Interdisciplinary Journal of e-Skills and Lifelong Learning **Volume 12, 2016**

Cite as: Mor, D., Laks, H., & Hershkovitz, A. (2016). Computer skills training and readiness to work with computers. *Interdisciplinary Journal of e-Skills and Life Long Learning, 12,* 95-112. Retrieved from http://www.informingscience.org/Publications/3451

Computer Skills Training and Readiness to Work with Computers

Dalit Mor, Hagar Laks, and Arnon Hershkovitz
Tel Aviv University, Tel Aviv, Israel

dalitmor@mail.tau.ac.il, ehrenfeldh@mail.tau.ac.il, arnonhe@tauex.tau.ac.il

Abstract

In today's job market, computer skills are part of the prerequisites for many jobs. In this paper, we report on a study of readiness to work with computers (the dependent variable) among unemployed women (N=54) after participating in a unique, web-supported training focused on computer skills and empowerment. Overall, the level of participants' readiness to work with computers was much higher at the end of the course than it was at its beginning. During the analysis, we explored associations between this variable and variables from four categories: log-based (describing the online activity); computer literacy and experience; job-seeking motivation and practice; and training satisfaction. Only two variables were associated with the dependent variable: knowledge post-test duration and satisfaction with content. After building a prediction model for the dependent variable, another log-based variable was highlighted: total number of actions in the course website along the course. Overall, our analyses shed light on the predominance of log-based variables over variables from other categories. These findings might hint at the need of developing new assessment tools for learners and trainees that take into consideration human-computer interaction when measuring self-efficacy variables.

Keywords: Work readiness, working with computers, log-based variables, decision tree.

Introduction

Information and communication technology (ICT) is part of the everyday life in the 21st century, and the rapid development of ICT requires a completely new set of skills related to technological literacy (Voogt & Roblin, 2012). Many recent studies have explored the changes in employment demands as a result of developing technologies and have specifically mentioned the high demand for skilled workers (Acemoglu, 2002; Autor, Levy, & Murnane, 2003; Kim & Hwang, 2013; Srour, Taymaz, & Vivarelli, 2014). As Lin (2000) suggests, "computer literacy" might no longer be the right term to be used to describe the current profile of employees in today's job market, but rather fluency with information technology. This notion is also related to the concept of computer self-efficacy.

Editor: Gila Kurtz
Submitted: December 22, 2015; Revised: April 10, 2016; Accepted: April 16, 2016

Computer self-efficacy is defined as "an individual's perceptions of his or her ability to use computers in the accomplishment of a task rather than reflecting simple component skills" (Compeau & Higgins, 1995). Many previous studies had examined individual differences in computer self-efficacy, suggesting various explaining measures, like attitudes towards computer usage and previous experience with computers (e.g., Hasan, 2003; Lam, Cho, & Qu, 2007; G. Torkzadeh & Van Dyke, 2002). Furthermore, positive associations between computer training and computer self-efficacy (or similar constructs) were found (e.g., Salanova, Grau, Cifre, & Llorens, 2000; R. Torkzadeh, Pflughoeft, & Hall, 1999). There is no wonder, therefore, that unemployed older workers express a desire to receive additional training on technology, preferably in a hands-on fashion (Lee, Czarja, & Sharit, 2008).

Therefore, training programs for employees often suggest both computer-related content and modules which aim on improving the participants' self-efficacy concerning working in today's job market; such a program is at the heart of the current study. While many previous studies have examined the efficiency of such programs in improving measures related to computer self-efficacy, the novelty of the current study is in examining the relationships between log-based (training-related) variables and a variable similar to computer self-efficacy.

Though very simple, these log-based measures outperform other variables—including such variables that were found in previous studies as good indicators to computer self-efficacy—in predicting the dependent variable, which measures perceptions of unemployed women's readiness to work with computers. Exploring and understanding these relationships are the main purposes of this article.

Related Work

Computer Training and Readiness to Work with Computers

That computer training positively influences computer self-efficacy is not surprising (cf. Kher, Downey, & Monk, 2013; G. Torkzadeh & Koufteros, 1994; R. Torkzadeh et al., 1999), nor that this correlation might be mediated by type of training (Beas & Salanova, 2006; Gist, Schwoerer, & Rosen, 1989); however, changes in attitudes towards computers are not always demonstrated after a computer training (cf. G. Torkzadeh & Van Dyke, 2002). There is also a debate whether the training method has an effect on post-training computer self-efficacy (cf. Brown et al., 2005). That said, older adults' computer self-efficacy is usually increased after computer training (cf. Laganá, Oliver, Ainsworth, & Edwards, 2011).

We focus on the case of people who work with computers. It was explicitly shown that time spent with computers is significantly positively correlated with attitudes toward working with computers (e.g., Orpen & Ferguson, 1991), hence the importance of well-designed training. This relationship might be mediated by attitudes toward computers: while for those workers showing high positive attitudes toward computers, their level of professional self-confidence rise as number of training hours increases, for those low in computer attitudes, professional self-confidence decreases with the increase in training hours (Beas & Salanova, 2006). When discussing employees who can choose whether to integrate computers into their practices or not (like often is the case with teachers), it was shown that computer training might indeed promote such an integration. (Colman, Gibson, Cotton, Howell-Moroney, & Stringer, 2015).

Of special interest to the current study are studies focusing on computer training immediately before, and related to, working with computers. One such study is that reported in Potosky (2002), in which SQL task-specific self-efficacy was explored after an SQL training for newly hired computer programmers. Interestingly, the measured self-efficacy was not found to be associated with training-related computer knowledge and experience (controlling for pre-training computer self-efficacy). Different findings were shown in McDonald (2004), demonstrating increase in self-efficacy for some trainees, however with an emphasis of the importance of the relationships between the trainees and the employer during the training. In addition, it was shown that self-efficacy beliefs regarding a given technology might be mediating between training for this system and the intention to adopt it (Wu, Wang, & Lin 2007).

