Investigation of teacher candidates' 21st century learner skills via PAMS[1]

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Abstract. In this study we aim to examine the latent profiles of Burdur Mehmet Akif Ersoy University teacher candidates' 21st century learner skills. In other words, we intend to discover the profiles of participant groups who hang together in terms of 21st century learner skill scores. The data were gathered from students who enrolled in either undergraduate programs in the school of education or pedagogical formation certificate programs. For data collection purposes, we used the 21st century learner skills usage inventory. In order to achieve our goal, profile analysis via multidimensional scaling approach was employed. Data analysis resulted in two-dimensional solution indicating two major profile patterns. Students whose observed patterns are similar to the first major profile tend to have lower ability in cognitive processing and coding of information and realization of the products. They tend to have higher abilities in self-management, self-control, designing more flexible learning environment, and adaptation of new technology. These students are expected to be better at collaboration-based activities. Students whose observed patterns are similar to the second major profile are expected to be good at self-management, self-control and they are expected to have higher self- and collaborative-learning abilities.

Keywords: Multidimensional scaling, profile analysis, PAMS, the 21st century learner skills

INTRODUCTION

Social and economic developments in the 21st century forces educational institutions to provide their students with new skills and competencies. The needs for these skills and competences resulted from social and economic developments that took place right after the change in industrial mode of production. These new skills and competencies are referred to as 21st century skills and competencies (Ananiadou & Claro, 2009; Van Laar, Van Deursen, Van Dijk, & De Haan, 2017). A careful review of the literature suggests that the framework of the 21st century learner skills are mainly formed by the works of two organizations— The Organization for Economic Co-operation and Development (OECD), and American Association of School Librarians (AASL)— and the pioneering works of Wagner (2008) and Trilling and Fadel (2009). Trilling and Fadel (2009) defined three sets of the 21st century skills that students are required to master in order to deal with the key issues and problems in the 21st century. These problems include but not limited to global awareness, environmental literacy, financial literacy, health literacy, and civic literacy (Trilling & Fadel, 2009).

Trilling and Fadel (2009) grouped the 21st century skills into three main types: (1) Learning and innovation skills, (2) information, media, and technology skills, and (3) life and career skills. These three main types of skills encompass the core subjects and interdisciplinary 21st century themes as it can be seen in Diagram 1 below.

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[1] Earlier version of this study has been presented at V. International Congress on Education and Social Sciences on 27-29 June 2019 in Istanbul, Turkey
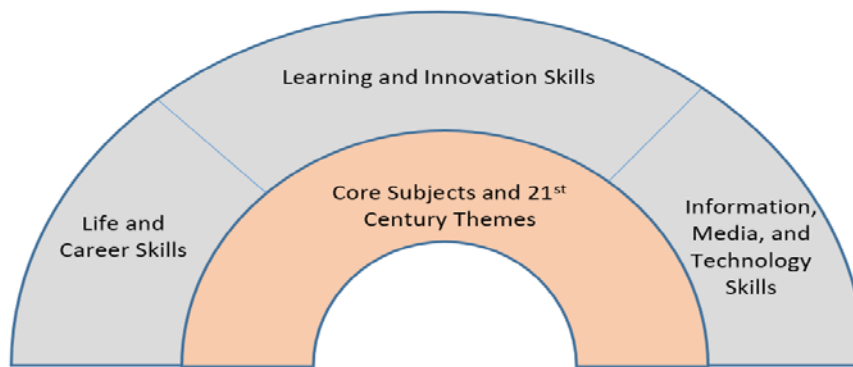
DIAGRAM 1. *The 21st century knowledge-and-skills rainbow. Adapted from the 21st century skills: learning for life in our times (p. 73), by B. Trilling & C. Fadel, 2009, San Francisco, CA: Jossey-Bass*

According to Wrahatnolo (2018);

"*Life and career skills include: (a) having life planning, (b) flexibility and adaptability, (c) initiative and self-management, (d) entrepreneurship, (e) social and cultural interactions, f) productivity and accountability, and (g) leadership, and responsibility. Learning and innovation skills include (a) critical, creative, and innovative thinking, (b) problem solving, (c) communication, (d) collaborative and teamwork, and (e) lifelong learning. Technological and information media skills include (a) information literacy, (b) media literacy and (c) information technology and communication literacy*" (p. 5).

