An Automated Test of Motor Skills for Job Selection and Feedback

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ABSTRACT

Motor skills are required in a large number of blue collar jobs today. However, no automated means exist to test and provide feedback on these skills. In this paper, we explore the use of touch-screen surfaces and tablet-apps to measure these skills. We design novel app-based gamified-tests to measure one's motor skills. We show this information to strongly predict the job performance of skilled workers in three different occupational roles. The results presented in this work make a strong case for using such automated, touch-screen based tests in job selection and to provide automatic feedback. To the best of the authors' knowledge, this is the first attempt at using touch-screen devices to scalably and reliably measure motor skills.

Keywords

Motor skills; Touch-screen devices; Tablets; Assessments; Blue collar jobs.

1. INTRODUCTION

There are many standardized automated tests of language, knowledge, cognitive skills and personality [8, 1, 2]. These tests, often taken on a computer, are good predictors of academic achievement and job performance in the knowledge economy. They have also enabled automated feedback and credentials for learners.

We are interested in automating assessments of motor skills required for vocational jobs such as tailoring, plumbing and carpentry. In the Occupational Information Network (O*NET) database of job descriptions [11], 350 out of 1,065 jobs need moderate to high motor skills. There has been tremendous interest worldwide among employers and professional organizations in training and efficiently identifying people that possess the skills for such hands-on occupations [3, 9]. There have been several validated, non-automated tests like the Purdue Pegboard test [13] and the O'Connor Tweezer Dexterity test [12]. However, no serious attempt has been made to develop and validate automated tests for this purpose. Automated assessments so far have exploited the power of PCs and laptops. We wish to make use of a touch interface, in the form of tablet devices, to test motor skills.

The ability to test motor skills automatically using touch interfaces would allow it to scale extremely well, given the high market penetration of inexpensive tablet devices in the last five years. This would enable people to measure their motor skills right from their homes and receive feedback toward self-improvement. There is substantial evidence that motor skills among adults can be improved [14] and that explicit motor skills feedback and instructions help do so [7, 5, 10]. Also, test takers can learn how suitable they are for a given job, get credentials for the skills they have acquired and apply for jobs that are the best match for their particular skill sets. Companies, for their part, can remotely administer these tests and can use the scores registered and the certificates offered to find a quality workforce, making the identification of suitable candidates easy, cheap, and scalable. This has the potential to make the blue-collar labor market considerably more efficient, similar to the effect automated testing has had on the white-collar labor market.

We apply the classical procedure used in developing skill assessments to develop tests which measure motor skills. We first identify the skills that are most useful to test. We then develop app-based tests that run on tablets and have the potential to measure these skills.[1] We use capacitive touch interfaces in this work, which are very popular these days. The app-based tests are designed in such a way that they *exercise* the motor skills of a person and are of varying degrees of difficulty. Candidates undergo testing through various movements of their fingers, hands and arms. We develop scores for each app based on the test taker's interaction with it. We then test whether these scores are predictive of job/task performance in three occupational roles: tailors, machinists/grinders and machine operators. If our test scores can indeed predict performance in job roles, they could be useful both to provide corporations with a way to filter/evaluate candidates for such jobs and to give feedback to job seekers and those interested in training for such specific fields.

We found that the app-based test scores can predict job performance across multiple parameters that are considered in

[1] We consider tablets instead of smartphones to assess wider movements of arms and shoulders.

evaluating the three job roles enumerated above. The correlation values range from 0.19 to 0.38. These are comparable to, and in cases outperform, those reported historically for manual motor skill tests in predicting job performance ($0.06 - 0.30$, Table 1). This provides strong support for the use of automated touch-screen tests for measuring motor skills for job selection and recruitment. The paper makes the following contributions:

- It is the first attempt to design a touch-screen based test of motor skills. We design a number of novel apps for this purpose.
- We show that there is firm supporting evidence for using app-based scores in the job selection/recruitment process for multiple jobs. This can yield tremendous scalability in the process of hiring blue-collar workers and providing them feedback.

This paper is organized as follows: §2 discusses the motor skills we measure; §3 discusses the design of our apps; §4 lays out the experiment objective and analyzes our results and finally, §5 concludes the paper.

2. MOTOR SKILLS TO MEASURE

We wished to identify motor skills that predict job performance for a range of jobs. We considered Fleishman's taxonomy of 52 human abilities [4] which includes skills such as verbal comprehension and selective attention. Ten of these, which are motor skills such as finger dexterity and arm steadiness, constitute the most widely recognized taxonomy of skills. These ten skills also figure prominently in the O*NET job and skill database.

