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ORIGINAL ARTICLE

Change gently: an agent-based virtual interview training for college students with great shyness

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Abstract
Virtual Reality (VR) training systems are gaining popularity for psychological and skills training. Shy college students may perform poorly in interviews due to a fear of being evaluated, anxiety about real interview scenarios, and a lack of interviewing skills. In response, a pre-training environment (VR training system) was designed and developed, combining Virtual Reality Exposure Therapy (VRET, simulating a safe and controlled real interview environment) with biofeedback therapy (intuitive multimodal assessment and feedback). Virtual agents can play a positive role in psychological intervention and skill training. Different personalities of interviewers may help shy individuals overcome interview anxiety and enhance their interviewing skills. Therefore, we created virtual interviewer agents with three distinct personalities based on Eysenck's personality theory. We improved on existing methods for designing agent personality traits by defining expressive traits (e.g., different physical, behavioral, and verbal traits) and reactive traits (differential evaluative feedback based on the user's mental state). This self-training system requires no additional labor and provides initial training for shy college students prior to actual interviews. Ultimately, we recruited and selected 16 shy college students who underwent three VR-simulated interviews using our system. Expert evaluation and physiological measurements were employed to assess their interview anxiety and performance. The results of the user study indicate that our agent-based VR training system effectively assists shy college students in overcoming interview anxiety and improving interview performance.

Keywords And phrases: virtual interview · Agent-based interaction · Self-training · Persona effect · Shyness

1 Introduction

VR serious games, with game-like interactions and conversations, allow users to acquire specific knowledge and skills (Borges et al. 2016; Stupar-Rutenfrans et al. 2017). Furthermore, VR possesses immersive characteristics, simulating real-life scenarios. As a result, serious VR games have been applied in therapeutic interventions for emotional disorders such as anxiety, depression, stress, and cognitive rehabilitation (Borges et al. 2016; Damian et al. 2015; Jerdan et al. 2018; Porayska-Pomsta and Chryssafidou 2018). One of the most common types of VR interventions is Virtual Reality Exposure Therapy (VRET), which can effectively support anxiety treatment in various VR environments (e.g., interviews and public speaking) (Baghaei et al. 2021; Jerdan et al. 2018). VRET provides a safe, controlled, and customized environment that guides individuals to gradually approach anxiety-inducing situations repeatedly until these situations no longer evoke feelings of anxiety and fear (Wang 1996). Shyness, defined as a tendency to avoid social interactions and to fail to participate appropriately in social situations, is a surprisingly common characteristic among college students (Pilkonis 1977). Research indicates an increasing prevalence of shyness among college students (Dou et al. 2015). Shyness often results in anxiety and withdrawal during interviews, adversely affecting overall interview

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performance (Miller and Coll 2007). Existing interview systems tailored for students primarily focus on specific domains such as healthcare education (Halan et al. 2018), internal audit (Pickard et al. 2020), English communication (Lee et al. 2023), or cater to specific populations like individuals with psychiatric disabilities (Smith et al. 2014, 2015, 2017; Downey et al. 2022), and autism spectrum disorders (ASD) (Kumazaki et al. 2019; Smith et al. 2014, 2020, 2021). However, these systems do not specifically address the characteristics of shy college students, such as experiencing anxiety in real interview scenarios, fearing evaluation, and needing to face interviewers with various personality types. There is a lack of training systems tailored specifically for shy college students to enhance their interview performance through targeted interventions.

In virtual training systems, it's crucial to objectively and comprehensively assess the performance of shy users based on their characteristics. Firstly, individuals who are shy tend to fear evaluation by others. To achieve the goals of training, it becomes necessary to induce a sense of evaluation in them to elicit anxiety responses (DeGroot and Gooty 2009; Russell et al. 2008), which helps identify critical events that may impact actual interview outcomes (Naim et al. 2016). However, previous research has somewhat overlooked conducting a comprehensive multimodal assessment of the performance of shy users, which includes behavioral, emotional, and physiological indicators (Damian et al. 2015; Kwon et al. 2013). Secondly, shy individuals need guidance on how to improve their interview performance. It is worth noting that culture is a significant factor in interviews (Arseneault and Roulin 2021; Vatrapu and Pérez-Quiñones 2006). In different cultural contexts, interview content and performance evaluation criteria vary, making existing interview evaluation systems not entirely suitable for Chinese users. This study needs to address this gap by considering cultural nuances in the design and evaluation process, ensuring that the training system is relevant and effective for Chinese students. Thirdly, biofeedback therapy processes an individual's biological signals and presents them intuitively (e.g., visually and auditorily), enabling individuals to consciously regulate their psychological states (BIO International Organization Textbook Writing Group 2007). The combination of biofeedback therapy and VRET can enhance the effectiveness of intervention measures (Alneyadi et al. 2021). Effectively providing intuitive, multimodal feedback tailored specifically for shy individuals is a key consideration of this study, helping them to better manage their interview anxiety.

In virtual training scenarios, virtual agents play a crucial role. Research shows that using virtual agents as interviewers can effectively enhance interviewees' skills and reduce anxiety (Langer et al. 2016; Mitrut et al. 2021). Different types of agents significantly influence users' training experiences and performance, known as the "persona effect" (Lester et al. 1997; Pan et al. 2015). Since university students face diverse interviewers in real-life, it's important to design virtual interviewers with varied characteristics, such as different personality types. While the Big Five model is often used to develop virtual agent personalities (Allbeck and Badler 2002; Dekker 2012; Read and Miller 2002), it doesn't categorize personalities into distinct types. In contrast, Eysenck's model (Saggino 2000) allows for classifying personalities into distinct types, enabling the creation of virtual characters with specific personality traits. Based on this, despite research efforts to design personalities for agents, most existing agent models cannot infer or respond to the user's psychological state (Hoque et al. 2013; Paiva et al. 2004; Pareto et al. 2009). Furthermore, they lack the evaluative responsiveness needed to adapt to the user's condition (McRorie et al. 2011; Read and Miller 2002). However, in human psychology, the Theory of Mind (ToM) highlights the human capacity to infer the mental states of others and even influence their behavior (Baron-Cohen 1997). This underscores the necessity of integrating ToM principles into the modeling of virtual agents, and this study aims to improve the design of virtual agents by incorporating different personality traits.

In summary, there is a lack of interview training systems specifically designed for shy individuals. Additionally, existing interview assessment mechanisms are inadequate and do not fully align with the cultural context in China. Lastly, current methods for designing virtual agents with personality traits are not yet refined and lack responsiveness to the user's mental state. Based on these considerations, we have developed an agent-based VR interview training system that combines Virtual Reality Exposure Therapy (VRET) and biofeedback therapy. VRET provides a gentle transitional training approach to gradually boost the confidence of shy individuals, while biofeedback therapy offers effective and intuitive feedback to enhance interview performance. The combination of these two methods comprehensively presents multimodal assessment results, externalizing the emotional experiences of shy individuals into visible forms, helping them better understand their current feelings and improve their self-control abilities. Building upon Theory of Mind and Eysenck's personality theory, we have improved existing methods for designing agent personality traits by defining both expressive features (such as distinct physical, behavioral, and verbal characteristics) and responsive features (varying feedback based on the user's mental state). Ultimately, user research indicates that the agent-based VR training system is effective in helping shy college students overcome interview anxiety and enhance their interview performance.

Our contributions are as follows:

(1) We designed and developed an agent-based VR training system by integrating VRET with biofeedback therapy to help shy college students improve interview skills and deal with social anxiety (see Fig. 1b).

(2) We improved a previous method for designing agents' personality features by defining both expressive and reactive characteristics. Using this method, we created three agents (interviewers) who display different personality types (see Fig. 1a).

(3) We conducted an empirical study, and the results supported the effectiveness of this system in helping shy individuals overcome interview anxiety and improve their interview performance.

2 Related work

2.1 VR technology for social anxiety intervention

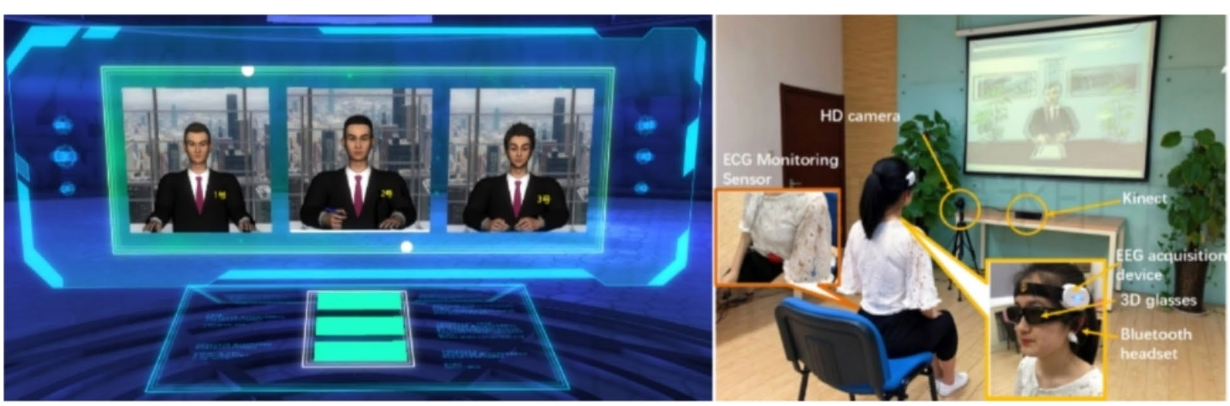
VR has demonstrated its effectiveness in enhancing exposure therapy interventions. It can create immersive environments, providing stimuli that are beneficial for individuals who struggle with imagining scenes or are too phobic to experience them in reality. Parsons and Rizzo conducted a comprehensive review of 21 articles evaluating anxiety and/or phobia before and after VRET (Parsons and Rizzo 2008). The results indicated a significant impact of VRET on emotional domains, making it a suitable approach for reducing anxiety-related symptoms. Similarly, Powers and Emmelkamp compared the efficacy of VRET to in vivo exposure and other control conditions (Powers and Emmelkamp 2008). Their findings revealed that VRET had a consistently more significant impact than control conditions and, notably, outperformed in vivo exposure.

Interview anxiety is a kind of social anxiety. For shy people, interactions with strangers, especially those of the opposite sex or in positions of authority, can trigger intense social anxiety. Moreover, situations requiring assertive behavior and evaluative settings (e.g., job interviews) can also trigger strong social anxiety (Russell et al. 1986). Thus, for the shy, direct face-to-face interview training can make them too anxious and scared. A gentle form of transitional training is needed to slowly increase their confidence. Given the advantages of VRET for social anxiety, particularly in the context of job interviews (Luo et al. 2023; Ohsuga and Koba 2022; Emmelkamp et al. 2020), it could provide individuals struggling with shyness a training environment to overcome anxiety and enhance their preparation for face-to-face interactions.

2.2 Computer-aided interview training systems

VR technology holds significant potential for training skills in social interaction contexts, such as interviews (Borges et al. 2016; Damian et al. 2015; Porayska-Pomsta and Chryssafidou 2018), public speaking (Stupar-Rutenfrans et al. 2017), and more. Anderson et al. introduced the TARDIS framework, designed to establish a scenario-based serious-game simulation platform for European NEETs and job-inclusion associations, offering social training and coaching within the context of job interviews (Anderson et al. 2013). The platform was developed to allow young people to explore, practice, and enhance their social skills in various interview situations through interactions with virtual agents serving as recruiters.