Wagner (2008), on the other side, determined seven survival skills the 21st century learners need to master to succeed in the new world of work. These skills are:

- Critical thinking and problem solving
- Collaboration and leadership
- Agility and adaptability
- Initiative and entrepreneurialism
- Effective oral and written communication
- Accessing and analyzing information
- Curiosity and imagination (Wagner, 2008, p. 67).

The works of Trilling and Fadel (2009) and Wagner's (2008), along with the works of two aforementioned organizations leaded Orhan Göksun (2016) to determine the 21st century learner skills of undergraduate students in Turkey. In her work, Orhan Göksun (2016) grouped Turkish undergraduate students' 21st century learner skills into four categories: (1) cognitive skills, (2) autonomous skills, (3) collaboration and flexibility skills, and (4) innovativeness skills. In Orhan Göksun's work; the cognitive skills refer to cognitive processing and coding of information and realization of the products resulted from cognitive processes. Autonomous skills refer to self-management, self-control, autonomous learning abilities which arise from the convergence of self- and collaborative-study abilities. Furthermore, collaboration and flexibility skills refer to success in collaboration-based activity as well as the ability of making learning environments flexible. Lastly, innovativeness skills refer to adaptation of new technologies (2016).

The first step in the instructional design process is the learner analysis to make sure that instruction is appropriate for the learner. In this step, the focus should be on learner characteristics since teachers must know what his/her students' attributes are. Because learners to which current educational system serves are the 21st century learners, we had to identify their skills to develop curriculum successfully and to implement instructions accordingly (Orhan Göksun, 2016). To identify learners in our educational system and to define their skills may help our instructional designers to develop more effective curriculum and instructions. In this regard, the purpose of the current study is to determine major learner

profiles of teacher candidates at Burdur Mehmet Akif Ersoy University on predetermined 21st century skills.

METHODS

Educational and psychological studies frequently deal with profiles of test scores. These profiles generally indicate participants' performance on a set of test scores on a test battery. Participants' score profiles are used to represent their strengths and weaknesses on given tests. In addition to profiles depicting simple test scores, various exploratory techniques are also used to identify participants' profile patterns given a set of data (Ding, 2001). Among various techniques, in this research, we employed multidimensional scaling approach to uncover major profiles of undergraduate students on 21st century learner skills. Profile Analysis via Multidimensional Scaling (PAMS) is based on a linear latent variable model for test scores (Davison, Kim, & Ding, 2001).

Participants	Measurement Tool				Factor Analysis			
	$Item\ 1$	$Item\ 2$	.....	$Item\ J$	F_1	F_2	.....	F_k
1	X_{11}	X_{12}	.....	X_{1J}	Y_{11}	Y_{12}	.....	Y_{1k}
.....	.....	.....	.....	.....	.....	.....	.....	.....
.....	.....	.....	.....	.....	.....	.....	.....	.....
N	X_{N1}	X_{N2}	.....	X_{NJ}	Y_{N1}	Y_{N2}	.....	Y_{Nk}

			Multidimensional Scaling	
$Factors$	D_1	.....	D_p	
F_1	Z_{11}	.....	Z_{p1}	
.....	.....	.....	.....	
F_k	Z_{1k}	.....	Z_{pk}	

FIGURE 1. *Moving from observed responses to latent profiles.*

Each row in Figure 1 indicates the observed responses (e.g., X_{11}) of participants on a test battery, from which we can obtain sub-scores (e.g., Y_{11}) defined through factor analysis. Using the sub-scores one can cluster participants where each cluster represents a prototypical person or dimension. In general, PAMS describes participants in terms of continuous person profile indices specifying the extent to which they vary around several dimensions (Davison, Kim, & Ding, 2001). For example, Figure 1 depicts a case where N participants has answered J items on a measurement tool that resulted in k sub-scores. Then, each of N participants has a score-profile. These profiles are reduced to p dimensions, each of which represents a prototypical person. First prototypical person's score profile is represented by the scores on the first dimension such that Z_{11}, ..., Z_{1k}. Then, *p* continuous profile indices are assigned to the participants specifying how close they are to each of the prototypical person profiles.