It was found in [6] that four of these ten motor skills consistently predicted job performance based on empirical evidence. The four skills reported to correlate consistently with job performance are - finger dexterity, manual dexterity, wrist finger speed and multiple coordination (see Table 1). Detailed definitions of these skills can be obtained in [4]. In brief, finger dexterity refers to the accuracy in finger movements while manual dexterity refers to the speed of arm movements. Wrist finger speed refers to the speed of wrist and finger movements and multiple coordination refers to the proficiency in performing coordinated movements with two or more limbs.

A large number of manual tests have been used to measure these motor skills. In all these tests, a candidate is asked to perform a task and is rated on the time taken to complete it and the accuracy achieved, if applicable. For example, one test to measure manual dexterity requires a candidate to unscrew pegs from one board, turn them over and attach them to another board [6]. A test for finger dexterity requires a candidate to insert a rivet in a hole and secure it with a washer, where this process is repeated multiple times. These tests measuring motor skills correlate with job performance in the range of $0.06 - 0.30$ (Table 1).

We seek to develop automated assessments to measure these four skills, which could serve as an alternate to the manual tests described. Our intuition is that these skills involve movements of different joints: wrist/finger accuracy and speed - movements of finger and wrist joints; manual dexterity - movement of shoulder and elbow joints and multiple coordination - coordinated manual dexterity. We develop apps based on this intuition. We limited our work to the action of hands and no other limbs.

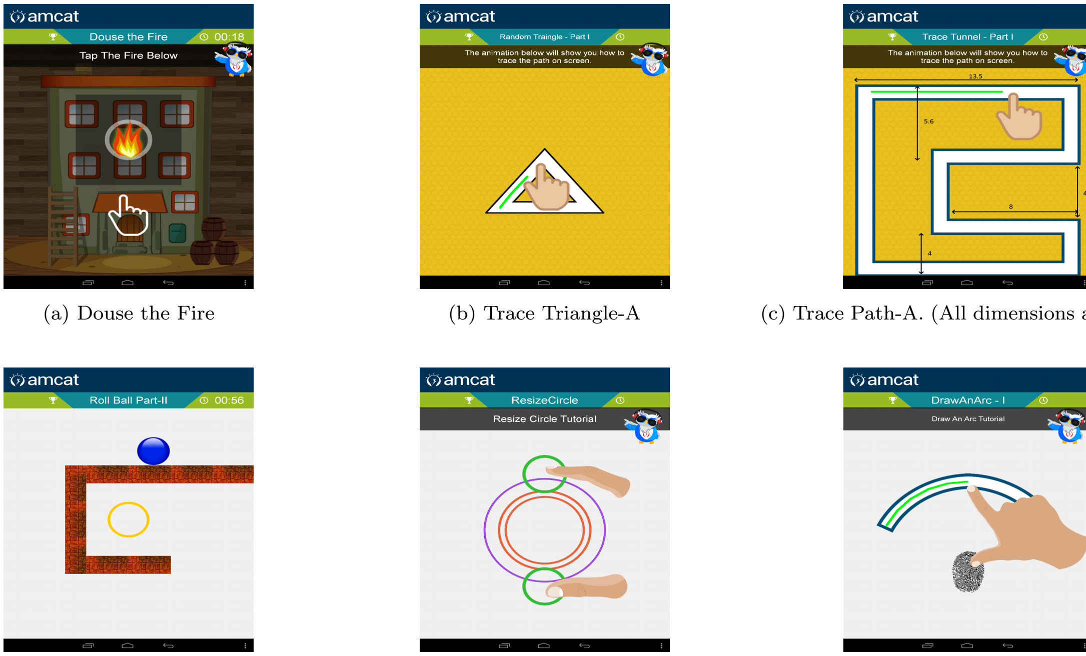
Skill	**Correlations [min-max]**	**Weighted Mean Correlations**
Finger Dexterity	$0.07 - 0.21$	0.19
Manual Dexterity	$0.08 - 0.24$	0.22
Wrist-Finger Speed	$0.14 - 0.30$	0.18
Multiple Coordination	$0.06 - 0.15$	0.14

Table 1: Skills and their minimum, maximum and weighted average correlation values with job performance [6].

