

Taylor & Francis
Taylor & Francis Group

Disability and Rehabilitation: Assistive Technology

ISSN: 1748-3107 (Print) 1748-3115 (Online) Journal homepage: www.tandfonline.com/journals/iidt20

A GenAI-supported job interview training robot for young adults with special education needs

Ka Yan Fung

To cite this article: Ka Yan Fung (19 Oct 2026): A GenAI-supported job interview training robot for young adults with special education needs, Disability and Rehabilitation: Assistive Technology, DOI: 10.1080/17483107.2026.2748786

To link to this article: https://doi.org/10.1080/17483107.2026.2748786

Published online: 19 Oct 2026.

Submit your article to this journal

View related articles

View Crossmark data

Full Terms & Conditions of access and use can be found at
https://www.tandfonline.com/action/journalInformation?journalCode=iidt20

DISABILITY AND REHABILITATION: ASSISTIVE TECHNOLOGY
https://doi.org/10.1080/17483107.2026.2748786

Taylor & Francis
by informa

RESEARCH ARTICLE

Check for updates

A GenAI-supported job interview training robot for young adults with special education needs

Ka Yan Fung

Institute of Special Needs and Inclusive Education, The Education University of Hong Kong, Hong Kong, China

ABSTRACT

Background and aims: Employment opportunities for young adults with special education needs (YA-SEN) are often less favourable compared to their peers without SEN. They are often anxious during interviews, especially when answering open-ended questions with unfamiliar interviewers and unexpected interruptions occur. To fill the gap, we developed an interactive job interview training (JIT) system featuring a cat-shaped robot – *JIT-bot*.

Sample: *JIT-bot* was designed to provide an engaging, adaptive, and personalised training experience that supported users to practice and refine their interviewing skills in a less stressful environment. We recruited 28 participants in our study.

Methods: A mixed-method approach was employed, including proficiency tests, interviews, and questionnaires.

Results: Results provided preliminary evidence that the experimental group showed a statistically significant improvement in intrinsic motivation. In contrast, the behavioural engagement of the control group decreased slightly. These findings and feedback will suggest future enhancements to *JIT-bot*'s features and functions, making it a valuable tool to support JIT for YA-SEN.

➢ IMPLICATIONS FOR REHABILITATION

1. Job interview trainers and educators might consider integrating robot-assisted plaDorms (e.g., JIT-bot) into pre-employment programs. The technology advancement suggests a capacity to boost intrinsic motivation. This is a key predictor of training persistence and success for young adults with special education needs (YA-SEN).
2. The decline in behavioural engagement observed in the control group raises the possibility that traditional job interview training (JIT) approach may inadvertently increase anxiety for YA-SEN. Practitioners can explore adaptive and low-stress options (e.g., robot-based) to create a safer learning environment to YA-SEN before having a real interview in the job market.
3. Rehabilitation technologists and service providers might prioritise the development of personalized and engaging user interfaces (UIs) in assistive technologies. The positive feedback on JIT-bot indicates that features reducing environmental stress might be important for effective JITs with YA-SEN.

ARTICLE HISTORY
Received 22 February 2026
Revised 24 August 2026
Accepted 3 October 2026

KEYWORDS
Job interview training (JIT); motivation; special education needs (SEN); robot-assisted language learning (RALL); GenAI

Introduction

Young adults with special education needs (YA-SEN) find it difficult to secure a job [1]. They encounter less self-confidence, feel anxious and nervous when answering interview questions [2]. These challenges are distinct in the transition from education to open employment. However, there is a lack of personalised support systems to help them. In this section, we discuss the challenges YA-SEN face in real-world job interviews, the importance of realistic and low-stakes practice (LSP) environments, and existing technological interventions for job interview training (JIT).

Challenges faced by YA-SEN in job interviews

Research demonstrates that YA-SEN often experience difficulties in job interviews because the formats of most interviews are heavily coupled with neurotypical norms of communication, social inference, and

CONTACT Ka Yan Fung kyfungag@connect.ust.hk Institute of Special Needs and Inclusive Education, The Education University of Hong Kong, D1-G/F-05.

© 2026 Informa UK Limited, trading as Taylor & Francis Group

self-presentation [3]. The difficulties of YA-SEN stem from a complex mix of neurological differences that affect social communication, such as the ability to understand social signals [4]. In addition, poor communication may lead to misunderstandings and miscommunication in the workplace [5]. Ultimately, they have a lower chance of securing a job [6].

Empirical work with autism spectrum disorder (ASD) shows that conventional interviews often overload them with simultaneous social, sensory and cognitive demands [7]. This makes them difficult to interpret implicit cues, manage eye contact, modulate tone, or respond to abstract, open-ended questions under time pressure [8]. These social-communication challenges are closely tied to underlying neurological differences rather than a lack of competence. However, YA-SEN are frequently misread by interviewers as indicators of poor fit, lack of interest, or limited interpersonal skills [9]. As a result, they have a much higher chance of being filtered out at an early stage of the recruitment process.

This transition barrier represents a major global issue. In Hong Kong, policy reports likewise document that YA-SEN encounter substantial barriers in their school-to-work transition, including limited access to tailored preparatory experiences and discriminatory assumptions about their capabilities [10]. For instance, research commissioned by the Hong Kong Equal Opportunities Commission (EOC) highlights that around one-third of young people with disabilities experience severe misunderstandings by their employers, who routinely underestimate their capabilities and assign oversimplified tasks [11].

The gap underscores the paramount importance of education in facilitating a smoother school-to-work transition. However, traditional learning environments are less flexible in supporting them [12]. Conventional JIT systems emphasise teacher-directed delivery and practice-oriented preparation [13]. Interaction-rich designs are still the exception in most vocational preparation for Y-SEN [14]. To bridge the gap, there is an urgent need for technology-enhanced JIT approaches, which can provide safe, customisable, and adaptive simulated environments to build real-world interview self-efficacy.

Importance of realistic and low-stakes practice environments

YA-SEN require structured environments to develop complex social and behavioural skills [15]. Low-stakes, realistic activity settings, such as JIT, can reduce stress and performance inhibition, allowing repeated practice without real-world consequences [16]. However, high-stakes JITs are often experienced as exposing one's vulnerabilities [17]. YA-SEN may lower self-efficacy and impair performance for those with SEN, as they have already anticipated failure or stigma. Providing an LSP environment therefore helps YA-SEN manage stress, experience a greater sense of control, and gradually build perceived capability before participating in actual interviews [18].

According to self-efficacy theory (SET) [19], an LSP environment is conducive to YA-SEN obtaining mastery experiences, ultimately building self-belief and competence [20]. Through repeated practice, YA-SEN can gradually achieve success without fear of negative consequences [21]. The LSP environment can foster a resilient mindset where the learner attributes failure to "insufficient effort" (things they can change) rather than "insufficient ability" (things they cannot change) [22].

Existing technological interventions for job interview training

Existing research demonstrates promising results for different SEN groups. For example, Virtual Reality Job Interview Training (VR-JIT) demonstrated efficacy in adults with ASD across multiple randomised controlled trials, including improvements in standardised interview performance and self-confidence [16]. Similarly, other platforms, such as JobTIPS, JOBSS, and CIRVR, have been developed by incorporating video modelling and multimodal data collection to provide individualised feedback [23]. However, current technological interventions for JIT focus on specific populations, such as ASD and undergraduates [24]. The emerging technological opportunities are under-investigated for a broader SEN population.

The use of human-robot interaction (HRI), such as social robots, large language models (LLMs), generative AI (GenAI), has shed light on assistive tools for YA-SEN [25]. For example Bertacchini et al. [26], developed an innovative social robotics application using a Pepper robot to connect to ChatGPT. Their

design improved communication skills for people with ASD in Italian. The system integrated facial emotion recognition, natural language processing, and adaptive responses to create personalised interactions that address communication challenges and promote social skill development.

Most existing systems do not support YA-SEN in Hong Kong, whose mother tongue is Cantonese (Traditional Chinese). An interview training system in Cantonese for learners with multiple special needs to improve their learning motivation, engagement, efficacy, readiness, confidence, and competency development is under-researched. The emergence of social robots and GenAI present unprecedented opportunities to bridge these gaps. To this end, we developed a GenAI-supported job interview training system, *JIT-bot*, and incorporated it into a cat-shaped robot to provide JIT to YA-SEN who speak Cantonese, read and write in Traditional Chinese. Through a customised design approach, *JIT-bot* provided young adults with personalised dialogue speech rates, loudness, preferred interview scenarios (role), and interview durations (number of dialogues) to meet their specific needs.

The paper is organised as follows: Section "Literature review" provides an overview of interview skills training for SEN, social robots in education, engagement and motivation, and SET in special education. Section "Methods" describes the method, including system development, curriculum, instrument, testing, setup, and performance analysis rubrics. Section "Results" analyzes the differences in motivation and engagement between human- and robot-led interview training, and interview feedback from participants. Section "Discussion" discusses implications of robot-assisted interview training, real-life practice, limitations, and future approaches. Finally, Section "Conclusion" summarises the work.

Literature review

The development of effective JIT interventions for YA-SEN is essential, as they experience persistent and significant employment disparities. YA-SEN often struggle to progress beyond the interview stage. As a result, scaffolded practice can improve their interview performance, highlighting the need to adapt and extend such approaches. In this section, we discuss interview skills training approaches for SEN populations, social robots in educational contexts, engagement and motivation frameworks, and SET applications in SEN.

Interview skills training for SEN

Effective JITs for YA-SEN have evolved from traditional and human-centric approaches to technology-mediated platforms. Traditional human-led interview training for YA-SEN is well-intentioned, but faces limitations in scalability, consistency, and anxiety reduction. Research demonstrates that conventional training often adopts a one-size-fits-all approach that fails to accommodate the diverse, individualised needs characteristic of YA-SEN [27]. Interventionists in traditional programs frequently report concerns about inconsistent delivery methods that depend on the interventionist's expertise, training, and personality [28]. This may limit the reliability of the administration and ultimately the effectiveness of the intervention.

