An Algorithm for Providing Adaptive Behavior to Humanoid Robot in Oral Assessment

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***Abstract*—Assistance humanoid robots (AHR) are the category of robotics used to offer social interaction to humans. In higher education, the teaching staff supports the acceptance of AHRs as a social assistance tool during the learning activities, with the whole responsibility of the correct operation of the device and providing a more comprehensive view of the objectives and significance of AHR use. On the other hand, students deal with AHRs either as a friend or control figures as a teacher. This paper presents an algorithm for AHRs in oral assessments. The proposed algorithm focuses on four characteristics: adaptive occurrence, friendly existence, persuasion, and external appearance. This paper integrates AHRs in higher education to improve the value of psychological and social communication during oral assessment where can assist students in dealing with challenges, such as shyness, dissatisfaction, hesitation, and confidence, better than a human teacher can. Thus, AHRs have increased students' self-confidence and enriches active learning.**

Keywords—Algorithm; humanoid robot; social robots; oral assessment; assistance robots; higher education; adaptive behavior robot

I. Introduction

Robots are becoming beneficial components of the educational ecosystem. With their different capacities, which range from the ability to see people and their environment to the ability to reason and explain circumstances and people's emotions, robots are becoming useful components of the educational ecosystem. These robots have a physical presence as well as multimodal interaction skills, which are equally crucial. With their human-like look, humanoid robots bring even another dimension to our understanding of social cues and body language: Keys to more intuitive and natural human–robot interaction and robots in education interacting [1].

As humanoid robots become more prevalent and people engage with them, the social intelligence of artificial agents is receiving attention. The important social skills presented by the standardized evaluation method for humans, Evaluation of Social Interaction (ESI), include approaches, speaking, turn-taking, gazing, and gesturing. When speaking to others, people employ co-speech gestures to accentuate their words, convey their intentions, or give detailed descriptions. Co-speech gestures have been shown to have strong impacts in numerous social science studies [2], and a neuroscience study supports motions are created by human professionals. The only movements that may be made are those that were considered during the design stage, even though hand-produced gestures are natural and human-like. Furthermore, it takes significant human effort to create links between gestures and verbal phrases [4].

Due to their physical resemblance to humans, humanoid robots can give real-time feedback and interact with people more effectively. They have improved social abilities and are designed to show emotion through gestures, intonation, and facial expressions, as well as to respond with the right body language [5]. They can also display feelings, including shock, fear, rage, and disgust. Compared to human teachers, humanoid robots can assist in resolving issues connected to shyness, frustration, reluctance, and confidence. Humanoid robots are being widely employed in many nations, particularly for special education, and can assist students in dealing with challenges, such as shyness, dissatisfaction, hesitation, and confidence, better than a human teacher can. One of the factors contributing to humanoid robots' success in achieving learning objectives is that they never get tired, regardless of how many mistakes a pupil makes. Some humanoid robots support telepresence, which enables instructors to connect to the classroom remotely using display systems, which are typically built into the torsos of robots [6].

So, in the present paper, we focus on oral assessment to improve the value of psychological and social communications during oral assessment and to increase students' self-confidence and enrich active learning.

The remaining of this paper is organized as follows. Section 2 stated the problem statement. Section 3 is related to the work presented here. Section 4 presents an algorithm for AHRs. Section 5 describes the four recognized characteristics: adaptive occurrence, friendly existence, persuasion, and external appearance. These are described in Section 6. We conclude the paper and point future directions in Section 7.

II. Problem Statement

Assistance humanoid robots (AHRs) in higher education have become an enriching teaching tool. They are different from portable devices such as smartphones, and tablets. AHRs have been described as human-looking forms with a head, arms, legs, and torso. Moreover, AHRs have characterized automation, repeatability, flexibility, digitization, anthropomorphism, body motion, and interaction [7]. Furthermore, AHRs encourage students to interact with reality in studying halls during the oral assessment process [8]. Consequently, AHRs have been characterized by personifying, which provides more social interaction with students, such as instantly addressing them by name. In this environment, robots provide students with a more honest and realistic interaction than other technological devices [9].

On the other hand, dialogues support social interaction and create a shared experience of knowledge. Dialogue flow also provides a significant factor in increasing the quality of conversations [10]. As a result, a high degree of dialogue flow corresponds to favorable self-esteem, has an influence on the individual understanding of belonging, and can encourage solidarity [11].

