Opening the "Black Box" of VR for Workforce Development: Investigating Learners' Device, Usage, and Identities

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Abstract. Virtual reality (VR) technologies are increasingly used in workforce development and training, and studies show they can be effective tools to increase learning of procedural skills, content knowledge, and affective outcomes like confidence. Most studies of VR in education and training, however, have focused on the hardware by comparing learning with VR to other devices in controlled lab experiments. This "black box" approach does not attend to variation beyond the device, such as how learners use an application and the influence of their identity and context on their learning with VR. This study addressed the need for more research on learning with VR in authentic workforce development contexts to better understand how diverse participants use these programs and to what extent their individual characteristics impact their experience. Using data from 1,154 users of a VR-enabled job interview training for individuals affected by the criminal justice system, we assessed variation in how participants used the program and their reported changes in confidence, and estimated associations with device, usage, and learners' characteristics. We find learners' experience and context is a stronger predictor of increased confidence level than device or usage activities, particularly whether participants are currently or formerly incarcerated. Further, we demonstrate how cluster analysis on log-file data can distinguish learners' use patterns, a promising method for personalizing feedback and training.

Keywords: Workforce Development, Virtual Reality, Affective Learning Outcomes, Justice-Involved Individuals.

1 Introduction

Virtual reality (VR) technologies are increasingly used in workforce development and training, promising to make programs more efficient and effective by giving people "hands-on" practice in low-stakes environments [1]. Research on the effectiveness of learning with VR has primarily focused on comparing learners' change in content knowledge retention or procedural skills with a VR headset compared to a different device [2]. While such studies ask whether VR is an effective tool, the focus on hardware leads to a "black box" approach that does not attend to questions of how people learn in these immersive environments, or the importance of what they do while using them on their learning. Further, research has been primarily conducted in controlled experiments with small samples [3] and has not typically included some of the most vulnerable populations that workforce development programs aim to serve. Research on VR highlights the importance of people's identities and prior experiences in how they will experience such immersive environments [4], but work on how race, gender, and experience affect learning with VR in authentic workforce development contexts remains nascent. This exploratory study used data from a workforce development VR application to ask how participants varied in their use and self-reported outcomes, whether their use and ratings varied based on device or their individual characteristics and identities, and what their variation in activity within the simulation reveals about different patterns of usage. The findings shed light on the importance of how learners use VR, their characteristics, and their contexts to open the "black box" of learning with VR beyond the device. The study also demonstrates the need for more research on VR in authentic workforce development contexts that account for the scale and diversity of learners these technology-enabled programs aim to reach.

2 Related Work and Research Questions

Workforce development and corporate training programs are increasingly looking at the affordances of VR to improve instruction and learning outcomes [1]. Reviews of VR in education and training find it is more effective than other media at increasing participants' procedural and spatial skills, but is mixed in increasing other learning outcomes like knowledge acquisition [2],[5]—[7]. Because it engages participants in practice that feels real, studies also find that VR enhances affective dimensions of learning, including increasing learners' motivation and confidence [2],[5]. This affordance may be particularly beneficial for vulnerable jobseekers, including for incarcerated individuals, as simulated interviews provide practice that increase their skills and beliefs [8].

Much research on VR in education and workforce development has been "hardware focused," comparing the technology to other devices, but there is a need to understand not only if VR should be used, but how and for what [9], echoing calls to understand for whom and under what conditions educational technology is effective beyond whether the technology "works" [10]. Recent work on learning in immersive environments has suggested the way the experiences are designed and facilitated influences how learners use them and what they learn from them—for example interactivity, reflection, and activities outside of VR [11]—[13]. There is also increasing understanding of individual variation and the ways people's identities affect their experience in immersive environments [4].

This study addressed the need to open the "black box" of learning with VR by looking beyond a comparison of devices in a laboratory experiment to understand how people use an immersive application in an authentic workforce development program, and how their use and outcomes vary based on their experience with the justice system and identities. We asked how participants in a VR-enabled training program used the application in terms of completing different activities, their reported confidence changes, and in their patterns of responses. We also asked whether those variations were associated with the device, their program use, and their experiences and identities.