With technological advancements, the shift has been towards computer- and VR-based training tools (Table 1). These platforms offer a scalable and repeatable way for individuals to practice their skills [31]. For example, Virtual Reality Job Interview Training (VR-JIT) and Virtual Interview Training for Transition-Age Youth (VIT-TAY) [16,30] provided preliminary evidence of improvements in interview skills among transitioning youth with ASD. Moreover, some programs featuring realistic robots have been shown to improve learners' self-confidence, motivation, verbal, and non-verbal communication skills [29]. Technology-mediated JITs have shed light on improving non-verbal communication and reducing stress for those with ASD. For example, Chistol et al. [32] stated that interactive technologies, such as VR environments, social robots, and wearable or tactile devices, can create controllable, predictable social situations where learners with ASD can repeatedly rehearse eye contact, gestures, and facial expressions with immediate, multisensory feedback. By gradually adjusting task difficulty and sensory load, these tools desensitise learners to anxiety-provoking cues, support self-regulation, and thereby reduce stress during non-verbal communication practice.

Table 1. A table showing overview of relevant JIT tools.

	Paper	Aims	Region	Language	# of Participants	Target	Technology	Evaluation method
1	Adiani et al. [4]	To empower job seekers with ASD to overcome interview barriers through low-stress practice and visual feedback	USA	English	17	ASD	Facial expression. emotion detection	Survey, Questionnaire
2	Kumazaki et al. [29]	To assess the feasibility of the "GIT-VICS Program" a home-based system using a CG robot to improve interview skills.	Japan	Japanese	15	ASD	Web-based virtual robot	Rubrics, Interview
3	Genova et al. [30]	To evaluate a combined intervention to improve personal strength articulation during job interviews.	USA	English	15	ASD	An internet-delivered, computerised job interview simulator	Interview
4	Migovich et al. [33])	To use a novel physiological dataset and machine learning to detect stress for youth with ASD during simulated job interviews.	USA	English	15	ASD	Physiological data for stress detection, machine learning	Data visualisation platform
5	Whittenburg et al. [31]	To test a program combining behavioural training and field practice to improve workplace conversation skills	USA	English	4	ASD	Video modelling	Single-case research design

Social robots and virtual agents in education

The integration of social robots in educational contexts is grounded in robust theoretical foundations in Social Cognitive Theory (SCT). Specifically, SCT emphasises that learning occurs through observation, imitation, and dynamic social interaction. Robot not only acts as a tool but also serves as a social agent to model behaviour and promote self-efficacy [34].

Research shows that virtual robots or animal-like designs help reduce fear and support engagement and motivation [35]. Additionally, expressive and empathetic designs can boost immersion and create emotional connection [36]. However, physical embodiment itself remains a valuable asset, as a human-like robot can create more engaging and enjoyable experiences [37]. In addition, the non-verbal communication function can reduce physiological stress for YA-SEN [38].

Moreover, technology can enhance learning engagement through personalised interaction modalities. Incorporating interactive elements can provide contextually appropriate design aesthetics and engaging animations [39]. For example, animated pedagogical agents use gaze, gesture, locomotion, and facial expressions to highlight key information, give unobtrusive feedback, and create engaging face-to-face tutoring experiences [40]. Also, applying film-inspired animation principles to robot motion has been shown to make a robot's behaviour more legible and emotionally expressive, helping users infer their intentions and perceive it as more engaging and lifelike [41].

In addition, Automatic Speech Recognition (ASR), Speech-to-Text (STT), and Text-to-Speech (TTS) are important because they make learning more accessible, interactive, and feedback-rich [42]. ASR/STT converts learners' speech into text, which gives immediate feedback on pronunciation or content [43]. TTS does the reverse by turning text into natural speech, supporting listening comprehension, independent reading, and learners who struggle with decoding or vision-related barriers [44]. Fung et al. [36] demonstrate that robots can utilise technological components to support Traditional Chinese (Cantonese) learning.

The design considerations for social robots emphasise the importance of accommodating individual differences. For example, Ackermann et al. [45] established that adaptive social robots respond to learners' individual needs and emotional states. However, research reveals mixed findings regarding the

optimal level of robot adaptivity. Some studies suggest that personalised adaptive guidance can provide superior learning outcomes compared to basic adaptive approaches [46].

Engagement and motivation frameworks

Self-Determination Theory (SDT) provides a comprehensive theoretical framework for enhancing motivation [47]. SDT identifies three fundamental psychological needs, including autonomy (the need for choice and self-direction) [48], competence (the ability to master tasks and achieve goals) [49], and relatedness (the need for meaningful relationships and connection) [50].

When YA-SEN fulfil these needs, they can demonstrate higher levels of engagement, well-being, and persistence. A well-structured system can promote autonomy. For example, the system can provide learners with choices, individualised learning pace, and content selection [51]. Also, competence support can be integrated into system design by providing challenging tasks, constructive feedback, and opportunities for mastery experiences [52]. The system can offer personalised interactions to foster a sense of relatedness. For example, robots can greet students by name [53] to establish meaningful connections with learners.

Measuring engagement requires attention to its multidimensional nature, encompassing behavioural, emotional, and cognitive dimensions. Behavioural engagement reflects active participation in learning activities [54]. Emotional engagement encompasses feelings of interest and belonging [55]. Cognitive engagement involves the strategic use of learning approaches and self-regulation [56]. This multidimensional conceptualisation is particularly relevant for populations with SEN, who may exhibit varying patterns of engagement across domains, requiring individualised assessment and intervention.

Self-Efficacy Theory in special education

SET is grounded in SCT [57], which provides insights into motivational processes. According to Bandura [58], self-efficacy is developed through four primary sources: mastery experiences (direct successful performance), vicarious experiences (observing others succeed), social persuasion (encouragement from others), and physiological and affective states. In SEN, mastery experiences represent a powerful source of self-efficacy development, as they provide direct evidence of one's capabilities to succeed in specific tasks [59].

SET can be applied in technology-mediated interventions for SEN. Williams and Rhodes [60] emphasised that SET specifies both the sources of efficacy beliefs and the mechanisms through which they influence behaviour, providing clear frameworks for intervention design. In JIT robots, mastery experiences are systematically provided through repeated practice opportunities [61]. At the same time, vicarious experiences are offered by allowing users to observe successful interview demonstrations [62]. Additionally, these robots deliver social persuasion through positive feedback and encouragement throughout the training process. Also, they help manage physiological states by creating an LSP environment that reduces anxiety [53].

Methods

In this work, we designed a JIT system (*JIT-bot*) on a cat-shaped robot. We utilised a two-stage design, including system development and testing.

System development

The system development includes robot design, system design, personalised functions, user interface (UI), curriculum, and instrument design.

A Cat-shaped robot. In this work, we adapted *Minibo* [63] to resemble a cat-shaped robot, *JIT-bot* using 3D printing. As shown in Figure 1, we designed four limbs for *JIT-bot* and made it look like a "cat" to have a sense of "closeness." The cat-shaped appearance can foster relatedness by encouraging emotional bonding [64]. From an SCT perspective, the customisable appearance makes *JIT-bot* a more relatable social model [65].

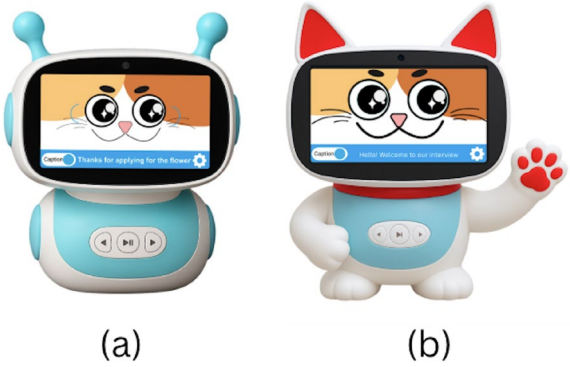


Figure 1. Diagram showing the appearance of the robot: (a) original design and (b) cat-like robot design.

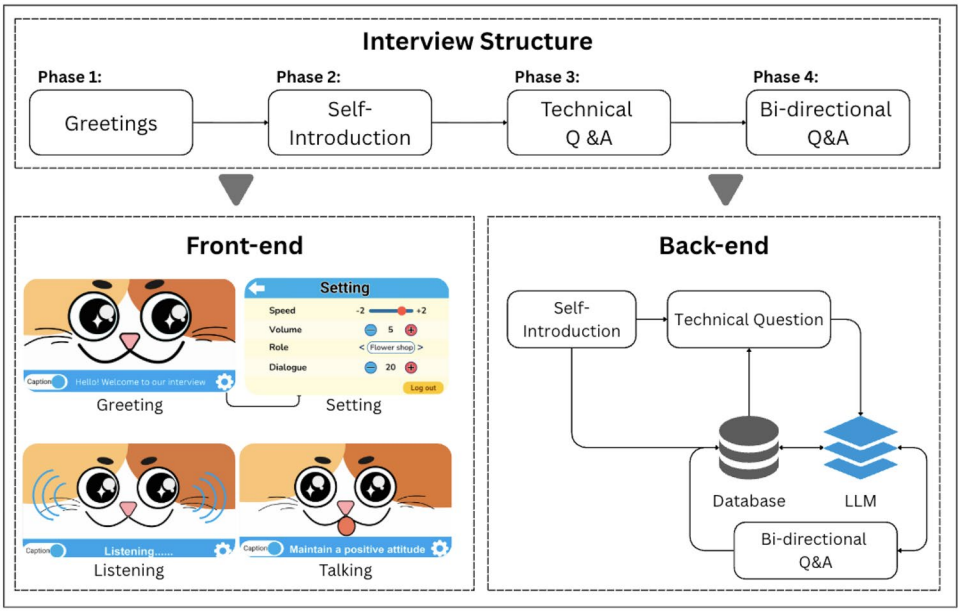


Figure 2. Diagram showing the system flow, including interview structure, front-end and back-end.

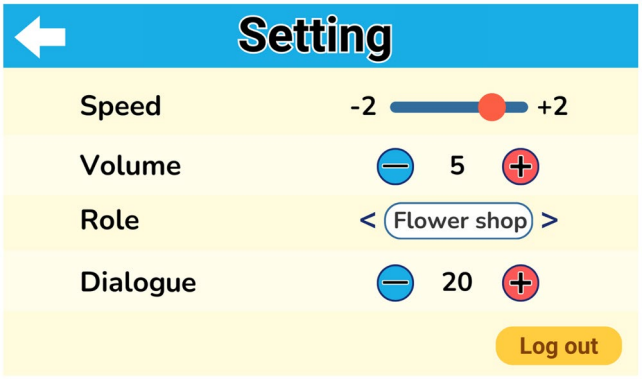


Figure 3. Diagram showing the setting function, including speed, volume, role and dialogue.