Relationships between Interaction-related Variables and Learners' Perceptions

In recent years, relationships between variables related to student-computer interaction (either extracted from log files or measured in other methods) and learners' perceptions of various learning-related constructs have been studied. Some studies suggest weak relationship—or no relationship at all—between these two types of variables. For example, students' perceptions of their goal orientation while learning (whether they are oriented towards mastering or towards achievements) was not found to be related to a log-based measure of carelessness (that is, when a student knows the skill needed to solve a problem but does not demonstrate that skill); also, goal orientation, as well as perceptions of self-efficacy, were not found to associated with engagement with a computer-based learning system (Hershkovitz, Baker, Gobert, & Nakama, 2012; Hershkovitz, Baker, Gobert, Wixon, & Sao Pedro. 2013). Similarly, there were very weak relationships found between domain- and unit-level self-efficacy and hint-seeking and glossary use in mathematics tutor (Fancsali, Bernacki, Nokes-Malach, Yudelson, & Ritter, 2014). Possible explanations for the absence of such relationships are the differences in data granularity and/or the potentially strong effect of contextual variables.

Indeed, when granularity is similar for both types of measures or when they take into account contextual variables, some studies were able to find relationships between student-computer interaction and self-efficacy. Computer Science self-efficacy, for example, was found to be predictive of engagement (Grafsgaard, Wiggins, Boyer, Wiebe, & Lester, 2014); as both these measures were based on students' self-reports, this finding makes sense in light of the limitation mentioned above (in this case, both variables are at the same granularity, and engagement measuring is not biased by contextual variables). Similarly, when both types of variables are measured on a finer-grained level, relationships are found, and contextual variables (e.g., log-based and physiological) are predictive of self-efficacy (McQuiggan, Mott, & Lester, 2008). In our study, different granularities and different contexts of measurements are presented.

Methodology

Research Field

Data analyzed for this study was drawn from Appleseeds Academy's "Technological Empowerment for Unemployed Women" course (TEUW) and included log-based variables and survey-based variables (full details are following, under *Participants and Data*). During this course, unemployed women are taught basic computer applications (e.g., using Internet browsers and searching for information online, using basic MS Office applications, and sending emails) and best job-seeking practices. In addition, the participants take part in an empowerment workshop, in order to enhance their chances of finding a job in today's computer-enriched market. A typical course includes 16 meetings (4.5-hour long each) taken within one month, of which 13 focus on technological topics and are led by Appleseeds Academy instructors, and 3 are focused on empowerment and are led by expert advisers.

The course is accompanied by a Moodle website, holding all of the materials used during the meetings and extra materials for self-learning. The website also includes a discussion forum, a message board, and a module to create an online glossary by the participants.

Appleseeds Academy

Established in 2000 as a business sector initiative, Appleseeds Academy aims to bridge social and economic gaps in the Israeli society by diminishing the country's digital divide. As Israel's hi-tech industry booms and those in weaker communities get left behind, Appleseeds Academy partners with businesses, government, and other NGOs to provide professional training, educational programming and hands-on personal development and social intervention opportunities for underserved populations in Israel. The TEUW course is organized in cooperation with the Israeli Employment Service, WIZO (Women's International Zionist Organization, a volunteer organization dedicated to social welfare of Jewish women in Israel and worldwide), and Microsoft Israel.

Participants and Data

Overall, we collected data of 54 participants, all women of ages 25-65, who took the TEUW course during February-March 2014. Participants were drawn from groups located in different areas of Israel, including both big cities and small towns. Data were collected via different tools (for a full list of the variables, see *Research Variables*).

Knowledge pre/post-test

The knowledge pre-test was administered online early during the first meeting of the course; the post-test at the end of the last meeting of the course.

Pre/post survey of computer use and attitudes towards computers

These surveys are measuring attitudes towards computers, previous experience with computers, and employment self-efficacy. They also collect some demographics variables (e.g., age, religion, place of birth) and employment-related variables (e.g., previous occupation, unemployment period). The post survey included items asking for feedback about the training, specifically satisfaction with various aspects of it. These pre/post surveys were administered immediately before the knowledge pre/post-tests, respectively, using the same system.

Log files

Moodle log files documented a total of 5,159 actions, widely ranging between 3-575 actions for participant, with an average of 96 actions per participant, a median of 76, and a high variance (SD=102). The frequency of actions per participant is exponential-like – that is, most participants present low activity, while only a few are very active – which is a very typical pattern for web access; it is referred to as the "participation inequality" (Nielsen, 2006) and was shown in many different educational contexts (e.g., Fournier, Kop, & Sitlia, 2011; Hershkovitz & Nachmias, 2010).

Research Variables

The dependent variable is Post-training Employment Readiness High/Low. It is binary (1/0 for high/low readiness), based on a median split of the average of five employment-efficacy items in the post-survey, each of which was scored on a 5-point Likert scale. The original items are:

- I feel confident to present my skills and strengths
- I feel confident to go to job interviews
- I believe in my ability to acquire knowledge independently
- I can use a computer independently to learn new areas
- I feel I can get a job that matches my abilities and skills

We chose to convert the Post-training Employment Readiness into a binary variable as for the relatively small size of population and due to its non-normal frequency (see previous section).

Over all, we have 17 independent variables from four categories:

Log-based variables (3 variables)

From Moodle log files, we computed for each participant the following:

- *Total Number of Actions* (Moodle only)
- *Knowledge Pre/Post-Test Length* (in minutes, time-difference between entrance to the test and hitting the "Finish" button)

Computer literacy, experience (4 variables)

- *Knowledge Pre/Post-Test Score* – each is the percentage of correct answers from the pre/post knowledge test
- *Computer Pre/Post-Use* – each is an average of six items from the pre/post survey referring to computer applications use (rated on a 5-point Likert scale)

Job-seeking motivation and practice (6 variables)

These variables are based on relevant items (scored on a 5-point Likert scale) from the pre/post survey. The variables are:

- *Pre-training Employment Readiness* is calculated the same way as the dependent variable, based on the pre survey (without a median split)
- *Motivation towards the Training* (1 item)
- *Pre/Post Job-seeking Activeness* (6 items, e.g., "I use family/friends during my job seeking", "I send out my CV via job search websites")
- *Pre/Post Beliefs in Finding Suitable Job* (1 item)

Training satisfaction (4 variables)

These variables are based on relevant items from the post survey, asking for feedback about the training (each items was scored on a 5-point Likert scale). The variables are:

- *Satisfaction with Content* (5 items)
- *Satisfaction with Instructor* (7 items)
- *Satisfaction with Empowerment Workshop* (9 items)
- *Satisfaction with Final Project* (3 items)

Results

Pre/Post-Training Employment Readiness

As a first step, we explored some statistics of the *Pre/Post-training Employment Readiness* variables (see Table 1). Overall, the mean *Post* (M=4.45, SD=0.61) is meaningfully and statistically significantly higher than the mean *Pre* (M=3.66, SD=0.88), with t(53)=5.33, at $p<0.001$ (a paired-sample t-test was used).