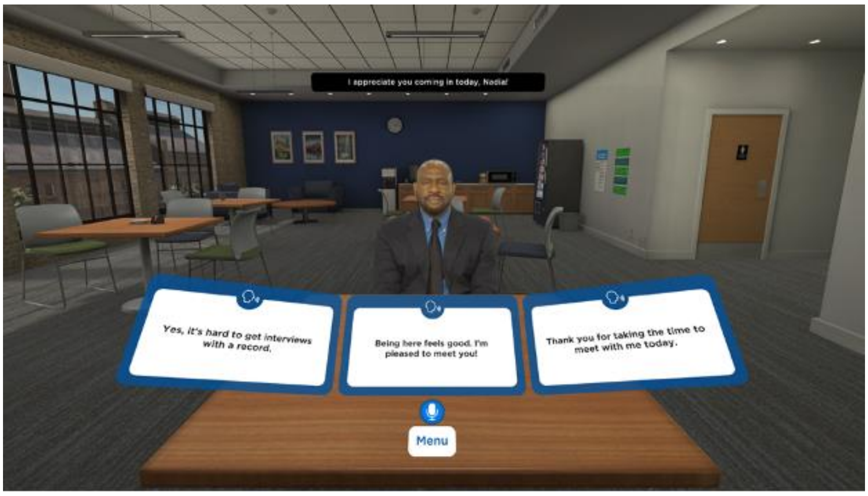

Fig. 1. Project OVERCOME screenshot

3 Methods

This study employs secondary data analysis using data collected in 2022 during the pilot implementation of Project OVERCOME, a VR application from Accenture designed to allow jobseekers who have been impacted by the criminal justice system (i.e., justice-involved individuals or JII) to practice interview skills. The program was piloted by 11 Goodwill Industry International sites as part of their reentry training programs that support JII gain employment to reenter society. A limited number of non-JII were also allowed to participate in the program during the pilot phase. The program has two main components: 1) Journeys, in which users hear stories from other JII who navigated the job search and 2) Interview simulation, in which participants participate in a mock interview with a hiring manager. In the simulation the user role plays as Nadia, who was formerly incarcerated and is interviewing for a position at an industrial laundry facility. It follows a branched narrative model, in which each response a participant selects determines the subsequent question from the interviewer: there are hundreds of potential pathways through the interview. Participants select an answer by reading it out loud. The narrative of the interview, including the questions asked and answer options provided were developed by interviewing justice-involved individuals about their job-seeking experience, including the types of jobs they interviewed for and where they struggled in the interviews. Additionally, they worked with Goodwill's employer partners who frequently hire JII through reentry programs on the types of questions they ask in interviews and what good performance looks like in this context.

Based on how they answer the interview questions, the hiring manager may ask them if they want to talk about their past and give them an opportunity to practice what is called the “elevator speech,” a brief description of their past justice involvement and how they are moving on. The interviewer does not know about Nadia’s prior justice involvement.

See Fig. 1 for a depiction of the interview simulation. The VR program aims to support JII to increase their confidence in interviewing and discussing their past, a challenge these jobseekers face in gaining employment [14]. All sites offered the program on a Quest 2 VR headset or on a PC. Typically, sites used the VR headset and offered the PC version to participants uncomfortable using VR. Each participant was instructed how to use the program by a facilitator, who met with them one-on-one to set up the program and debrief with them after.

3.1 Data

Data was collected by program implementers, not the research team, while participants used the application and via a post-survey. In-application data included: device used (Quest VR headset or a PC), whether the participant used the journeys, interview simulation, and if they engaged in the elevator speech, as well as whether the participant is JII, participating in a reentry program, had used VR before, and had used Project OVERCOME before. Additionally, participants who engaged in an interview simulation had each response recorded in log-file data. The post-survey asked their gender and racial/ethnic identity, type of justice-involvement (currently or formerly incarcerated or diversion), age, and whether they felt more, equally, or less confident about interviewing after using Project OVERCOME.

3.2 Participants

1,154 participants used the application, 537 completed the post-survey. Therefore, questions about application use could be assessed using all 1,154 participants, while questions about participant demographics and their reported confidence levels could only be assessed on the 537 participants who completed the post-survey with those items. Some participants were given an anonymous ID to link the data collected while they used the application to their post-survey data. There were 303 such participants, which we termed the linked dataset connecting the two sources of data.