System design

The development of *JIT-bot* was done in Android Studio. It incorporated GenAI (i.e. ChatGPT 4[1]) and ASR technology. The ASR component has both STT and TTS functions. *JIT-bot* helps convert colloquial language into text and supports Traditional Chinese (Cantonese). This provides participants with an opportunity to improve their interview skills in a local context. Figure 2 shows the system flow of *JIT-bot*. The interview consists of four phases: greetings, self-introduction, technical questions, and bi-directional Q&A. *JIT-bot* acts as the employer. It greets participants (i.e. interviewees) with phrases, such as "Welcome to your job interview!" Next, *JIT-bot* asks them to introduce themselves, such as "Please introduce yourself!" In this phase, young adults deliver their self-introductions to *JIT-bot*.

After the self-introduction, the GenAI model generates technical questions, such as: "If you are required to take photos at an indoor event, what kind of filter will you use?" *JIT-bot* can store communication dialogues in a database. A personalised profile is established. This allows *JIT-bot* to better understand the young adults with SEN. Then it can ask custom questions in later interview training conditions, helping them prepare for their job interviews.

Personalised functional design. By applying SDT, participants can select different functions to enhance autonomy. Under SCT, the individualised features act as relatable models that enable observational learning. They reinforce self-efficacy through graduated successes. These features situate behaviour within supportive and low-anxiety contexts. As shown in Figure 3, they can select the following functions:

1. Speech Rate: Ranging from −2 to +2, participants can choose a speech rate that suits their individual needs, as preferences and requirements for speech speed can vary among them.
2. Volume: Ranging from 1 to 10, participants can adjust the volume to meet their individual preferences, as different participants may have varying needs regarding sound levels.

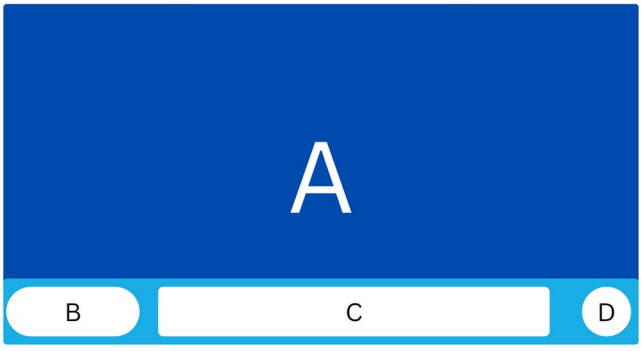


Figure 4. Diagram showing standardised specification: A is for communication visualisation, B is for turning-on/off caption function, C is for caption display, and D is for setting function.

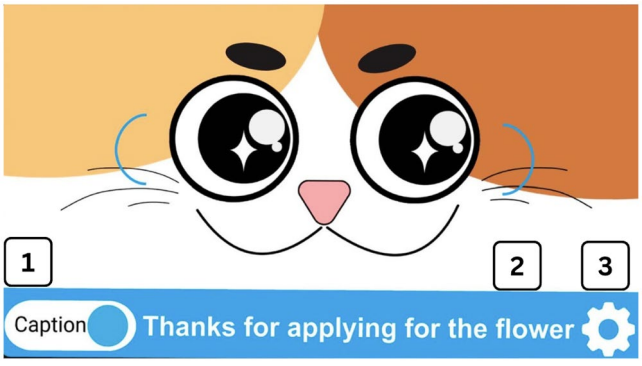


Figure 5. Diagram showing the main JIT interface. #1: Turning-on/off caption. #2: Displaying caption if #1 is turned-on. #3: Setting.



Figure 6. Diagram showing the UI of listening process.



Figure 7. Diagram showing the UI of communication process.

3. Role: Participants can choose the scenario they wish to practice from a pool of scenarios that they have selected themselves. Their votes determine this pool and will be updated periodically based on their preferences and market needs.
4. Dialogue Duration: Participants can select the duration of their training, ranging from 5 to 20 minutes, which corresponds to the number of dialogues in the job interview.

User interface design. The game UI is based on standardised specifications to ensure consistent usability and features a cat-shaped design. As shown in Figure 4, the UI is clearly defined for each functional area, facilitating navigation. In addition, we selected high-contrast colour combinations to improve readability and accessibility [66]. As shown in Figure 2, participants can turn on/off captions at any time (Figure 5), #1. Some participants need text assistance to better understand the text, while others find it distracting. Furthermore, when *JIT-bot* listens to participants, it blinks and waves to represent "listening" (Figure 6). When *JIT-bot* interacts, it conveys communication effects intuitively (Figure 7).

Curriculum design

We offered two retail service scenarios (flower and camera shops) for the participants. These scenarios were derived from longitudinal records of our human-based job training programme, in which a substantial proportion of students expressed interest in and were placed in positions related to flower and camera shops. Based on these cumulative training and placement data, we selected the flower and camera shop as target scenarios for this pilot trial to maximise ecological validity and align the simulated interviews with participants' typical vocational preferences and opportunities. The GenAI prompts were set by professional interview trainers (PITs) who hold a Master Degree in SEN. PITs also provided job descriptions as shown below.

Flower shop assistant. The main responsibilities include supporting the store manager and florists by executing daily flower shop tasks such as: (1) Learning fresh flower knowledge and basic flower arrangement knowledge: (a) Fresh flower knowledge: Flower material handling, common fresh flower types in Hong Kong (b) Basic knowledge of flower arrangement: Types of flower pots, their uses, care, handling, and application of flower foam. (2) Flower shop operations: Include maintaining the cleanliness of the flower shop at all times, knowledge and storage of supplies/tools, and warehouse knowledge (3) Develop sales expertise by tailoring approaches for retail and subscription clients (4) Analyse customer preferences and purchasing behaviours. (5) Cultivate effective communication skills with co-workers and customers. *JIT-bot* poses these questions:

- What is your name?
- Why are you here today?
- Do you have any relevant experience?
- Why are you interested in working in our shop?

- Do you prefer to do paperwork or handle customers?
- If a customer enters our shop, what would you do?

Camera shop assistant. When assisting photographers in external work, the main tasks that photography assistants are responsible for include: (1) Check all equipment to ensure it is functioning properly. (2) Assist in setting up the shooting location according to the photographer's requirements. (3) Participate in the shooting work, and during this period, take shots of specific angles or scenes as instructed by the photographer. (4) Direct models or participants, helping them present their best condition during shooting. (5) Pack up and count equipment. (6) Ensure that all equipment is stored properly. *JIT-bot* poses these questions:

- What is your name?
- Why are you here today?
- Can you tell me what photography equipment you have used before?
- Which camera models do you use? Why?
- Do you have any experience taking photos at large events?
- If yes, please tell me the theme, your role, and the scope.

Instruments

SDT-based questionnaire. The adapted SDT-based questionnaire had previously been used in the local context [63]. SDT is measured by four categories: behaviour, emotion, cognitive engagement, and intrinsic motivation (Please refer to Section 2.3). Each category has three items. All items were measured using a 5-point Likert scale (1: Totally disagree, 5: Totally agree), administered both pre- and post-intervention. The example questionnaires were (1) I try my best to perform well in all JIT (behaviour), (2) I find the JIT content is very interesting (emotion), (3) I understand the content and purpose of JIT (cognition), and (4) I feel happy to participate in JIT (motivation). All questionnaires were originally written in English. All questionnaires were translated into Traditional Chinese, which has been employed in similar research (SEN – Dyslexia, College level) in the same region [67]. Two education experts reviewed the terminology to ensure it was suitable for participants. Additionally, an instructor received training from the first author to provide the necessary support for administering the questionnaire.

Interview protocol. Interviews were conducted to gain a deeper understanding of users' perceptions of *JIT-bot*. consents were sought from the participants (Section 3.2). All interviews were conducted in Traditional Chinese. Two education experts reviewed the content to ensure its suitability for participants and PITs. In total, 14 individual interviews (experimental group) were conducted. Each interview was scheduled for approximately 15 min. To accommodate participants who required more processing time, the interview duration ranged from 15 to 30 min. All questionnaire responses were recorded using Qualtrics XM [5]. The questions are shown in Appendix A.1 – Interview Questions (Participants).[2] The first author performed a thematic analysis and conducted initial coding to develop preliminary codes. All authors conducted two rounds of discussions to categorise and refine the codes.

Testing

We followed a four-stage approach during testing. First, we developed guidelines, inclusion criteria, and rubrics based on the study's aim. Second, we recruited participants in accordance with the guidelines and inclusion criteria. Third, we conducted a pilot test study. Fourth, we conducted an evaluation based on the rubrics.

Guideline

The study followed a set of guidelines and addressed ethical considerations by: (1) obtaining informed consent from guardians and participants prior to the experiment; (2) recruiting voluntary participants; (3) allowing participants to withdraw from the study at any time; (4) receiving approval from the Institutional Review Board (IRB).

Inclusion criteria

The inclusion criteria were: (1) Aged 18 to 30; (2) Enrolled in a school; (2) Diagnosed with at least one type of SEN, such as attention deficit/hyperactivity disorder (ADHD), emotional and behavioural disorders

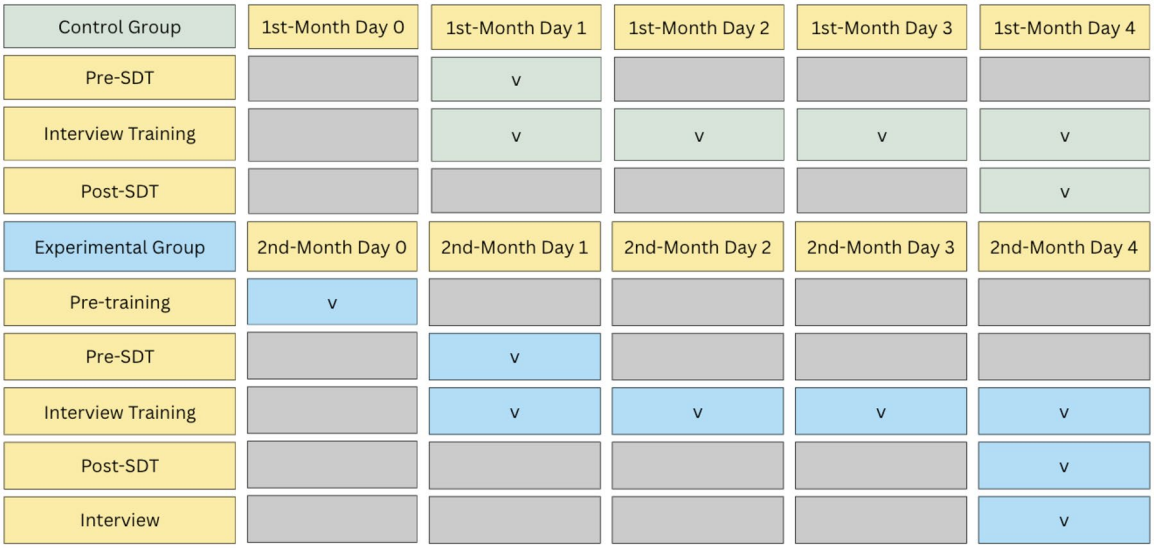


Figure 8. Diagram showing the study procedure of two groups.