However, culture plays a crucial role in interviews (Arseneault and Roulin 2021; Vatrapu and Pérez-Quiñones 2006). The content of interviews varies across different cultural backgrounds. For instance, in Chinese culture, the civil



(a) (b)

Fig. 1 The Agent-based virtual interview training system. **a** Three interviewers with different personality types (each interview scenario involves only one interviewer conducting the interview with the user.); **b** A snapshot of the virtual interview training environment where a shy college student is undergoing training service examination is a mainstream career choice with a relatively standardized interview process and topic types. Consequently, the existing interview system might not be suitable for interviews in China. Recognizing the importance of interview abilities to college students' careers, it is necessary to develop a specific VR interview training system to help college students enhance their interview skills in line with their cultural background.

2.3 The use of agents in interview systems

Virtual agents are commonly employed in virtual interview training systems to enhance communication competence in situations resembling face-to-face interactions. Studies have shown that practicing interviews with a virtual agent as an interviewer is more effective in improving interviewees' skills and increasing self-disclosure compared to conventional methods (DeVault et al. 2014; Lucas et al. 2014, 2017; Lee et al. 2020; Damian et al. 2015). Furthermore, virtual agents, when assuming roles as both interviewers and advisors during practice interviews, have been reported to reduce interview anxiety among candidates (Langer et al. 2016). Given that college students may encounter interviewers with diverse personalities, enhancing their ability to overcome anxiety in such situations is crucial. In this context, virtual agents with distinct personality types play a pivotal role in virtual training environments.

If we aim to design agents with psychologically plausible personality features, a theoretical approach rooted in psychology is necessary (McRorie et al. 2011). Psychological research on personality attribution is based on two main theories: the Big Five or Eysenck's trait model (Saggino 2000). While researchers often prefer the Big Five model for understanding and developing the personalities of virtual agents (Allbeck and Badler 2002; Dekker 2012; Read and Miller 2002), this model does not categorize personalities into distinct types. In contrast, Eysenck's model allows for the categorization of personalities into specific types, achieved by establishing stereotypical characteristics (such as appearance and behavior) consistent with defined personality types (Borkenau et al. 2004; Naumann et al. 2009). This approach enables the creation of virtual characters with different personality types. Despite some existing research efforts to design personalities for agents, there is often a lack of evaluative responsiveness features to adapt to user mental state (McRorie et al. 2011; Read and Miller 2002). This study aims to enhance the methodology for designing agents with varying personality characteristics, ensuring that these agents possess not only expressive but also responsive traits.

2.4 Evaluation methods of interview

In the virtual training system, it is crucial to evaluate users' performance from multiple dimensions and objectively. In Kwon's study, they used skin conductance response (SCR), pulse rate (PR), and eye-blink rate to indicate emotional arousal and valance to measure social anxiety (Kwon et al. 2013). In Damian's virtual job interview training game, the system analyzed the user's nonverbal behavior (gestures, postures, body expressivity, facial expressions, and use of voice) in real-time during the interaction using various sensors to facilitate reactive behavior (Damian et al. 2015). This helped to identify critical events that may influence the outcome of an actual interview. Therefore, it is necessary to evaluate users' interview performance using multiple signals—such as behavioral, facial, and physiological indicators—to gain a comprehensive understanding of their performance (Naim et al. 2016).

In addition, the evaluation criteria for interview performance vary across different cultural backgrounds, particularly in the interpretation of nonverbal behavior. Body language encompasses a wide array, including body movements, postures, head movements, gaze, facial expressions, limb movements, sitting postures, and more. Due to cultural differences, there may be variations in how interviewers interpret the same body movements. For instance, in China, interviewees are expected to exhibit effective 'impression management' during interviews, as excessive relaxed and casual actions may result in lower scores. In contrast, in Western countries, a more relaxed and authentic demeanor is often encouraged. Therefore, the development of a VR-aided training system for diverse users should consider the evaluation and feedback of users' interview performance, rooted in their respective cultural backgrounds. (Quan 2009).

3 Design of our virtual interview system

3.1 Overall design requirements

The motivation for our work is to help the shy overcome interview anxiety and improve performance. By combining the characteristics of shy college students with the advantages of VR, we proposed a series of design requirements:

Requirement 1 Simulate real, diverse face-to-face interaction scenarios as much as possible. Situations and interactions should closely mimic reality to provoke anxiety, and agents should be diverse.

Reasons and basis VR has the feature of immersion and can simulate realistic situations. The study indicated that a user's anxiety in a virtual job-interview simulation is similar to that in an actual environment (Villani et al. 2012). Additionally, even virtual humans at a lower level of realism and semi-immersive VR interview environments can induce considerable anxiety in users (Kwon et al. 2013). VR can provide a safe environment for shy people to interact face-to-face with diverse virtual interviewers. They can be exposed to simulated anxiety-provoking situations and learn to deal with the negative emotion (Riva 2004) rather than reinforce withdrawal behavior. In short, VR should help reduce the difference between human-agent interaction and human-human interaction.

Requirement 2 The VR interview system should integrate VRET with biofeedback therapy.

Reasons and basis VRET guides individuals to gradually approach their fearful situations repeatedly until these situations no longer cause anxiety and fear (Wang 1996). Biofeedback therapy processes individuals' biological signals and presents them intuitively (e.g., visually and audibly) to help them consciously control their psychological state (BIO International Organization Textbook Writing Group 2007). The combination of the two can externalize the invisible emotions of shy individuals into visible forms. This approach can help shy individuals achieve better self-recognition of their current feelings, contributing to improved control.

Moreover, a virtual interview system design should consider the actual interview process and topics to simulate realistic interview scenarios. For shy individuals, the actual interview often causes emotions like anxiety and fear (Posthuma et al. 2002). Interacting with strangers may induce anxiety and a sense of losing control (Jones and Pinkney 1989). Therefore, the VR interview system should provide shy individuals with a pre-training environment to overcome interview anxiety by familiarizing them with the interview situation.

Requirement 3 The VR interview system should naturally evaluate shy individuals according to their multimodal data during the interview.

Reasons and basis Shy individuals often fear being evaluated. When they feel they are being assessed by others, they become anxious and worried (Sarason and Sarason 1986). This can lead to negative outcomes such as speech disorders (e.g., stuttering), social withdrawal behaviors (e.g., avoiding eye contact), and other nervous behaviors (e.g., hand shaking) (Hollandsworth Jr et al. 1978). To achieve the training objectives, it is necessary to create a sense of evaluation to induce these outcomes (DeGroot and Gooty 2009; Russell et al. 2008). The system should assess these behaviors using multimodal data from shy individuals. Therefore, capturing the physiological data of shy individuals and providing an evaluation based on this multimodal data is essential for the VR interview system.

3.2 System architecture

This paper proposed an agent-based virtual interview training paradigm based on the above principles. As shown in Fig. 2, the system consists of four units: a stereoscopic display, personalized interview, multidimensional evaluation, and visual feedback.

3.2.1 Stereoscopic display

The realism of a virtual scene affects the user experience (Mania et al. 2003). To provide shy users with a realistic interview experience, we used 3D glasses and stereoscopic projections to present the simulated virtual interview environment. Compared with the virtual environment represented with an HMD, 3D projection can prevent the failure of facial expression recognition due to face occlusion.

3.2.2 Personalized interview

(a) *Design of Interviewers' Personalities*.

The interview situation is likely to exert stress on users, and this stress may be increased by the interviewer's specific verbal and nonverbal behavior (Gebhard et al. 2014). We designed three interviewers based on Eysenck's trait model (Eysenck and Eysenck 1985) and Bian et al.'s previous work (Bian et al. 2016). These interviewers exhibited different personality types, including choleric, phlegmatic, and sanguine. The melancholic type was not considered because melancholic individuals are introverted and anxious, making them rare in interview scenarios and unsuitable for this interview training.

We associated each interviewer's physical appearance, behavioral traits, and verbal features with their respective personality types (see Table 1) (Bian et al. 2016; Eysenck and Eysenck 1985; McRorie et al. 2011; Saggino 2000). Following Bian's design, we further defined the choleric and phlegmatic parameters and extended the sanguine

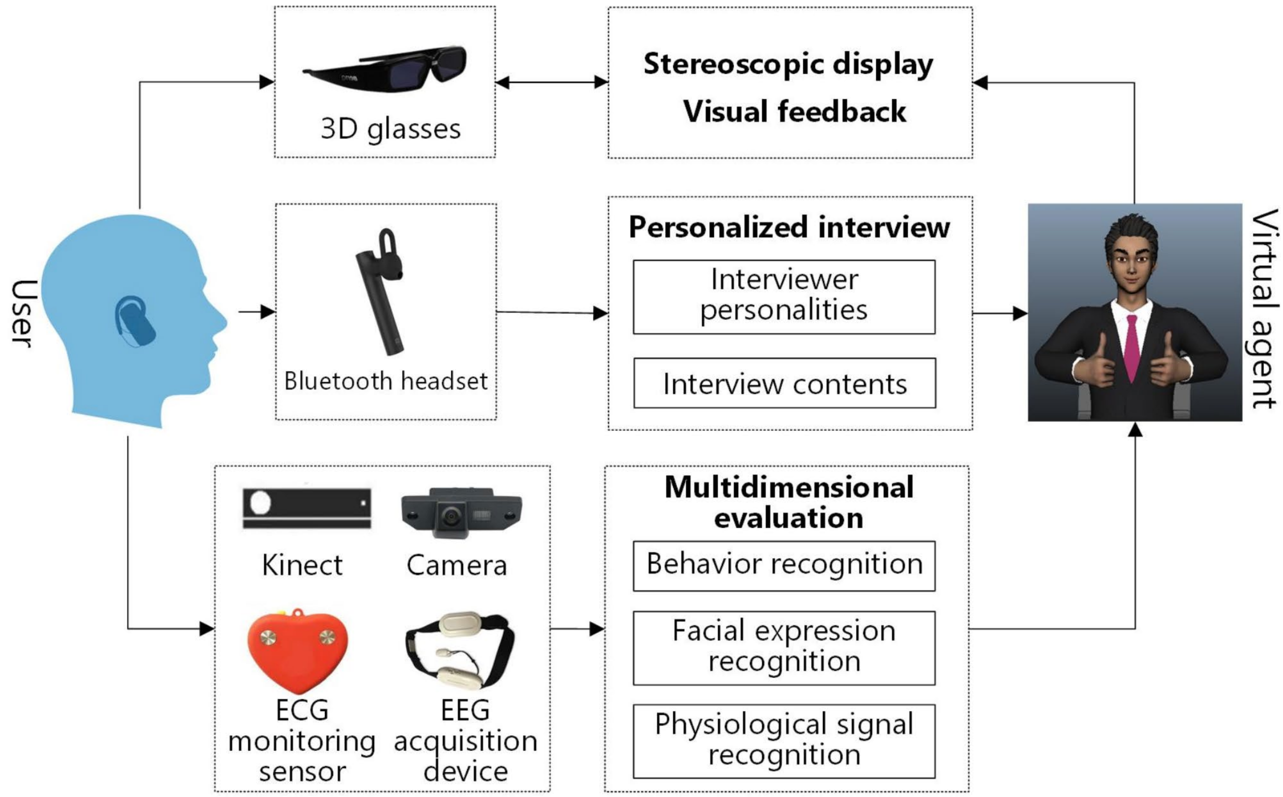


Fig. 2 The system architecture

personality traits (Bian et al. 2016). In addition to expressive features, we also designed reactive features.