Table 1. Descriptive statistics for the *Pre/Post-Training Employment Readiness* variables

VARIABLE	MEAN	SD	SKEWNESS
Pre	3.66	0.88	-0.65
Post	4.45	0.61	-1.10

However, it is interesting to explore the relationships between these two variables more deeply. As may be understood from the very different skewness values (see Table 1), the *Pre/Post* variables are distributed differently; while *Pre-Training Employment Readiness* can be seen as skewed from normality, *Post-Training Employment Readiness* is clearly not normal (see Figure 1); the *Post* variable might demonstrate a ceiling effect. Testing the *Pre/Post* variables for normality, using one-sample Kolmogorov-Smirnov test, results with both being non-normal, howev-

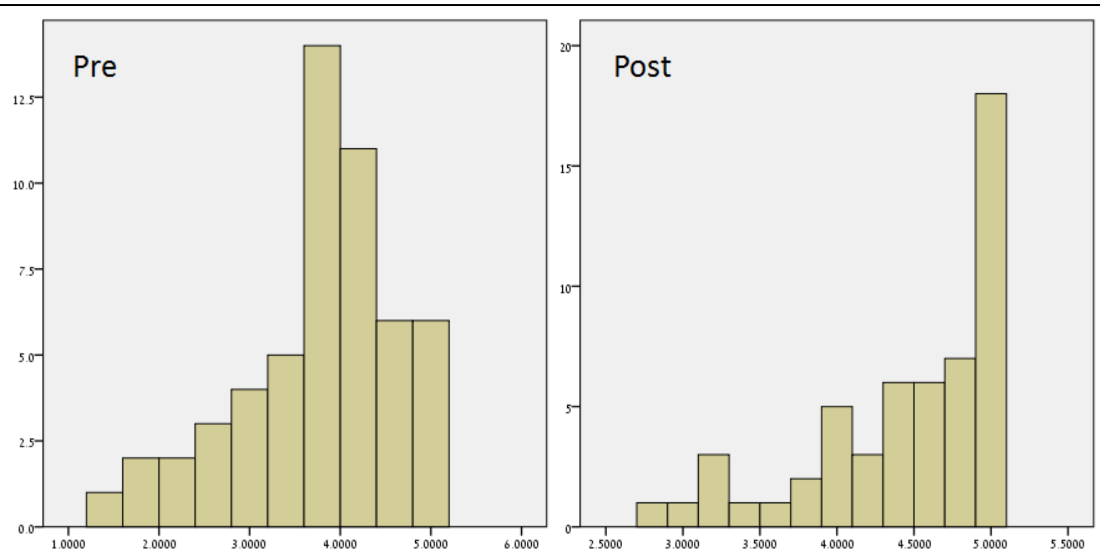

Figure 1. *Pre/Post-Training Employment Readiness* distribution (note the different scales on both axes)

er with different values of 0.13 and 0.05, respectively (both at $p<0.05$). Therefore, it is of no surprise that these two variables are not statistically significantly correlated ($r=-0.04$, at $p=0.8$).

Overall, it seems that the course had dramatically increased the level of participants' readiness to work with computers, and that the *Post-training Employment Readiness* might even demonstrate a ceiling effect.

Direct Relationship between the Dependent and the Independent Variables

Before highlighting some interesting relationships between *Post-training Employment Readiness High/Low* and the independent variables, it is important to comment about the variable *Post-training Employment Readiness* (that is, before the median split). It was found that no independent variable was correlated with this pre-median split variable. This surprising finding might be explained by the non-normality of the continuous version of the dependent variable (see previous section); hence, we will focus our analyses on the binary version of it.

The following analyses are based on independent sample t-test values, comparing the independent variable means between the two groups formed by the dependent variable values (high/low employment readiness). Unless otherwise stated, $df=52$. T-test values are presented in absolute value.

Log-based variables

When comparing mean values of the three log-based variables, only one shows significant difference between the high and the low employment-ready participants; this variable is *Knowledge Post-Test Length* (see Table 2 for the full comparison results). The average of the low employment-ready group (~37 minutes) is more that 60% higher than the average of the high employment-ready group (~23 minutes); this difference is statistically significant, with $t(24.8)=2.4$, at $p<0.05$. As Levene's test for equality of variances was significant (with $F=11.2$, at $p<0.01$), we did not assume equal variances.

Table 2. Comparing means of log-based variables by high/low employment-readiness

VARIABLE	MEAN (SD) FOR HIGH (N=31)	MEAN (SD) FOR LOW (N=23)	t
Total Number of Actions	104.0 (122.7)	84.2 (65.0)	0.7
Knowledge Pre-Test Length [sec]	881.6 (310.9)	904.5 (368.3)	0.2
Knowledge Post-Test Length [sec]	1365.2 (528.2)	2206.0 (1818.8)	2.4[*,a]

[*] $p<0.05$, [a] $df=24.8$, Levene's test for equality of variances was significant, hence equal variances were not assumed

This finding of relationship between employment-efficacy and log-based measures of online activity is in line with the more general established relationship between self-efficacy beliefs and persistence/engagement (which are often measured by time on task or number of items completed) (cf. Multon, Brown, & Lent, 1991; Ouweneel, Schaufeli, & Le Blanc, 2013). It is possible that the participants with high employment-efficacy were more engaged and/or more persistent during the post-test than the participants low on employment-efficacy, which helped the former finish it faster than the latter. One might think that these differences in post-test duration imply on differences in actual knowledge, but, as will be shown in the next sub-section, no differences were found between the two groups with regards to computer knowledge or experience.