(EBD), ASD, communication disorders (CD), intellectual disabilities (ID), or down syndrome (DS); (3) Completed relevant assessments prior to training; (4) Ability to communicate in Cantonese; (5) No medical, hearing, or physical disabilities that could hinder the ability to read aloud; (6) Previous experience with digital tools, such as tablets.

Setup

The experiment was conducted within a three-year post-school vocational training programme in Hong Kong that serves school leavers with SEN in a tertiary-style environment. A local tertiary institution hosts the programme but operates as a non-regular track, offering an adapted vocational curriculum (rather than a degree programme) to support students' learning, communication, and career readiness. Eligible students are school leavers with identified SEN who have completed the local secondary school curriculum and are aged 18–30 at enrolment. Participants were allocated according to a fixed schedule designed by the programme team. All sessions were conducted in the same classroom setting. The human-led condition was delivered by the same instructor across all four sessions, and the same robot and algorithm delivered the robot-based condition across all four sessions. All instructors completed a common training workshop to ensure consistency in their approach.

Participants

The study included 28 participants (15 males, 13 females), divided into an experimental (R01 – R14) and a control group (H01 – H14). The experimental group consisted of 14 participants (7 female and 7 male), aged 19 to 26 ($M = 22.55$-year-old, $SD = 1.73$-year-old). The control group consisted of 14 participants (6 female and 8 male), aged 19 to 26 ($M = 22.63$-year-old, $SD = 1.75$-year-old). All participants have at least one type of SEN. Each training session paired one student with one instructor. We obtained participants' consent prior to the study.

Procedure

Prior to the experiment, the instructor provided pre-training to participants (experimental group) on interacting with the robots, including the robot's communication procedures. The experiment consisted of two groups (Figure 8). *Control group (human-led):* Participants participated in a 15-min JIT session each day for four consecutive days. *Day 1:* They completed a pre-SDT questionnaire before starting the interview training. *Day 4:* They finished the interview training and then completed a post-SDT questionnaire. *Experimental group (robot-led):* Participants completed a 15-min session each day for 4 consecutive days.

Day 1: They completed a pre-SDT questionnaire before starting the interview training. *Day 4:* They finished the interview training and then completed a post-SDT questionnaire and interview.

Human-led job interview training

We engaged two PITs to deliver one-on-one JIT, with participants randomly assigned to each instructor. One instructor holds a master's degree in Special and Inclusive Education. The other is a registered teacher with 10 years of experience working in special schools.

Robot-led job interview training

A trained instructor provided standardised technical and emotional support to each participant. For quality control, support was delivered to each instructor under a unified protocol: (1) Technical support: The instructor assisted with login and reported technical issues (e.g. Wi-Fi disruption, frozen screens) to the research team, without influencing task flow or student responses. (2) Emotional support: The instructor monitored the young adults's willingness. If signs of distress or disengagement emerged, the instructor offered neutral encouragement. When necessary, they notified the teacher or social worker for follow-up.

Performance analysis

Rubrics

The rubrics were adopted from Kumazaki et al. [29]. We selected four main categories that were relevant in our context. To analyse performance, we compared results from human experts with those from GenAI-supported evaluation. The rubrics are shown in Appendix A.2.

Human expert evaluation

Two research assistants (RAs), who served as human raters, conducted the scoring. They evaluated four predefined criteria. Both RAs have backgrounds in inclusive and special education, with two years of experience in research analysis. The kappa value for their agreement was 0.606, indicating a good level of consistency.

Results

How do motivation and engagement differ between human- and robot-led interview training

As shown in Figures 9, 10 and Table 2, the robot-led training showed a 7.69% increase in intrinsic motivation, with a medium effect size, whereas human-led training yielded only a 1.70% gain. Behavioural engagement remained stable under robot-led conditions but declined by 2.75% under the human-led conditions. Emotional and cognitive engagement showed small, non-significant improvements in both conditions, effect sizes were descriptively larger in robot-led conditions. In general, the pattern suggested a possible advantage for the robot-led training. The details are shown as follows:

Behavioural engagement

The experimental group showed a slight improvement of 0.55% (pre-test: $M=86.19$, $SD=12.67$, CI[78.88; 93.50]; post-test: $M=86.67$, $SD=11.98$, CI[79.75; 93.59]), but this change was not statistically significant ($p=.83$, $t(13) = .22$), with a small effect size (Cohen's $d=.06$). The control group exhibited a decline of 1.65% (pre-test: $M=86.67$, $SD=9.78$, CI[81.02; 92.32]; post-test: $M=85.24$, $SD=12.03$, CI[78.29; 92.19]), but this change was not statistically significant ($p=.19$, $t(13) = -1.39$), with a small effect size (Cohen's $d=-0.37$).

Emotional engagement

The experimental group improved by 3.51% (pre-test: $M=81.43$, $SD=17.58$, CI[71.28; 91.58]; post-test: $M=84.29$, $SD=12.16$, CI[77.27; 91.30]), but this change was not statistically significant ($p=.37$, $t(13) = .92$), with a small effect size (Cohen's $d=.25$). The control group demonstrated a slight decrease of 0.57%

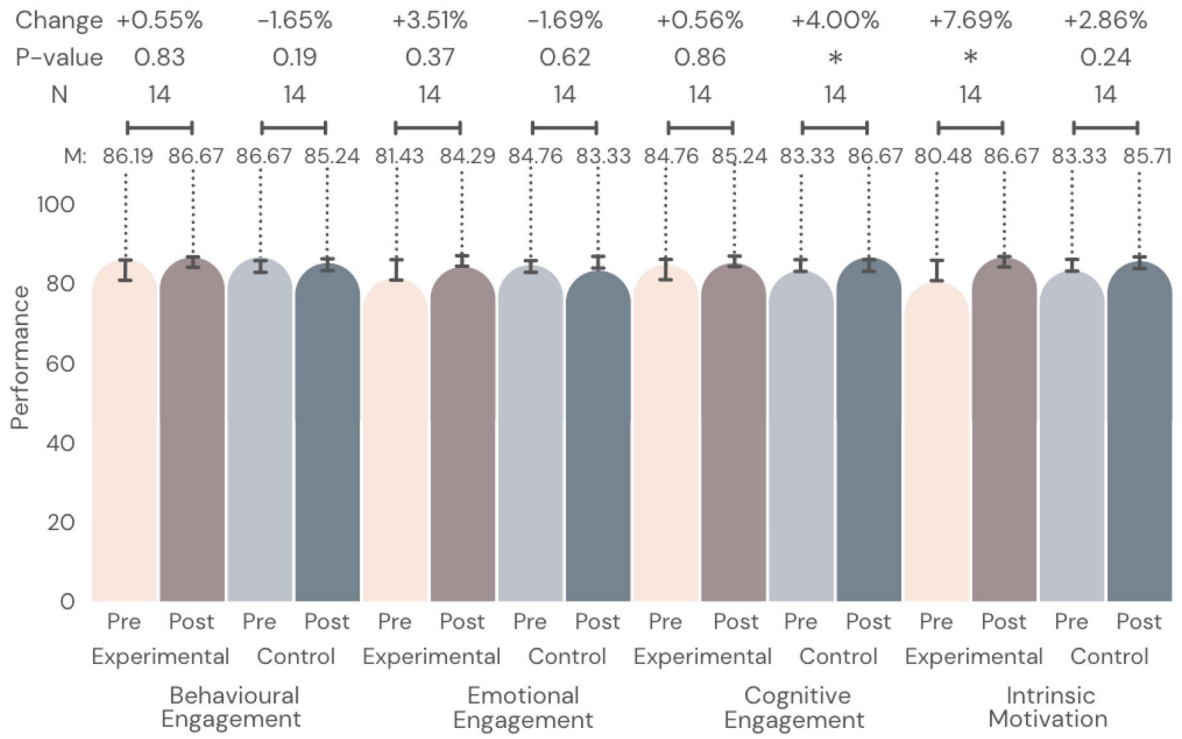


Figure 9. Diagram showing Performance of pre-/post-questionnaire for both groups. Error bars show standard deviation. "*" denotes p <.05.

(pre-test: M=84.76, SD=13.69, CI[76.85; 92.67]; post-test: M=83.33, SD=14.26, CI[75.10; 91.57]), but this change was not statistically significant (p=.62, t(13) = −0.51), with a small effect size (Cohen's d=−0.14).

Cognitive engagement

The experimental group slightly improved by 0.56% (pre-test: M=84.76, SD=12.92, CI[78.66; 92.77]; post-test: M=85.24, SD=13.12, CI[77.66; 92.81]), but this change was not statistically significant (p=.86, t(13) = .19), with a small effect size (Cohen's d=.05). The control group observed an improvement of 4.00% (pre-test: M=83.33, SD=13.01, CI[75.82; 90.84]; post-test: M=86.67, SD=11.69, CI[79.91; 93.42]), this change reached statistical significance (p < .05, t(13) =2.46), with a medium effect size (Cohen's d=.66).

Intrinsic motivation

The experimental group showed a 7.69% improvement (pre-test: M=80.48, SD=19.47, CI[69.23; 91.72]; post-test: M=86.67, SD=13.07, CI[79.12; 94.23]), which was statistically significant (p < .05, t(13) =2.18), with a medium effect size (Cohen's d=.58). The control group demonstrated a 2.86\% improvement (pre-test: M=83.33, SD=13.77, CI[75.38; 91.29]; post-test: M=85.71, SD=14.53, CI[77.33; 94.10]), but this change was not statistically significant (p=.24, t(13) =1.24), with a small effect size (Cohen's d=.33).

To what extent does robot-led interview training impact learning efficacy?