For physical appearance, the choleric agent was characterized as active, restless, impulsive, aggressive, hot-tempered, and angry. His facial features were set in a permanently angry configuration or a severe facial appearance. Anger was demonstrated with staring eyes and frowning eyebrows, typified by prolonged direct gaze and wide eyes. These features are related to neuroticism (Bian et al. 2016; Eysenck and Eysenck 1985; Farabee et al. 1993; Howarth and Zumbo 1989; Tipples 2007). The phlegmatic agent was defined as passive, controlled, peaceful, careful, even-tempered, and calm. He was given peaceful and symmetrical facial features without any obvious expression (Bian et al. 2016; Eysenck and Eysenck 1985; Howarth and Zumbo 1989). The sanguine agent was characterized as optimistic and outgoing, with a handsome appearance and friendly facial expressions (McRorie et al. 2011).

For behavior, the choleric agent's facial expressions, movements, and gestures were defined by higher speed and larger movement range (Bian et al. 2016; Borkenau et al. 2004; La France et al. 2004). In contrast, the phlegmatic agent exhibited lower speed and smaller movement range (Bian et al. 2016). The sanguine agent displayed moderate speed and a larger movement range (McRorie et al. 2011).

In terms of voice, the choleric and sanguine agents were given loud and powerful voices consistent with their temperaments (Bian et al. 2016; Borkenau et al. 2004; McRorie et al. 2011). Conversely, the phlegmatic agent had a soft and calm voice, in line with his temperament (Bian et al. 2016; Borkenau et al. 2004).

(b) *Design of Interview Contents*.

Taking interviews in the Chinese cultural context as an example, we designed three types of interview training content for college students: company interviews, civil service examination interviews, and national entrance examination for postgraduate (NEEP) interviews. The civil service examination interview differs from company and NEEP interviews as it focuses more on comprehensive analytical ability, interpersonal communication competence, and organizational coordination ability (Wang 2011). Table 2 displays ten excerpts from the NEEP interview questions.

Our interview questions were sourced from existing question banks. For civil service and postgraduate interviews, we collected questions from the syllabus and previous years' questions released by official government departments and university websites. For corporate interviews, we gathered a collection of widely used interview

Table 1 Personality parameters of each agent

Agent	Personality	Characteristics	Appearance manipulation	Verbal features	Behavioral features
Agent 1	Choleric (neurotic extravert)	Active, restless, aggressive, impulsive, hot-tempered, touchy	Asymmetrical faces, frowning eyebrows, staring eyes, prolonged direct, eye gaze, wide eyes	Strong, confident, powerful words and phrasing	Higher movement speed, larger movement range
Agent 2	Phlegmatic (stable introvert)	Passive, peaceful, controlled, careful, even-tempered, calm	Symmetrical face, peaceful face, no facial expression, formal clothes	Calm, less direct and confident phrasing	Lower movement speed, smaller movement range
Agent 3	Sanguine (stable extravert)	Outgoing, optimistic	Attractive face, friendly facial expressions	Fewer pauses, shorter silences, fewer hesitations	General movement speed, larger movement range

Table 2 Ten excerpts from graduate student interview questions

Items
1. Please introduce yourself.
2. Why have you chosen to pursue a graduate degree?
3. What led you to select our graduate program?
4. Could you describe your past academic research or project experiences?
5. What are your interests and plans in your research area?
6. What is your role and experience in teamwork?
7. What do you consider your greatest strengths in terms of academic or career development?
8. Have you been involved in internships or practical experiences?
9. How do you handle academic challenges?
10. What are your thoughts on your future career goals and research directions?

questions in the industry from open-source repositories such as LeetCode[1], GeeksforGeeks[2].

3.2.3 Natural Interaction

The system adopted two kinds of interactions: voice interaction and brain-computer interaction (BCI).

Voice interaction Compared with touch or gestures, language commands are richer, more accurate, easier, and have a lower learning cost. Language, being the most common and direct form of human communication, is also considered an effective way to interact with smart devices. Users were supported in wearing Bluetooth headsets to engage in conversations with interviewers.

BCI BCI utilizes EEG caps to collect EEG activity signals, identifies human state information through amplification, analysis, decoding, and other processes, and then uses it as feedback regulation indicators for human-computer interaction (HCI) (Wolpaw et al. 2020). The human body state information decoded by EEG enables external intelligent devices to understand people's physical and mental states, such as fatigue and emotions, in real-time, achieving a more user-friendly, efficient, and high-functioning HCI (Dornhege 2007). For our system, we utilized NeuroSky BCI technology to enable brain-computer interaction.

The workflow of brain-computer interface is as shown in Fig. 3:

①*Signal calibration*: Adaptive calculation and synchronization of EEG signals for different users are necessary, followed by signal calibration.

②*Signal acquisition*: The EEG acquisition process should be simple, user-friendly, and ensure accurate signal collection. NeuroSky utilizes single-lead dry electrode technology, and the EEG signals from the NeuroSky system closely resemble those from the Biopac system (NeuroSky 2009a).

③*Signal extraction*: Brainwave signals must be isolated from a noisy environment to generate clear signals after amplification processing.

④*Information interpretation*: Brainwaves must be interpreted as parameters representing the current mental state of the user.

⑤*Human-computer interaction*: The parameters are then transmitted to a computer device, enabling human-computer interaction (HCI) through brainwaves. The NeuroSky eSense algorithm employs a slow-adaptive approach to dynamically compensate for fluctuations and individual

[1] LeetCode, https://leetcode.com/.

[2] GeeksforGeeks, https://www.geeksforgeeks.org/.

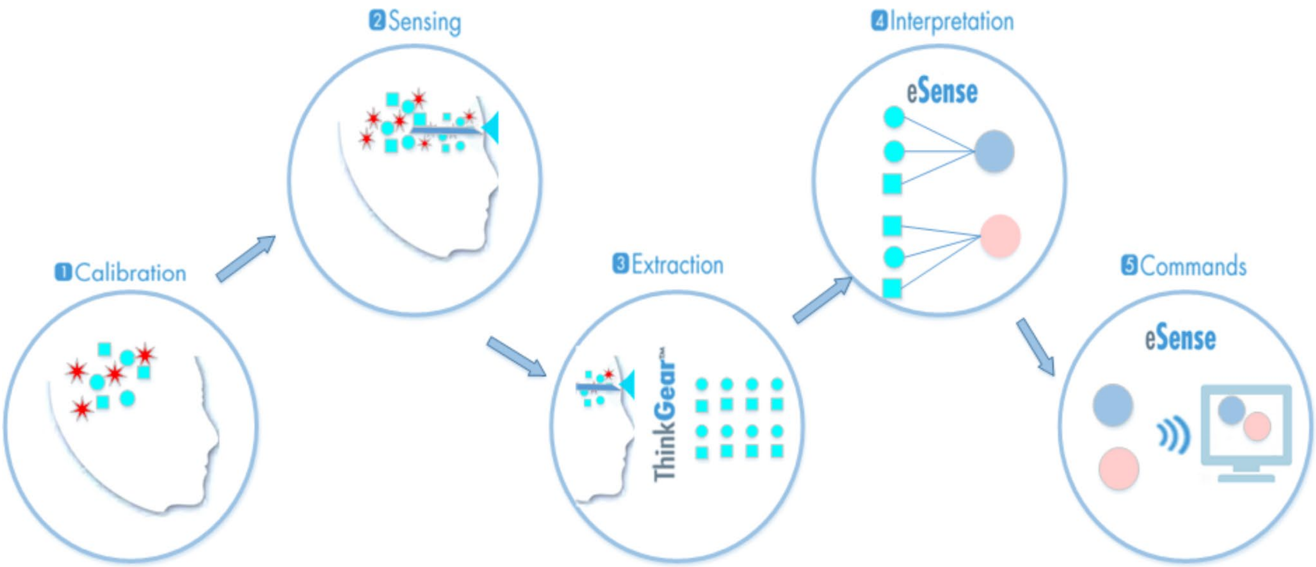


Fig. 3 Brain-computer interface workflow

differences. Therefore, ThinkGear's dry sensor technology (Saini et al. 2022; Yang et al. 2023) can be highly accurate and reliable across various individuals and application scenarios (Bhatti et al. 2016; NeuroSky 2009b; Rogers et al. 2016).

3.2.4 Design of multidimensional evaluation

The system evaluates interview performance from three aspects:

Behavioral performance Certain candidate behaviors during the interview process can easily lead the interviewer to make negative inferences about their traits or abilities. These actions include improper body tilt, excessive body shaking, crossing arms, scratching the head, crossing legs, etc. (Deng 2008; Wang 2001). Our system needed to identify users' inappropriate behaviors and encourage them to control themselves consciously during the interview to avoid these actions.

Expression management evaluation Numerous facts have proven that smiling is the best way to convey the confidence and friendliness of candidates. In contrast, indifference, nervousness, or overly serious expressions can negatively affect candidates' interview results (Deng 2008; Wang 2001). We needed to identify the user's facial emotions to prompt the interviewee to consciously convey the desired facial expressions, leaving a positive impression on the interviewer (Liu 2009).

Mental state The interviewee's mental state during training was difficult to observe directly. ECG and EEG signals contain reliable characteristics that reflect states of anxiety, relaxation, and concentration. We needed to collect the user's physiological signals in real-time to analyze their state.

3.2.5 Visual feedback

To help shy college students understand their interview performance, the system should present visual feedback. The feedback includes their performance in expression management and their mental states of concentration and anxiety during the entire training. An interview report would be generated, containing multidimensional evaluation results of the shy college students.

4 System implementation

4.1 Diversified interview implementation

In the training process, the system provided a series of selection interfaces for the user to diversify the interview training, including interviewer selection, scene selection, and interview type selection.

4.1.1 Creating interviewers

Personality types were constructed by manipulating physical appearance, behavioral features, and verbal features (Bian et al. 2016). We used Maya animation to create interviewers with three personality traits (see Fig. 4). The Maya animation production process included: (1) Modeling: importing original images into Maya and outlining the

Fig. 4 Interviewers with different personalities in the interview system. Left: choleric, middle: phlegmatic, right: sanguine

characters; (2) Texture Mapping: smoothing the model and applying textures and materials; (3) Adding Skeletons: adding skulls, limbs, and other components based on human skeleton positions; (4) Skeleton Binding: conducting skinning operations to adjust poses and creating controllers for movement; (5) Weight Adjustment: fine-tuning skeletons using weight brushing; (6) Animation Setting: recording state parameters at specific time points with keyframes; (7) Rendering Animation: baking keyframe animations onto models and exporting them as FBX files for use in Unity3D (Yu 2014).

4.1.2 Different interview types

This paper created three interview question banks for different interview types. We chose SQLite to store the questions due to its lightweight, self-contained, and serverless design. Its simplicity, ease of integration with the VR training system, and efficient data management make SQLite an ideal choice.

During the training sessions, questions are randomly selected from the SQLite database to assess users. The system dynamically queries the database to retrieve questions, ensuring a diverse and unpredictable set of interview scenarios. This random selection process simulates real-life interviews, enhancing users' adaptability and response skills.

