

Student Reactions to AI-Generated Feedback in Simulated Employment Interview Sessions

Sakilé K. Camara

California State University Northridge

Abdul Rehmen

University of Education Jauharabad Campus

Suggested Citation:

Camara, S. K., & Rehmen, A. (2026). Student reactions to AI-generated feedback in simulated employment interview sessions. *Utah Journal of Communication*, 4(1), 12-18. <https://doi.org/10.5281/zenodo.20741630>

Abstract

Artificial intelligence (AI) is increasingly used to evaluate communication performance during employment interviews, yet little is known about how candidates perceive algorithmic feedback. This pilot study examined student reactions to AI-generated interview evaluations produced by the TMBravofolio Interview Plus platform. Using a convergent parallel mixed methods design, data were collected from 34 mock interview sessions completed by 15 undergraduate students. Findings revealed substantial disagreement with AI-generated confidence scores and concerns regarding transparency, trust, and accuracy. Qualitative analysis identified issues related to eye-contact tracking, environmental limitations, filler-word penalization, and the absence of human interaction. Recommendations for improving AI interview assessment systems are discussed.

Keywords: *artificial intelligence, communication confidence, employment interviews, algorithmic assessment*

Communication confidence is a central construct in employment interviewing (Tompsett et al., 2017) and hiring managers interpret observable behaviors (i.e., eye contact, vocal steadiness, message organization, posture, and environmental professionalism) as signals of readiness for workplace participation (Argyle, 2013). In high-stakes interview settings, even subtle variations in delivery, gaze stability, or structural coherence can influence evaluative judgments and hiring outcomes (Martín-Raugh et al., 2023).

The mechanisms through which these judgments are formed are rapidly changing. Over the past decade, employment interviewing has shifted from exclusively human-mediated encounters to hybrid and fully automated systems in which artificial intelligence (AI) evaluates recorded responses. Research suggests that as many as 86% of employers reported using technology-driven job interviews by 2022, with many adopting automated video interviews as a preferred

screening method (Jaser, et al., 2022). As (AI) continues to automate business functions (Barker, 2025), communication studies programs face pressure to rethink what communication competence means and how to prepare students for algorithmically mediated evaluation contexts.

This raises a central empirical question: Can algorithms evaluate communication confidence in ways that align with human self-perception? While machine-learning systems can quantify signals such as filler frequency, gaze alignment, and vocal intensity, confidence as a psychological state is internal. Divergence between algorithmic outputs and human experience may signal construct validity concerns, interpretive gaps, or design limitations in AI-mediated systems. The present pilot addresses this question by examining student reactions to AI-generated feedback from TMBravofolio's mock interview feature, which evaluates performance across eight communication dimensions: (1) facial engagement

units, (2) eye stability, (3) vocal delivery, (4) gestures, (5) posture, (6) space and framing, (7) background and lighting, and (8) message structure, and provides confidence-related feedback derived from these signals. Students then assessed whether AI feedback aligned with their own perceptions of performance.

By analyzing patterns of convergence, misalignment, and user-identified inaccuracies, this pilot contributes to emerging scholarship on algorithmic evaluation, communicative competence, and the human perception of confidence in digitally mediated interviews.

Literature Review

Simulated mock interviewing is widely used in university career centers to prepare students for the workforce and enhance self-confidence (Dey & Cruzvergara, 2014; Hansen et al., 2009; Rowell & Mihuta, 2016). Research documents a consistent positive relationship between structured interview practice and increased student confidence (Quinlan & Renner, 2005; Tross & Maurer, 2008) consistent with Bandura's (1997) self-efficacy theory, which identifies mastery experiences as a primary source of confidence development. Recent studies confirm that practice-based career interventions enhance both perceived employability and confidence (Jackson & Wilton, 2017; Okay-Somerville & Scholarios, 2017). Hudak et al. (2019) found statistically significant increases in self-reported confidence following technology-supported interview practice in introductory communication courses, suggesting that the design of AI feedback tools must preserve rather than undermine self-efficacy.