Because we are interested in types of latent person profiles, rather than factors among the variables, we used the PAMS model to obtain major profile patterns in the data. Having said that we do not intent to outline the exploratory multidimensional scaling-based profile analysis approach here. Further discussion on the PAMS model including model and person parameter estimations and interpretation of the parameters can be found in Davison, Kim, and Ding (2001)

and Ding (2001). For our purposes, an R package, namely profile R (Bulut & Desjardins, 2016), was employed to conduct the analysis. All analyses were conducted in R language and environment for statistical computing using version 3.3.3. The R code is provided in the Appendix.

Participants

Total 212 teacher candidates participated the study. 90 participants were gathered from undergraduate programs whereas 122 participants were gathered from pedagogical formation certificate programs in Education Faculty at Burdur Mehmet Akif Ersoy University. Two stage sampling strategy was used to determine the participants. In the first stage, three programs (Computer education & instructional technology, math education, and Turkish education) from undergraduate and three formation certificate field (social science, English education, and physical education) were randomly selected. Then within each program / field, one class was randomly selected and every student in those classes were asked for participation. Since the participation was voluntary based, total 212 participants agreed to participate. All participants are the students of the same Education Faculty since the study aimed to reveal the profiles of teacher candidates that the faculty raises. Distribution of the participants by department is as follows: Math (N=18), physical education (N=75), social science education (N=30), Turkish education (N=36), Computer education & instructional technology (N=36), and English education (N=17). The 48% of the participants is female whereas 52% of the participants is male. The participants' ages varied from 19 to 28 years old.

Measurement tools

For data collection purposes, we employed the 21st Century Learner Skills Usage Inventory, which was developed by Orhan and Kurt (2015). The inventory consisted of four dimensions: cognitive skills, autonomous skills, collaboration & flexibility, and innovativeness skills. The total number of items in the inventory is 31. The inventory, according to Orhan and Kurt (2015) is grounded on the works of American Association of School Librarians (2007), The Organization for Economic Co-operation and Development (2012), Trilling & Fadel (2009), and Wagner (2008). Reported total explained variance and internal consistency coefficient for the measurement tool are %34.75 and .892, respectively (Orhan & Kurt, 2015).

RESULTS

First of all, sub-scores obtained from the measurement instruments were transformed into z-scores to put all scores in the same scale. These scores were plotted in Figure 2 where all four variables normally distributed. The lowest and largest variances are observed in innovativeness skills and cognitive skills scores, respectively.