Robot-led JIT showed larger improvements than human-led training across the four performance domains. In all four domains, the robot-led training produced higher mean improvement rates, with three domains demonstrating statistical significance (p < .05), compared with none in the human-led training. The largest gains were observed in verbal competence and paralinguistic skills. The details are shown as follows:

Verbal competence

For the robot-led training, verbal competence improved by 30.19% and was statistically significant (p < .01) (pre-test: M=56.79, SD=13.10; post-test: M=73.93, SD=12.28). For the human-led training, the intervention

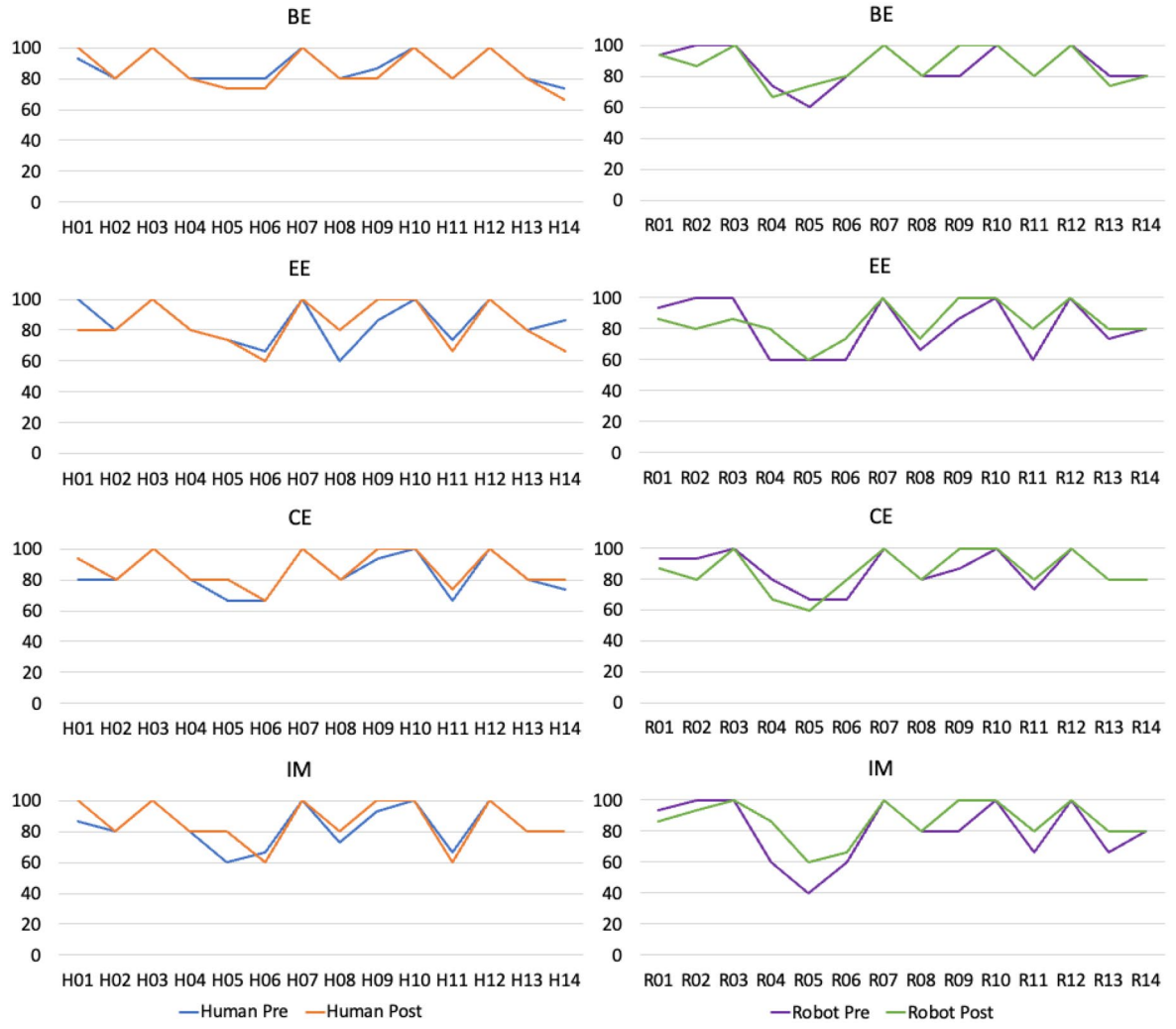


Figure 10. Diagram showing Individual Performance of pre-/post-questionnaire for both groups. The acronyms of BE, EE, CE, and IM are behavioural, emotional, cognitive engagement, and intrinsic motivation.

Table 2. Pearson correlations among post-test motivational and engagement variables.

	Experimental group				Control group			
	1	2	3	4	1	2	3	4
1. Behavioural Engagement	1	.822**	.935**	1	.767**	.802**	.754**	1
2. Emotional Engagement	–	1	.899**	.904**	–	1	.943**	.891**
3. Cognitive Engagement	–	–	1	.837**	–	–	1	.966**
4. Intrinsic Motivation	–	–	–	1	–	–	–	1

Note.$p < .05$; **$p < .01$.

showed improvement by 16.96%, but this change was not statistically significant ($p = .13$) (pre-test: $M = 61.07$, $SD = 18.73$; post-test: $M = 71.43$, $SD = 16.22$). As shown in Figure 11, most participants showed gradual improvement across the four rounds in the robot-led training, whereas improvement was less pronounced in the human-led training.

Non-Verbal competence

For the robot-led training, non-verbal competence improved by 8.89%, and was statistically significant ($p < .05$) (pre-test: $M = 75.00$, $SD = 9.13$; post-test: $M = 81.67$, $SD = 7.01$). For the human-led training, the

intervention showed improvement by 2.59%, but this change was not statistically significant ($p = .68$) (pre-test: $M = 73.81$, $SD = 12.87$; post-test: $M = 75.71$, $SD = 10.97$). As shown in Figure 11, scores increased modestly in the four rounds in the robot-led training, while the human-led training showed only a slight improvement. To summarise, both training conditions showed limited change in non-verbal competence.

Paralinguistic & interactional skills

For the robot-led training, paralinguistic and interactional skills improved by 20.87%, but this change did not reach statistical significance ($p = .06$) (pre-test: $M = 57.62$, $SD = 16.71$; post-test: $M = 69.64$, $SD = 14.94$). For the human-led training, the intervention showed improvement by 5.65%, but this change was not statistically significant ($p = .60$) (pre-test: $M = 65.36$, $SD = 17.46$; post-test: $M = 69.05$, $SD = 19.22$). As shown in Figure 11, robot-led performance increased steadily from Round 1 to Round 4, whereas the human-led scores fluctuated and showed a smaller overall increase.

Interview performance score

For the robot-led, interview performance score improved by 11.95% and and was statistically significant ($p < .01$) (pre-test: $M = 68.75$, $SD = 7.95$; post-test: $M = 76.96$, $SD = 7.22$). For the human-led, the intervention showed improvement by 9.00%, but this change was not statistically significant ($p = .18$) (pre-test: $M = 71.43$, $SD = 14.13$; post-test: $M = 77.86$, $SD = 10.18$). As shown in Figure 11, nearly all participants improved across the rounds of robot-led training, whereas the human-led scores showed a flatter pattern of change. Overall, the robot-led condition showed a slightly larger descriptive gain in interview performance.

Average performance

For the robot-led training, average performance improved by 17.06%, and was statistically significant ($p < .01$) (pre-test: $M = 64.54$, $SD = 10.84$; post-test: $M = 75.55$, $SD = 9.57$). For the human-led training, the intervention showed improvement by 8.24%, but this change was not statistically significant ($p = .28$) (pre-test: $M = 67.92$, $SD = 14.06$; post-test: $M = 73.51$, $SD = 12.68$). As shown in Figure 12, robot-led training demonstrated consistent incremental improvement across four rounds, with most participants showing steady progress. In contrast, human-led training showed a less stable performance trend. Although both groups improved, the robot-led condition showed a larger descriptive gain over time.

What are young adults experiences of human- and robot-led system?

Thematic analysis was used to analyse the qualitative interview data of participants. We followed a six-phase approach [68] to code interview transcripts. The reasons were to identify recurring patterns and themes from participants' responses. The six-phase approach included: (1) be familiar with the data, (2) code meaningful segments of the data, (3) identify potential themes, (4) review and refine the themes, (5) define and name the final themes, and (6) compile an analytical report.

Young adults's interview

Theme 1: motivational engagement and learning readiness. Theme 1 captures the learning orientation towards JIT with *JIT-bot*, with 92% of the respondents in agreement that robot-led learning is more interesting than conventional JIT. The response aligns with the intrinsic motivation component of SDT, suggesting that most young adults possess a foundational level of motivational readiness that robot-assisted interventions can leverage and build upon. They exhibited varying levels of participation, ranging from high enthusiasm (R02: 我對面試訓練的興趣較大, Literally: I am more interested in interview training.) to a curiosity focused on learning (R08: 我只係想更深入了解面試技巧; Literally: I want to understand interview techniques deeply). Notably, one participant demonstrated technology-mediated familiarity development (R10: 我覺得十分有興趣。我跟 robot 進行了四次訓練, 開始有點熟悉; Literally: It is very interesting. After four rounds of robot training, I am getting familiar with it).