Automated video interview platforms modernize this tradition by providing immediate, multimodal feedback (Campion et al., 2016). These systems leverage computer vision and natural language processing to analyze facial expressions, vocal tone, physical posture, and gaze patterns producing composite behavioral profiles of applicants. However, as these platforms transition from experimental to enterprise tools, concerns have emerged regarding how candidates experience and trust algorithmic evaluation.

Nonverbal Communication in Employment Interviews
A substantial body of research affirms that nonverbal behaviors are critical to interview outcomes. A meta-analysis spanning more than 70 years found that professional appearance, eye contact, and head movement were among the strongest predictors of interview ratings (Martín-Raugh et al., 2023), consistent with Argyle's (2013) observation that bodily communication serves as a primary channel for forming interpersonal impressions. Gifford et al. (1985) demonstrated that social skill was more accurately inferred through nonverbal cues than verbal content alone, yet the mapping between behavioral signals and internal states is far from direct. This gap is amplified in digitally mediated contexts where camera quality, environmental lighting, and physical framing introduce variables that affect the legibility of nonverbal signals (Bailenson, 2021).

Automated Video Interviews and Algorithmic Assessment

As automated video interview tools have entered mainstream recruitment, documented concerns have grown regarding algorithmic transparency and candidate experience (Suen & Hung, 2023; Jaser et al., 2022). Survey evidence suggests that only 26% of job candidates trust AI to evaluate them fairly (Langer et al., 2017), reflecting concerns about opacity, lack of contextual understanding, and perceived dehumanization. Research grounded in organizational justice theory indicates that applicants evaluate interview fairness not only on outcomes but on the transparency and relational quality for the assessment itself (Xu et al., 2025; Chan, 2000). When AI systems fail to provide comprehensible explanations for scores, candidates tend to perceive the evaluation as arbitrary and procedurally unjust (Suen & Hung, 2023).

AI-driven interview tools have drawn scrutiny for potential bias. Chen (2023) and others have documented that algorithmic bias in recruitment may manifest along lines of race, gender, and socioeconomic status, often rooted in unrepresentative training data. The U.S. Equal Employment Opportunity Commission (EEOC) has launched initiatives to monitor AI bias in employment screening, recognizing that algorithms measuring speech patterns and facial expressions risk disadvantaging individuals with disabilities, non-native accents, or neurodiverse communication styles (Ajunwa, 2023).

Zoom Fatigue and the Camera-Screen Offset Problem

One structural constraint in AI-mediated interviewing is the physical separation between the camera lens and the screen display (Suen & Hung, 2025). In face-to-face interaction, mutual gaze is natural; in digital environments, candidate's who look at the screen to read prompts appear to be looking downward from the camera's perspective, potentially triggering penalty scoring from gaze-tracking algorithms. Bailenson (2021) articulated the broader psychological cost of this constraint arguing that forced continuous webcam gaze violates social norms regarding interpersonal distance. A large-scale study of 9,787 participants confirmed that managing nonverbal cues in video-based communication predicted Zoom fatigue, with women disproportionately affected (Fauville et al., 2021).

Cognitive Load Theory and Interview Performance

Cognitive load theory (CSL; Sweller, 1988) provides a useful framework for understanding candidate behavior in AI-evaluated interviews. CLT distinguishes between intrinsic load (task complexity), extraneous load (demands imposed by poor task design), and germane load (effort directed toward schema construction). When responding to complex interview questions, candidates allocate substantial cognitive resources to semantic processing and verbal organization, leaving fewer resources for impression management behaviors such as maintaining posture, adjusting vocal tone, and sustaining camera gaze. AI interview systems, however, evaluate behavioral data streams

without contextualizing them against the cognitive demands of the question. This misalignment between AI assessment logic and human cognitive architecture is a central source of the divergence examined in the present study. These considerations led to the following research questions:

RQ1: To what extent do student validators agree or disagree with AI assessment of interviewing performance?

RQ2: How can AI interviewing platforms be refined to better align with the user experience?