Interestingly, the *Knowledge Pre/Post-Test Length* are not statistically significantly correlated with each other (r=-0.08, at p-0.56); also, neither of them is significantly correlated with *Total Number of Actions*. This might hint on *Knowledge Post-Test Length* depicting some constructs that are different from those depicted in *Knowledge Pre-Test Length.*

Computer literacy, experience variables

Comparing mean values of the four variables related to computer literacy and experience, none shows significant difference between the high and the low employment-ready groups (see Table 3). This is surprising, as previous studies have shown relationships between similar variables.

For example, Potosky (2002) had shown that post-training software efficacy (after a software training) was correlated with both computer knowledge and training performance (which may refer to our *Knowledge Pre/Post-Test Score)*; and, generally, computer self-efficacy has been shown to be related to prior experience with computers (e.g., Cassidi & Echaus, 2002; Rex & Roth, 1998; Topkaya, 2010). This is further discussed in the *Conclusions and Discussion* section.

Table 3. Comparing means of computer literacy and experience variables by high/low employment-readiness

VARIABLE	MEAN (SD) FOR HIGH (N=31)	MEAN (SD) FOR LOW (N=23)	t
Knowledge Pre-Test Score	0.50 (0.13)	0.54 (0.13)	1.0
Knowledge Post-Test Score	0.80 (0.10)	0.83 (0.08)	1.2
Computer Pre-Use	3.47 (0.43)	3.52 (0.41)	0.4
Computer Post-Use	3.82 (0.34)	3.71 (0.46)	1.1

Analyzing correlations of pairs of these variables results with some interesting insights. First, *Knowledge Pre-Test Score* is significantly correlated with *Computer Pre-Use* (r=0.36, at p<0.05). This is of no surprise, as the relationship between prior computer experience and performance (as well as with computer self-efficacy) has been long established (cf. Marakas, Yi, & Johnson, 1998). However, the lack of correlation between *Knowledge Post-Test Score* and neither *Computer Pre-Use* (r=0.23, at p=0.09) nor *Computer Post-Use* (r=0.09, at p=0.52) is surprising.

A paired-sampled t-test reveals that across the whole population (N=54), *Knowledge Pre/Post-Test Score* means are significantly different from each other (M=0.52, SD=0.13, and M=0.81, SD=0.09, respectively), with t(53)=15.3, at p<0.001; the same goes for the difference between *Pre/Post Computer Use* means (M=3.49, SD=0.43, and M=3.77, SD=0.39, respectively), with t(53)=3.9, at p<0.001. However, while *Knowledge Post-Test Score* is over 50% higher than *Knowledge Pre-Test Score*, the increase between *Computer Pre/Post-Use* is only minor. It is only natural that the latter is much less prominent than the former, as one-month timeframe (the length of the course) is long enough to accumulate knowledge, while it is too short for changing computer use habits. Indeed, across the whole population, *Pre/Post Computer Use* means are not significantly correlated (r=0.20, p=0.15), which might indicate on the irregular computer use changes adopted by the participants.

Therefore, we suggest that the reasons for *Pre Computer Use* and *Computer Post-Use* not being correlated with *Knowledge Post-Test Score* are different; for the former, the explanation probably lies in the dramatic increase in knowledge, which is incomparable to the increase in computer use, and for the latter it might be the irregular patterns of computer use adopted by the participants which changed the dynamics between computer use and knowledge.

Job-seeking motivation and practice variables

Comparing mean values of the six variables related to computer literacy and experience, none shows significant difference between the high and the low employment-ready groups (see Table 4).

Table 4. Comparing means of job-seeking motivation and practice variables by high/low employment-readiness

VARIABLE	MEAN (SD) FOR HIGH (N=31)	MEAN (SD) FOR LOW (N=23)	t
Pre-training Employment Readiness	3.59 (0.96)	3.75 (0.77)	0.64
Motivation towards the Training	4.84 (0.52)	4.83 (0.49)	0.09
Pre Job-seeking Activeness	0.32 (0.31)	0.69 (0.33)	0.80
Post Job-seeking Activeness	0.82 (0.29)	0.83 (0.26)	0.12
Pre Beliefs in Finding Suitable Job	4.61 (0.92)	4.57 (0.90)	0.19
Post Beliefs in Finding Suitable Job	4.58 (1.12)	4.39 (1.27)	0.58

Across the whole population (N=54), *Post Job-seeking Activeness* is higher than *Pre Job-seeking Activeness*, with means of 0.65 (SD=0.32) and 0.82 (SD=0.27), respectively. These differences are statistically significant, with t(53)=3.27 (paired-sample t-test), at p<0.01. This is of no surprise, as one of the goals of the course was to empower the participants to an active job search.

Therefore, the non-significant difference between the means of *Pre/Post Beliefs in Finding Suitable Job* (4.59, SD=0.9, and 4.50, SD=1.18, respectively) is surprising, with t(53)=0.43, at p=0.67. One should expect that after such an empowerment, and after gaining relevant knowledge, attitudes towards a successful job-seeking would positively change. This might be a result of a ceiling effect in the *Pre* variable, or maybe a dissatisfaction with the Israeli job market.

Training satisfaction variables

Comparing mean values of the five variables related to computer literacy and experience, only one shows significant difference between the high and the low employment-ready groups, *Satisfaction with Content* (see Table 5).

As previous works showed, satisfaction with training is correlated with post-training self-efficacy and ability to cope (e.g., Saks, 1995).

Table 5. Comparing means of training satisfaction variables by high/low employment-readiness

VARIABLE	MEAN (SD) FOR HIGH (N=31)	MEAN (SD) FOR LOW (N=23)	t
Satisfaction with Content	4.59 (0.42)	4.23 (0.68)	2.39[*,a]
Satisfaction with Instructor	4.77 (0.49)	4.83 (0.42)	0.41
Satisfaction with Empowerment Workshop	4.42 (0.66)	4.57 (0.44)	0.92
Satisfaction with Final Project	4.57 (0.53)	4.71 (0.53)	0.96

[*] $p<0.05$

[a] df=34.3, Levene's test for equality of variances was significant, hence equal variances were not assumed

Summary of relationships

While exploring direct relationships between the dependent variable and the independent variables – using independent-sample t-tests – we have found only two significant relationships. These relationships were found to log-based and satisfaction-related variables:

- Participants with high *Post-training Employment Readiness* values took the knowledge post-test (*Knowledge Post-Test Length*) much quicker than those with low values (~23 minutes, compared with ~37 minutes);
- Participants with high *Post-training Employment Readiness* values were satisfied with the course content (*Satisfaction with Content*) more than those with low values (4.59 on a 5-point Likert scale, compared with 4.23).