Of the total participants, 75% of all participants were JII, 81% were reentry program participants, 21% had used VR before. Of the participants who completed the post-survey, 42% were currently incarcerated, 38% were formerly incarcerated, 11% diversion, and 9% none. 66% identified as female, 41% as Black or African American, 47% as White, 7% Hispanic or Latino, and 5% other. The mean age was 37.9. No personally identifying information was collected. This study was approved by the Harvard University Institutional Review Board.

3.3 Analysis

We used regression analyses to estimate the associations between device and individual characteristics with program use (interview simulation completion, elevator speech use, and journeys use), and participants' confidence ratings. Logistic regression was used for binary program component usage variables and ordinal logistic regression for confidence ratings. For example, (1) illustrates the model for predicting interview completion for participant i:

$$logit(Interview_i = 1) = \beta_0 + \beta_1 Device_i + \beta_2 ProgramParticipant_i + \beta_3 JusticeInvolved_i + \beta_4 UsedVR_i + \beta_5 MultipleUse_i + \epsilon_i \quad (1)$$

This model was repeated to predict likelihood of engaging in the elevator speech (for those who used the interview simulation) and journeys. An ordinal logistic regression model predicted likelihood of reporting feeling more confident controlling for racial/ethnic identity, gender identity, type of justice involvement, age, and for those whose data could be linked, device and usage of the application. We report the results of the analyses in odds ratios in tables 1 and 2, but also report predicted probabilities of significant predictors for ease of interpretation. These predicted probabilities hold control variables at the mean, unless otherwise noted.

Additionally, we used cluster analysis of the log-file data to identify patterns in the way participants answered the questions in the interview simulation. We used k-modes clustering, a machine learning method that assesses the similarity of observations based on their responses to categorical variables. It is an extension of the k-means algorithm, but rather than using the centroids of mean values, it assesses mismatches between categorical responses to determine the distance between observations [15], as illustrated in (2):

$$d_1(X,Y) = \sum_{j=1}^{m} \delta(x_j, y_j) \quad \text{where:} \quad \delta(x_j, y_j) = \begin{cases} 0 \ (x_j = y_j) \\ 1 \ (x_j \neq y_j) \end{cases} \quad (2)$$

Where X and Y are two categorical objects defined by m categorical attributes. The smaller the number of mismatches, the more similar the two objects are. In our dataset, the objects are participants using the interview simulation, and the categorical attributes are the questions to which they responded in order of their response.

We identified prototypical participants by looking at descriptors of the data including which questions led to which other questions, how many questions participants answered, and where were common points to reach the elevator speech or the conclusion. We identified seven prototypical users and used these as the modes in the k-modes clustering algorithm, reducing the number of clusters until they had balanced numbers and were interpretable as distinct use patterns. These seven prototypical users were identified by looking at the most and least commonly answered questions in the interview simulation, whether they engaged in the elevator speech, and how many questions varied participants tended to answer. Our focus was on identifying important characteristics we hypothesized would change a user's pattern of usage including whether they had completed the simulation multiple times. In this sense, we identified users as what we called common trajectories that we could see across all the 1,154 participants and that we could identify as qualitatively important differences in how participants answered the questions.

4 Results

4.1 Regression Analyses

Of the total 1,154 participants, 67% (*N*=770) used the application on a VR headset. Fig. 2 shows how participants varied in their use of the VR application, as nearly two-thirds completed an interview simulation (*N*=749), but only 25% reached the elevator speech practice portion (*N*=294) and just 10% used the journeys (*N*=119).

Of the 537 participants who completed the post-survey, 50% (*N*=273) said they felt more confident in their interview skills after using the simulation, 48% (*N*=264) felt equally confident, and 2% (*N*=10) felt less confident.

