100.0

The majority of the respondents were women (73.3 per cent), whereas 26.7 per cent were men. Most of them were in their last year, and all the participants had prior experience in customer service role-plays or internships. The fact that they had such experience shows that they were not entirely new to customer service and so were able to assess ServeSmart in light of the experiences they had already had.

Table 2 presents students' reported challenges when dealing with different customer types during practical learning activities.

Table 2: Students' reported challenges

Variables	Category	Frequency (n)	Percentage (%)
Difficulty responding to different customer types	Sometimes	22	73.3
	Yes	8	26.7
	No	0	0.0
Real-time guidance would enhance performance.	Yes	28	93.3
	Not sure	2	6.7
Specific learning challenges (Multi-select)	Difficulty understanding customer emotions	20	66.7
	Limited guidance during activity	18	60.0
	Not sure how to respond	16	53.3
	Lack of confidence	14	46.7
	Do not know the correct approach	10	33.3
	Other challenges	6	20.0

All the participants said that dealing with different kinds of customers was difficult. Most of the students (73.3%) mentioned that they had this difficulty at times, while 26.7% said it was more of a challenge. No one stated that they had no difficulty. The challenge most often cited was understanding customer emotions

(66.7%), then coming up with inadequate guidance during the activities (60.0%) and uncertainty about how to react (53.3%). Furthermore, 46.7% expressed a lack of confidence. This pattern indicates that the students' difficulties went beyond just recognizing customer needs to also include deciding how to respond while managing the interaction. The fact that students wanted support was also clear from their response to real-time guidance. 93.3 per cent of them said that immediate guidance would help them to do better in their customer service activities. This shows that there is a great deal of interest in getting assistance while the interaction is happening rather than only after it has finished.

Table 3 presents students' perceptions of the usefulness of ServeSmart and their intention to use the system in future learning activities.

Table 3: Perceived Usefulness and Intention to Use ServeSmart

Variable / Feature	Statistic / Category	Value / Count	Percentage (%)
Perceived Concept Usefulness	Very useful	22	73.3%
	Useful	8	26.7%
Intention to Use ServeSmart	Rating 5 (Very Likely)	20	66.7%
	Rating 4 (Likely)	10	33.3%

Students had a favorable view of ServeSmart. 73.3 per cent considered the system to be 'Very Useful' and 26.7 per cent called it 'Useful'. None of the participants chose a negative category regarding usefulness. Similarly positive was their intention to use the system again: 66.7 percent said, 'Very Likely' and 33.3 percent said 'Likely'. The average score for the intention to reuse the system was 4.67 out of 5.

Table 4 presents the features that students considered most helpful. Respondents were allowed to select more than one feature.

Table 4: Student Preferences for ServeSmart Functional Features

ServeSmart Feature	Frequency (n)	Percentage (%)
Emotional handling tips	26	86.7
Quick decision support	24	80.0
Suggested responses	22	73.3
Step-by-step guidance	18	60.0
Scenario-based learning	18	60.0

The emotional-handling tips were the feature chosen most often, with 86.7% of participants selecting it. This is in agreement with the previous result, in which it was found that understanding customer emotions was the main challenge. Eighty per cent of the students picked quick decision support, and 73.3% chose suggested responses; step-by-step guidance and scenario-based learning were each selected by 60.0%. In general, the features most preferred were those which offered immediate help when students encountered difficult customer situations.

Table 5 presents students' perceptions of the potential educational impact of ServeSmart.

Table 5: Perceived Pedagogical Impact of ServeSmart

Perceived Learning Outcome	Frequency (n)	Percentage (%)
Improved confidence in handling customer interactions	30	100.0
Enhanced understanding of customer service principles	30	100.0

Every participant (100%) stated that ServeSmart had increased their confidence when dealing with customers and had improved their understanding of the key concepts in customer service. This indicates that the students saw value in the system with regard to both the development of their confidence and their conceptual understanding, especially in cases where learning involved combining knowledge, communication, decision-making, and confidence. It is important to remember that these findings refer to perceptions rather than constituting direct evidence of an improvement in skills. The survey did not objectively assess changes in the students' performance. Yet the participants believed that ServeSmart was useful for use in customer service and said that they had greater confidence and a better understanding of the SERVQUAL-related concepts such as empathy and assurance. Furthermore, all the participants stated that they intended to use the system again.

Discussion

The results show that the students had difficulties that were closely linked to the requirements of providing real-time customer service. There is a considerable cognitive and interpersonal demand on learners when they have to manage customers' emotions at the same time as deciding on their response. If immediate guidance is not available, it will be hard for the students to apply what they know to the situation during the interaction. The students' reactions to ServeSmart indicate that having real-time assistance was seen as useful when addressing these problems; the feature most often chosen was emotional-handling support, which is in direct agreement with the major difficulty noted by the participants. Quick decision support and suggested responses were also highly regarded. Taken together, these findings show that the students particularly valued help that could be used at the moment a decision had to be made. This type of support might enable students to pay more attention to understanding the customer while applying service concepts such as the SERVQUAL dimensions (Olivares et al., 2021).