3. DESIGN OF APPS

In this section, we describe the design of our touch screen apps to measure motor skills. We constructed each app to elicit specific hand and finger movements. We considered the simplicity and ease of comprehension of the apps as a key criterion. One should not be penalized for not understanding what has to be done, which could happen as a result of either cognitive or knowledge limitations. A set of instructions and a video/animation was shown before each app, to show how to perform the task. Each of these apps is described below:

1. **Douse the Fire (DOUSE)**: In this app, the candidate is shown 'fire' at random spots on a house shown on the screen (see Figure 1a). A candidate has to tap on the fire to douse it. As soon as the fire is doused at one spot, it appears at another spot on the house. In order to ensure that the fire occurs randomly, the distance between the two spots is probabilistically controlled using a uniform distribution between 0 and a number. The candidate has to douse as many fires within 30 seconds. We observed that the task requires elbow and shoulder movements and thus possibly measures manual dexterity.
2. **Trace a triangle-A (TRI_A)**: In this app, the candidate traces a path shown on the screen by dragging a finger over it. We initially considered having the candidate trace a line. However, we recognized that a candidate could not do this accurately because of the large surface area of the finger tip, restricting visual feedback of performing the activity incorrectly. We thus modified our exercise to contain two concentric equilateral triangles. The candidate was required to trace the path in between the triangles (see Figure 1b). The candidate was given feedback on the path traced by her through the use of colors. The path traced was green as long as it was confined to the designated area (space between the concentric triangles) and would turn red as soon as it went off the area. The width of the path is set to be more than the width of the fingertip (roughly 1 cm) to keep the task simple. The edge-lengths of the inner and outer triangles were 4.2 cm and 5.8 cm respectively. The candidate has



(a) Douse the Fire (b) Trace Triangle-A (c) Trace Path-A. (All dimensions are in cm)

(d) Roll Ball-B (e) Resize (f) Draw an arc-A

Figure 1: Snapshots of the apps

to trace as many triangles as possible in 30 seconds. As soon as one triangle was traced, another would appear. The app required moving one's hand quickly to trace the triangles and was designed to measure the speed element of manual dexterity. In principle, the task could be completed by finger movements, but we found that the default action made by the candidates which was comfortable to them involved shoulder and elbow movements.

3. **Trace a triangle-B (TRI_B)**: This app is similar to TRI_A with a difference that the width of the path was decreased. The width was kept a little lesser than the width of the finger tip. We hypothesized that the app required *careful* tracing and measured the accuracy element of manual dexterity.

4. **Trace a path-A and B (PATH_A and PATH_B)**: These apps are similar to the previous triangle apps. The difference is that candidates would trace over paths of much larger concentric polygons instead of a triangle, which shall require arm/hand movements (see Figure 1c). The polygons included rectangles, ellipses and those having zig-zag patterns. Figure 1c describes the dimensions of a sample path which was used. The path width shown in PATH_A is larger than those shown in PATH_B. The candidate has a maximum of two minutes to complete both the exercises and is required to trace as many polygons in the least possible time. These apps are designed to measure manual dexterity by tracing larger lengths and shapes, requiring different kinds of manual movements.

5. **Roll the ball-A (ROLL_A)**: In this app, a circle (symbolizing a hole) is positioned at the center of the screen and a ball is positioned at one of its corner. The ball rolls around on the screen on tilting the surface of the tablet. This is based on the tablet's accelerometer readings.[2] The candidate is required to guide the ball completely inside the circle. On the completion of one such exercise, the screen is refreshed with the ball placed at another point on the screen. The candidate has to complete four such exercises in the least possible time. The total time allotted is 40 seconds. The candidate moves the tablet with both her hands to guide the ball in the right direction. The test hence measures multiple coordination.

6. **Roll the ball-B (ROLL_B)**: This app is similar to ROLL_A. In this app, obstructions are placed in the path of the ball's movement (see Figure 1d). This is introduced to increase the degree of difficulty of the exercise. The time allotted to complete this exercise is 60 seconds.

7. **Fit a circle (FIT)**: We designed an app similar to the act of grabbing an object. The candidate is asked to perform a pinching action in a controlled environment. Two concentric circles were shown on the screen. The diameter of the inner concentric circle was fixed while that of the outer circle could be changed by the candidate. In order to change the diameter, the candidate had to place her thumb and her index finger on two points provided on its circumference and move them inwards or outwards without lifting them up. The diameter changed as the person dragged the two points.