4.1.3 Different interview scenarios

As illustrated in Fig. 5, to avoid singularity, we devised two typical interview scenarios using Unity 3D and Maya. Although the scenes differ slightly in their settings, there are no significant disparities, making them equivalent. By designing parallel scenarios, our aim is to provide a more immersive and enriched interview training experience.

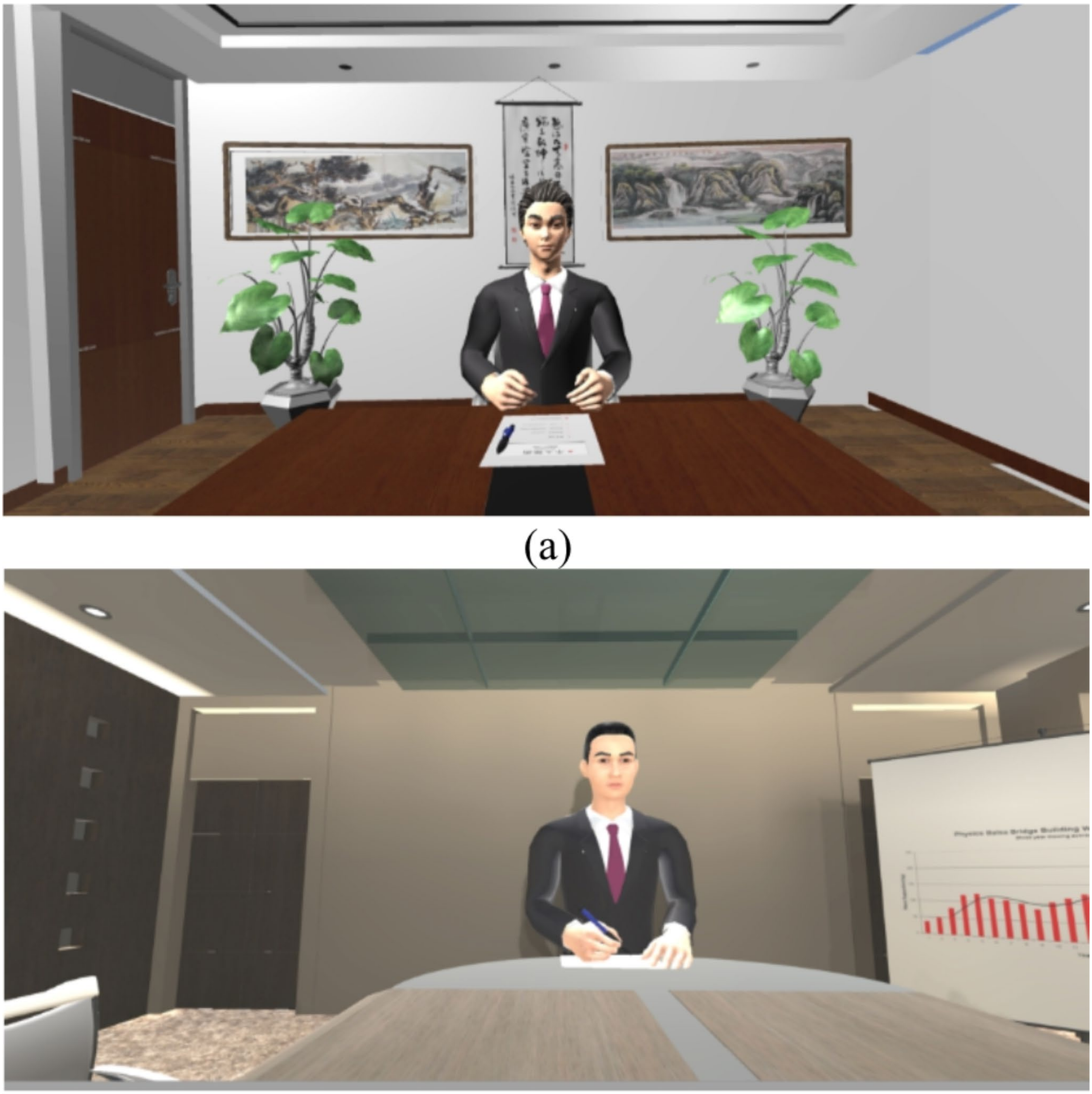
To create these interview scenarios, we first used Maya for detailed 3D modeling of the interview environments. This process involved designing realistic office settings complete with furniture, lighting, and various background elements. Leveraging Maya's powerful modeling tools, we ensured that the virtual environments closely mimic real-world interview settings. After modeling, the assets were exported to Unity 3D. Unity 3D's robust engine allowed us to integrate interactive elements, such as animated virtual interviewers, enhancing the realism and effectiveness of the training scenarios.

4.2 Implementation of natural interactions

To emulate human-human interaction, the system employs natural interaction methods, including voice interaction and brain-computer interaction (BCI). The specific interaction is illustrated in Fig. 6, and we will subsequently elaborate on the core interaction modules depicted in this figure.

4.2.1 Implementation of voice interaction

To allow interviewers to have distinct voices and accurately determine whether the user has answered the question, we employed speech synthesis and speech recognition technology to ensure the smooth progress of the interview.



(a)

(b)

Fig. 5 Interview scenarios

Speech recognition Unity DictationRecognizer listened to speech input, striving to discern the uttered phrases. The instruction database served as a pivotal module within our system. Each identified phrase from the Unity DictationRecognizer underwent matching with the instruction database, facilitating the identification of the user's command. In our system, users were guided through prompts. For instance, we would instruct them, "When you have finished answering, please say 'answer completed.'".

Speech synthesis We integrated IFLYTEK (Chen et al. 2021; iFlytek 2023) offline speech synthesis to give interviewers different sounds, tones, and speech rates. It used the synthesis engine of the industry's advanced machine

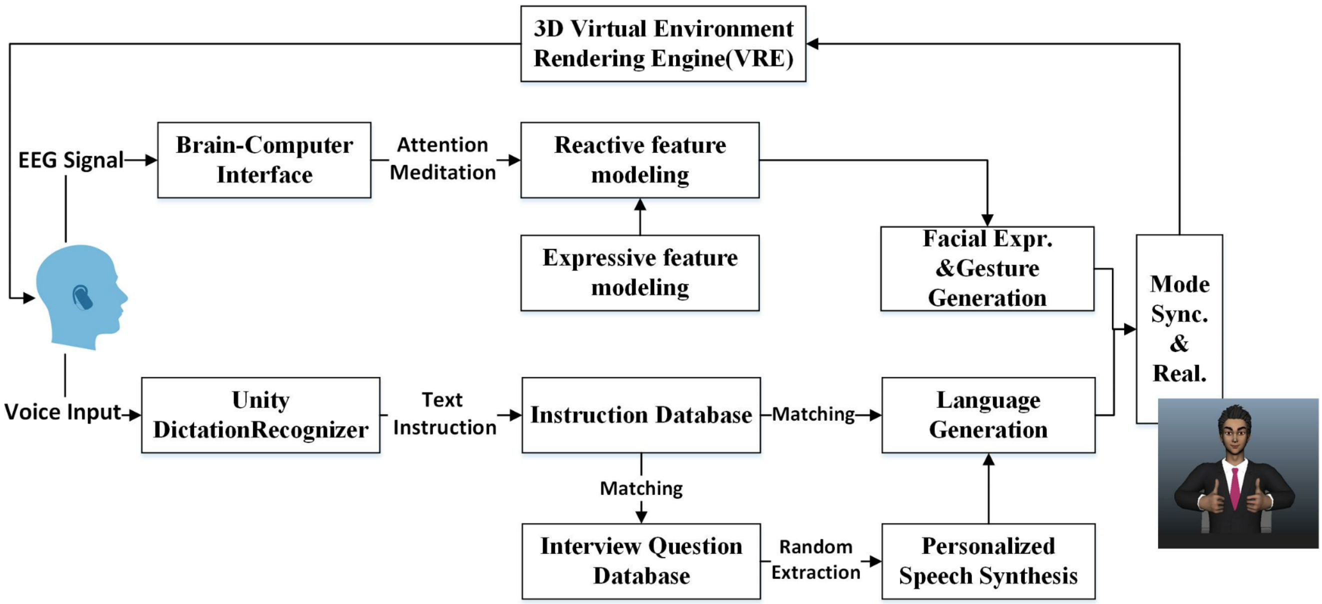


Fig. 6 Interview interaction

learning algorithm. The rich emotional corpus made the synthesized sound more natural and approached the reading level of ordinary people. The offline speech synthesis engine met the needs of real-time speech conversion in environments without network access.

4.2.2 Implementation of brain-computer interface

The brain-computer interface (BCI) should serve two primary functions: (1) calculating the user's mental state (attention and meditation) based on EEG signals and providing biofeedback to the user; (2) establishing the foundation for agents to deliver personalized evaluative responses and feedback.

The overall framework of the BCI is illustrated in Fig. 7, encompassing data acquisition, analysis, processing, output control, and feedback. EEG data were collected using a brainwave headset, and data analysis was performed using the ThinkGear chip (NeuroSky 2009a, b). The analyzed data were transmitted to a PC via Bluetooth, where the PC played a central role in data processing. The Unity platform converted the algorithmic data received from the PC's Bluetooth module into a control signal for virtual agent manipulation. The state of the virtual agent was then fed back to the user (refer to Sect. 4.2.3 for details on the feedback process).

Through EEG analysis, we could obtain eSense™ parameters to describe the degree to which subjects entered a state of Attention or a state of Meditation (with values ranging from 0 to 100). (1) Attention indicated the intensity of the user's "concentration" level. Distractions, wandering thoughts, a lack of focus, or anxiety might lower the Attention meter levels. (2) Meditation indicated a user's level of mental "calmness" or "relaxation". It should be noted that the relaxation index reflected the user's mental state rather than their physical state. Studies have shown that the Attention index obtained by the NeuroSky eSense algorithm is positively correlated with self-assessed and other physiological-based attention metrics (Chen and Huang 2014; Chen and Wu 2015; Rebolledo-Mendez et al. 2009), and the eSense algorithm could accurately classify the attentional states of learners (Bitner and Le 2022; Crowley et al. 2010).

4.2.3 Feedback of agents during Training

The feedback manner of virtual agents with different personality types varied.

Setting baseline. During the interaction, we set the respective baseline states with different frequencies for the three interviewers. When no feedback was required, the interviewer acted and expressed according to the baseline settings.

Setting emotional feedback rules. According to Eysenck's theory of personality types (Eysenck and Eysenck 1985), three distinct reaction models for agents with different personalities were proposed. Based on our proposed reactive models (see Fig. 8), there were four reactive conditions for each personality type, determined by different combinations of the user's mental state in two dimensions: attention and meditation (Eysenck and Eysenck 1985).