Method

This study employed a convergent parallel mixed methods design, collecting quantitative and qualitative data concurrently, analyzing each independently, and integrating findings during interpretation (Creswell & Plano Clark, 2018). This approach was selected because the study sought to evaluate both measurable perceptions of an AI interview assessment tool and participants' narrative experiences with the technology. The goal was not to generalize findings but to inform the refinement and validation of the AI system.

The study examined data generated through the TMBravofolio Interview Plus platform, which combines Google MediaPipe computer vision technology with OpenAI natural language processing tools. MediaPipe analyzes facial expressions, eye gaze, posture, and head positioning from recorded interviews, while OpenAI processes these inputs to generate communication confidence scores and performance feedback. The interview process included accessibility checks, interview customization, calibration, recording, self-assessment, and automated feedback generation.

Participants were undergraduate students enrolled in a Communication Internship course during Spring 2026 at a mid-sized university. The course primarily serves juniors and seniors completing professional internships. Thirty-five students were enrolled at the time of implementation. Mock interviews were a required course activity used to assess career readiness. Students provided consent for the use of de-identified data for research and AI recalibration purposes. The project qualified for exemption from institutional review board review as a normal educational practice.

Data were collected using two instruments embedded within the Interview Plus platform. First, participants completed a five-item survey using a seven-point Likert scale (1 = Strongly Disagree, 7 = Strongly Agree). Items measured perceptions of AI score accuracy, trust in the system, usefulness of feedback, transparency of scoring, and willingness to use the technology again. Second, participants responded to an open-ended prompt asking, "What did the AI miss or capture well?" This question was designed to gather detailed feedback regarding the system's strengths, weaknesses, and overall user experience.

Quantitative data were analyzed using descriptive statistics and frequency distributions. Responses were

grouped into disagreement (1–3), neutral (4), and agreement (5–7) categories. Cross-tabulations were also conducted to examine whether interview difficulty levels (easy, medium, hard) influenced perceptions of trust and satisfaction. Qualitative responses were analyzed using inductive thematic coding. Initial open coding was followed by focused coding to identify recurring themes. Findings from both datasets were compared to identify areas of convergence and divergence, consistent with mixed methods integration procedures. Four themes emerged: camera-screen offset issues, computer vision limitations related to lighting and framing, concerns regarding filler-word penalization, and feelings of human disconnection from automated evaluation.

The pilot dataset consisted of 34 interview sessions from 15 unique users, limiting statistical power and generalizability. Additionally, participants completed the surveys as part of a course requirement, introducing the possibility of response bias. Researcher positionality is also acknowledged, as the authors were directly involved in the development and implementation of the platform. Despite these limitations, the findings provided actionable insights for improving system performance and user experience.

Results and Findings

The analysis covers 34 interview practice sessions generated by 15 unique users, distributed across three difficulty tiers: Easy ($n = 14$; 41.2%), Medium ($n = 12$; 35.3%), and Hard ($n = 8$; 23.5%). Quantitative Likert-scale data and qualitative open-ended responses are examined jointly to address RQ1, with qualitative themes informing the recalibration discussion addressing RQ2.

Quantitative Distribution of Student Sentiment

Table 1 presents the aggregate distribution of student responses across five evaluation dimensions. The overall pattern shows a pronounced skew toward disagreement, particularly on accuracy, trustworthiness, and transparency.

For the primary alignment metric (Q1), approximately 67.6% of responses (23 of 34) fell into disagreement categories. Disaggregated by difficulty (Table 2), this pattern was most pronounced in Medium sessions (75.0%, mean = 2.25), compared to Easy (64.3%, mean = 3.21) and Hard sessions (62.5%, mean = 2.75), suggesting that mid-range task demands may produce the sharpest mismatch between algorithmic and self-reported performance, a pattern further examined below.