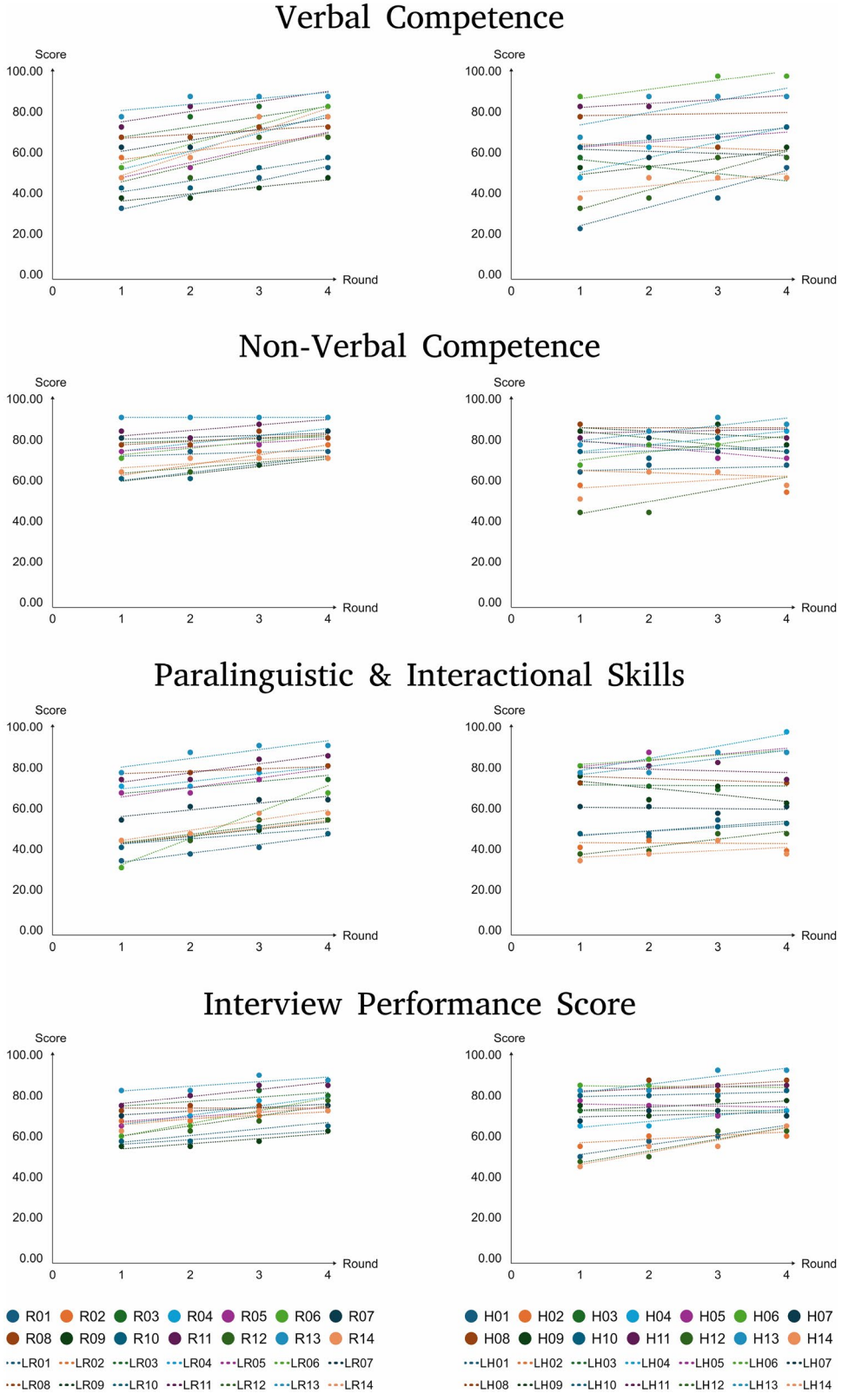


Figure 11. Diagram showing individual category performance of two groups in interview training.

Theme 2: value perception and future-oriented importance

Eighty-five percent of the respondents agreed on a strong connection between interview training and future career success. It indicates that participants have clear perceptions of the utility of support to sustain engagement in training interventions. The most common perspective emphasised its critical

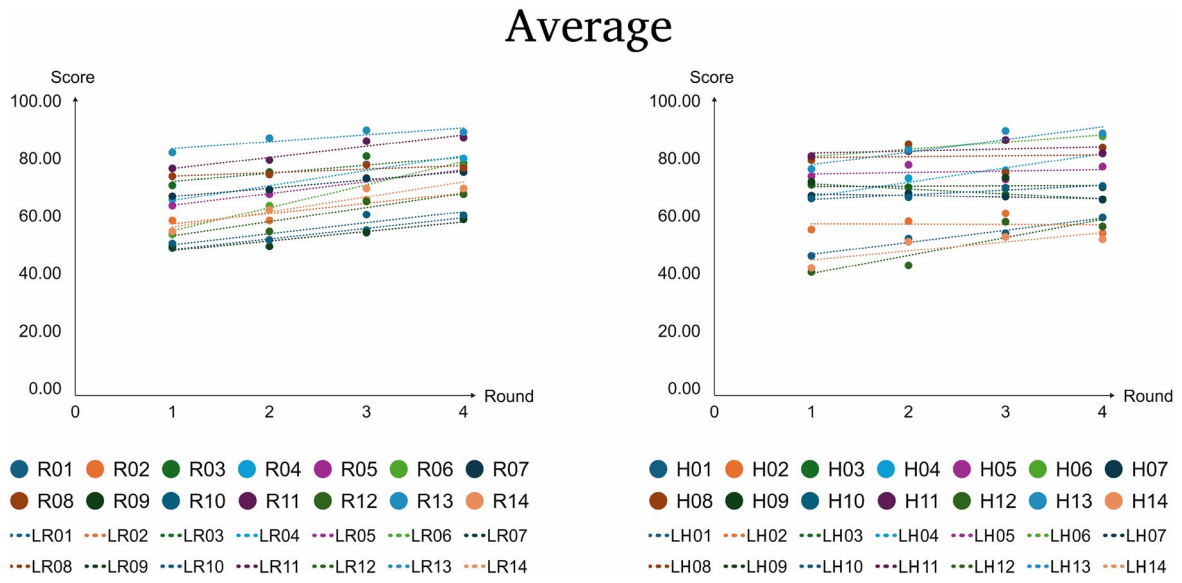


Figure 12. Diagram showing average rating of two groups in interview training.

importance (R02: 我覺得進行面試訓練對自己至關重要; Literally: I think interview training is very important for me). Building communication competence emerged as a key value (R08: 我覺得重要, 因為可以知道自己與陌生人溝通的流暢程度; Literally: It is important because it can help me understand how fluent I am in communicating with strangers), with clearly articulated practical job-related benefits (R10: 我覺得很重要, 這個對我將來的工作很有幫助; Literally: It is very important and will be very helpful for my future work).

Theme 3: self-efficacy beliefs and performance confidence

92% of the respondents indicated a positive change in confidence levels and improvements in anxiety management. The result highlights the need for differentiated approaches that address varying levels of confidence in robot-assisted interventions. Several participants expressed high confidence (R02: 我對自己能成功記住面試訓練內容有較大信心; Literally: I have great confidence that I can successfully remember the training content of the interview), while others demonstrated reduced anxiety through practice (R08: 跟以前相比, 我訓練的緊張程度大大減少; Literally: My level of tension is much lower than before).

Theme 4: strategic competency development approaches

85% of respondents agreed that they had adopted new strategies to improve their interview skills. Theme 4 relates to the theory of strategic learning, suggesting that most participants possess or can develop strategic thinking capabilities that robot-assisted training can enhance and systematise. Specific strategies ranged from verbal techniques (R02: 我的聲線要夠響亮; Literally: My voice needs to be loud enough) to non-verbal skills (R03: 我需要有眼神接觸; Literally: Eye contact).

Discussion

The robot-led intervention offered preliminary indications of potential efficacy and was associated with increases in intrinsic motivation. However, there was a non-significant decline in behavioural engagement in the human-led approach. In this section, we provide an in-depth discussion of the insights.

Differential mechanisms of motivation: intrinsic drive vs. cognitive effort

Small differences in motivational and behavioural engagement were observed between the two modalities. The implementation of robot-led training appeared to be associated with higher levels of intrinsic motivation. In contrast, human-led training seemed to be more effective in prompting deep cognitive

engagement. The interactive robot may create a relatively low-pressure environment. With self-driven practice, it may help to fulfil the psychological need for perceived competence [69], while a human trainer may be better positioned to drive immediate, critical synthesis through dynamic social interaction. The robot-led training showed a 7.69% improvement in intrinsic motivation ($p < .05$, Cohen's $d = .58$). With repeated practice, they may experience increased confidence (Theme 3), suggesting that intrinsic motivation is possibly supported by perceived competence and mastery in a non-judgmental setting [70].

Robot-led consistency in vocational skill acquisition

Robot-led interview training tended to demonstrate learning efficacy in all measured skill categories. The GenAI-supported system (e.g. ChatGPT 4) may provide consistent support to participants. GenAI may help to translate repeated practice into measurable competence in complex communication skills [71]. Robot-led training demonstrated statistically significant improvements in three core measures: Verbal Competence (+30.19%, $p < .01$), Non-Verbal Competence (+8.89%, $p < .05$), and Interview Performance Score (+11.94%, $p < .01$). The outcomes suggest the potential benefit of adaptive learning progression and personalised support [72].

Young adults experiences of human- and robot-led interview training

Participants reported many positive experiences with the robot-led system. They emphasised novelty, establishing confidence, and perceived utility. Most participants agreed that *JIT-bot* enhanced their motivational readiness, aligning with intrinsic motivation components of SDT [73,74].

Modest intervention effects

Several contextual factors likely contributed to the small differences observed between human- and robot-led training. All participants in the human-led condition were taught and interviewed by instructors they already knew from their vocational courses, whereas the robot was a novel interaction partner. For young adults with SEN, familiarity and perceived friendliness may help to reduce anxiety and promote more stable performance [75], which could partly explain why human-led pre–post scores show less fluctuation and why cognitive engagement in the control group showed a statistically significant improvement. At the same time, baseline performance in both conditions was relatively high, especially for behavioural engagement, leaving limited room for change (e.g. behavioural increases of only 0.55% in the experimental group and 0.56% in the cognitive engagement condition). These factors may have constrained the magnitude of detectable between-condition differences, and thus the present results should be interpreted as exploratory.

Implications for real-world interview preparation

Instructor feedback suggests that the robot-led interview training may have potential to transfer to real employment interview contexts. They recommended shorter and more segmented questions, as young adults with SEN may have limited cognitive load. Clearer time prompts could also support time management. In addition, a response-completion button, a fixed number of questions, and more job-relevant content could be further refined to better reflect authentic interview demands. These suggestions indicate that the intervention may have practical relevance for employability preparation and point to the need to strengthen its ecological validity so that the training environment more closely approximates real interview settings.

Limitations and future work

Small sample size and generalizability

Our sample size was small due to challenges in recruiting participants (young adults with SEN). This constraint is recognised within this population. The small sample may limit the statistical power of the

study, particularly for detecting small between-group differences. This introduces uncertainty around the estimated effects. Therefore, the reported Cohen's d values and confidence intervals should be interpreted as exploratory estimates of intervention effects. Also, non-significant findings should be interpreted with caution, as they may reflect insufficient power rather than the absence of meaningful change. Despite these limitations, the results offer valuable insights into theoretical and practical HRI interventions [76]. In the future, we will scale up to target more SEN groups.

GenAI-supported auto-evaluation

Reliance on human ratings of participants' interview performance constitutes a methodological limitation. It introduces inherent subjectivity into the assessment process [77]. The subjective nature of human evaluation may compromise the reliability and consistency of performance measurements, particularly when multiple raters are involved [78]. To address this concern, we will implement GenAI-supported automated assessment systems. Automated approaches have demonstrated performance comparable to that of human evaluators in educational assessment contexts [79].