As shown in Fig. 8, when the user is in a state of high attention and meditation, all three interviewers are displayed

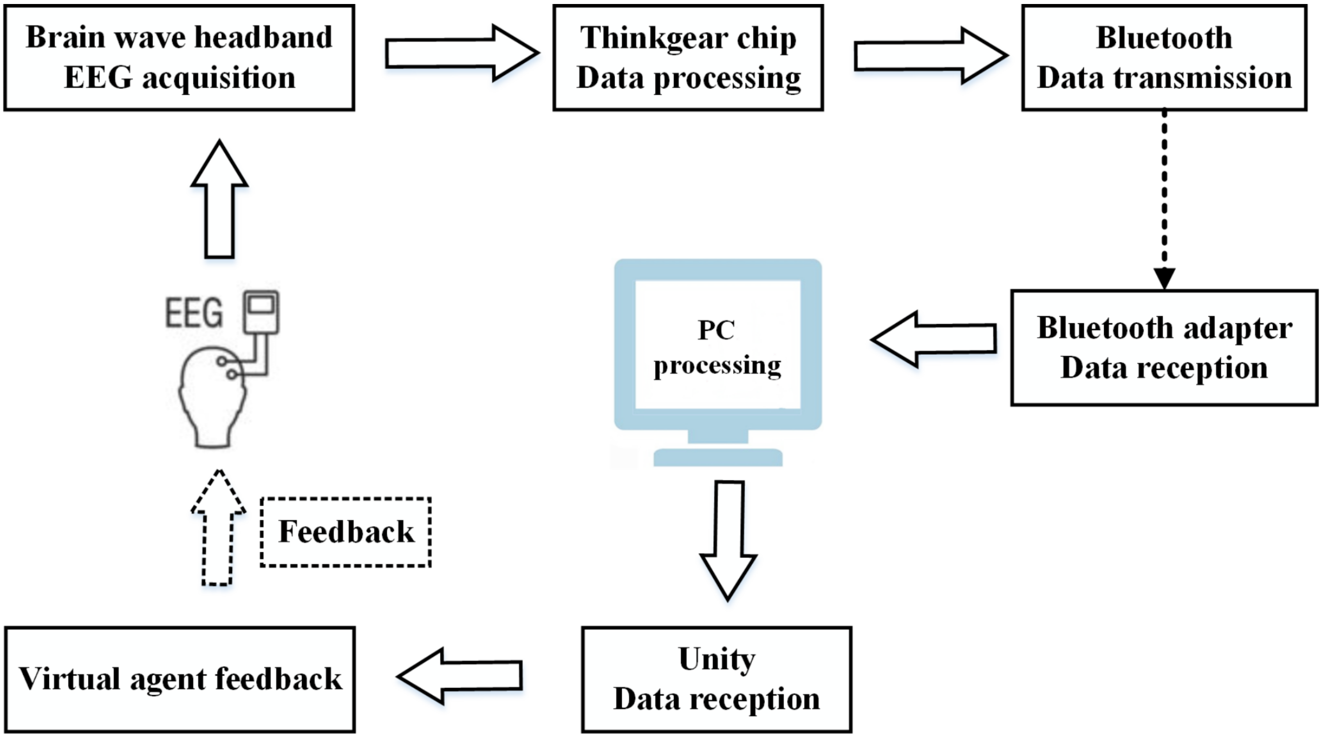


Fig. 7 Brain-Computer Interface work flow

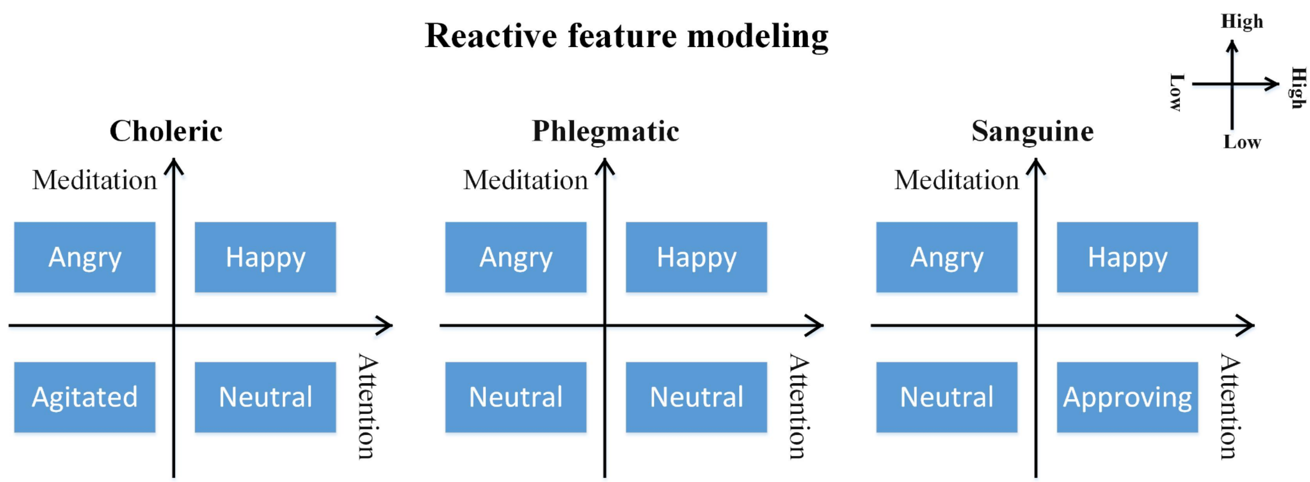
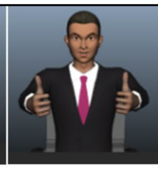
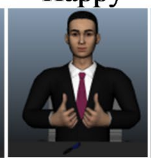
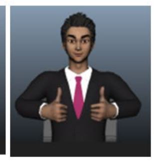


Fig. 8 Reactive feature modeling

as "Happy." When the user is in a state of low attention and high meditation, the three interviewers are depicted as "Angry." Low attention levels may indicate user distraction, while high meditation suggests a relaxed state of mind. Users in this state might be indifferent to the test task and lack motivation, thus affecting the training effect. Consequently, we do not anticipate users being in this state. Phlegmatic and Sanguine interviewers appear as "Neutral" when both the user's attention and meditation are low, while Choleric interviewers appear "Agitated." When the user is in a state of high attention and low meditation, the Phlegmatic and Choleric interviewers behave as "Neutral," while the Sanguine interviewer behaves as "Approving."

Setting emotional feedback behaviors. Based on the survey data, we primarily designed head movements, facial expressions, and upper-body movements to express emotional feedback (Table 3). These movements are tailored based on personality types, resulting in distinct features. For instance, when expressing anger, the actions of the Choleric agent are more intense and negative. Model animations of facial expressions and body movements are created to

Table 3 The different reactions to attention and meditation feedback are consistent with three personalities

Agent	feedback			
Choleric	 Angry	 Happy	 Neutral	 Agitated
Phlegmatic	 Angry	 Happy	 Neutral	
Sanguine	 Angry	 Happy	 Neutral	 Approving

represent different emotions and states for various virtual interviewers.

Model animations of facial expressions and body movements were created to represent different emotions and states for various virtual interviewers.

4.3 Multidimensional evaluation

To comprehensively assess the user's training performance, we developed a multidimensional evaluation method that considers behavioral performance, facial expression management, and mental state.

4.3.1 Behavioral performance

Improper postures. The virtual interview system in this paper utilized the Kinect BodyBasics-WPF skeleton API to recognize the 3D coordinate information of the user's bone points (refer to Fig. 9; Table 4) and provided data object types in the form of bone frames. By analyzing these skeletal points (i.e., joint points), we described posture features using joint angles to accurately capture the user's behavior.

Based on investigations and surveys, we defined several improper behaviors that might occur in interviews, such as crossing arms, scratching the head, and crossing legs, among others (see Fig. 10) (Powers and Emmelkamp 2008). Next, we introduce how to recognize improper behavior:

Judgment of crossing arms: Take joint points Elbow_left (E point: left elbow), Elbow_right (H point: right elbow), Wrist_left (F point: left wrist), and Wrist_right (I point: right wrist). Calculate the intersection of the two line segments of the left and right arm parts, and record the number of time points at which the intersection occurs. If the value is greater than 2 s, the user must have crossed their arms.

Judgment of scratching the head: Take the joint points Hand_left (Q point: left hand), Hand_right (R point: right hand), and Head (U point: head). Calculate the distance between the two hand nodes and the head. When the distance is less than 8 cm, and the ordinate of the hand node is higher, it indicates the action occurred. When the time point satisfying the condition is greater than 2 s, it is determined that the user has scratched their head or frequently manipulated their hair.

Judgment of crossing legs: Take joint points Knee_left (K point: left knee), Knee_right (N point: right knee), AnkleLeft (L point: left ankle), Ankle_right (O point: right ankle), Hip_left(J point: left hip), and Hip_right (M point: right hip), from which we could get line segments representing the left and right calf and thigh. Take 30% of the segments on the left and right calf close to knees, and calculate their intersection part. Then, calculate the intersection part of the left and right thigh segments. When the number of time points for any of the two intersections exceeds 2 s, the user must have crossed their legs.

Judgment of body tilt: Take joint points Spine_shoulder (C point: center of the shoulders) and Spine_mid (B point: center of the spine), and calculate the reciprocal of the slope of the line formed by these two points on the xoy plane (the z-axis represents the distance between the person and the device and can be ignored). When the number of time points satisfying this value exceeds tan(10°) for more than 2 s, it is determined that the user's body has tilted.