Since dialogue flow can encourage social bonds and satisfy social conversation needs, education institutions should manage this knowledge when considering using AHRs in student oral assessments. Consequently, this can contribute to promoting dialogue between students and AHRs, especially in oral assessments. This paper has presented an algorithm for designing AHRs in higher education and put the main features of its external appearance and behavior.

III. Related Work

Artificial intelligence, sensors, mechatronics, and power are all components of humanoid robots. The main aim of modern humanoid robots is to acquire the ability to recognize visual expressions and perceptions to solve tasks, such as correctly predicting the emotion of a human by monitoring their visual facial expressions. Therefore, the only information that humanoid robots need supplied is the data that will supply enough relevant information to be processed, allowing them to do and expand the range of learning and performing activities that are already available to them. It will be up to the algorithms and other methodologies, such as deep learning and neural networks, to extract the features from photos that have been given to them. All these goals for humanoid robots present considerable difficulties and processing power needs, and it should be highlighted that a humanoid robot cannot employ this kind of enormous computing power alone. To install the cloud, which will further analyze the information and give it back to the humanoid robot, the humanoid robots must absorb, integrate, and collect the information from the environment [12].

Research in the disciplines of robotics that is currently considered critical technologies include multisensory perception, cognition, and man-machine interaction. Robotic systems are given theses and procedures from the field of artificial intelligence (AI). Significant biological principles can be used as recruiting tools and role models for robots. With remarkable accuracy, the human body is replicated in its greatest potential kinematic form. The main new area of research in AI is humanoid, complicated mechatronic systems inspired by biology. The psychological features of humanoid robots are just as fascinating as their technological ones [13].

More robots are being created for use in practical fields, such as education, healthcare, eldercare, and other assistive applications. For robots to have a positive impact on human life, there must be natural human–robot interaction (HRI). A human-like interaction is built on an understanding of the other person’s needs and emotional condition at the time of the interaction. To achieve this goal, Chiara and others proposed an ecological technology called thermal infrared imaging, which can give information on physiological characteristics related to the subject’s emotional state. This ecological technology was presented and surveyed here. The technology can lay the foundation for the continued development of powerful social robots as well as for HRI. In the literature, thermal IR imaging has already proven effective for identifying emotions. This review can serve as a roadmap and encourage the usage of thermal IR imaging-based affective computing in HRI applications, which are meant to enable a natural HRI with a focus on people who find it challenging to convey their feelings [14].

Aburlasos et al. [15] proposed an organized and comprehensive modeling behavioral method to guide the activities of two interactive NAO robots with the goal of gradually evoking the Gestalt game in the mind of an autistic child. More specifically, the goal is to teach Gestalt’s game first to robots and then to autistic children. In the end, children with autism will discover that playing with other children is more fun than playing alone with robots.

Teaching robots using hand gestures is now possible thanks to a framework developed by Mazhar et al. [16]. The background invariant robust hand gesture detector is the foundation of the suggested system. This was accomplished by applying a modern convolutional neural network that has already been trained, Inception V3, to the classification of 10 hand movements. The experiment validates the effectiveness of the suggested framework and guarantees a natural way to program robots. The combination of Kinect V2 and Open Pose allows the robot to understand its distance from the human worker to ensure the safety of nearby human coworkers.

Alemi, Meghdari, and Haeri [17] conducted a study in which they attempted to examine the attitudes of young EFL learners toward RALL. An experiment with a humanoid robot acting as a teacher’s helper was carried out in a private kindergarten in Iran. They monitored the students’ motivation, interaction, and anxiety as they studied with the humanoid robot. The outcomes demonstrated that the students’ motivation increased because of their positive interactions with the humanoid robot. Additionally, they showed no indicators of nervousness while engaging with the humanoid robot during the learning process since it made the classroom feel welcoming. In conclusion, this study has served as a superb model for subsequent investigations using humanoid robots in second robots, which are seen as attractive and practical instruments in language learning and teaching circumstances. They can also accommodate the various needs of the students.