We now move on to exploring more complicated relationships, using a prediction model.

Predicting the Dependent Variable

We now use a decision tree model in order to explore more complex relationships between the dependent (predicted) variable and the independent variables (the predictors). We choose a decision tree model as for its interpretability.

We developed the decision tree model using RapidMiner Studio (Mierswa, Wurst, Klinkenberg, Scholz, & Euler, 2006), with a manual forward feature selection. This process starts with building and assessing single-feature models for each of the variables, selecting the best model. Then, each of the remaining variables (not already in the model) is tested for model improvement (now, as a two-feature model). The process goes on until no improvement is gained. Prediction goodness was tested using kappa, and was validated using leave-one-out cross-validation (LOOCV).

Of the single-feature models, only one performed better than chance. This is the model built with *Knowledge Post-Test Length*, which resulted with a LOOCV kappa of 0.334. This is not surprising as for the lack of relationships between the dependent variable and all but two of the independent variables, one of which was *Knowledge Post-Test Length*. Recall that the other variable that was found related to the dependent variable was *Satisfaction with Content*, and indeed this was the second variable to be added to the model.

The final model has a LOOCV kappa of 0.524. The full tree is presented in Figure 2; its corresponding confusion matrix is presented in Table 6. Overall, three variables entered the best decision tree in the following order:

1. *Knowledge Post-Test Length*
2. *Satisfaction with Content*
3. *Total Number of Actions*

The tree size is 16, its height is 7, and it has 9 leaves. The paths to the leaves define the groups that were predicted as high/low in post-training employment readiness.

```
Post Test Length > 2911: L {L=7, H=0}
Post Test Length ≤ 2911
| Satisfaction with Content > 3.7
| | Num. of Actions > 14
| | | Num. of Actions > 19
| | | | Post Test Length > 1008
| | | | | Post Test Length > 1299
| | | | | | Post Test Length > 1596
| | | | | | | Num. of Actions > 61: H {L=1, H=7}
| | | | | | | Num. of Actions ≤ 61: L {L=2, H=1}
| | | | | | Post Test Length ≤ 1596: H {L=0, H=8}
| | | | | Post Test Length ≤ 1299: L {L=7, H=1}
| | | | Post Test Length ≤ 1008: H {L=0, H=6}
| | | Num. of Actions ≤ 19: L {L=2, H=0}
| | Num. of Actions ≤ 14: H {L=0, H=8}
| Satisfaction with Content ≤ 3.7: L {L=4, H=0}
```

Figure 2. Best decision tree prediction model for *Post-training Employment Readiness* (L=Low, H=High). Variable names are shortened for having a better presentation; prediction is marked in bold red letters; true values distribution in each leaf are brought in curly brackets

Characterization of participants predicted as having high post-training employment readiness

We now follow the corresponding four paths to the "High" leaves (see Figure 2), in order to characterize participants predicted as having high post-training employment readiness.

Participants who took the knowledge post-test in more than 49 minutes or that were satisfied with the course content at a level of 3.7 or less (out of 5) are predicted as having low post-training employment readiness. Of the rest of the participants, either of the following characterizations refer to the "High" group:

- Performed at most 14 actions on the course website throughout the course
- Performed more than 19 actions on the course website throughout the course
  AND
  took the knowledge post-test in 17 minutes or less
- Took the knowledge post-test in between 22-27 minutes
- Took the knowledge post-test in 27 minutes or more
  AND
  Performed more than 61 actions on the course website throughout the course

Table 6. Confusion matrix for the best prediction model of Post-training Employment Readiness High/Low

		ACTUAL		PRECISION
		LOW	HIGH	
PREDICTION	LOW	13	2	86.7%
	HIGH	10	29	74.4%
	RECALL	56.5 %	93.5%	

For having a better understanding of the interaction between *Knowledge Post-Test Length* and *Total Number of Action* and its effect of the dependent variable prediction, we present an illustration of the High/Low predictions of these two independent variables, see Figure 3. This chart refers only to the group of participants who took the knowledge post-test in no more than 49 minutes and were satisfied with the course content at a level greater than 3.7.

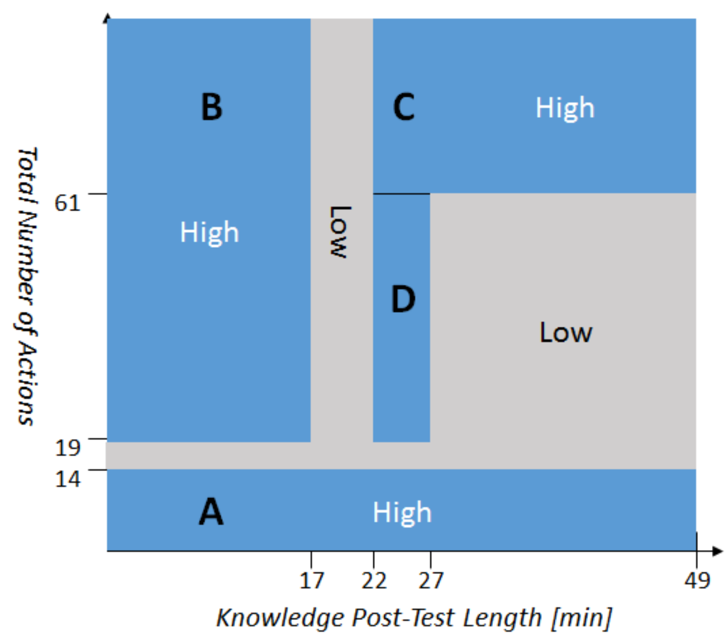

Figure 3. Prediction of *Post-training Employment Readiness* as an interaction between *Knowledge Post-Test Length* and *Total Number of Action*; this chart refers only to the sub-group who took the knowledge post-test in 49 minutes or less and were satisfied with the course content at a level greater than 3.7 (out of 5). The "High" regions are marked with letters (A-D) for ease of reference in the text

From the illustration, we can easily observe the group of participants who took the knowledge post-test in relatively a short time and were active online to some degree (group B). That this group is predicted as “High” in post-training employment readiness is only reasonable. Another easily explained group is D, which gathers participants with both values in the mid-range.