Trust in the platform's predictive validity (Q2) followed a similar trajectory: 58.8% of respondents expressed distrust overall, with Medium sessions again producing the highest rate (75.0%, mean = 2.58) compared to Easy (42.9%, mean = 3.50) and Hard (62.5%, mean = 2.62). These patterns are consistent with research documenting fragile trust in automated interview systems (Langer et al., 2019). Score transparency

Table 1:*Distribution of Responses Across Core Evaluation Metrics*

Assessment Metric	SD	D	SwD	Neutral	SwA	A	SA
Q1: AI score accuracy	12	6	5	5	2	3	1
Q2: Future trust in AI	13	2	5	6	4	3	1
Q3: Skill improvement utility	8	3	2	6	9	5	1
Q4: Score transparency	11	3	6	6	4	3	1
Q5: Willingness to re-engage	8	1	0	12	5	4	1

Note. SD = Strongly Disagree; D = Disagree; SwD = Somewhat Disagree; N = Neutral; SwA = Somewhat Agree; A = Agree; SA = Strongly Agree. Disagree = ratings 1–3; Neutral = rating 4; Agree = ratings 5–7; n=33 (one missing response).

(Q4) showed the most acute dissatisfaction in Medium sessions (66.7% disagreeing, mean = 2.83), reflecting the “black box” problem in AI identified in AI-driven recruitment (Chen, 2023).

The Medium Difficulty Paradox

A theoretically notable pattern is the consistently highest rejection of AI scoring in Medium, rather than Hard, sessions across nearly all metrics. CLT offers a partial explanation: Under Hard conditions, candidates may attribute degraded nonverbal performance to question difficulty, providing a cognitive account for the AI’s negative scores that softens rejection. Medium difficulty questions, by contrast, impose sufficient cognitive demand to degrade nonverbal performance but not enough for candidates to attribute that degradation to task complexity. The result is a failure mode in which neither the candidate nor the algorithm can account for the misalignment, producing frustration and minimum trust. This interpretation should be treated as tentative given the small sample, but it warrants further investigation in larger-scale studies.

Algorithmic Output Versus Human Self-Efficacy

A recurring pattern in the data is incongruence between the AI’s behavioral scores and candidates’ self-reported confidence. One student who reported feeling “Very confident” across three sessions received AI scores of “Low,” “Needs Improvement,” and “Major Improvements Needed.” A similar pattern appeared with another student who reported high confidence but received consistently low AI ratings, ultimately dismissing the tool. Overconfident User Gap, defined as sessions where users reported high confidence while receiving low AI scores was most prevalent in “Medium” sessions (41.75%), compared to Easy (28.6%) and Hard (25.0%), further supporting the “Medium” difficulty interpretation.

This dynamic is theoretically consistent with Bandura’s (2001) social cognitive theory: when evaluative feedback contradicts a learner’s existing sense of competence without adequate explanation, it risks eroding self-efficacy and reducing motivation to engage. Conversely, alignment between algorithmic and human assessment occurred most frequently when candidates reported low confidence, raising the possibility that

Table 2:*Distribution of Responses by Question Difficulty Level (Easy, Medium, Hard)*

Assessment Metric	Easy (n=14)			M	Medium (n=12)			M	Hard (n=8)			M
	D%	N%	A%		D%	N%	A%		D%	N%	A%	
Q1: AI score accuracy	64%	14%	21%	3.21	75%	17%	8%	2.25	63%	13%	25%	2.75
Q2: Future trust in AI	43%	29%	29%	3.50	75%	8%	17%	2.58	63%	13%	25%	2.62
Q3: Skill improvement utility	21%	21%	57%	4.43	58%	17%	25%	3.00	50%	13%	38%	3.12
Q4: Score transparency	29%	21%	50%	4.21	67%	17%	17%	2.83	63%	13%	25%	2.88
Q5: Willingness to re-engage	15%	46%	38%	4.23	50%	17%	33%	3.08	38%	38%	25%	3.25

Note. D% = percentage disagreeing (ratings 1–3); N% = neutral (rating 4); A% = agreeing (ratings 5–7); M = mean on 7-point scale. Bold values indicate the highest disagreement and agreement rates within each row. Q5 Easy: n = 13 (one missing response).

apparent satisfaction with AI output may in some cases reflect confirmation rather than objective algorithmic accuracy. This observation warrants caution given the pilot's scope.