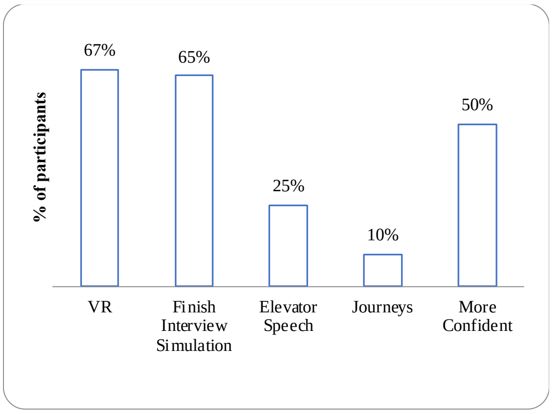

Fig. 2. Participant use of the program and reported confidence

Logistic regression analysis revealed that the device was predictive of participants' completion of the interview simulation and engaging in the elevator speech practice, but not in a consistent way: VR users were more likely to complete an interview but less likely to engage in the elevator speech. However, being a participant in a reentry services program was a stronger predictor of completing an interview simulation. Fig. 3 visualizes the predicted probability for participants to complete the interview simulation based on the device they use and whether they are a reentry program participant. For example, the likelihood a reentry program participant using VR will complete the interview simulation is 82% compared to 26% for a non-reentry program participant using a PC.

Table 1. Predictors of program component use, odds ratio

	Dependent variable		
	Interview completion	Elevator speech	Used journeys
Device: PC	0.26***	1.52*	1.25
Reentry program participant	3.22***	0.83	0.56*
Justice-Involved	1.43	1.21	0.68
Used VR	1.14	1.29	1.61*
Multiple Uses of Application	0.52**	0.60	0.70
Intercept	*0.96*	*0.51**	*0.20****
N	1151	747	1151
R^2 Tjur	0.20	0.01	0.02

**p<.05 **p<.01 ***p<.001*

Note: Odds ratios greater than 1 indicate greater likelihood for participants in that category, less than 1 indicates a lesser likelihood.

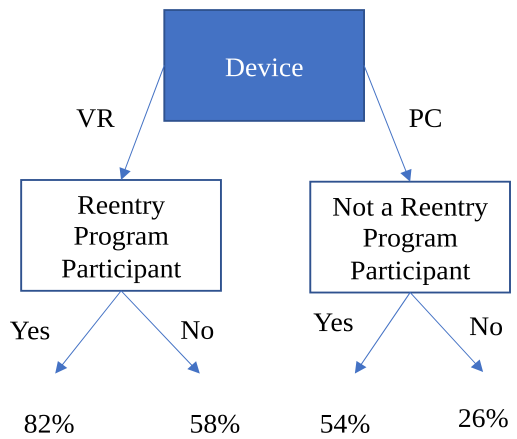

Fig. 3. Predicted probabilities of completing the interview simulation

Using data from the participants who completed the post-survey, logistic regression results indicate that participants' type of justice involvement and racial/ethnic identity are both associated with their confidence ratings. Gender is not a significant predictor.

Participants who were currently incarcerated were less likely to report feeling more confident after using the VR simulation than those who were formerly incarcerated or diversion. The predicted probabilities illustrated in Fig. 4 show substantive importance of these associations, highlighting how a currently incarcerated individual would be 28-46% likely to feel more confident, while a formerly incarcerated individual would be 48-67% likely. Further, the graph illustrates that those who identify as Black or African

American are predicted to report feeling more confident than White and Hispanic or Latino participants across all justice-involvement groups.

Table 2. Predictors of reporting more confident, odds ratios (post-survey data)

Justice involvement (Reference: Currently incarcerated)	
Formerly incarcerated	2.42***
Diversion	4.35***
None	2.19*
Racial/ethnic identity (Reference: Black or African American)	
White	0.57**
Hispanic or Latino	0.46*
Other	0.77
Age	0.99
Gender: Male	0.85
Intercept - less | equally	*0.01****
Intercept - equally | more	*0.96*
N	537
R^2Tjur	0.15