Group C holds participants who took the knowledge post-test in relatively a long time and were relatively highly active online. These might be participants who—despite being relatively slow in the exam—were truly engaged with the course materials, hence eventually feeling ready for the job market.

Group A holds participants with relatively low online activity, and they were predicted to have high post-training employment readiness no matter the length they took the knowledge post-test. This finding is surprising and why it was predicted as “High” is yet to be explored.

Conclusions and Discussion

In this study, we explored relationships between post-training readiness to work with computers and variables of different categories: log-based, computer literacy and experience, job-seeking motivation and practice, and training satisfaction. This was done in the context of unemployed women taking a computer training in order to improve their readiness to work with computers.

Of the many interesting findings reported here, we would now elaborate on a few. First and foremost, the absence of relationships between the independent variable, *Post-training Readiness to Work with Computers*, and all but two of the variables, namely, *Knowledge Post-Test Length* (that is, the duration it took the participants to take the knowledge post-test) and *Satisfaction with Content* (of the training). Of these two, the difference in post-test duration between participants with high and low values of readiness to work with computers is striking. This variable was found prominent while constructing a prediction model of the independent variable with a nice LOOCV kappa of 0.334, a model that was improved—besides by the only other variable that was found associated with the independent variable—with another log-based feature, *Total Number of Actions* (within the course site); the final model shows an impressive LOOCV kappa of 0.524.

The prominence of these rather simple log-based variables in predicting readiness to work with computers is emphasized when recalling that there were no differences between the high/low employment-efficacy groups concerning computer knowledge or experience. This means that the differences in the time it took the participants to finish the post-test might be indicative of something other than knowledge. We hypothesize that the post-test time-on-task depicts some other constructs, either the mere ability to work with computers (as the tests were taken online) or some other personal attributes. This is a possible future direction, motivated by the promises of log-based prediction being efficient and cheap when compared to other alternatives.

A second interesting finding (already mentioned above) is the lack of relationships between *Post-training Readiness to Work with Computers* and the computer literacy and knowledge variables, namely *Knowledge Post-Test Score* and *Computer Post-Use*, which seem counterintuitive. In the context of the current study, the lack of relationships might be a result of the trained content itself; it was shown already that while training in advanced computer tasks (like programming) is indeed related to higher computer self-efficacy, training in simple tasks (like word processing or spreadsheets) have only little effect on computer self-efficacy (Hasan, 2003).

In the training researched in this study, most of the content was indeed related to simple computer tasks, which might explain the lack of relationships to *Post-training Employment-readiness*. Another possible explanation is given in Burger and Blignaut (2004), who had found that both attitudes toward computers decreased after a five-month computer literacy course; the authors suggest that the course might have made the students realize how little they actually knew about computers. A positive change in attitudes toward computers might have occurred were a longer course given. An important implication of this finding relates to the duration of computer literacy programs. In order to be effective, these should be planned based on participants' previous experience and expectations.

Finally, the lack of relationships between the vast majority of the independent variables and the dependent variable make us think of either examining other types of variables or applying more advanced analyses. It might be that second- or higher-order effects have not yet been fully revealed. An example for such effect is the appearance of *Total Number of Actions* in the decision tree model. Important to notice, this study is unique in both population and the purpose of the computer training involved, so contradictory findings to previous findings should be examined with this in mind.

Implications of this study may be thought of in a few levels. Understanding of the factors related to readiness to work with computers is important with regards to numerous populations, mainly those low in employability. As the job-market keeps changing, and as more and more jobs become computer-enriched, computer training for such populations are crucial not only for them, but also for the society at large (Kalef, Barrera, & Heymann, 2014; Ktoridou & Eteokleous-Grigoriou, 2011). Our findings concerning one such program highlight the need of more research for exploring the factors that affect post-training readiness to work with computers, in order to plan similar programs accordingly.

On another level, our findings shed light on the strong associations between log-based variables and measures related to computer self-efficacy. Two of the three features in the final prediction model are log-based. Obviously, the use of log-based variables is far more efficient than any other variable, hence our study suggests this direction as promising in exploring the complexity of constructs related to either computer or employment self-efficacy. Having a further understanding of the role of these variables in predicting self-efficacy may assist in improving its prediction and might lead to the ability to detect critical issues in real-time.

The relationships found between log-based variables and the dependent variable, which measures readiness to work with computers, can be examined through recent trends in learners' assessment. In recent years, it has been suggested – and empirically shown – that other measures rather than post-learning tests are to be considered while evaluating learners' success. Of the suggested measures are log-based variables (e.g., Baker, Hershkovitz, Rossi, Goldstein, & Gowda, 2013; Gobert, Sao Pedro, Raziuddin, & Baker, 2013; Iglesias-Pradas, Ruiz-de-Azcárate, & Agudo-Peregrina, 2014; Ventura & Shute, 2013). Along this line is also a recent study showing the power of measuring engagement with a computer-based learning environment during secondary school in predicting college enrollment (San Pedro, Baker, Heffernan, & Ocumpaugh, 2015). This stream of research might enable a better understanding of adult education and its efficiency and might add on the currently, coarse-grained measures of such programs (cf. Badescu, Garrouste & Loi, 2013).

This study is not without limitations. One limitation is the definition of the dependent variable, namely, readiness to work with computers. This construct is somewhat a combination of readiness to work and attitudes toward computers. As this was the first exploration of the relationships of this construct with log-based variables, we decided to test it as one measure. This decision might not be unjustified, as for many jobs in today's job-market one can barely distinguish between working with computers and working per se. Specifically, this might be the case in the population and training discussed in this study, as the unemployed women who took the training were taught computer skills while being motivated to work – all in the purpose of being prepared to work in a computer-enriched environment. As was previously shown, attitudes toward computers and attitudes toward working with computers might not be significantly different from each other (Jawahar & Elango, 1998). Still, one obvious future direction would be to test this construct for possible different components, like general self-efficacy, computer self-efficacy, and professional self-confidence, maybe even to distinguish between general computer self-efficacy and different software self-efficacy measures (cf. Argawal, Sambamurthy, & Stair, 2000; Beas & Salanova, 2006; G. Torkzadeh & Koufteros, 1994).