Based on the known groups (i.e., departments in which participants were enrolled), score profiles (i.e., group means on four sub-scores) were plotted in Figure 3. The 21st century learner skills mean scores of students under the math education department are under the average (i.e., below zero). Scores of the students in physical education indicate that they are about the mean in the first and the fourth factors, whereas, they performed slightly higher than the average in the second and third factors. Social science education students' mean-score profile indicates that they are high on the cognitive and collaboration & flexibility skills, average on innovativeness skills and slightly lower on autonomous skills. Level of cognitive skills of the students enrolled in Turkish language education is above the mean and they are about the mean on the rest of the factors. Mean scores of computer education & instructional technology students indicate that they are about the mean for the first two factors and they are above the mean for the last two factors. Finally, students in English teaching department performed lower on the first and the third factors whereas their scores are on average on the second and the fourth factors.
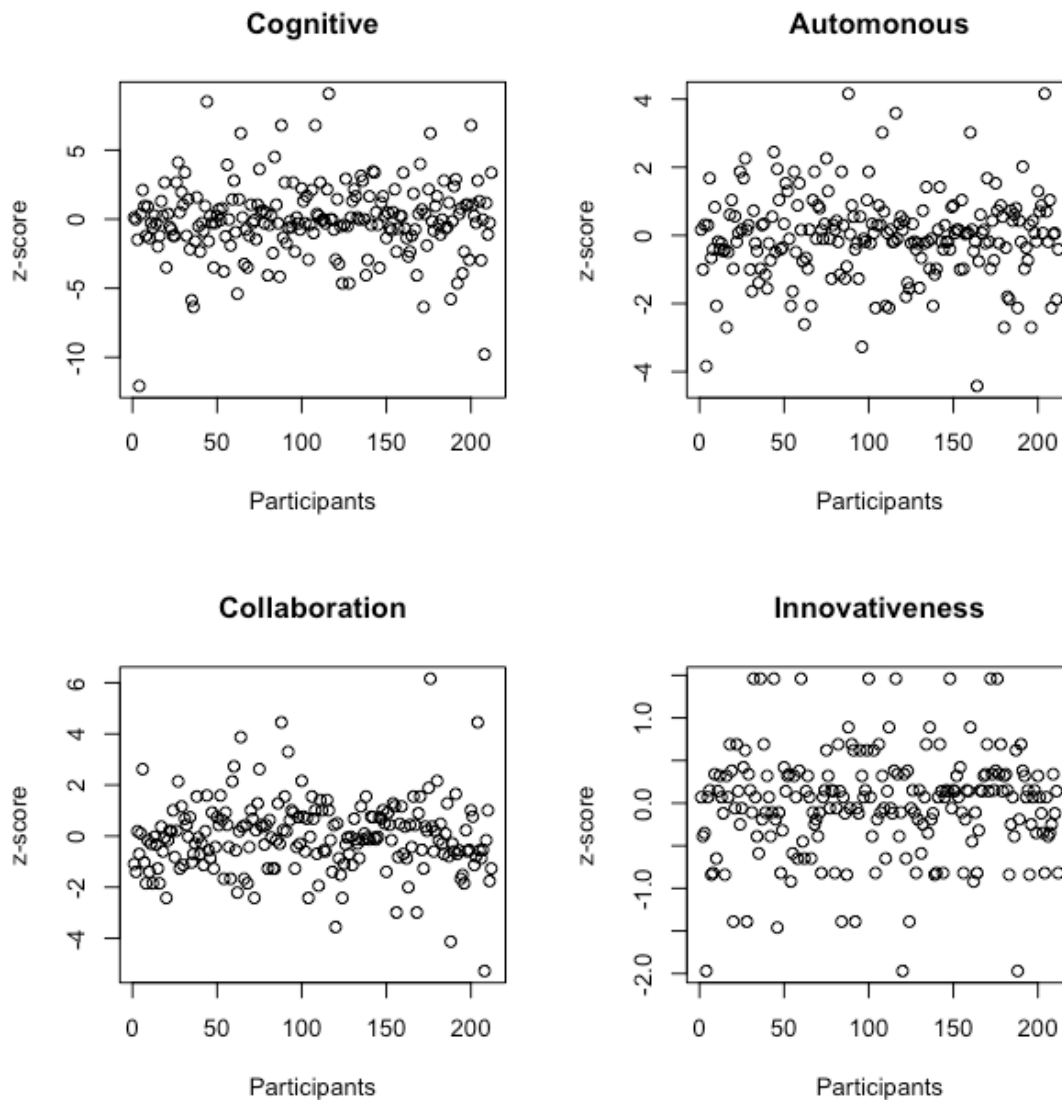
FIGURE 2. *Distribution of z-scores by the sub-scales.*