Deconstruction of Algorithmic Sensing Failures

Optical Constraints. Participants consistently reported that despite looking directly at their camera, the system scored them as lacking eye contact. This failure reflects the camera-screen offset problem: when candidates look at the screen to read prompts, the camera captures their gaze as pointing downward. The AI's geometric gaze-tracking penalizes natural screen-reading as disengagement (Bailenson, 2021).

Computer Vision Vulnerabilities. Participants reported that the AI missed hand gestures and incorrectly penalized posture. One student hypothesized that dark clothing against a poorly illuminated background made it difficult for the system to track her body, consistent with documented optical tracking vulnerabilities (Ajunwa, 2023). Spatial constraints of a standard webcam's field of view also inhibit natural gesture expression, as candidates must sit close to screens to ensure facial capture, truncating arms from the frame.

Linguistic Constraints. Several participants described bewilderment at the penalization of filler words. Decades of psycholinguistic research indicate that "um" "uh" and "like" are functional communicative devices, signals of cognitive processing, turn-taking management, and upcoming syntactic complexity, not defects in professional communication (Fox Tree, 2003, 2007). Similarly, users expressed confusion at vocal tone feedback, noting disconnects between their perceived projection and the algorithm's acoustic assessment. The algorithm analyzes raw acoustic metrics but lacks the semantic comprehension to differentiate expressive delivery from erratic speech.

Human Alienation. Beyond technical issues, the data reveal emotional resistance to the automated format. One student observed that the algorithm fail to account for her being an actual person with real feelings, noting that recording oneself differs fundamentally from speaking to a human face to face. This reflects the relational deficit inherent in automated video assessments: the traditional interview is bidirectional social interaction providing micro-affirmations (nods, smiles) that allow candidates to self-regulate. Automated platforms strip away this dynamic, consistent with organizational justice research linking perceived process dignity to evaluation fairness (Suen & Hung, 2023; Jaser et al., 2022).

Discussion

The qualitative data reveal a consistent pattern of false negative assessments in which rigid tracking parameters penalized natural human behavior or environmental limitations. Discrepancies were primarily identified in eye stability, gestures and framing, and vocal delivery. The recalibration process addressed

three issues in response to RQ2.

First, the eye contact algorithm was recalibrated to accept a downward pitch up to 20 degrees, mapping this coordinate range as Maintained Eye Contact to eliminate punitive scoring for natural reading behavior. Second, a Dynamic Exclusion protocol was implemented so that when a dimension such as Hand Visibility fails to meet the minimum tracking confidence threshold, the data point is marked as NULL and excluded from the final average, ensuring evaluation only on behaviors the system can confidently observe. Third, a weighted vocal override heuristic was added so that when a student demonstrates high volume stability alongside an optimal speech rate, the filler word penalty is actively deprioritized, appropriately weighting fluency, pacing, and vocal tone as primary confidence indicators.

These recalibrations represent a first step toward aligning algorithmic design with human communicative experience. Larger-scale validation will be necessary to assess whether these adjustments produce meaningful improvements in alignment across diverse user populations.

Conclusion

This pilot exposes critical friction points between AI-generated interview assessment and human communicative experience. While automated platforms offer scalability and immediacy for career readiness development, the data suggest meaningful gaps between algorithmic scoring and student self-perception, particularly regarding eye contact tracking, gesture recognition, filler word penalization, and the relational dimensions of performance. These findings are exploratory and context-specific, but they point toward a broader challenge: AI systems that evaluate communication confidence must account for the environmental, cognitive, and relational variability inherent in human interaction.

Rebuilding trust in automated interview platforms requires intentional redesign centered on accessibility, transparency, and respect for human variability. Systems should allow dynamic calibration of environmental conditions before scoring: implement Explainable AI (XAI) principles with time stamped, behavior-specific feedback; and train models on diverse datasets that reflect cultural and neurodiverse communication styles (Chen, 2023; Ajunwa, 2023). The recalibrations reported here offer one model for iterative, evidence-based platform refinement.