Another limitation is the relatively small population size. Conducted as an exploratory phase, N=54 might be considered as a nice population, however for validating our results a larger population is needed. Focusing on more complex log-based features, we plan on keep studying the phenomena discussed here with a larger population and with improved research tools.

References

Acemoglu, D. (2002). Technical change, inequality, and the labor market. *Journal of Economic Literature 40*(1), 7–72.

Argawal, R., Sambamurthy, V., & Stair, R.M. (2000). Research report: The evolving relationship between general and specific computer self-efficacy – An empirical assessment. *Information System Research*, *11*(4), 418-430.

Autor, D., Levy, F., & Murnane, R. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics, 118*(4), 1279–1333.

Badescu, M., Garrouste, C., & Loi, M. (2013). The distribution of adult training among European unemployed: Evidence from recent surveys. *International Journal of Continuing Engineering Education and Life-Long Learning, 5*(2), 103-120.

Baker, R. S. J. d., Hershkovitz, A., Rossi, L. M., Goldstein, A. B., & Gowda, S. M. (2013). Predicting robust learning with the visual form of the moment-by-moment learning curve. *Journal of the Learning Sciences, 22*(4), 639-666.

Beas, M. I., & Salanova, M. (2006). Self-efficacy beliefs, computer training and psychological well-being among information and communication technology workers. *Computers in Human Behavior*, 22(6), 1043-1058.

Brown, L., Johnson, T., O'Connor, D., Khalil, M., Huang, X., Lee, Y., & Lee, M. (2005). Effect of training method on performance and computer-self efficacy. *Proceedings of the Annual Convention of the Association for Educational Communications and Technology (October 18-22, Orlando, FL)*, 69-75.

Burger, A., & Blignaut, P. (2004). A computer literacy course may initially be detrimental to students' attitudes towards computers. *Proceedings of the 2004 annual research conference of the South African institute of computer scientists and information technologists on IT research in developing countries (October 4-6, Stellenbosch, Western Cape, South Africa)*, 10-14.

Cassidi, S., & Echaus, P. (2002). Developing the computer user self-efficacy (CUSE) scale: Investigating the relationship between computer self-efficacy, gender and experience with computers. *Journal of Educational Computing Research*, *26*(2), 133-153.

Colman, L. O., Gibson, P., Cotter, S. R., Howell-Moroney, M., & Stringer, K. (2015). Integrating computing across the curriculum: The impact of internal barriers and training intensity on computer integration in the elementary school classroom. *Journal of Educational Computing Research, 54*(2), 275-294.

Compeau, D. R., & Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and initial test. *MIS Quarterly*, *19*(2), 189-211.

Fancsali, S. E., Bernacki, M. L., Nokes-Malach, T. J., Yudelson, M., & Ritter, S. (2014). Goal orientation, self-efficacy, and "online measures" in intelligent tutoring systems. *The 36th Annual Meeting of the Cognitive Science Society (July 23-26, Quebec City, QC)*.

Fournier, H., Kop, R., & Sitlia, H. (2011). The value of learning analytics to networked learning on a personal learning environment. *Proceedings of the 1st International Conference on Learning Analytics and Knowledge*, 104-109, ACM New York, NY.

Gist, M. E., Schwoerer, C., & Rosen, B. (1989). Effects of alternative training methods on self-efficacy and performance in computer software training. *Journal of Applied Psychology*, *74*(6), 884-891.

Gobert, J. D., Sao Pedro, M., Raziuddin, J., & Baker, R. (2013). From log files to assessment metrics: Measuring students' science inquiry skills using educational data mining. *Journal of the Learning Sciences, 22*(4), 521-563.

Grafsgaard, J. F., Wiggins, J. B., Boyer, K. E., Wiebe, E. N., & Lester, J. C. (2014). Predicting learning and affect from multimodal data streams in task-oriented tutorial dialogue. *The 7th International Conference on Educational Data Mining* (July 4-7, London, UK).

Hasan, B. (2003). The influence of specific computer experiences on computer self-efficacy beliefs. *Computers in Human Behavior*, *19*(4), 443-450.

Hershkovitz, A., Baker, R. S. J. d., Gobert, J., & Nakama, A. (2012). A data-driven path model of student attributes, affect, and engagement in a computer-based science inquiry microworld. *The Tenth International Conference of the Learning Sciences* (July 2-6, Sydney, Australia).

Hershkovitz, A., Baker, R. S. J. d., Gobert, J., Wixon, M., & Sao Pedro, M. (2013). Discovery with models: A case study on carelessness in computer-based science inquiry. *American Behavioral Scientist, 57*(10), 1480-1499.

Hershkovitz, A., & Nachmias, R. (2010). Online persistence in higher education Web-supported courses. *The Internet and Higher Education*, *14*(2), 98-106.

Kim, S. M., & Hwang, J. T. (2013). Technical change, heterogeneity in skill demand, and employment polarization. *Seoul Journal of Economics, 26*(3), 361-381.

Iglesias-Pradas, S., Ruiz-de-Azcárate, C., & Agudo-Peregrina, Á.F. (2014). Assessing the suitability of student interactions from Moodle data logs as predictors of cross-curricular competencies. *Computers in Human Behavior, 47*, 81-89.

Jawahar, I. M., & Elango, B. (1998). Predictors of performance in software training: Attitudes toward computers versus attitudes toward working with computers. *Psychological Report*, *83*(1), 227-233.

Kalef, L., Barrera, M., & Heymann, J. (2014). Developing inclusive employment: Lessons from Telenor Open Mind. *Work: A Journal of Prevention, Assessment and Rehabilitation*, *48*(3), 423-434.

Kher, H. V., Downey, J. P., & Monk, E. (2013). A longitudinal examination of computer self-efficacy change trajectories during training. *Computers in Human Behavior, 29*(4), 1816-1824.

Ktoridou, D., & Eteokleous-Grigoriou, N. (2011). Developing digital immigrants' computer-literacy: The case of unemployed women. *Campus-Wide Information Systems*, *28*(3), 154-163.

Laganá, L., Oliver, T., Ainsworth, A., & Edwards, M. (2011). Enhancing computer self-efficacy and attitudes in multi-ethnic older adults: A randomised controlled study. *Ageing and Society*, *31*(6), 911-933.