The field of social robotics is undergoing significant change because of neuroscience-based human–robot interaction, which is also improving our understanding of the human brain. Recent findings have demonstrated that more sophisticated analysis techniques and the trend of gathering data during real-time, embodied interactions with robots can deepen our understanding of the fundamental mechanisms underlying social cognition beyond simply perceiving robots in screen-based experiments. The development and design of the next generation of social robots, the same robots that may one day function as social companions who support and care for their owners, stands to benefit from the additional (and natural) knowledge gained from this basic human brain research [18]. However, in less than 10 years, major problems about human–robot interaction have emerged from the field of neuroscience, such as: How can our relationships with these unique, mechanical companions benefit from the complex neural architecture of the human brain? How does the representation of social cognition evolve as robots become more pervasive in our social lives? Future research fusing human neurology and social robotics will shed light on how to live with autonomous robots that connect with us socially.

IV. Humanoid Robot Imitation Learning

Imitation learning refers to a humanoid robot's acquisition of skills or behaviors by observing a teacher demonstrating a given task. With motivation from neuroscience, imitation learning is a significant portion of AI, and human-computer interaction, and in turn, is taking a part in the future of robotics [19]. Another approach to imitation learning depends on trial and error, which introduces valuable models to understand desired behavior from a set of collected instances [20].

Imitation learning works by extracting features about the instructor's actions and the surrounding environment, including any manipulated objects, and understanding a mapping between the current position and revealed behavior. Traditional machine learning algorithms do not scale to high-dimensional agents with high degrees of freedom. Particular algorithms are therefore needed to build satisfactory representations and predictions to simulate motor processes in humans [21].

In the complete method of robotic imitation learning, demonstration teaching provides a teaching sample containing made options, operation characterization characterizes the options within the teaching sample as valid forms that the golem will acknowledge. The last word goal of imitative learning is to create the robot "master" behavior, which implies that the robot has got to reproduce the behavior and generalize the behavior into different unknown scenes. The method that robots use the teaching data to "master" behavior will be referred to as operation imitation. This thought methods of operational imitation are roughly divided into three categories: activity biological research, inverse reinforcement learning, and adversarial imitation learning.

V. From Human Assessment to Robot

Although oral assessment has a wide record in examination practice in higher education and is a well-established component of such proceedings, concerns remain regarding its use. Therefore, there has been some move away from oral assessment for students, partly through a consideration of validity, trustworthiness, and justice [22].

Given the long history of oral assessment, which has some distinct advantages, it reflects the oral form document of communication that dominates professional practice. Also, it can test the limits of a student's knowledge and understanding. Moreover, it is thought to be an especially practical way of assessing individual types of capabilities. Furthermore, it supports intra-personal differences, such as trust and self-awareness [23].

AHRs have become an essential component of higher education infrastructure as teachers; they might take over assigned tasks that professors carry out. For example, AHRs deliver hints upon request to students [24].

In this case, the AHR keeps students' inspiration at a high level by prompting them. AHRs can be friends with students and share learning with them. Also, AHRs could assist in preserving student inspiration at a high level by encouraging them. Consequently, the AHR can play a valuable role in oral assessments. Oral assessment supports active learning through its empowerment of creating confidence among teaching staff and students during the oral assessment process of AHR technology [25]. That is, in turn, it may create more confidence for professors and higher education about the integration of AHR technology into their strategy.

VI. Proposed Algorithm

This paper presents an algorithm for AHRs, which is described by four recognized characteristics: adaptive occurrence, friendly existence, persuasion, and external appearance. This is detailed in this section.

Algorithm1: AHR generates gestures during dialogue acts information.

Step 1: Start.
Step 2: Collect speech datasets.
Step 3: Determine the consideration of speech.
Step 4: Define the dialogue acts based on speech consideration.
Step 5: Classify the dialogue acts information into categories.
Step 6: Discover the gestures happening combined with dialogue acts.
Step 7: Extract main motion features.
Step 8: Cluster these features to reduce dimensionality and increase the representability of gesture motions.
Step 9: Develop conceptual models to connect dialogue information with gesture motion.
Step 10: Analyze the intention of dialogue information related to gestures motion.
Step 11: Discover the period of different gestures motion regarding dialogue information.
Step 12: Determine the phases of gestures motion generation during dialogue information.
Step 13: End.

Fig. 1. The AHR Generates Gestures during Dialogue Acts Information.