[2]The accelerometer is calibrated at the beginning of the test by asking the candidate to place it on a flat table.

Skill Type	TT
Spot	Douse the Fire
Trace	Trace Triangle A and B
	Trace Path A and B
Multiple	Roll Ball - A and B
Grab/Pinch	Fit Circle
	Resize Circle
Rotate	Draw an Arc - A
	Draw an Arc - B

Table 2: List of tablet-based tests (TT).

The objective was to reduce the outer circle's circumference to match that of the inner circle. As soon as the two circles coincide, the screen is refreshed with two circles of different radii picked randomly. The candidate was required to perform this pinching action as many times as possible in 40 seconds. The app requires the rapid movements of fingers, say in grabbing many objects, one after the other and thus measures wrist-finger speed.

8. **Resize the circle (RESIZE)**: This is similar to the FIT app. The difference is that the outer circle now has to be shrunk and fit into a target ring as against placing it in a smaller concentric circle (see Figure 1e). On placing the outer circle within the target ring, the candidate is expected to lift her fingers from the screen, which then triggers the appearance of another target ring on the screen. The action is not considered until the fingers are lifted from the screen. This test measures the accuracy aspect, i.e. finger dexterity.

9. **Draw an arc-A (ARC_A)**: This app attempts to capture a candidate's wrist and finger rotation movement, as required, say, to screw or unscrew a nut and bolt. An arc is shown on the screen along with a pivot point (see Figure 1f). The candidate has to place her thumb on the pivot point and trace an arc shaped path with her index finger. On completing a trace, the screen is refreshed and a path with a different radius is presented. The candidate is required to trace six paths of varying radii in the least possible time. The arc paths are narrow (0.8 cm) requiring the candidate to be precise in her tracing. The entire task needs to be completed within 30 seconds. This test requires controlled and precise circular movements of the fingers. This test measures finger dexterity.

10. **Draw an arc-B (ARC_B)**: This app is similar to the ARC_A app but has wider arc paths. These arcs have 200% wider paths as compared to the arc paths presented in ARC_A. The candidate is required to trace as many arcs as possible in 30 seconds. This test requires rapid movement of wrists, say, in screwing a light bulb into a socket. This test measures wrist finger speed.

For each app, the candidate is instructed whether to place the tab on a table or hold it in her hands.

Skills measured	MST
Finger dexterity	O'Connor Tweezer Dexterity test [12]
Manual dexterity	GATB Manual Dexterity test [6]
Wrist-finger speed	Large Tapping test [6]
Multiple coordination	Purdue Pegboard test [13] We used the specific part of the test corresponding to coordination of both hands.

Table 3: List of non-automated manual motor skill tests (MST).

#	App	Score
1	Douse the Fire	Number of Correct douses
2	Trace Triangle - A	In-distance - Out-distance
3	Trace Triangle - B	In-distance
4	Trace Path - A	$\frac{\text{Time}}{\text{In-distance}-\text{Out-distance}}$
5	Trace Path - B	$\frac{\text{Time}}{\text{In-distance}}$
6	Roll Ball - A	$\frac{\text{Number of Rolls}}{\text{Time taken}}$
7	Roll Ball - B	$\frac{\text{Number of Rolls}}{\text{Time taken}}$
8	Fit Circle	$\frac{1}{\text{Number of fits}}$
9	Resize Circle	$\frac{1}{\text{Number of resizes}}$
10	Draw an Arc - A	$\frac{\text{Arcs}}{\text{Time taken}}$
11	Draw an Arc - B	In-distance

Table 4: Selected scores for each app. In-distance: Distance traced within path. Out-distance: Distance traced outside path.

4. EXPERIMENTS

We wish to answer whether the performance on tablet-based tasks can predict job performance. Specifically, we find out how our tablet-based tests and manual, non-automated motor skill tests compare in predicting job performance in industrial tasks like operating a lathe machine or tailoring clothes. This would act as a true indictor to suggest the practical use of the tablet-based tests in talent hiring. We note here that critical steps of non-automated motor skill tests like setting up the equipment, conducting the exercises and reporting scores are prone to human errors. Tablet-based tests have the distinct advantage of being devoid of such standardization issues. This advantage is likely to contribute towards its better predictive power.