Lam, T., Cho, V., & Qu, H. (2007). A study of hotel employee behavioral intentions towards adoption of information technology. *International Journal of Hospitality Management, 26*(1), 49-65.

Lee, C. C., Czarja, S. J., & Sharit, J. (2008). Training older workers for technology-based employment. *Educational Gerontology*, *35*(1), 15-31.

Lin, H. (2000). Fluency with information technology. *Government Information Quarterly, 17*(1), 69-76.

Marakas, G. M., Yi, M. Y., & Johnson, R. D. (1998). The multilevel and multifaceted character of computer self-efficacy: Toward clarification of the construct and an integrative framework for research. *Information System Research*, 9(2), 126-163.

McDonald, D. S. (2004). The influence of multimedia training on users' attitudes: lessons learned. *Computers & Education*, *42*(2004), 195-214.

McQuiggan, S., Mott, B., & Lester, J. (2008). Modeling self-efficacy in intelligent tutoring systems: An inductive approach. *User Modeling and User-Adapted Interaction*, *18*(1-2), 81-123.

Merriam, S. B., Caffarella, R. S., & Baumgartner, L. (2007). *Learning in adulthood: A comprehensive guide* (3rd ed.). San Francisco: Jossey-Bass.

Mierswa, I., Wurst, M., Klinkenberg, R., Scholz, M., and Euler, T. (2006). YALE: Rapid prototyping for complex data mining tasks. *In Proceedings of the 12th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (August 20-23, Philadelphia, PA), 935-940.

Multon, K. D., Brown, S. D., & Lent, R. W. (1991). Relation of self-efficacy beliefs to academic outcomes: A meta-analysis investigation. *Journal of Counseling Psychology*, *38*(1), 30-38.

Nielsen, J. (2006). Participation inequality: Encouraging more users to contribute. *Alertbox*. Retrieved 12 January 2015 from http://www.nngroup.com/articles/participation-inequality

Orpen, C., & Ferguson, C. (1991). The attitudes of accounting students to working with computers: A preliminary study. *Accounting & Finance*, *31*(2), 113-119.

Ouweneel, E., Schaufeli, W. B., & Le Blanc, P. M. (2013). Believe, and you will achieve: Changes over time in self-efficacy, engagement, and performance. *Applied Psychology: Health and Well-being*, *5*(2), 225-247.

Potosky, D. (2002). A field study of computer efficacy beliefs as an outcome of training: The role of computer playfulness, computer knowledge, and performance during training. *Computers in Human Behavior*, *18*(2002), 241-255.

Rex, K., & Roth, R. M. (1998). The relationship of computer experience and computer self-efficacy to performance in introductory computer literacy course. *Journal of Research on Computers in Education*, *31*(1), 14-24.

Saks, A. M. (1995). Longitudinal field investigation of the moderating and mediating effects of self-efficacy on the relationship between training and newcomer adjustment. *Journal of Applied Psychology*, *80*(2), 211-225.

Salanova, M., Grau, R. M., Cifre, E., & Llorens, S. (2000). Computer training, frequency of usage and burnout: The moderating role of computer self-efficacy. *Computers in Human Behavior*, *16*(6), 575-590.

San Pedro, M. O. Z., Baker, E., Heffernan, N., & Ocumpaugh, J. (2015). Exploring college major choice and middle school student behavior, affect and learning: What happens to students who game the system? *Proceedings of the 5th International Learning Analytics and Knowledge Conference*, 36-40.

Srour, I., Taymaz, E., & Vivarelli, M. (2014). *Globalization, technology and skills: Evidence from Turkish longitudinal microdata (No. 1405).* ERC-Economic Research Center, Middle East Technical University.

Topkaya, E. Z. (2010). Pre-service English language teachers' perceptions of computer self-efficacy and general self-efficacy. *Turkish Online Journal of Educational Technology*, *9*(1), 143-156.

Torkzadeh, G., & Koufteros, X. (1994). Factorial validity of computer self-efficacy scale and the impact of computer training. *Educational and Psychological Measurement*, *54*(3), 813-821.

Torkzadeh, G. & Van Dyke, T.P. (2002). Effects of training on Internet self-efficacy and computer user attitudes. *Computers in Human Behavior*, 18(5), 479-494.

Torkzadeh, R, Pflughoeft, K., & Hall, L. (1999). Computer self-efficacy, training effectiveness and user attitudes: An empirical study. *Behaviour & Information Technology*, *18*(4), 299-309.

Ventura, M. & Shute, V. (2013). The validity of a game-based assessment of persistence. *Computers in Human Behavior, 29*(6), 2568-2572.

Voogt, J., & Roblin, N. P. (2012). A comparative analysis of international frameworks for 21st century competences: Implications for national curriculum policies. *Journal of Curriculum Studies, 44*(3), 299-321.

Wu, J.-H., Wang, S.-C., & Lin, L.-M. (2007). Mobile computing acceptance factors in the healthcare industry: A structural equation model. *International Journal of Medical Informatics, 76*(1), 66-77.

Biographies

Dalit Mor is a graduate student at the Department of Mathematics, Science and Technology Education, in the School of Education, Tel Aviv University (Israel); she holds a B.Sc. in Computer Science. She is as a content and pedagogy advisor at Appleseeds Academy, an NGO the main purpose of which is to close the digital divide through the development and implementation of basic and advanced technology programs, vocational trainings, and life skills development.

Hagar Laks is a graduate student at the Department of Mathematics, Science and Technology Education, in the School of Education, Tel Aviv University (Israel); she holds a B.A. and a Teaching Certificate in Special Education. She is an elementary school teacher.

Arnon Hershkovitz is a Senior Lecturer at the Department of Mathematics, Science and Technology Education, in the School of Education, Tel Aviv University (Israel). He holds a Ph.D. in Science Education, an M.A. in Applied Mathematics and a B.A. in Mathematics and Computer Science. His research interests lie at the intersection of education and technology, using various methodologies, including educational data mining and learning analytics. Among his research interests are one-to-one computing in the classroom, learning/teaching processes in the social media era, information credibility assessment, student-teacher relationship, and genealogy as a unique lifelong learning experience in the information age.