A. Friendly Existence

Friendly existence expresses sociable presences. Students tend to humanize robots as technological devices, such as the AHR, and treat them socially when the technology shows social cues. The aim of this algorithm is to investigate the dialogue flow with AHR in the real oral assessment environment and to examine the extent to which oral flow is present in AHR–student interactions. Algorithm 1 described in Fig. 1 shows how AHR generates gestures.Dialogue acts as information in oral assessments. This algorithm classifies dialogue gestures into categories and develops conceptual models to understand the intention of dialogue during oral assessment. Algorithm 1 can be compatible with generating hand gestures. It limits the whole arm's movements and manages the five fingers' movements. Also, there is a lack of head and torso motion. Another limitation can be indicated by eye gazing control issues. Algorithm 2, described in Fig. 2, generated laughing gestures during the dialogue assessment.

Algorithm 2: AHR generates laughing gestures during dialogue information.
Step 1: Start.
Step 2: Collect laughing speech dataset.
Step 3: Analyze laughter types.
(social, bitter, dumbfounded, and softening laughter).
Step 4: Analyze laughter style.
(secretly, giggle, guffaw, and sneer.
Step 5: Analyze intensity level.
Step 6: Analyze laughter function.
(funny, amused, joy, mirthful laugh, social polite laugh, bitter/embarrassed laugh, self-conscious laugh, inviting laugh, contagious laugh, depreciatory/derision laugh, dumbfounded laugh, untrue laugh, softening laugh).
Step 7: Detect the facial expressions during laughter.
eyelids(closed, narrowed, open).
cheeks(raised, not raised).
lip concerns(raised, straightly stretched, lowered).
Step 8: Detect the head and upper body motion during laughter.
head(no motion, up, down, left or right up- down titled nod, others(including motions synchronized with motions like upper-body)).
upper body(no motion, front, back, up, down, left or right, titled, turn, others(including motions synchronized with other motions like head and arms)).
Step 9: End.

Fig. 2. The AHR Generates Laughing Gestures during Dialogue Information.

B. Adaptive Occurrence

Adaptive occurrence represents adaptiveness as a key characteristic of oral assessment quality. Regarding AHRs in oral assessment, perceived adaptiveness may be expressed as the extent to which students consider the AHR to keep in touch with their individual learning assessment needs. For example, an AHR selects to begin a dialogue with the student to offer assistance, as depicted in Algorithm 3 in Fig. 3. According to Algorithm 3, student assistance suggests more known keywords to help the AHR understand the student-robot dialogue. Then, the AHR solves the problem itself, or student assistance can offer more additional information to enhance the AHR's understanding. The problem includes understanding keywords or informing unclear messages not inserted into loaded sound files. This assistance provides an appropriate learning pace and introduces personal feedback during the oral assessment.

Furthermore, an AHR can address the unclear content in the oral assessment, as depicted in Algorithm 4 in Fig. 4.

Concerning the social behavior of AHR is a key facet of adaptiveness. The AHR stimulates social interaction in oral assessment with students by calling students by their name and capturing a photo, as depicted in Algorithm 5 in Fig. 5.

Algorithm 3: AHR starts a dialogue for student's assistance
Step 1: Start.
Step 2: AHR identifies a problem in student-robot dialogue.
Step 3: AHR searches in loaded sound files on it.
Step 4: If AHR finds the answer
Then AHR completes the student-robot dialogue.
Else AHR asks for student assistance.

Step 5: Student's assistance provides AHR with the required support.
Step 6: **If** AHR solves the problem
Then AHR completes the student-robot dialogue.
Else AHR requests additional support.

Step 7: AHR tries again to solve the problem after student support.
Step 8: AHR solves the problem thanks to Student assistance.
Step 9: End.

Fig. 3. The AHR Starts a Dialogue for Student Assistance.

Algorithm 4: AHR adapts the dialogue content.
Step 1: Start.
Step 2: AHR greets students.
Step 3: AHR introduces itself and the educational institution.
Step 4: AHR explains its role in the dialogue which includes to clarifies the aim of the dialogue.
Step 5: AHR receives questions from students and provides them with answers.
Step 6: If AHR detects any misunderstanding in the students' dialogue.
Then AHR alerts their attention and provides them with complete right explanations.

Step 7: AHR supports its dialogue with suitable references from the university's library or internet resources or practical examples.
Step 8: AHR updates its dialogue regularly to develop its skills in student-robot interaction.
Step 9: AHR supports student dialogue by using gestures and expressing empathy motions.
Step 10: End.