4.1 Setup

The tests were administered to a workforce (referred to as *candidates* henceforth) belonging to three different occupations - tailors at a garment manufacturer, machinists and grinders at a machine-shop training company and machine operators at a skill training company. Each candidate was administered two sets of tests - tablet-based tests (TT henceforth) and non-automated, manual motor skill tests (MST henceforth). Four tests, as described in Table 3, were part of the MSTs. The standard set-up as described in [6] was followed in administering these tests. The eleven app-based tests described in §3 were part of the TTs.

TT and MST scores: In order to quantify a candidate's performance on our apps, we derived a single score for each

Job Performance Metrics	TT Scores				MST Scores				ATD Scores	
	Spot	Trace	Grab/Pinch	Rotate	MD	WFS	FD	MC	ATD	ATT
Tailors ($N = 74$)(Age range: $20 - 55$ years)										
Rate the tailor on the neatness of his/her completed work.	**0.22***	**0.37****	0.08	0.08	-0.09	-0.09	0.10	-0.10	NA	NA
Would you entrust him/her with a complicated task?	0.16	**0.33****	-0.10	-0.04	-0.08	**-0.33****	0.20*	-0.14	NA	NA
Rate how quickly s/he is able to complete her/his tasks.	**0.21***	**0.21***	-0.02	0.04	-0.13	**-0.20***	0.01	-0.13	NA	NA
Machinists and Grinders ($N = 68$)(Age range: $17 - 24$ years)										
Practical scores	**0.38****	**0.29****	**0.34****	0.07	0.07	-0.14	0.13	0.02	-0.06	NA
Electric Machine Shop score	**0.27****	0.11	**0.21***	-0.15	0.22*	**-0.29****	-0.03	0.10	0.12	NA
Machine Operators ($N = 78$)(Age range: $19 - 38$ years)										
Is s/he able to finish all the sub-tasks in a given operation?	0.15	**0.23****	0.00	-0.02	0.05	0.00	0.11	0.01	**0.20***	**0.27****
Rate how quickly s/he is able to complete the assigned operations.	0.17	**0.19***	0.04	-0.07	-0.14	**-0.19***	-0.01	-0.03	0.06	NA

* p<0.1; ** p<0.05; ATD : Attention to Detail scores; ATT : ATD + Best TT score;

FD - Finger Dexterity; WFS - Wrist-Finger Speed; MD - Manual Dexterity; MC - Manual Coordination.

Table 5: Correlations with job performance.

app (tabulated in Table 4). Further, the 11 tests were grouped into 5 skill types: *Spot* (DOUSE), *Trace* (TRI_A, TRI_B, PATH_A, PATH_B), *Multiple* (ROLL_A, ROLL_B), *Grab/Pinch* (FIT, RESIZE) and *Rotate* (ARC_A, ARC_B) (see Table 2). Each of these 5 skills was represented by a separate score. These scores were calculated by averaging the z-scores of apps contained in the skill[3]. For the four MSTs, scores were calculated as described in [6]. They generally measured the time taken to complete the task.

4.2 Data Set

The tests were administered to candidates belonging to three different occupations - 81 tailors, 74 machinists and grinders and 82 machine operators. The sample size was limited by the strength of the organizations. All three tests were administered by two event managers who had received a week's training on setting up the tests. Candidates performed the two tests (TTs and MSTs) with a gap of 5-6 hours. Each candidate's test was fully video-recorded. A review of these videos revealed that the standard process was not followed in 7.2% of the sample. These were discarded. The time recorded in nearly 3.7% samples for one or more of the MSTs was corrected. Post these changes, we finally had samples from 74 tailors, 68 machinists and grinders and 78 machine operators. We only considered the dominant hand in our analysis, except in the case for *multiple-coordination* which involves co-ordination between both hands. For machinists, grinders and machine operators, we also administered a multiple choice test of attention to detail (ATD)[4]. This was done to find what additional predictive power the TT scores added over the cognitive ability test scores to predict job performance.

[3]Considering scores separately added no insight but increased complexity

[4]This is a criterion valid test used in hiring professionals in retail, sales, marketing etc. The 74 tailors had no formal education and hence could not take this test.

Job performance scores: In the case of tailors and machine operators, a performance questionnaire (column 1 of Table 5) was developed on discussing with the candidates' managers. The managers were then asked to score the candidates on these metrics on a scale of 1 to 5. In the case of machinists and grinders, the training organization had documented scores from the candidates' lab-sessions. These scores were based on their performance on various job tasks given to them during their training. These ratings and scores formed the job performance data for our analysis.