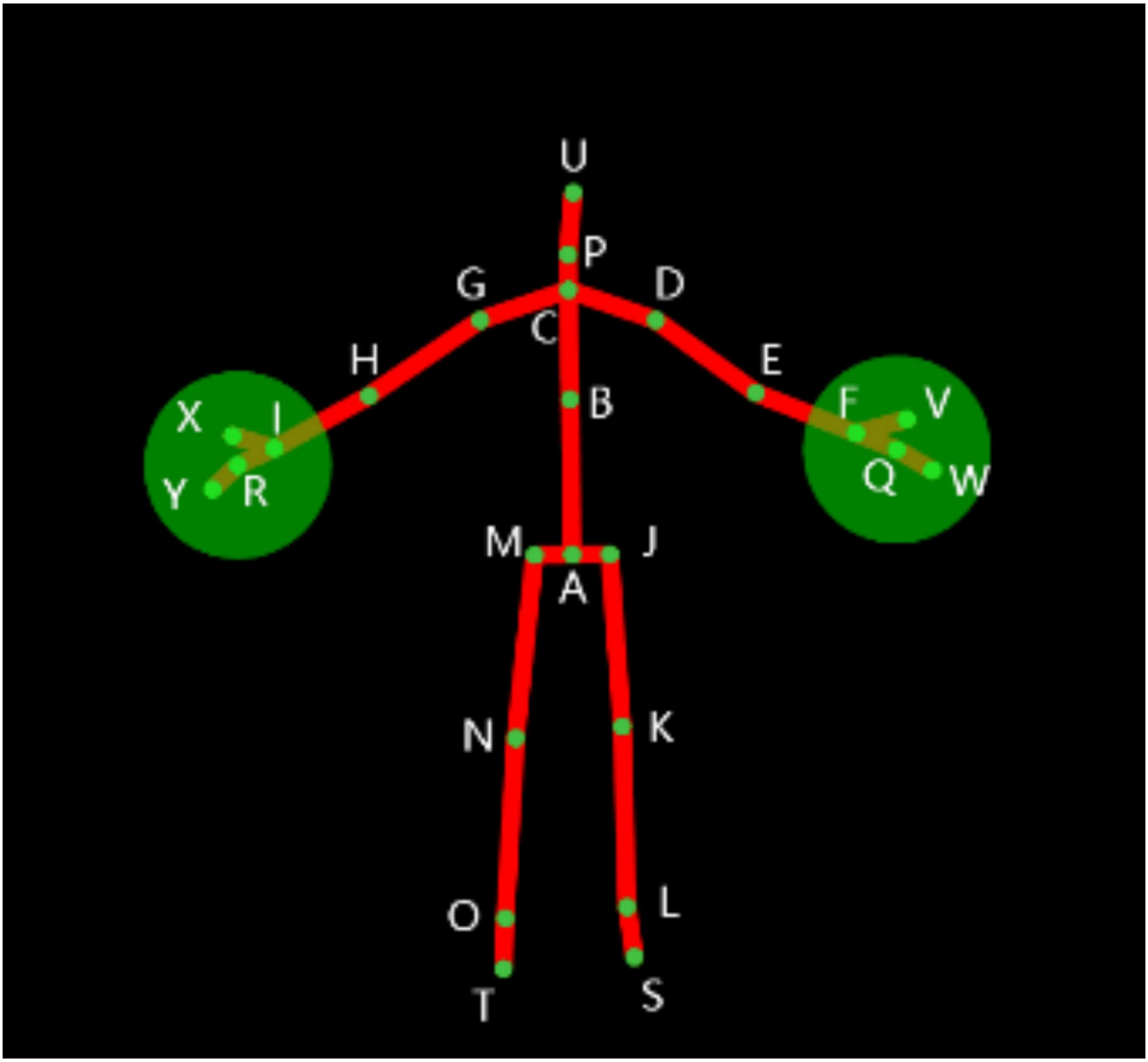


Fig. 9 The 25 joint points on one's body that a Kinect can recognize

Table 4 The 25 joint points corresponding to the numbers in Fig. 9

No.	Name	No.	Name	No.	Name	No.	Name	No.	Name
A	Spline_base	B	Spine_mid	C	Spine_shoulder	D	Shoulder_left	E	Elbow_left
F	Wrist_left	G	Shoulder_right	H	Elbow_right	I	Wrist_right	J	Hip_left
K	Knee_left	L	Ankle_left	M	Hip_right	N	Knee_right	O	Ankle_right
P	Neck	Q	Hand_left	R	Hand_right	S	Foot_left	T	Foot_right
U	Head	V	Thumb_left	W	Hand_tip_left	X	Thumb_right	Y	Hand_tip_right

Judgment of body shaking Similar to body tilt, calculate the maximum value of the reciprocal of the slope of the line formed by these two points, and then calculate the tangent of the angle formed by the leftmost and rightmost positions. Compare it with tan(10°). If it is greater than tan(10°), it indicates that the tilt exceeds 10°, and it is determined that the user's body is shaking.

The above algorithm was utilized to test five actions. Subjects were required to hold a specific posture for 2 s

Fig. 10 Improper behaviors: crossing arms (**a**), scratching the head (**b**), crossing legs (**c**), body tilt (**d**), and body shaking (**e**)

Table 5 Statistical of improper postures recognition experiments

Improper postures	Number of person	Number of tests / person	Correct recognition times	Recognition rate(%)
Crossing arms	5	10	50	100
Scratching the head	5	10	50	100
Crossing legs	5	10	48	96
Body tilt	5	10	50	100
Body shaking	5	10	50	100

before the posture was correctly recognized, facilitated by the addition of a timer. Five individuals were selected as subjects, and each participant faced the Kinect while maintaining a distance of between 1.5 m and 2 m. Table 5 illustrates the high recognition rate for these actions. During the recognition process, each experimenter acted freely without limitations on speed, demonstrating the effectiveness of this method.

4.3.2 Facial expression management

Facial expression recognition technology was based on Microsoft's Azure cloud service and was trained with image datasets that mark human emotions. It recognized the facial emotions in a picture (see Fig. 11).

The virtual interview system described in this paper captured the user's video stream in real-time through a network camera, extracting a video frame every three seconds. These frames were then submitted to the Face API for emotion detection and analysis. Based on the facial expression recognition provided by the Microsoft Face API, a credibility score was returned for a range of expressions (such as anger, contempt, disgust, fear, happiness, neutral, sadness, and surprise) on the user's face in the image. These facial expressions were found to transcend cultural boundaries, enabling real-time detection of the user's facial expressions during the interview process.

4.3.3 Mental state evaluation

This paper mainly measured two physiological signals, ECG and EEG.

We employed an ECG monitoring sensor to measure ECG signals. NeuroSky's CardioChip software displayed real-time information on heart rate, average heart rate, relaxation, and respiratory rate. Heart rate analysis was utilized to estimate stress levels, as demonstrated in previous studies (Bethel et al. 2007; de Santos Sierra et al. 2011). Individuals with high social anxiety tend to experience significant increases in heart rate in response to various social situations, such as direct gaze (Rösler et al. 2021; Wieser et al. 2009), social interactions (Shimizu et al. 2011), speech tasks (Gramer et al. 2012), and social-evaluative situations (Gerlach et al. 2003). In this paper, heart rate served as an indicator to assess the user's anxiety level. Additionally, we

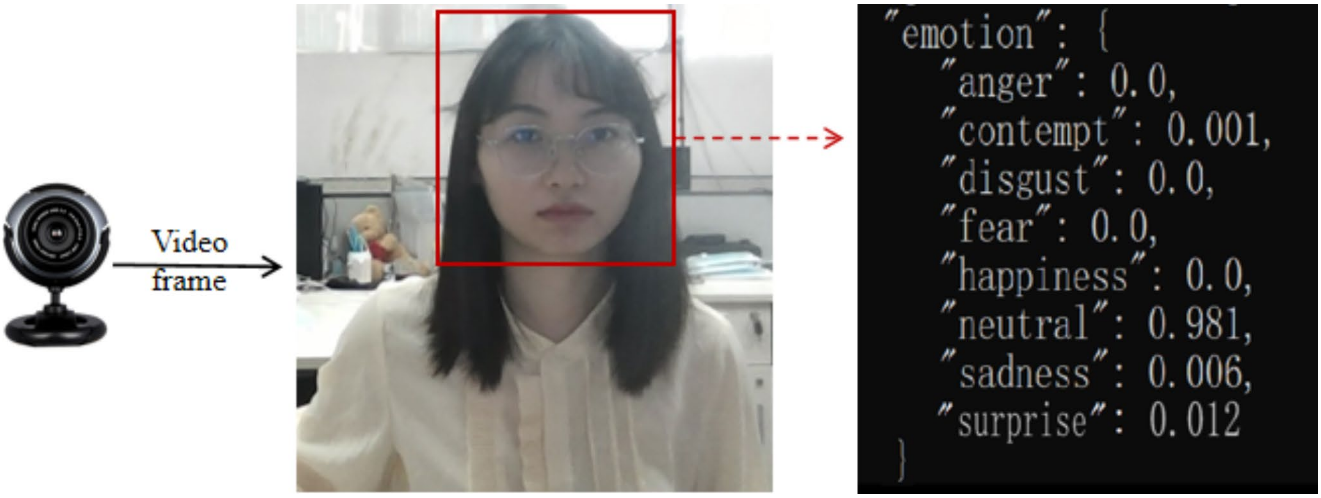


Fig. 11 Facial expression recognition

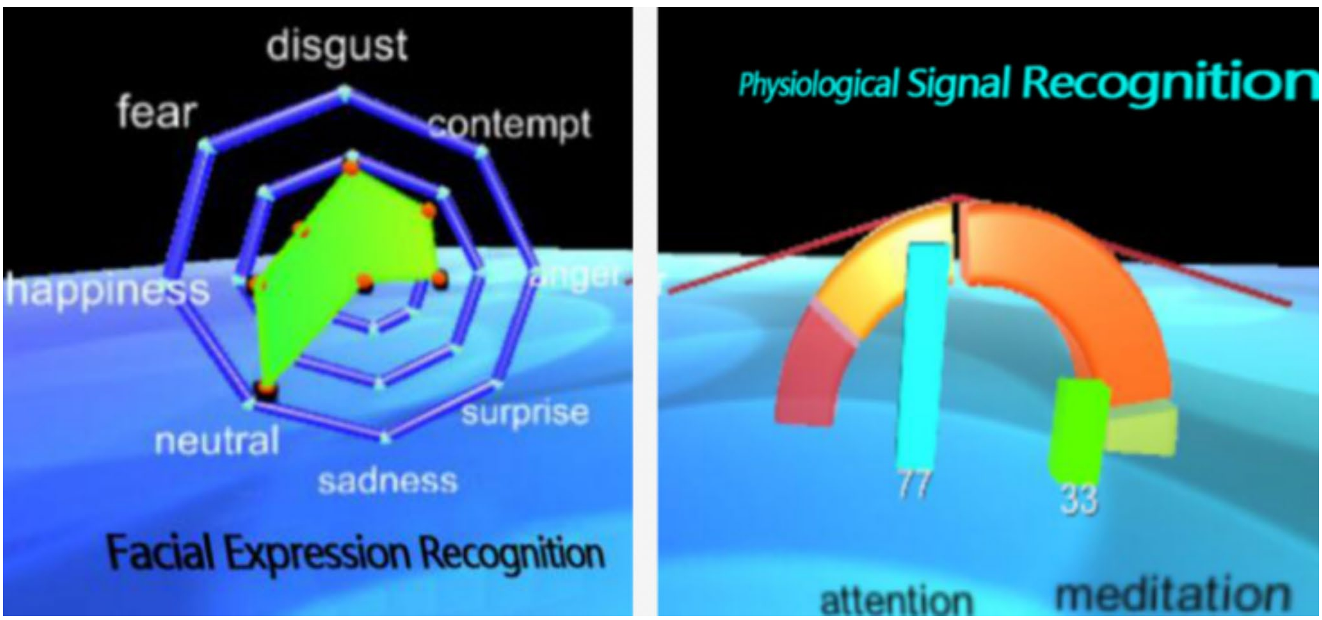


Fig. 12 The radar chart (left) displays the emotional state, and the bar chart (right) shows the attention level and relaxation state

utilized an EEG acquisition device to collect users' brainwave data (see details in Sect. 4.2.2).

4.4 Feedback on interviews performance

The feedback included voice feedback, graphical interface feedback, and an interview report.

In the voice feedback section, the system broadcasted the user's inappropriate behaviors during the interview process, such as improper body tilt, excessive body shaking, crossing arms, scratching the head, and crossing legs. The system was designed to alert individuals to avoid inappropriate body language during interviews (particularly within the context of Chinese cultural norms), aiming to create a positive impression in future interactions.

In the graphical feedback section, the user's facial expression state throughout the entire interview process was depicted in a radar chart. The average attention and meditation levels were presented as a bar chart (see Fig. 12, where the "arc chart" serves as a visual guide, directing users' attention to the results in the bar chart). The facial expression recognition results and mental states of users throughout the interview process were visually and clearly displayed. By informing users about the distribution of their expressions during the interview, we aimed to help them consciously manage their facial expressions, leaving a positive impression on the interviewer.

At the same time, an interview feedback report was generated, primarily comprising three components. The first part evaluated the user's behavioral performance, encompassing inappropriate behaviors exhibited during the interview process. The second part assessed the user's expression management, showcasing the results of facial expression management throughout the interview. Both of these components fell within the realm of impression management. The third part recorded the user's mental state during the interview, capturing the average attention and meditation levels (see Fig. 13).

5 User study

We conducted a user study to test the effectiveness of our designed VR interview training system on anxiety coping and performance improvement for shy individuals.

5.1 Experimental design

We adopted a single-factor within-subject design with training times (first/second/third) as the independent variable. The dependent variables were interview anxiety and performance.