Participant allocation schedule

In our study, participants were allocated according to a fixed schedule rather than by an unpredictable random sequence. Therefore, the design could be considered systematic rather than truly randomised. This predictable allocation might introduce selection bias because foreknowledge of upcoming group assignments could inadvertently influence recruitment and lead to baseline imbalances between groups. In the future, we will employ concealed randomisation procedures to reduce selection bias.

Measurement properties of questionnaire

Although the translation procedures and expert review provide preliminary support for content validity, the instrument has been examined primarily using Pearson correlation coefficients to assess associations. This analytic approach might not provide a comprehensive assessment of reliability or validity. Therefore, findings derived from this instrument should be interpreted with caution. Future research will prioritise comprehensive psychometric validation before the questionnaire is employed as a primary outcome measure in subsequent studies.

Conclusion

To conclude, two groups participated in a four-day interview training intervention. The control group received instruction from human trainers, while the experimental group engaged with *JIT-bot*. Overall, the experimental group showed improvements in engagement and motivation, with a statistically significant increase in intrinsic motivation. In contrast, the control group exhibited mixed outcomes in terms of engagement and motivation. Throughout the interview, participants emphasise the importance of learning interests, perceptions of future value, self-efficacy beliefs, self-confidence, and strategic competency.

Notes

1. OpenAI: https://openai.com/index/gpt-4-research/
2. Qualtrics XM: https://www.qualtrics.com/

Author contributions

CRediT: **Ka Yan Fung**: Conceptualization, Formal analysis, Investigation, Methodology, Project administration, Writing – original draft, Writing – review & editing.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

The author(s) reported there is no funding associated with the work featured in this article.

Notes on contributor

Ka-Yan Fung received the PhD degree in Human-Computer Interaction in 2024 and M.Phil. degree in technology, leadership, and entrepreneurship from the Hong Kong University of Science and Technology, Hong Kong, in 2021, and the M.Phil. degree in contemporary east Asian studies from the University of Duisburg-Essen, Duisburg, Germany, in 2021. Her research interests include special learning disabilities, human–computer interaction, human–robot interaction, data visualization, and inclusive education.

Data availability statement

Data cannot be made available for reasons disclosed in the data availability statement.

References

[1] Sankardas SA, Rajanahally J. Skills training for young adults with special educational needs for transition into employment. Support Learn. 2015;30(3):252–267. doi: 10.1111/1467-9604.12094.
[2] Hellendoorn J, Ruijssenaars W. Personal experiences and adjustment of Dutch adults with dyslexia. Remed Special Educ. 2000;21(4):227–239. doi: 10.1177/074193250002100405.
[3] Breen M. Multimodal job interview simulator for training of autistic individuals. Assist Technol Off J Resna. 2023;2188907.
[4] Adiani D, Itzkovitz A, Bian D, et al. Career interview readiness in virtual reality (cirvr): a platform for simulated interview training for autistic individuals and their employers. ACM Trans Access Comput. 2022;15(1):1–28. doi: 10.1145/3505560.
[5] Adiani D, Breen M, Migovich M, et al. Multimodal job interview simulator for training of autistic individuals. Assist Technol. 2024;36(1):22–39. doi: 10.1080/10400435.2023.2188907.
[6] Jans LH, Kaye HS, Jones EC. Getting hired: successfully employed people with disabilities offer advice on disclosure, interviewing, and job search. J Occup Rehabil. 2012;22(2):155–165. doi: 10.1007/s10926-011-9336-y.
[7] Arnab S, Varga MN, Dolby T, et al. Bridging realities: co-creating virtual reality scenarios to support autistic adults in job interview preparation. Res Neurodivers. 2026;2:100033. doi: 10.1016/j.rin.2026.100033.
[8] Finn M, Flower RL, Leong HM, et al. 'If I'm just me, I doubt I'd get the job': a qualitative exploration of autistic people's experiences in job interviews. Autism. 2023;27(7):2086–2097. doi: 10.1177/13623613231153480.
[9] Maras K, Norris JE, Nicholson J, et al. Ameliorating the disadvantage for autistic job seekers: an initial evaluation of adapted employment interview questions. Autism. 2021;25(4):1060–1075. doi: 10.1177/1362361320981319.
[10] EO Commission. 2023. Study on effective strategies to facilitate school-to-work transition of young persons with disabilities in Hong Kong. https://www.eoc.org.hk/Upload/files/research-report/YoungPWDs/Report_Chi_final.pdf.
[11] EOC. 2023. EOC releases findings of study on effective strategies to facilitate school-to-work transition of young persons with disabilities in Hong Kong. https://www.eoc.org.hk/en/PressRelease/Detail/18539.
[12] Cabielles-Hernandez D, Perez-Perez J-R, Paule-Ruiz M, et al. Specialized intervention using tablet devices for communication deficits in children with autism spectrum disorders. IEEE Trans Learning Technol. 2017;10(2):182–193. doi: 10.1109/TLT.2016.2559482.
[13] Plush SE, Kehrwald BA. Supporting new academics' use of student centred strategies in traditional university teaching. JUTLP. 2014;11(1):16. doi: 10.53761/1.11.1.5.
[14] Liu X, Lau N, Chuin A, et al. Enhancing design competencies for students with special educational needs for future career development. In De Sainz Molestina, D., Galluzzo, L., Rizzo, F., Spallazzo, D. (eds.), IASDR. 2023. Life-Changing Design, pp. 9-13 October, Milan, Italy. 10.21606/iasdr.2023.370
[15] Bureau E. 2010. Operation guide on the whole school approach to integrated education. Hong Kong: Printing Department.
[16] Genova HM, Lancaster K, Morecraft J, et al. A pilot rct of virtual reality job interview training in transition-age youth on the autism spectrum. Res Autism Spectr Disord. 2021;89:101878. doi: 10.1016/j.rasd.2021.101878.
[17] Mattison ML, O'Mahony BM, Risan P. Complex vulnerability. Invest Interviewing: Psychol Practice. 2025:235.

[18] Conrad M, Kablitz D, Schumann S. Learning effectiveness of immersive virtual reality in education and training: a systematic review of findings. Comput Educ X Real. 2024;4:100053.
[19] Lopez-Garrido G. Bandura's self-efficacy theory of motivation in psychology. Simply Psychol. 2023;10(1):17–25.
[20] Kleppang AL, Steigen AM, Finbråten HS. Explaining variance in self-efficacy among adolescents: the association between mastery experiences, social support, and self-efficacy. BMC Public Health. 2023;23(1):1665. doi: 10.1186/s12889-023-16603-w.
[21] Schweder S, Raufelder D. Students' interest and self-efficacy and the impact of changing learning environments. Contemp Educ Psychol. 2022;70:102082. doi: 10.1016/j.cedpsych.2022.102082.
[22] Wang H, Hall NC. A systematic review of teachers' causal attributions: prevalence, correlates, and consequences. Front Psychol. 2018;9:2305. doi: 10.3389/fpsyg.2018.02305.
[23] Baker-Ericzén MJ, ElShamy R, Kammes RR. Current status of evidence-based practices to enhance employment outcomes for transition age youth and adults on the autism spectrum. Curr Psychiatry Rep. 2022;24(3):161–170. doi: 10.1007/s11920-022-01327-2.
[24] Maslowski AK, Owens RL, LaCaille RA, et al. A systematic review and meta-analysis of motivational interviewing training effectiveness among students-in-training. Train Educ Prof Psychol. 2022;16(4):354–361. doi: 10.1037/tep0000363.
[25] Voultsiou E, Moussiades L. A systematic review of ai, vr, and llm applications in special education: opportunities, challenges, and future directions. Educ Inf Technol. 2025;30(13):19141–19181. doi: 10.1007/s10639-025-13550-4.
[26] Bertacchini F, Demarco F, Scuro C, et al. A social robot connected with chatgpt to improve cognitive functioning in asd subjects. Front Psychol. 2023;14:1232177. doi: 10.3389/fpsyg.2023.1232177.
[27] Sharma BU. Adaptive learning technologies: personalizing education for students with special needs. Int J Sci Res (IJSR). 2024;13:1452–1455.
[28] Genova HM, Haas M, Chen Y-L, et al. Development and adaptation of a strength-based job interview training tool for transition age youth on the autism spectrum using community engaged methods. Front Psychiatry. 2023;14:1098334. doi: 10.3389/fpsyt.2023.1098334.
[29] Kumazaki H, Yoshikawa Y, Muramatsu T, et al. Group-based online job interview training program using virtual robot for individuals with autism spectrum disorders. Front Psychiatry. 2021;12:704564. doi: 10.3389/fpsyt.2021.704564.
[30] Genova HM, Elsayed HE, Haas M, et al. A combined interventional approach to train interview skills in autistic transition-age youth. J Autism Dev Disord. 2025;55(7):2228–2239. doi: 10.1007/s10803-024-06299-1.
[31] Whittenburg HN, Xu Y, Thoma CA, et al. Effects of behavioral skills training with video modeling and in situ training on workplace conversational skills of students with autism. Focus Autism Other Dev Disabl. 2023;38(3):188–198. doi: 10.1177/10883576221127971.
[32] Chistol M, Danubianu M, Barîla A-L. Technology-mediated interventions for autism spectrum disorder. IJACSA. 2023;14(12):54. doi: 10.14569/IJACSA.2023.0141205.
[33] Migovich M, Adiani D, Breen M, et al. Stress detection of autistic adults during simulated job interviews using a novel physiological dataset and machine learning. ACM Trans Access Comput. 2024;17(1):1–25. doi: 10.1145/3639709
[34] Latikka R, Turja T, Oksanen A. Self-efficacy and acceptance of robots. Comput Human Behav. 2019;93:157–163. doi: 10.1016/j.chb.2018.12.017.
[35] Sierra Rativa A, Postma M, Van Zaanen M. The influence of game character appearance on empathy and immersion: virtual non-robotic versus robotic animals. Simul Gaming. 2020;51(5):685–711. doi: 10.1177/1046878120926694.
[36] Fung KY, Lee LH, Sin KF, et al. Humanoid robot-empowered language learning based on self-determination theory. Educ Inf Technol. 2024b;29(14):18927–18957. doi: 10.1007/s10639-024-12570-w.
[37] Deng E, Mutlu B, Matarić MJ. Embodiment in socially interactive robots. Found Trends® Robot. 2019;7(4):251–356. doi: 10.1561/2300000056.
[38] Wainer J, Feil-Seifer DJ, Shell DA, et al. The role of physical embodiment in human-robot interaction. In: ROMAN 2006-The 15th IEEE International Symposium on Robot and Human Interactive Communication, Hatfield, UK. IEEE; 2006, p. 117–122.
[39] Shrestha S, Shan Y, Emerson R, et al. Developing and usability testing of an augmented reality tool for online engineering education. IEEE Trans Learning Technol. 2025;18:13–24. doi: 10.1109/TLT.2024.3520413.
[40] Johnson WL, Rickel JW, Lester JC, et al. Animated pedagogical agents: face-to-face interaction in interactive learning environments. Int J Artif Intell Educ. 2000;11:47–78.
[41] Schulz T, Torresen J, Herstad J. Animation techniques in human-robot interaction user studies: a systematic literature review. J Hum-Robot Interact. 2019;8(2):1–22. doi: 10.1145/3317325.
[42] Luria E. Revolutionizing English language learning through social robots and artificial intelligence: towards inclusive and personalized education. In: Social robots and artificial intelligence in education: integrating AI in K-12 and higher education. Cham, Switzerland: Springer; 2026. p. 61–90. doi: 10.1007/978-3-032-03977-4_4.
[43] Hromada DD, Kim H. Proof-of-concept of feasibility of human–machine peer learning for german noun vocabulary learning. Front Educ. 2023;8:1063337. doi: 10.3389/feduc.2023.1063337.