We can obtain the level parameters by adding z-scores on the four 21st century learner skills and diving by four. In our case, level parameters for the six groups varied between -0.635 and 0.146. Math teaching and English teaching students had the lowest level parameters (i.e., -0.635 and -0.473, respectively). Social students' level parameter was the highest (i.e., 0.146) and the other three groups' level parameters varied around the zero. We can also check the profile dispersions, which is defined as magnitude of deviation of each score from the group's profile level. We can observe that dispersions of social science teaching and English teaching student groups are larger than the rest of the groups. Notice that these profile-scores are just the mean vectors of the scores obtained from four factors by the group. Although these results may be useful in certain situations, in this research, we are more interested in the latent person profiles that are obtained via PAMS.
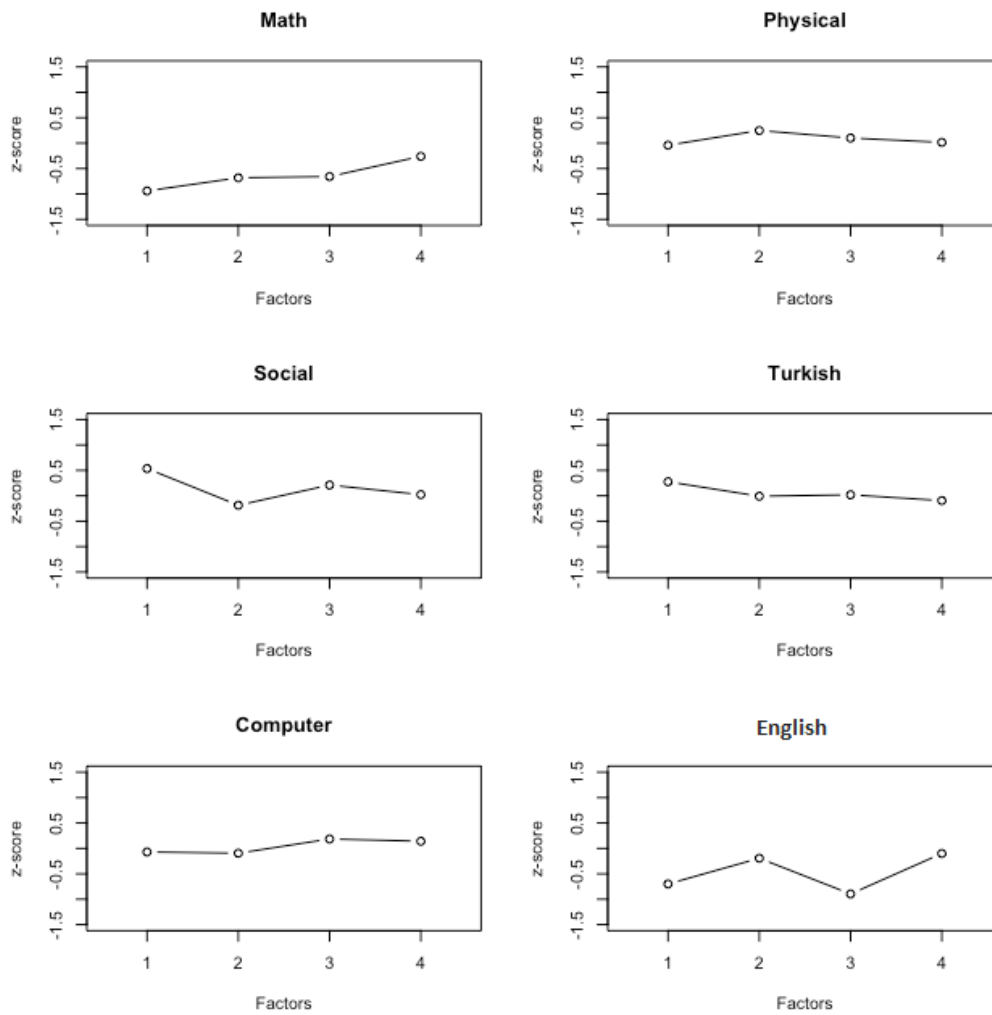
FIGURE 3. *Group sub-score profiles.*

Figure 4 presents the proportion of variance in the participants' observed profiles accounted for by the two multidimensional scaling dimensions. Variations in the observed profile of many participants are accounted for quite well by the model, whereas some observed profiles are not well accounted for. The mean R2 in this data set was .79. In general, data-model fit was considered acceptable as these two dimensions can account for a great deal of the variation in participants' observed profiles.
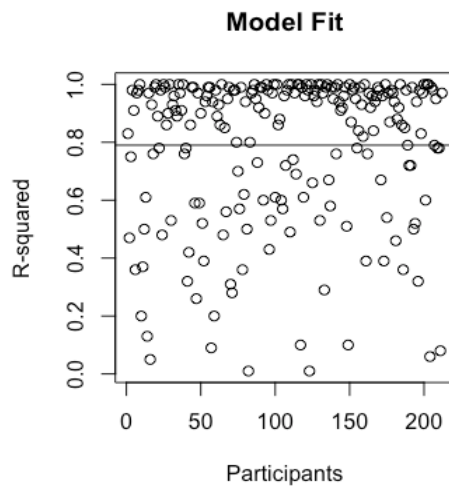
FIGURE 4. *Data-model fit in terms of explained variation.*