5.2 Participants

A total of 55 undergraduate students (including 29 males and 26 females) were randomly selected from a university in China. As shown in Appendix 1, Wang Qianqian's College Shyness Scale (Wang et al. 2009), originally developed by Zimbardo and Henderson (Henderson and Zimbardo 2002), which consists of 17 items scored on a 5-point Likert scale (with a Cronbach's α of 0.86), was used to conduct a questionnaire survey on the students. In our study, we followed the classic grouping rule of the top 27% and bottom 27% (Han et al. 2016). The 27% of students with the highest shyness scores were enrolled in the shy group. From this group, we selected 16 participants (8 males and 8 females, M = 20.67 years, SD = 1.66 years) to participate in the experiment. In our sample, two participants with identical scores at the critical threshold were included in the high-scoring group, constituting the top 27%. None of the participants had any experience participating in job interviews. Before the test, participants ensured they had enough sleep and did not smoke or exercise. Written consent was obtained from all participants.

5.3 Procedure

The experimental environment utilized was our constructed VR system, as depicted in Fig. 14. Upon entering the system, participants first selected the interview scenario and virtual interviewer. The system then generated an interview scene based on these selections. As participants entered the interview scene, various devices, including a Kinect, HD camera, electrocardiograph (ECG) monitoring sensor, and electroencephalograph (EEG) acquisition device, were activated to acquire and analyze multimodal signals. Throughout the interview training, the virtual interviewer interacted with participants according to their attention and meditation performance. At the conclusion of the training, the system provided graphic feedback and generated an interview report based on the participants' behavior, facial expressions, and physiological signals recorded during the entire training session.

Each participant underwent three training sessions with our VR interview system. At the end of each session, a simulated VR interview was conducted. The intervals between the three interviews ranged from 15 to 30 min, during which participants were encouraged to relax and clear their minds with activities such as listening to music.

Training Sessions In our study, "training sessions" are practice sessions designed to familiarize participants with the procedural and interaction aspects of the VR interview system. These sessions do not involve actual interview content and primarily aim to help participants become comfortable with the system's interface and operations, allowing them to freely choose their interviewers. These training sessions serve as a preparatory step before participants engage in the "simulated interviews".

Simulated interviews The "simulated interview" phase follows the training sessions. During this phase, participants undergo a virtual interview conducted by a virtual agent acting as the interviewer. A cross-design approach is used, where each participant experiences interviews with different types of interviewers. In this experiment, all simulated VR interviews are the national entrance examination for postgraduate (NEEP) interviews. The order in which participants encounter the three agents is randomly assigned, and users are required to select a designated interviewer based

INTERVIEW

REPORT

Behavior recognition

Improper interview behaviors:
Leaned your body
Shook your body
Crossed your arms

Do not scratch your head or play with your hair frequently.

Do not cross your legs.

Facial expression recognition

Anger: 0.00209459459459459
Contempt: 0.029027027027027
Disgust: 0.000229729729729730
Fear: 0.0010270270270273
Happiness: 0.0025945945945946
Neutral: 0.92177027027027
Sadness: 0.0174054054054054
Surprise: 0.0256081081081081

Physiological signal recognition

Mean of attention: 54
Mean of meditation: 29

Fig. 13 The interview feedback report given to the user

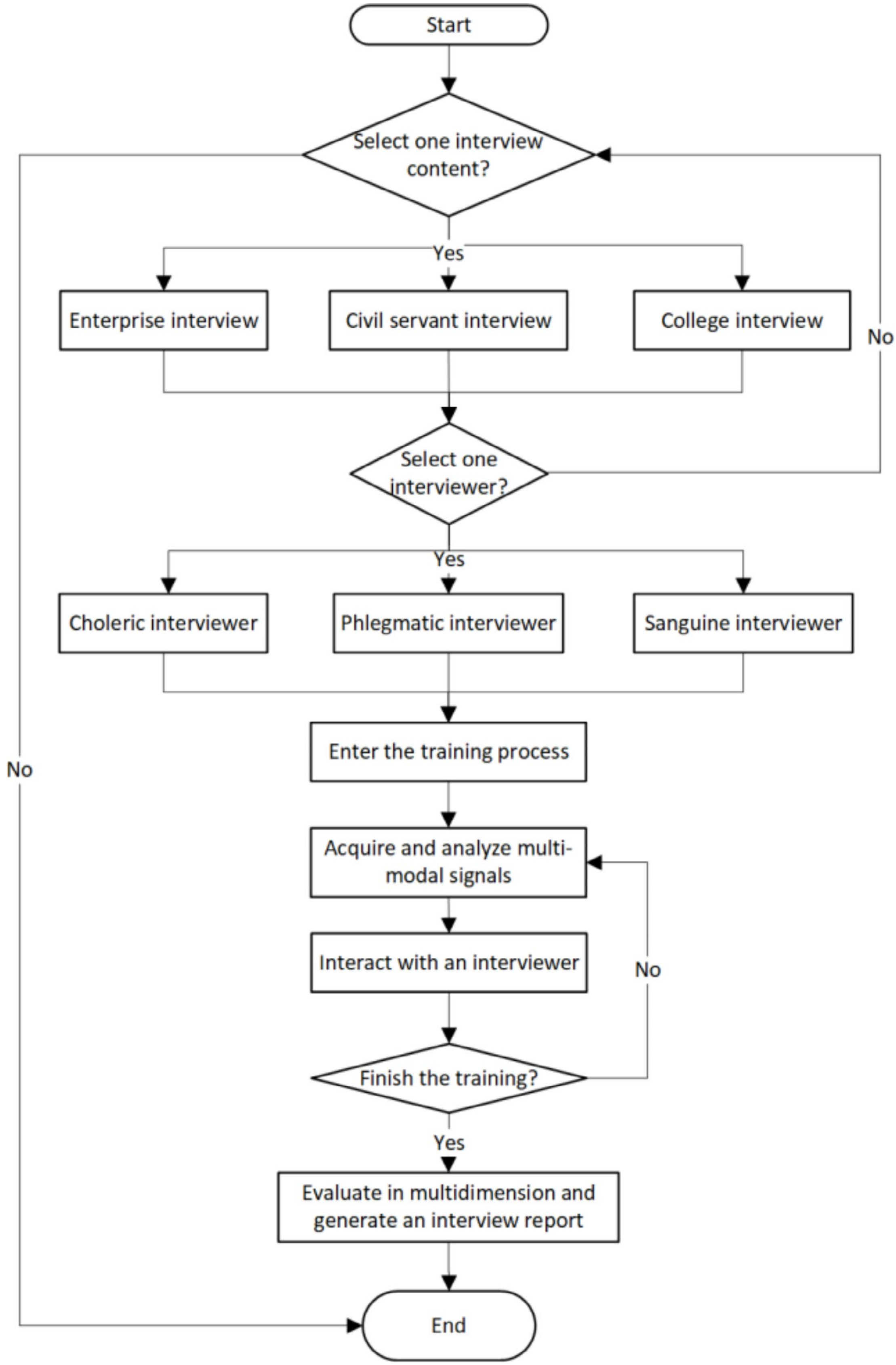


Fig. 14 The flow chart of the system

on these assignments. This approach helps reduce internal variation and enhances the reliability of the research results.

5.4 Measures

In our study, the assessment of user interview anxiety and performance involves two methods: expert evaluation and physiological measurements.

Expert evaluation Expert evaluation is a widely used method in studies of behavioral performance (Bian et al. 2016; Johnsen et al. 2007). To ensure objectivity and mitigate individual biases, three highly experienced experts were engaged in our study. Each simulated interview was recorded using a camera, allowing the experts to evaluate participants' behaviors on a 0–10 Likert scale based on the recorded videos. The final scores were determined by averaging the ratings of the three experts. These experts were selected for their extensive experience in the interview field, contributing to the validity and credibility of our evaluation method. The high level of consistency among the experts, reflected in an impressive inter-rater reliability score of 0.85, indicates the reliability and robustness of our scoring methodology.

Physiological measurements The integration of physiological measurements offers invaluable insights into participants' physiological responses during simulated interview sessions. We utilized an ECG monitoring sensor to measure physiological indicators. The ECG monitoring sensor provided objective data on participants' autonomic nervous system activity, reflecting their physiological reactions to emotional arousal.

5.4.1 Measures of interview anxiety

Interview anxiety was measured with two kinds of indicators: *behavioral* and *physiological indicators*.

The behavioral indicator reflects the level of anxiety conveyed through body language. For instance, nervous gestures, uneasy eye movements, and other anxious behaviors frequently expose an individual's genuine emotional state. Since body language is predominantly driven by unconscious processes in the brain, it tends to operate with minimal influence from human consciousness. Consequently, it often reveals more accurate insights into anxiety behaviors than self-reported methods. This indicator is assessed through expert evaluation.

The physiological indicator is heart rate (HR). Because the relaxation degree calculated by EEG was designed to be used for training, we chose a different physiological indicator to evaluate anxiety. HR is closely related to anxiety in many studies, where the user's HR values correlate with their level of anxiety Therefore, HR was chosen as the physiological measure of anxiety.

5.4.2 Measures of interview performance

Interview performance was measured with three indicators: *average time to answer each question*, *adequacy*, and *fluency*.

The average time to answer each question is calculated from the start of the verbal response to the conclusion of the answer. For shy users who fear and avoid social interaction, an increase in average response time signifies improvement, irrespective of the answer quality. We aim for users to enhance their average response time while simultaneously improving the adequacy and fluency of their answers. This, to some extent, reflects a reduction in users' anxiety, allowing more time for interaction with interviewers and ultimately resulting in better performance. This indicator is recorded by a timer.

Adequacy pertains to evaluating response quality through the examination of key points addressed in each answer. This metric delves into the depth and completeness of participants' articulation, providing valuable insights into their proficiency in delivering comprehensive and well-rounded responses throughout the interview. This indicator is assessed through expert evaluation.

Fluency concerns the coherence and smoothness of linguistic expressions in responding to each question. It evaluates how participants navigate the logic of their responses, offering insights into their ability to articulate ideas fluently and maintain a logical flow during the interview. This indicator is assessed through expert evaluation.

5.5 Results

5.5.1 Effects of Training Times on interview anxiety

We first conducted two repeated-measures analyses of variance (RM-ANOVAs) to investigate the differences in the two indicators of interview anxiety across three time points. The descriptive results are shown in Fig. 15; Table 6. Results show a significant difference in anxiety by body language ($F=48.012$, $p<0.001$, $\eta_P{}^2=0.762$). Post hoc comparisons found that anxiety by body language measured after the second training is significantly lower than that after the first training ($t=2.531$, $p=0.023$), and the third training is significantly lower than that after the second training ($t=4.961$, $p<0.001$).