[44] Mulloy AM, Gevarter C, Hopkins M, et al. Assistive technology for students with visual impairments and blindness. In: Assistive technologies for people with diverse abilities. New York, NY: Springer; 2014. p. 113–156. doi: 10.1007/978-1-4899-8029-8_5.
[45] Ackermann H, Lange AL, Hafner VV, et al. How adaptive social robots influence cognitive, emotional, and self-regulated learning. Sci Rep. 2025;15(1):6581. doi: 10.1038/s41598-025-91236-0.
[46] Wu S, Cao Y, Cui J, et al. ; 2024 A comprehensive exploration of personalized learning in smart education: from student modeling to personalized recommendations. *arXiv preprint arXiv:2402.01666*.
[47] Ryan RM, Moller AC. Competence as central, but not sufficient, for high-quality motivation. Handb Compet Motiv Theory Appl. 2017;2:216–238.
[48] Deci EL, Ryan RM. The support of autonomy and the control of behavior. J Pers Soc Psychol. 1987;53(6):1024–1037. doi: 10.1037/0022-3514.53.6.1024.
[49] Tang J. The impact of smart learning technologies on students' cognitive competence: enhancing critical thinking. Educ Inf Technol. 2025;30(8):10073–10089. doi: 10.1007/s10639-024-13250-5.
[50] Deci E, Ryan R. The" what" and" why" of goal pursuits: human needs and the self-determination of behavior. Psychol Inq. 2000;11(4):227–268. doi: 10.1207/S15327965PLI1104_01.
[51] Fung K-Y, Fung K-C, Lui TLR, et al. Motivating students with different needs to learn chinese in a mixed-background classroom by robot-assisted learning. IEEE Trans Learning Technol. 2025b;18:369–386. doi: 10.1109/TLT.2025.3551256.
[52] Páez J, González E. Human-robot scaffolding: an architecture to foster problem-solving skills. J Hum-Robot Interact. 2022;11(3):1–17. doi: 10.1145/3526109.
[53] Matus S, Cano S. Human-robot interaction in higher education: a literature review. In: International Conference on Human-Computer Interaction. Cham, Switzerland: Springer; 2025. p. 236–256.
[54] Xie N, Li Z, Lu H, et al. Msc-trans: a multi-feature-fusion network with encoding structure for student engagement detecting. IEEE Trans Learning Technol. 2025;18:243–255. doi: 10.1109/TLT.2025.3530457.
[55] Gur A, Bina R. Facilitators of sense of belonging among people with intellectual and developmental disabilities: a systematic review. J Intellect Disabil. 2023;27(2):516–538. doi: 10.1177/17446295211068424.
[56] Johnson E, Masser JS, Spears L. Self-regulated learners: a comprehensive, translational framework for students with learning disabilities. Exceptionality. 2023;31(1):52–68. doi: 10.1080/09362835.2021.1938063.
[57] Dubovi AS, Sheu H-B. Testing the effectiveness of an sct-based training program in enhancing health self-efficacy and outcome expectations among college peer educators. J Couns Psychol. 2022;69(3):361–373. doi: 10.1037/cou0000592.
[58] Bandura A. Cultivate self-efficacy for personal and organizational effectiveness. In: Principles of organizational behavior: the handbook of evidence-based management. 3rd ed. 2023. p. 113–135. Hoboken: John Wiley and Sons.
[59] Gale J, Alemdar M, Cappelli C, et al. A mixed methods study of self-efficacy, the sources of self-efficacy, and teaching experience. In Frontiers in Education. 2021;6:750599. Frontiers Media SA. doi: 10.3389/feduc.2021.750599.
[60] Williams DM, Rhodes RE. The confounded self-efficacy construct: conceptual analysis and recommendations for future research. Health Psychol Rev. 2016;10(2):113–128. PMID: 25117692. doi: 10.1080/17437199.2014.941998.
[61] Görer B, Aydemir FB. Roboreit: an interactive robotic tutor with instructive feedback component for requirements elicitation interview training. J Software Evolu Process. 2024;36(5):e2608. doi: 10.1002/smr.2608.
[62] Yoshikawa Y, Muramatsu T, Sakai K, et al. A new group-based online job interview training program using computer graphics robots for individuals with autism spectrum disorders. Front Psychiatry. 2023;14:1198433. doi: 10.3389/fpsyt.2023.1198433.
[63] Fung KY, Fung KC, Lui TLR, et al. Exploring the impact of robot interaction on learning engagement: a comparative study of two multi-modal robots. Smart Learn Environ. 2025a;12(1):12. doi: 10.1186/s40561-024-00362-1.
[64] Kumazaki H, Warren Z, Muramatsu T, et al. A pilot study for robot appearance preferences among high-functioning individuals with autism spectrum disorder: implications for therapeutic use. PLoS One. 2017;12(10):e0186581. doi: 10.1371/journal.pone.0186581.
[65] Fox J, Gambino A. Relationship development with humanoid social robots: applying interpersonal theories to human–robot interaction. Cyberpsychol Behav Soc Netw. 2021;24(5):294–299. doi: 10.1089/cyber.2020.0181.
[66] Fung KY, Fung KC, Lui T-LR, et al. A robot-assisted scenario training for students with asd. In International conference on computers in education. 2024. doi: 10.58459/icce.2024.4891.
[67] Fung KY, Fung KC, Lee LH, et al. A study on using chatgpt to help students with dyslexia learn chinese and english writing. ECNU Review of Education. 2026;9:20965311251358269.
[68] Braun V, Clarke V. Using thematic analysis in psychology. Qual Res Psychol. 2006;3(2):77–101. doi: 10.1191/1478088706qp063oa.
[69] Deci E, Ryan R. ; 2013. Intrinsic motivation and self-determination in human behavior. New York: Springer Science & Business Media.
[70] Qureshi F, Khawaja S, Sokić K, et al. Exploring intrinsic motivation and mental well-being in private higher educational systems: a cross-sectional study. Systems (Basel). 2024;12(8):281. doi: 10.3390/systems12080281.

[71] Prompiengchai S, Narreddy C, Joordens S. A practical guide for supporting formative assessment and feedback using generative AI. 2025. arXiv Preprint. *arXiv:2505.23405*.
[72] Villegas-Ch W, Buenano-Fernandez D, Navarro AM, et al. Adaptive intelligent tutoring systems for stem education: analysis of the learning impact and effectiveness of personalized feedback. Smart Learn Environ. 2025;12(1):31. doi: 10.1186/s40561-025-00389-y.
[73] Alberts L, Lyngs U, Lukoff K. Designing for sustained motivation: a review of self-determination theory in behaviour change technologies. Interact Comput. 2026;38(3):447–468. doi: 10.1093/iwc/iwae040.
[74] Osei PC, Bjorklund DF. Motivating the learning process: integrating self-determination theory into a dynamical systems framework. Educ Psychol Rev. 2024;36(3):89. doi: 10.1007/s10648-024-09934-6.
[75] Avramidis E. Self-concept, social position and social participation of pupils with sen in mainstream primary schools. Res Pap Educ. 2013;28(4):421–442. doi: 10.1080/02671522.2012.673006.
[76] Bacchetti P, Deeks SG, McCune JM. Breaking free of sample size dogma to perform innovative translational research. Sci Transl Med. 2011;3(87):87ps24. doi: 10.1126/scitranslmed.3001628.
[77] Jana U. Rating scales institutionalise a network of logical errors and conceptual problems in research practices: a rigorous analysis showing ways to tackle psychology's crises. Front Psychol. 2022;13:1009893.
[78] Cowley HP, Natter M, Gray-Roncal K, et al. A framework for rigorous evaluation of human performance in human and machine learning comparison studies. Sci Rep. 2022;12(1):5444. doi: 10.1038/s41598-022-08078-3.
[79] Liew PY, Tan IK. On automated essay grading using large language models. In: Proceedings of the 2024 8th International Conference on Computer Science and Artificial Intelligence; 2024. p. 204–211. New York, NY: Association for Computing Machinery (ACM).

Appendix A

A.1 Interview questions (participants)

1. Are you interested in interview training? Why?
2. Do you think JIT is important to you? Why?
3. Are you confident in remembering the JIT content?
4. What strategies do you usually use in JIT?
5. How do you improve your job interview skills?
6. Will you seek help from your mentors for additional practice? Why?

A.2 Performance analysis (rubrics)

1. Verbal Competence
   - Use job-relevant terms
   - Avoid filler words such as "um"
   - Provide concise and relevant answers
2. Non-Verbal Competence
   - Maintain a steady tone without nervous fluctuations
   - Demonstrate authenticity in responses
   - Show interest in the job
3. Paralinguistic & Interactional Skills
   - Have appropriate eye contact
   - Demonstrate natural facial expressions
   - Show natural gesture
   - Have appropriate speaking speed
   - Respond with appropriate timing
   - Have appropriate vocal volume
4. Interview Performance Score
   - Highlight challenges as learning opportunities
   - Avoid misrepresenting skills and experiences
   - Ask insightful questions about the role and company
   - Build rapport with the interviewer.
   -