Figure 5 displays the two-dimensional MDS solution for the given dataset. In the figure, the 21st century learner skill scale has been plotted along the horizontal axis and dimension scale values have been plotted along the vertical axis. In the first dimension (i.e., profile 1), cognitive skills scale falls at the negative end while the remaining scales, although not as far, fall at the positive end. A participant with this profile will have lower cognitive skill; however, will have higher autonomous skills, collaboration & flexibility skills, and innovativeness skills. Second dimension (i.e., profile 2) has higher scale value on the autonomous skills and lower scale value on collaboration & flexibility skills. Then, participants with this profile will have higher autonomous skills and lower collaboration & flexibility skills. Their cognitive and innovativeness skills will be moderate.
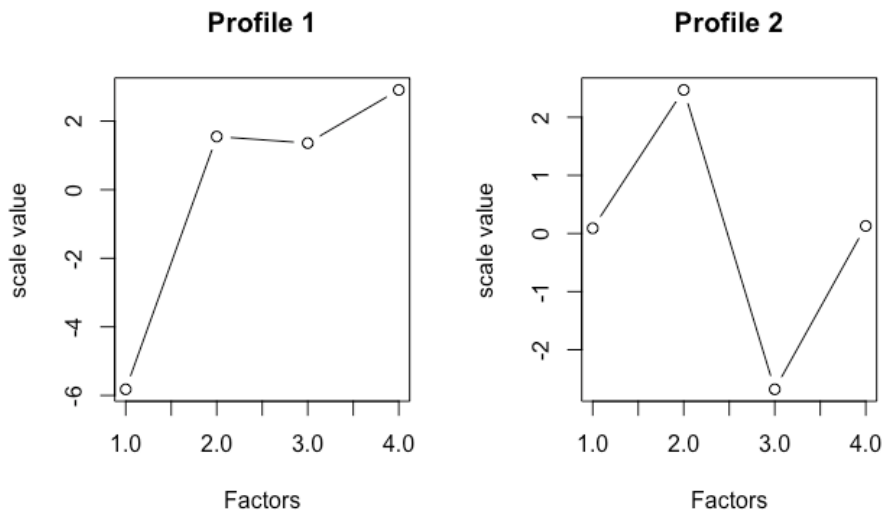
FIGURE 5. *Major profile-patterns.*

Table 1 presents person parameters for six selected participants for demonstration purposes of the interpretation of these parameters. Dimension-1 parameter of first person (i.e., participant 36) is quite high and the second-dimension parameter is low. These two-dimension parameters indicate that this person's profile is similar to the first profile pattern given in Figure 5. Similarly, in case of participant 44, dimension-1 parameter is high but negative and dimension-2 parameter is low. These parameters indicate a trend in the participant's profile that is the mirror image of first profile pattern. Parameters of participants 160 and 180 may be interpreted similarly. Profile patterns of participant 160 and 180 are similar to profile 2 and its mirror image, respectively.

Table 1. *Person parameters for six selected participants*

Participant ID	Weight for Dimension 1	Weight for Dimension 2	Level parameter	R-square
36	0.83	-0.07	-1.64	0.97
44	-0.84	0.21	3.50	0.99
84	-0.62	0.62	0.93	0.97
123	0.00	0.05	-0.76	0.01
160	-0.28	0.73	1.64	0.99
180	-0.21	-0.92	0.36	0.94

Dimension parameters for participant 84 indicate a trend that is mixture of profile 2 and the mirror image of profile 1. By looking at the dimension parameters of the participant 123, we can see that the model does not account for variation in the observed profile patterns of this participant. That is why the R-square for this participant is reported as 0.01. We should also

note here that level parameters specific for the participants are given in the fourth column of the table. Larger level parameters (e.g., participants 44 and 160) indicate more elevated profile than average participant profile, whereas smaller level parameter (e.g., participants 36 and 123) stands for lower skill profile than average skill profile.
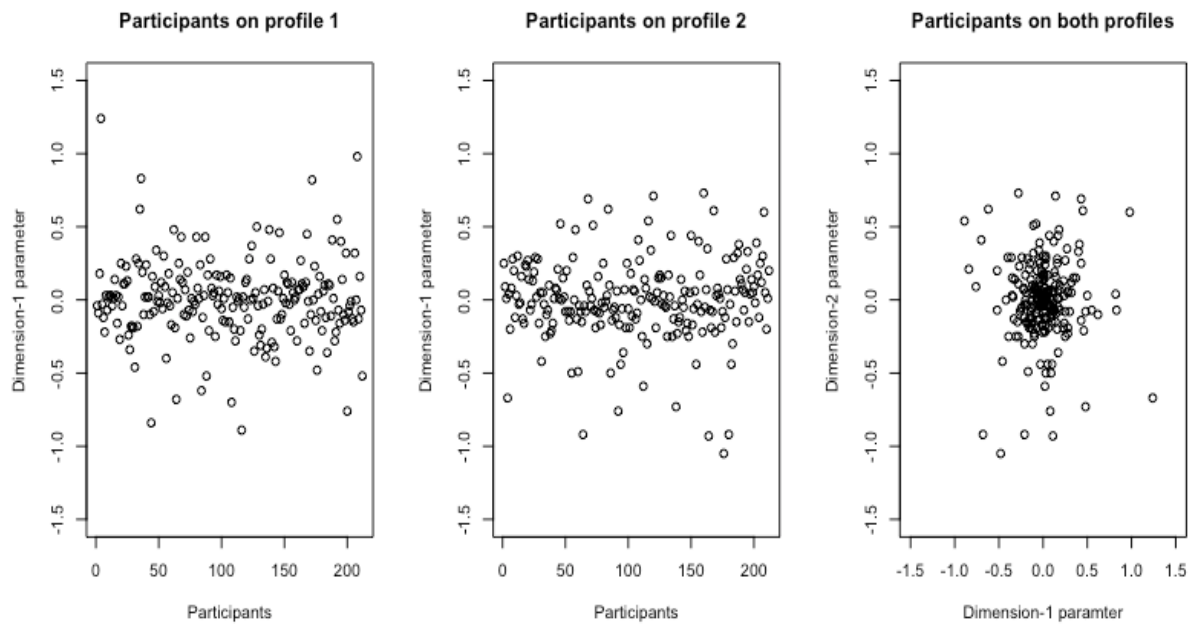
FIGURE 6*. Participants on dimensions.*