Implications

The technical limitations and user frustrations documented here carry practical implications when these tools are deployed at scale. The algorithm's inability to account for variables such as dark clothing, eyewear, or physical room constraints means that evaluations may reflect environmental and hardware conditions rather than professional competencies. This introduces a socioeconomic bias into the confidence assessment, as candidates with lower-quality equipment

or less-controlled recording environments may be systematically disadvantaged (Springle & Bourdage, 2023).

Strict penalization of filler, non-standard gaze, and postural variation also inherently disadvantages marginalized groups. The EEOC has increasingly scrutinized AI tools, warning that speech patterns and facial expressions can unlawfully screen out individuals with disabilities, speech impediments, or non-native accents (Ajunwa, 2023). As candidates become aware of these heuristics, there is a risk that they abandon authentic communication in favor of algorithmic appeasement, homogenizing behavior in ways that ultimately undermine the predictive validity of the interview itself. The deployment of opaque behavioral-scoring systems thus risks reducing human communicative potential to discrete, decontextualized data points.

References

- Ajunwa, I. (2023). Automated video interviewing as the new phrenology. *Berkeley Technology Law Journal*, 36(3), 1173–1226.
- Argyle, M. (2013). *Bodily communication* (2nd ed.). Routledge.
- Bailenson, J. N. (2021). Nonverbal overload: A theoretical argument for the causes of Zoom fatigue. *Technology, Mind, and Behavior*, 2(1), 1–6. <https://doi.org/10.1037/tmb0000030>
- Bandura, A. (1997). Self-efficacy: The exercise of control. W. H. Freeman.
- Bandura, A. (2001). Social cognitive theory: An agentic perspective. *Annual Review of Psychology*, 52(1), 1–26.
- Barker, A. (2025). How to improve your communication skills: How to build trust, be heard, and communicate with confidence. Kogan Page.
- Campion, M. C., Campion, M. A., Campion, E. D., & Reider, M. H. (2016). Initial investigation into computer scoring of candidate essays for personnel selection. *Journal of Applied Psychology*, 101(7), 958–975.
- Chan, M. (2000). Organizational justice theories and landmark cases. *The International Journal of Organizational Analysis*, 8(1), 68–88.
- Chen, Z. (2023). Ethics and discrimination in artificial intelligence-enabled recruitment practices. *Humanities and Social Sciences Communications*, 10, 567. <https://doi.org/10.1057/s41599-023-02079-x>
- Creswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). SAGE.
- Creswell, J. W., & Plano Clark, V. L. (2018). *Designing and conducting mixed methods research* (3rd ed.). SAGE.
- Dey, F., & Cruzvergara, C. (2014). Evolution of career services in higher education. *New Directions for Student Services*, 148, 5–18.
- Fauville, G., Luo, M., Queiroz, A. C. M., Bailenson, J. N., & Hancock, J. (2021). Nonverbal mechanisms predict Zoom fatigue and explain why women experience higher levels than men. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.3820035>
- Fox Tree, J. E. (2003). Disfluencies in spoken language. In L. Nadel (Ed.), *Encyclopedia of cognitive science* (Vol. 1, pp. 983–986). Nature Publishing Group.
- Fox Tree, J. E. (2007). Functional spontaneous speech phenomena. *Perspectives on Fluency and Fluency Disorders*, 17(2), 17–19.
- Gifford, R., Ng, C. F., & Wilkinson, M. (1985). Nonverbal cues in the employment interview: Links between applicant qualities and interviewer judgments. *Journal of Applied Psychology*, 70(4), 729–736. <https://doi.org/10.1037/0021-9010.70.4.729>
- Hansen, K., Oliphant, G. C., Oliphant, B. J., & Hansen, R. S. (2009). Best practices in preparing students for mock interviews. *Business Communication Quarterly*, 72(3), 318–327.
- Hudak, K., Kile, A., Grodziak, E., & Keptner, E. (2019). Advancing student interview skills: Incorporating virtual interview technology into the basic communication course. *International Journal for the Scholarship of Teaching and Learning*, 13(1), Article 3. <https://doi.org/10.20429/ijstl.2019.130103>
- Jackson, D., & Wilton, N. (2017). Perceived employability among undergraduates and the importance of career self-management, work experience, and individual characteristics. *Higher Education Research & Development*, 36(4), 747–762.
- Jaser, Z., Petrakaki, D., Starr, R., & Oyarbide-Magaña, E. (2022, January 26). Where automated job interviews fall short. *Harvard Business Review*. <https://hbr.org/2022/01/where-automated-job-interviews-fall-short>
- Langer, M., König, C. J., & Krause, K. (2017). Examining digital interviews for personnel selection: Applicant reactions and interviewer ratings. *International Journal of Selection and Assessment*, 25(4), 371–382. <https://doi.org/10.1111/ijsa.12191>
- Langer, M., König, C. J., & Papathanasiou, M. (2019). Highly automated job interviews: Acceptance under the influence of stakes. *International Journal of Selection and Assessment*, 27(3), 217–234. <https://doi.org/10.1111/ijsa.12246>