The effect on HR is significant ($F=2.672$, $p=0.01$ $\eta_P{}^2=0.219$). Post hoc comparisons show anxiety indicated by a heart rate that was measured after the second and third

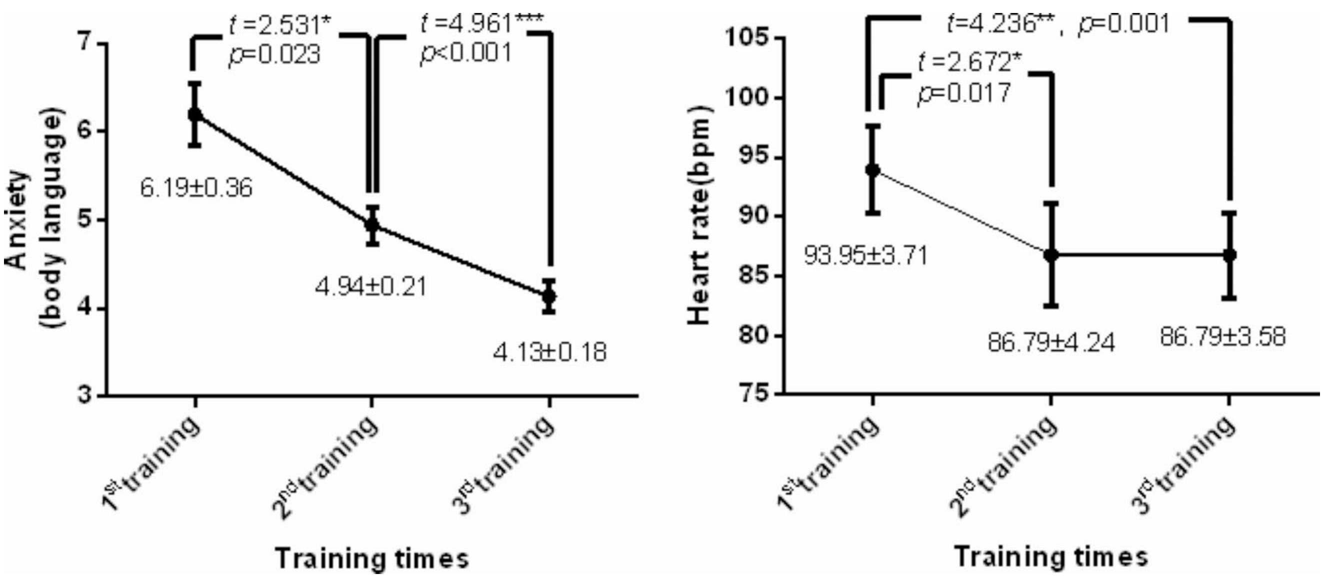


Fig. 15 Effects of training times on interview anxiety. Left: body language; Right: heart rate

Table 6 Descriptive statistics of each measurement indicator

Measures	Time 1	Time 2	Time 3
Anxiety indicated by body language	6.19 (0.36)	4.94 (0.21)	4.13 (0.18)
Heart rate(bpm)	93.95 (3.71)	86.79 (4.24)	86.79 (3.58)
Fluency	5.06 (1.18)	6.63 (0.81)	7.25 (0.68)
Adequacy	5.63 (1.36)	6.56 (1.50)	7.06 (1.34)
Average time to answer each question (s)	40.10 (4.86)	42.85 (6.48)	39.81 (6.12)

training are both significantly lower than that after the first training ($t=2.672$, $p=0.017$; $t=4.236$, $p=0.001$). However, the difference in HR between second and third training is not significant ($t=0.001$, $p=0.99$).

5.5.2 Effects of training times on interview performance

We conducted three RM-ANOVAs to test the effects of training times on interview performance. The descriptive results are shown in Fig. 16; Table 6. The effect of training times on the average time to answer each question is not prominent ($F=6.051$, $p=0.006$, $\eta_P{}^2=0.287$).

However, the effects of training times on fluency ($F=56.907$, $p<0.001$, $\eta_P{}^2=0.791$) and adequacy ($F=9.723$, $p=0.001$, $\eta_P{}^2=0.393$) in answering questions are significant. Post hoc comparisons show that fluency and adequacy in answering questions after the second training are significantly better than those after the first training ($t=8.592$, $p<0.001$; $t=2.531$, $p<0.001$). Similarly,

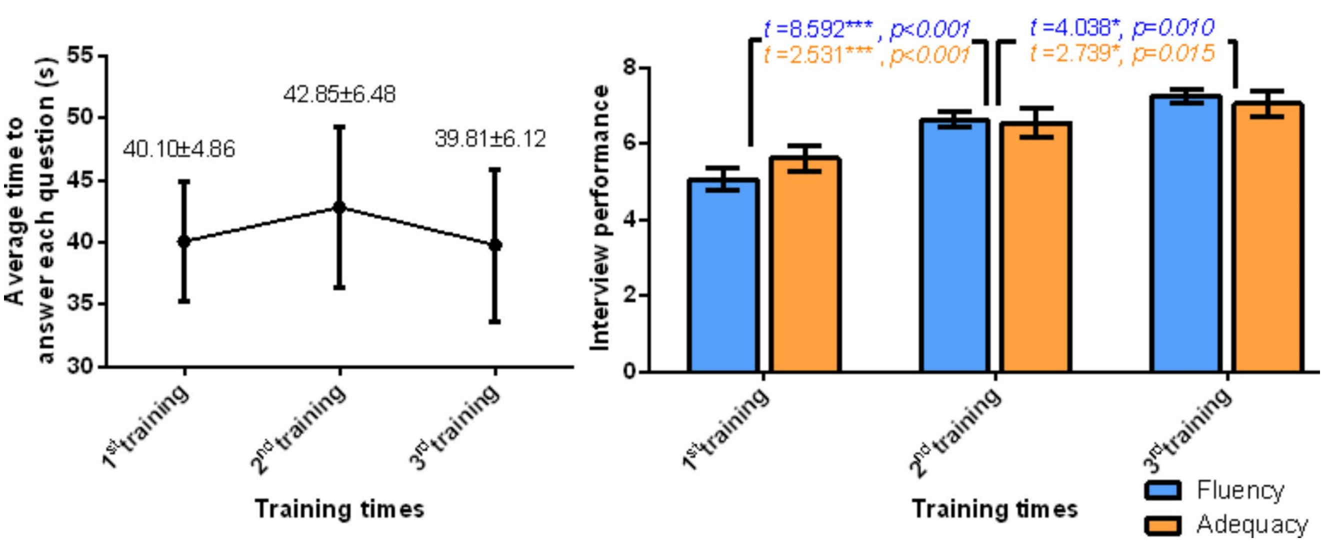


Fig. 16 Effects of training times on interview performance. Left: Average time to answer each question indicator; Right: Adequacy and fluency indicators

fluency and adequacy in answering questions after the third training are significantly better than those after the second training ($t = 4.038$, $p = 0.010$; $t = 2.739$, $p = 0.015$).

6 Discussion

In this study, we designed and developed an agent-based virtual interview training system for shy college students. By combining biofeedback therapy with virtual agents exhibiting different personality types, the system aimed to help shy college students improve their interview skills and deal with social anxiety. The effectiveness of the system was examined, and several important findings were identified, which are discussed as follows.

Firstly, individuals with shyness often experience anxiety and a tendency to withdraw in real interview scenarios (Pilkonis 1977). Our study addresses this challenge by integrating Virtual Reality Exposure Therapy (VRET), aiming to create a secure and reliable customized environment that simulates real and diverse face-to-face interaction scenarios, leveraging the immersive capabilities of VR technology. It guides them gradually and repeatedly towards anxiety-inducing interview situations until these circumstances no longer evoke feelings of anxiety and fear (Wang 1996). Results show that the more times shy college students used this system, the lower their anxiety levels were during the interview. In addition, although the average time spent answering each question did not increase, the adequacy and fluency of their responses improved. The positive impact on anxiety levels and interview skills underscores the effectiveness of this immersive approach.

Secondly, individuals with shyness are often apprehensive about being evaluated, and their anxiety may lead to numerous unconscious facial expressions and actions that are detrimental to the interview, ultimately impacting their performance (DeGroot and Gooty 2009; Russell et al. 2008). Rooted in the Chinese cultural background, our study integrates biofeedback therapy to provide shy individuals with intuitive multimodal assessment and feedback (including behavioral performance, facial expression management, and mental state). VRET facilitates a gradual approach to anxiety-inducing situations, while biofeedback externalizes users' invisible emotions into visible forms (Alneyadi et al. 2021). The combination offers shy individuals a comprehensive toolset for self-recognition and control of their psychological state during interviews. Our theory and algorithm can be easily adapted to other ethnic groups.

Thirdly, individuals with shyness need to face interviews with various personality types of interviewers to cope with anxiety (Langer et al. 2016; Mitrut et al. 2021). We enhanced existing methods for designing agent personality traits by defining expressive traits (e.g., distinct physical, behavioral, and verbal characteristics) and reactive traits (differential feedback based on the user's mental state). It is important to note that the feedback actions designed for virtual agents are adaptive and evaluative, such as nodding or giving a thumbs-up. These actions are specifically aimed at assisting shy individuals who fear evaluation in handling diverse interview scenarios. However, this paper does not explicitly test the effect of the agent personality types. We want to make it clear that different agents were developed to prepare students for different interviewers, but comparing the effects of agent personality on anxiety was not the focus of the present work. In addition, many studies have shown that the gender of the virtual interviewer did not affect users' answers except for gender-related questions (Conrad et al. 2019; Huddy et al. 1997; Kane and Macaulay 1993). Since our question bank did not cover the issue of equality of power between men and women, we only included male interviewers.

7 Conclusion and future work

In conclusion, this study provides valuable insights into developing effective virtual interview training systems for shy college students. By integrating Virtual Reality Exposure Therapy (VRET) with biofeedback, we created a VR training system that significantly enhances interview skills and manages social anxiety. Our innovative approach includes virtual agents designed with expressive and reactive personality traits, offering realistic and varied interview scenarios. Empirical evidence from our study shows that the system effectively reduces anxiety and improves interview performance, highlighting its potential as a promising solution for helping shy individuals succeed in job interviews.

For future work, we plan to enhance our system by analyzing and providing feedback on users' response content to further improve its effectiveness. Additionally, we will specifically examine the impacts of agents with different personality types on the interview training effect and explore the interaction between these personality types and the users' level of shyness. To meet potential user needs, we will include female interviewers in future studies, expanding the scope to ensure the inclusivity and applicability of the system. Furthermore, future studies should consider validating these findings in more naturalistic and diverse settings to improve ecological validity, addressing the limitations of the controlled laboratory environment used in this study. Finally, to better understand the long-term effectiveness of the VR interview system, we plan to conduct longer-term follow-up studies.

Appendix 1

The College Student Shyness Scale					
1. I am afraid of looking immature in social situations.	Completely Inconsistent	Slightly Applicable	Uncertain	Somewhat Applicable	Completely Applicable
2. I often feel insecure in social situations.					
3. Other people appear to have more fun in social situations than I do.					
4. If someone rejects me I assume that I have done something wrong.					
5. It is hard for me to approach people who are having a conversation.					
6. I feel lonely a good deal of the time.					
7. It is hard for me to express my real feelings to others.					
8. I find myself unable to enter new social situations without fearing rejection or not being noticed.					
9. Personal questions from others make me feel anxious.					
10. I judge myself negatively when I think others have negative reactions to me.					
11. I try to figure out what is expected in a given situation and then act that way.					
12. I feel embarrassed when I look or seem different from other people.					
13. I am disappointed in myself.					
14. I blame myself when things do not go the way I want them to.					
15. I sometimes feel ashamed after social situations.					
16. I am frequently concerned about others approval.					
17. I spend a lot of time thinking about my social performance after I spend time with people.					

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Ethical statement The study was conducted according to the guidelines of the Declaration of Helsinki and approved by the Ethics Committee of The Jining First People's Hospital, China.

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