4.3 Analysis and Observations

We compute the Pearson correlation coefficient (r) of all TT scores, MST scores and ATD scores (where available) with each metric contributing to job performance. The TT scores are fashioned to signal higher skill with higher magnitude whereas MST scores are fashioned to signal lower skill with higher magnitude. Hence, the correlation of job performance scores with TT scores is expected to be positive while the correlation with MST scores is expected to be negative. In our analysis, we observed the correlation between TT scores and MST scores to be in the range -0.27 to -0.34. This shows shared variance between the two scores. We noticed however that the scores of Multiple Coordination (one of the TTs) correlated positively with other MST scores. We hence do not include it in any further analysis. Additionally, by doing a regression, we found what incremental value the best correlating TT scores added over and above the ATD scores. These values and their respective significances are reported in Table 5.

First, and most importantly, we find that for every job performance metric, at least one TT score shows a significant correlation (at $p \leq 0.1$) ranging from $0.19 - 0.38$ (mean: 0.27). This clearly establishes that TT scores are able to predict job performance and can be used for hiring/selection decisions by following standard practices. Second, MST scores show a significant correlation with four out of the seven performance metrics, where they range from -0.19 to -0.33 (mean:-0.25). We note here that the correlations between the four MSTs and job performance scores are in line with historically observed values (Table 1). ATD scores show a significant correlation in one case, where the *Trace* score adds significant incremental correlation (0.07) over and above it (column ATT, Table 5).

Among the app scores, there is maximum support for the *Trace* app which shows the highest correlation with job performance in five out of the seven metrics. In the remaining two metrics, the *Spot* app scores show the maximum correlation with job performance. While there is some support for the *Grab/Pinch* scores, there is hardly any support for the *Rotate* app scores. Among MST scores, the *Wrist-finger Speed* scores consistently correlate with job performance.

Discussion: We find that the TT scores are predictive of job performance in all cases in our study. The validity indices are comparable (and in cases bests) those observed for MST scores in the past (Table 1). The maximum support is for the *Trace* app. These are extremely encouraging results. This implies that the test may practically be used in making hiring decisions. The best way to do this would be to first perform a validity study with incumbents in a job in order to establish which TT apps distinguish on-job performance. These apps could then be used on new applicants and their scores be considered in the hiring process. While there is evidence for the *Trace* scores to be a universal predictor, the same may be established with further validity studies and meta-analysis. We envision that through such extended studies, a mapping could be formed between job roles and TT scores, akin to what has been established for MST scores. One would then know a priori which TT app and scores to use when hiring for a particular job role.

In four out of seven metrics, the MST and TT scores do equally well. One may observe that the MST scores did not do as well as the TT scores in three cases. This was surprising to us. A couple of reasons could explain this - first, the TT scores measure a larger variety of movements than the MST scores and some of these could potentially correlate better with job performance. For instance, there isn't any MST task similar to the structured tracing task in the TT. The other reason, as noted earlier, could be non-standardization and human errors in MST as compared to a controlled, completely standardized tablet-based test.

5. CONCLUSION AND FUTURE WORK

In this work, we explore the use of touch screen surfaces to measure motor skills. We show the scores of blue-collar workers on tasks performed on touch screen tablets to correlate with their respective job performances in the range of 0.19 to 0.38. These results make a strong case for using such automated, touch-screen based tests in job selection processes and in providing automated feedback. Such tests would make the process of identifying and credentialing skilled labor highly scalable and efficient, thereby benefiting both, individuals and corporations.

Our current work paves the way for substantial future work. The design of novel apps for motor skill measurement is a nascent area of research and could be further developed. By analyzing scores from such apps, we could create a map to suggest what scores are suitable for a given job role. Having such a map would help in automatically providing feedback to candidates on the skills they have. We could also perform the current tab tests for a number of other different job roles, which would help validate its design. Other devices and technologies such as smartphones[5] and resistive touchscreens could be experimented with, which could potentially make these tests more accessible, help do more accurate assessment and also grade new skills. For instance, a pressure detecting screen may help measure how soft the touch is, which might be relevant in nursing. We believe that the ideas introduced in this work can lead to substantial innovations in the blue-collar labor market.

6. ACKNOWLEDGEMENT

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[5]Most apps here can be used on a smartphone with some adjustment in the scale and aspect ratio of the apps and recalibration of scores. It may not effectively measure wider movements of the arms.