- Lingg, M. (1996). Training for job-skill confidence. *Journal of Career Development*, 22, 261–271. <https://doi.org/10.1177/089484539602200404>
- Martín-Raugh, M. P., Kell, H. J., Randall, J. G., Anguiano-Carrasco, C., & Banfi, C. (2023). Speaking without words: A meta-analysis of over 70 years of research on the power of nonverbal cues in job interviews. *Journal of Organizational Behavior*, 44(1), 132–156. <https://doi.org/10.1002/job.2670>
- Okay-Somerville, B., & Scholarios, D. (2017). Position, possession or process? Understanding objective and subjective employability during university-to-work transitions. *Studies in Higher Education*, 42(7), 1275–1291.
- Quinlan, K. M., & Renner, P. (2005). Mock job interviews: Improving the self-efficacy and interview performance of college students. *Journal of Career Development*, 32(1), 75–88.
- Rowell, A., & Mihuta, T. (2016). Technology and career preparation: Using virtual interview recordings (VIRs) in an apparel, design, and textiles (ADT) professional seminar course. *Journal of Family and Consumer Sciences*, 108(2), 27–32.
- Springle, A., & Bourdage, J. (2023). Home environment and performance in asynchronous video interviews: Possible sources of adverse impact and candidate reactions. *International Journal of Selection and Assessment*.
- Suen, H. Y., & Hung, K. E. (2023). Building trust in automatic video interviews using various AI interfaces: Tangibility, immediacy, and transparency. *Computers in Human Behavior*, 143, 107713. <https://doi.org/10.1016/j.chb.2022.107713>
- Suen, H. Y., & Hung, K. E. (2025). Comparing job applicant deception in asynchronous vs. synchronous video interviews, with and without AI-assisted assessments. *Information Technology & People*, 38(2), 963–983.
- Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science*, 12(2), 257–285. [https://doi.org/10.1016/0364-0213\(88\)90023-7](https://doi.org/10.1016/0364-0213(88)90023-7)
- Sweller, J., van Merriënboer, J. J. G., & Paas, F. G. W. C. (1998). Cognitive architecture and instructional design. *Educational Psychology Review*, 10(3), 251–296. <https://doi.org/10.1023/A:1022193728205>
- Tompsett, H., Henderson, K., Byrne, J. M., Gaskell Mew, E., & Tompsett, C. (2017). On the learning journey: What helps and hinders the development of social work students' core pre-placement skills? *Social Work Education*, 36(1), 6–25.
- Tross, S. A., & Maurer, T. J. (2008). The effect of coaching on interview performance: Practice makes perfect? *Journal of Vocational Behavior*, 73(3), 398–405.
- Xu, Y., Chen, Z., & Dong, M. (2025). Shaping the fairness journey: The roles of AI literacy, explanation, and interpersonal interaction in AI interviews. *International Journal of Human-Computer Studies*, 205, Article 103629. <https://doi.org/10.1016/j.ijhcs.2025.103629>