Fig. 4. The AHR Adapts the Dialogue Content.

Algorithm 5: AHR adapts social behavior with students.
Step 1: Start.
Step 2: AHR asks the student about his/her name.
Step 3: AHR greets the student.
Step 4: AHR captures a photo of the student.
Step 5: AHR determines the student's face and performs face recognition.
Step 6: AHR extracts the face features.
Step 7: AHR predicts the student's age and emotional state.
(e.g. happy, unhappy, worried, sad, anxious).
Step 8: **If** there is an academic database about the students' degrees or personal profiles.
Then AHR can be reached and collects the whole information about the student.

Step 9: AHR confirms the learning processes(e.g. oral assessment process, suggests some activities according to the social behavior of students or emotional state).
Step 10: End.

Fig. 5. The AHR Adapts Social behavior with Students.

C. Persuasion

According to Fig. 6, AHR provides students with more trust and persuasion through its physical shape like humans, which adds more flexibility and comfort during student-robot interaction. Also, the AHR design provides feedback based on social norms and friendship relations. Moreover, the AHR introduces a personalized service with the mutual gaze communicated along with contextual information.

Additionally, it incorporated traditional communicative processes, such as jokes. Through jokes, the AHR can deal with students with double-friendly interaction. Consequently, jokes can motivate students toward effective cooperation and create a community-centered learning environment. Also, jokes encourage students in the learning process and enrich social interaction.

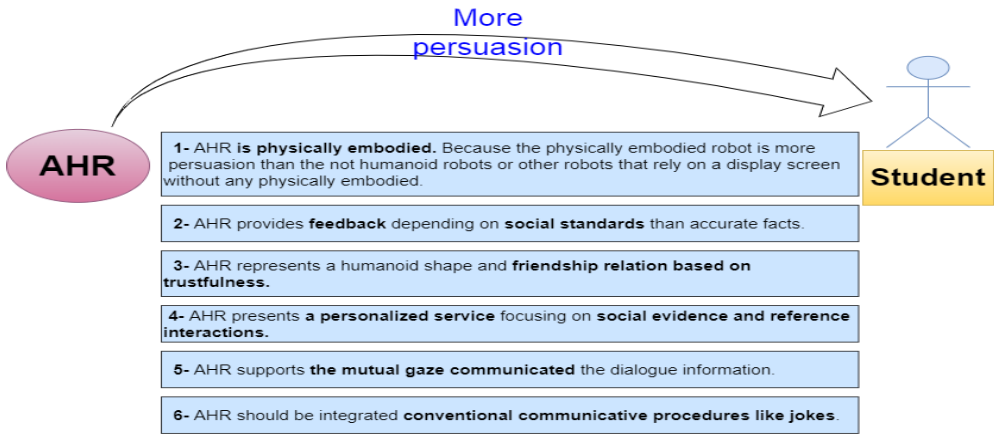

Fig. 6. Persuasion Features of the AHR.