**p<.05 **p<.01 ***p<.001*

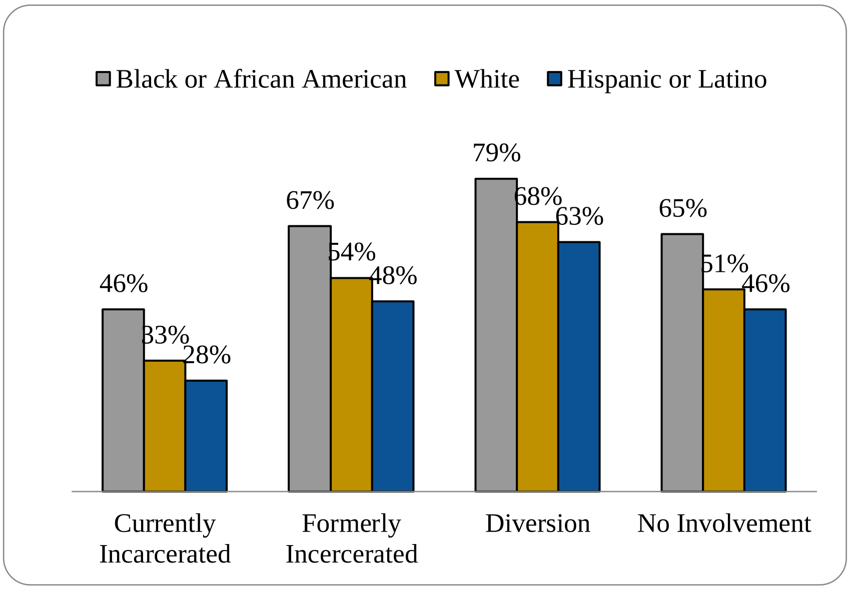

Fig. 4. Predicted probabilities of reporting feeling more confident (post-survey data)

Using the data that could be linked between participants' program use and their survey responses, Table 3 shows how the device used, racial/ethnic identity, and gender are not predictive in reporting feeling more confident, but justice involvement type has a significant association. This model also controls for participants' usage of the application in terms of engaging in the elevator speech and journeys but does not find a significant association between these activities and participants reporting feeling more confident. The association between justice involvement type and reporting feeling more confident is substantial. For a woman of average age who identifies as Black or African American, we would predict she is 82% likely to report feeling more confident after using the program if she is formerly incarcerated, and only 33% likely if she is currently incarcerated.

Table 3. Predictors of reporting more confident, odds ratios (linked dataset)

Device: PC	0.71
Justice involvement (Reference: Currently incarcerated)	
Formerly incarcerated	9.47***
Diversion/none	9.79***
Gender: Male	0.83
Racial/ethnic identity (Reference: Black or African American)	
White	0.94
Hispanic or Latino	0.64
Other	1.03
Age	1
Used VR	1.13
Journey	0.51
Elevator	1.68
Intercept - less | equally	*0.03****
Intercept - equally | more	*2.93*
N	303
R^2Tjur	0.291

4.2 Cluster Analysis

While the regression analyses describe the ways participants varied in their activities within the simulation and those associations with their confidence ratings, the cluster analysis provided another way to explore variation in participants' activity in the branched narrative interview simulation. Based on prototypical responses to the interview questions in each cluster, we characterize the four clusters in Table 4. These clusters revealed there were patterns in how participants answered the interview questions not only in terms of the number they answered, but how likely they were to be asked a question that leads them into the elevator speech, and additionally if they answered in a way that allowed them to practice that speech.

This method illustrates how log file data can be valuable in understanding the differences between users in VR programs. Participants in clusters 1, 2, and 3 were all likely to complete the interview simulation, but those in clusters 1 and 2 were more likely to be asked questions that would provide an opportunity for the elevator speech. Users in cluster 1 were more likely to respond in a way that allowed them to actually practice the elevator speech, whereas those in cluster 2 were more likely to say they did not want to get into the details. Users in cluster 4 represent those who were in many ways least successful in using the program, meaning they either did not finish the interview or did not answer in an optimal way. This cluster may account for noise in the data, including users who were testing the program but not using it as a participant, as fewer of these users identified as JII.

The distinctions between cluster 1, 2, and 3 may provide a different way of identifying participants who need practice on different skills. For example, users in clusters 1 and 2 may need coaching on responding to questions about their past in ways that indicate they are open to discussing their history and how they want to move on. Users in cluster 3 may need training on the other interview questions to ensure the interviewer stays interested and allows them more opportunities to discuss their past. This can be a valuable way of connecting the way participants use a branched narrative program to ways they can improve that go beyond just whether they completed the simulation.