A further important aspect is the connection between experience and reflection in experiential learning. In a traditional role-play, feedback is usually only given after the interaction has finished. Because of this timing, students often find it hard to identify a problem and are unable to immediately try out an alternative response (Henderson, 2021). ServeSmart alters the timing of the support by giving guidance during the interaction. If a suggestion is offered while the student is dealing with a customer, they then have the chance to reconsider their approach and make an adjustment all within the same learning activity. As a result, there are more opportunities for practice, reflection, and improvement as the simulation goes on. The results show that ServeSmart could prove useful as a support tool in competency-based customer service education, since the real-time guidance was seen as beneficial in handling difficult customer situations, in understanding service concepts, and in building confidence. Furthermore, the findings offer initial support for investigating AI-assisted experiential learning in service management education, especially in those cases where students need to put theoretical concepts into practice when interacting with customers (Li et al., 2024).

5. Managerial Implications and Recommendations

The study advances the debates regarding educational technology and service management in two closely related respects. On the one hand, it shows that real-time guidance supported by AI can be integrated into experiential learning in such a way that feedback is provided during an activity rather than merely after it has ended; this enables students to revise their responses while the customer interaction is still taking place. On the other hand, the results show how an AI-assisted learning tool can help students go from merely discussing service quality models in a theoretical way to applying these models in their communication and service decisions. Academic leaders and curriculum designers should consider using tools such as ServeSmart in conjunction with traditional teaching methods. Instead of replacing role-play or the lecturer, the system can offer extra support to students as they take part in these activities. This could enable lecturers to focus more on mentoring, discussion, and reflection, while the AI system gives guidance at the point of action. Moreover, AI-assisted tools might provide a means of increasing opportunities for practice without at the same time needing to add more instructor time (Chernikova et al., 2020).

The idea of exposing students to AI-assisted customer service activities also has a bearing on their workplace preparation. Since digital tools and AI are becoming more and more common in service settings, it would be beneficial for students to learn how to use them as they are at the same time developing their own communication and judgement skills. Therefore, becoming familiar with these tools can constitute part of their

preparation for carrying out customer interactions in workplaces that use technology (Echeverria et al., 2023).

When concluding the results, several limitations must be taken into account. The study was based on only 30 students, and as a result, the findings can only be partly applied to larger populations. It also took place within a single academic program at one university, so the results might represent the features of that specific situation. Moreover, the study depended on the students' self-reported opinions rather than on direct measurements of their performance. Lastly, there was no control group, and therefore it is not possible to determine how the students who used ServeSmart compared with those who took part only in traditional role-play.

The initial results point to a number of avenues for further research. Future studies might use experimental or quasi-experimental approaches with treatment and control groups in order to find out if ServeSmart leads to measurable differences in performance, decision-making, response time, and knowledge retention when compared to traditional role-play. Only in this way could stronger evidence of learning effects be obtained than from people's own reports. The system could also be further developed by using more advanced language models in order to enable less predictable and more natural conversations. It might be worthwhile to look into speech-to-text and voice-analysis features so as to go beyond written feedback and give information regarding students' spoken communication. Moreover, a greater variety of customer profiles, service situations, and languages could be included so that the system matches the diversity found in today's service environments. Such developments could increase the usefulness of ServeSmart for students who are preparing for various kinds of customer service jobs.

Conclusion

The study looked at how students saw ServeSmart as an AI-assisted learning tool for customer service training. The system was intended to give students guidance while they were carrying out simulations and to assist them in linking service quality theory with actual customer interactions. The initial responses were favorable in that all the participants said that their confidence in customer communication had increased and that their understanding of the main customer service concepts had improved, and all of them expressed an interest in using the system once more. The findings also point to the value students placed on immediate support, particularly when they needed to interpret customer emotions or decide how to respond. Because guidance was available during the interaction, students could reconsider their approach while the scenario was still in progress. This feature may create additional opportunities for reflection and practice while strengthening students' confidence, communication, and application of SERVQUAL concepts. ServeSmart therefore provides an initial example of how AI can be incorporated into competency-based service management education without removing the role of the educator. The findings remain preliminary because they are based on a small sample, a single academic setting, and self-reported responses. Further research using larger samples and objective measures of performance is needed. Nevertheless, the study provides a basis for continued examination of AI-supported experiential learning as a way of making customer service education more practice-oriented and responsive to the situations students may encounter in the workplace.

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