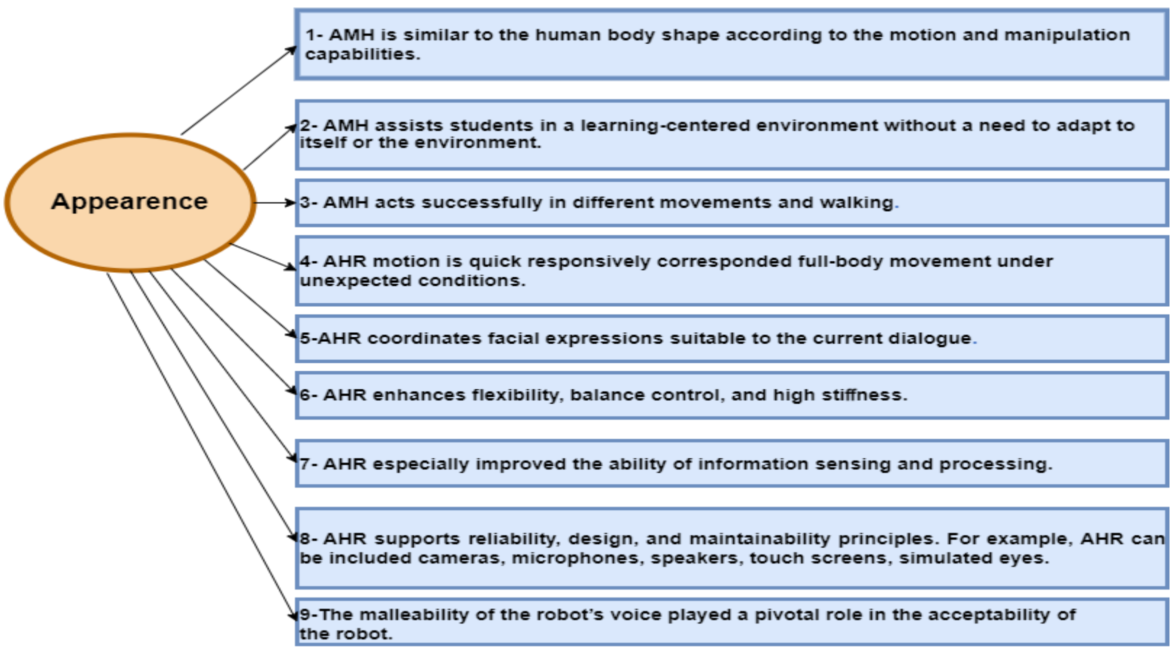

Fig. 7. External Appearance of the AHR.

D. External Appearance

AHR appearance should be designed to correspond to dialogue requirements in oral assessments. This appearance can be described as flexible. AHR dialogue contains different alternatives for each social interaction of dialogue, such as a greeting, end dialogue statement, jokes, and different keywords of various intentions. Fig. 7 explains the appearance of the AHR in detail.

VII. Discussion

To answer the research questions in this study according to the above analysis, we think it is possible for the robot to act as a tutor and automatically guide freshmen to conduct a group test.

We expect robots to judge students' answers fairly. In the past, when human teachers conducted oral tests, they sometimes let students pass the assessment with a looser standard. In addition, human teachers cannot maintain a certain concentration, objectivity and fairly for a long time, and robots can easily do it. However, we can find in the robot was not sensitive to students answers. In fact, sometimes the students should to try several times before the robot could receive the sound and recognize it. Although some monosyllabic words were heard by the robot, there may be some problems because of the pronunciation problems.

For example, since the pronunciation of numbers is very basic, this can be a blow to students. In the first case, students' pronunciation will affect the correct answer rate on the test. From the perspective of language teachers Technical problems can be overcome. Where, we suggest that when using a robot to conduct the oral test, the robot need to practice pronunciation before conducting formal test. It also could give the students the opportunity to pronounce before the test. Besides, the teacher could modify the way that students answer questions (e.g., by answering with whole sentences instead of just numbers) to make up for the robot's lack of recognition of monosyllables. A further test can be conducted by native speakers to compare the reception of sound to find out if this situation is mainly due to the pronunciation of foreign language learners or the experimental environment. Also about the design of the test, the robot can say the correct answer after each question to let the students know the correct answer or pronunciation immediately.

On the other side, Human–robot interaction also can be enhanced peer–peer interaction. When someone answers right, the peers cheer. Through their peers' affirmation, students can improve self- confidence or reduce the sense of distrust of their own pronunciation. In addition, in group learning students can learn important lessons from the answers made by other students.

VIII. Conclusion and Future Work

Humanoid robots play a catalyst role in higher education because they include human-like forms that support student satisfaction. They also encourage students to generate contemporary fluencies. The prosperous performance of emerging AHRs in learning needs cognizance of the investment principles on the part of those carrying out the performance. Oral assessment is a critical process in higher education. Consequently, oral assessment supports active learning through its empowerment of creating confidence among teaching staff and students during the oral assessment process of AHR technology. That is, in turn, it may bring professors and higher education more confidence about the integration of AHRs technology into their strategy. This paper has discussed an algorithm for applying AHR in oral assessments in higher education. This algorithm also depends on four perceived characteristics: adaptive occurrence, friendly existence, persuasion, and external appearance. Moreover, it presents the experiences of human–robot interaction.

In future work, we intend to discover substantial distinctions between oral assessment guided by the teaching staff and AHRs. Also, we hope to develop the proposed algorithm by adding more characteristics. We desire to be able to use the AHR to direct oral tests so that professors can exchange roles and monitor and assess students' complete ability and change the way the oral test is conducted.

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