Participants' dimension parameters are plotted in Figure 6 where the first two plots indicate person parameters on dimension-1 and -2, respectively. The third plot in the figure displays participants' locations on a two-dimensional space. In general, the figure shows that, regardless of the educational departments that the participants are enrolled, few of the participants tend to follow mainly either profile 1 or profile 2. In other words, many of the participants' observed profiles are mixtures of the two major profiles given in Figure 5.

DISCUSSION and CONCLUSIONS

Orhan Göksun (2016) argued that Turkish undergraduate students in the 21st century need to have the following skills to deal with the current key issues and problems: (1) cognitive skills, (2) autonomous skills, (3) collaboration and flexibility skills, and (4) innovativeness skills. Identifying the degree to which our students have such skills may be informative in design and development process of a more effective curriculum and instructions. In this study, as a case, we aimed to identify the skill profiles of undergraduate-level students in a local school of education.

When we looked at the profile scores of students by the departments that they are enrolled, math teaching and English teaching students had the lowest levels indicating that their 21st century learner skills are the lowest across all six groups. The highest-level parameter was observed for the social science teacher candidates. However, these profile-scores were based on the mean vectors of the scores. Although these results may be useful in some situations, in this study, we were more interested in the latent person profiles that might be obtained via PAMS.

Analysis of the data and the model-data fit indicators confirmed a two-dimensional MDS solution for the given dataset. Two major profiles defined by the two dimensions of the model were emerged. In the first profile, cognitive skills scale falls at the negative end while the remaining scales, although not as far, fall at the positive end. Students demonstrating similar profile patterns to the first major profile have quite lower cognitive skill and scores above average on autonomous skills, collaboration & flexibility skills, and innovativeness skills. These students tend to have lower ability in cognitive processing and coding of information and

realization of the products. However, they tend to have higher abilities in self-management, self-control, designing more flexible learning environment adaptation of new technology. These students are also better at collaboration-based activities.

Second major profile had autonomous skills at the higher end and collaboration & flexibility skills at the lower end. Student tend to have such a profile will be good at self-management, self-control and will have higher self- and collaborative-learning abilities. Furthermore, by plotting the students' person parameters on both dimensions, we have observed that few of the examinees tend to have a profile that is similar to either of the major profiles. In other words, most of the participating students' skill profiles are the mixture of both major profiles. Lastly, some of the students tend to have a profile that is close to the mirror image of either one or both of the major profiles. A student who have a mirror image of a major profile will have higher abilities on the lowest end of the major profile and s/he will have lower abilities on the highest end of the major profile.