Table 4. Cluster results

Cluster number & description		Pattern of usage	Int	Qs	Elev	*N*	VR	JII
1	Most likely to practice the elevator speech	Highly likely to complete the simulation, and most likely to engage in the elevator speech. Answered questions in a way that prompted the interviewer to ask if they want to talk about their mistakes: prototypical user answered "it is time to be open and honest."	95%	10.3	47%	390	75%	84%
2	Most likely to miss an opportunity to practice the elevator speech	Highly likely to complete the simulation, and answered similar questions to cluster 1, and prompted interviewer to ask if they want to open up about their mistakes: prototypical user answered "I don't want to get into the details right now."	97%	10.8	17%	141	77%	85%
3	Likely to complete the interview in a short time	Highly likely to complete the program, but in fewer questions than clusters 1 and 2. The prototypical user did not answer questions in a way that prompted the interviewer to ask about their past mistakes.	95%	8.7	21%	149	84%	79%
4	Least likely to complete the program	Less likely to complete the simulation. Many of the users in this cluster either stopped using the program without finishing or answered the first few questions in a way that prompted the interviewer to cut it short.	46%	4	22%	246	53%	59%

Column labels: Int = Interview completed, Qs = Mean interview questions answered, Elev = Elevator speech, N = Number of participants, VR = Device used was VR, JII = Justice-involved individuals.

5 Discussion

Our findings reveal important considerations for learning with VR beyond the device and begin to open the "black box" by looking at learners' identities and how they use immersive applications. Regression analysis showed how the device can be a factor in participants' use of the program, for example predicting whether they completed an interview simulation, but that the device is relatively less predictive than other characteristics of the participants. Being in a reentry program was more predictive of completing the interview simulation, indicating that a user's purpose and context is important, as these participants are more likely committed to training that will help them in their job search.

Further, participants' identities and experience were more predictive of whether they reported feeling more confident in their interview skills after using the application than the device or usage characteristics. In terms of identity, in some analyses participants' racial/ethnic identity predicted reporting feeling more confident: those who identified as black or African American were more likely than other groups to report feeling more confident. This may be due to the race of the interviewer in the simulation, or because those participants had lower levels of confidence to begin with. As this is a correlational study, we cannot identify the reason for this association. Interestingly, however, gender was not a predictor of confidence in the regression analysis, even though the participant was in the shoes of Nadia, a woman.

Across the varied models and subsets of data we found that participants who were currently incarcerated were less likely than other participants to report feeling more confident. This association was strong even after controlling for the device used, which aspects of the program they used, and other characteristics like racial, ethnic, and gender identity. The association between reported confidence and justice involvement type raises questions about targeting the use of VR in workforce development for specific populations or contexts. On one hand, there may have been systematic differences in how currently incarcerated participants used the application or the way it was facilitated that made VR less impactful on their reported feelings of confidence. Alternatively, the variation may be due to the simulation's scenario in which participants role play as Nadia, a formerly incarcerated individual, whose story may be less relatable or less relevant for currently incarcerated people. Our analysis suggests that these issues go beyond which aspects of the program or device the participants used and raises important questions about the target population and context in which VR-enabled workforce development programs are implemented.

We also find that using a cluster analysis on participants' log file data reveals patterns of usage based on the way different participants navigated the program. This data-driven method is a promising way of distinguishing user profiles that may identify the types of training the participants need. For example, users in clusters 1 and 2 may need support in how to answer questions from an interviewer about their past mistakes in a way that allows them to construct an elevator speech about their past, while users in cluster 3 may need feedback on how to answer the interview questions to keep the interviewer interested and have them ask about their past. Such profiles reveal subtle differences in usage of the program beyond whether they completed an interview or engaged in specific parts of the program and may be useful in workforce development programs to help identify targeted interventions for learners. Such interventions like receiving feedback and additional practice opportunities could be integrated into a VR program itself or could be part of the larger training program tailored to the needs of the individual based on their pattern of activity in the simulation.

This study also highlights the need for more research to be conducted on VR-enabled programs in authentic workforce development contexts, rather than only in controlled lab experiments. While our findings are correlational due to using secondary data analysis on data collected during a pilot rather than in an experiment, the sample we worked with is larger, more diverse, and represents actual participants workforce development programs aim to support. In this sense the noisiness of the data represents the complexity of implementing VR in workforce development programs that we would expect to see in other contexts. Our results highlight the importance of participants' experience, racial and ethnic identity, and varied usage of the program that may not have surfaced in a smaller and more controlled study. Future research should continue to investigate issues of participants' identities, purpose, context, and experience along with their within-VR activity in both controlled and authentic environments. Such studies will provide the field of workforce development a better understanding of the potential and limitations for immersive technologies to enhance learning opportunities for vulnerable jobseekers.

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