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Appendix

```
setwd("~/Desktop/PA")
data1<-as.matrix(read.table("PA.txt",sep="",header = TRUE))
install.packages("profileR")
N<-nrow(data1)
ncol(data1)
TFCLS1<-
      cbind(data1[,3],data1[,4],data1[,6:14],data1[,23],data1[,24],data1[,25],data1[,27],data1[,30],data1[,31])
TFCLS2<-cbind(data1[,5], data1[,19],data1[,20],data1[,28],data1[,32],data1[,33])
TFCLS3<-cbind(data1[,15:18],data1[,26],data1[,29])
TFCLS4<-cbind(data1[,21],data1[,22])
  cognitive<-rowSums(TFCLS1)
  autonomous<-rowSums(TFCLS2)
  collaboration<-rowSums(TFCLS3)
  innovativeness<-rowSums(TFCLS4)
LS<-as.matrix(cbind(cognitive,autonomous,collaboration,innovativeness))
ORT=as.matrix(colSums(LS)/nrow(LS))
a=matrix(1,nrow(LS))
b=a%*%t(ORT)
DIFF=LS-b
STD=sqrt(colSums((DIFF*DIFF)/nrow(LS)))
STDN=round(DIFF/STD, digits=3)par(mfrow=c(2,2))
  plot(STDN[,1], ylab="z-score", xlab="Participants", main = "Cognitive")
  plot(STDN[,2], ylab="z-score", xlab="Participants", main = "Automonous")
  plot(STDN[,3], ylab="z-score", xlab="Participants", main = "Collaboration")
  plot(STDN[,4], ylab="z-score", xlab="Participants", main = "Innovativeness")
model=pams(STDN,2)
profiles=round(model$dimensional.configuration, digits=2)
person=round(model$weights.matrix, digits=2)
mean(person[,4]) # mean R-squared
  par(mfrow=c(1,1))
  plot(person[,4], main = "Model Fit", ylab="R-squared", xlab="Participants")
  abline(a=.79, b=0)
  par(mfrow=c(1,2))
  plot(profiles[,1], type = "b", main = "Profile 1", ylab="z-score", xlab="Factors")
  plot(profiles[,2], type = "b", main = "Profile 2", ylab="z-score", xlab="Factors")
  par(mfrow=c(1,3))
plot(person[,1], type = "p", main = "Participants on profile 1", ylab="Dimension-1 ", xlab="Participants",
      ylim=c(-1.5,1.5))
plot(person[,2], type = "p", main = "Participants on profile 2", ylab="Dimension-1 ", xlab="Participants",
      ylim=c(-1.5,1.5))
plot(person[,1], person[,2], type = "p", main = "Participants on both profiles", ylab="Dimension-2",
      xlab="Dimension-1", xlim=c(-1.5,1.5), ylim=c(-1.5,1.5))
Math<- rbind(STDN[1:17,],STDN[196,])
Physical<- rbind(STDN[18:53,],STDN[65:75,],STDN[80:100,],STDN[116:122,])
Social<- rbind(STDN[54:64,],STDN[76:79,],STDN[101:115,])
Turkish<- rbind(STDN[123:149,],STDN[195,],STDN[197:204,])
Computer<- STDN[150:185,]
ESL<- rbind(STDN[186:194,],STDN[205:212,])
  par(mfrow=c(3,2))
  plot(colMeans(Math), type = "b", main = "Math", ylab="z-score", xlab="Factors", xlim=c(0.5,4.5), ylim=c(-
      1.5,1.5))
  plot(colMeans(Physical), type = "b", main = "Physical", ylab="z-score", xlab="Factors", xlim=c(0.5,4.5),
      ylim=c(-1.5,1.5))
  plot(colMeans(Social), type = "b", main = "Social", ylab="z-score", xlab="Factors", xlim=c(0.5,4.5), ylim=c(-
      1.5,1.5))
  plot(colMeans(Turkish), type = "b", main = "Turkish", ylab="z-score", xlab="Factors", xlim=c(0.5,4.5),
      ylim=c(-1.5,1.5))
  plot(colMeans(Computer), type = "b", main = "Computer", ylab="z-score", xlab="Factors", xlim=c(0.5,4.5),
      ylim=c(-1.5,1.5))
```

```
plot(colMeans(ESL), type = "b", main = "ESL", ylab="z-score", xlab="Factors", xlim=c(0.5,4.5), ylim=c(-1.5,1.5))
# level parameters
sum(as.matrix(colMeans(Math)))/4
sum(as.matrix(colMeans(Physical)))/4
sum(as.matrix(colMeans(Social)))/4
sum(as.matrix(colMeans(Turkish)))/4
sum(as.matrix(colMeans(Computer)))/4
sum(as.matrix(colMeans(ESL)))/4
```