Middle School Teachers' Perceptions of Computer Vision

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Abstract: For decades, the use of computer vision as a component of STEM learning has been encouraged at all levels of education—from K-12 to the university levels. A program was developed to support in-service teachers' development of computer vision. Professional development was provided to middle school teachers while middle school students also attended a summer camp on computer vision. Our research question was: After in-service teachers engaged in artificial intelligence professional development emphasizing computer vision, how did their perceptions of computer vision change? Personal Construct Theory (Kelly, 1955) was used as our methodology. Pairwise comparisons yielded constructs administered in the form of repertory grids. Hierarchical cluster analysis was performed and clusters were identified. Results showed that in-service teachers' perspectives of computer vision changed after engaging in computer vision-based professional development.

Keywords: artificial intelligence, computer vision, middle school teachers, Personal Construct Theory

Introduction

Computer vision is the computerized assessment of images by computers using algorithms to identify objects and reason about those objects. Computer vision has been an integral and growing area of artificial intelligence (AI). There are a plethora of approaches to computer vision that are currently being developed and extended (Chai et al., 2021). Technology in the classroom is important; it offers students the ability to think through challenges and problem solve, but it has not reached its potential in the classroom (Ali et al., 2018; Muir-Herzig, 2004; Wali & Popal, 2020). For decades, the use of computer vision as a component of STEM learning has been encouraged at all levels of education—from K-12 to the university levels (Bebis et al., 2003; Waks, 1990).

The Intervention: Computer Vision Professional Development (PD)

Our intervention consisted of AI PD that emphasized computer vision technologies. Roughly two months before the PD was scheduled to begin, in-service teachers from Title I schools/districts were recruited in the states of Arizona and Georgia. Each location selected six in-service teachers. The subject area of the in-service teachers was not a component of selection; some were in STEM fields but others were from other fields like social science or language arts. The PD in Arizona started in June, 2022, and in Georgia, it started in July 2022.

Methodology

Personal Construct Theory (Kelly, 1955; 1970) was used to explore our research questions. The benefits of this theory include the lack of a predetermined, predefined survey instrument (Ding & Ng, 2008; Green, 2004). There is less researcher bias because constructs come directly from the participants (Boyle, 2005; Tan & Hunter, 2002). While research bias is not eliminated, it is reduced (Hunter & Beck 2000).

Participants compare how elements (or items) are alike and how they are different, and these responses are used to create the instrument. The constructs (or survey questions rated on a Likert scale) come directly from the participants using pairwise comparisons.

Participants

Data were gathered from in-service teachers in the states of Arizona and Georgia. Six participants in each state completed a survey connected to standard data collection procedures for Personal Construct Theory (Kelly, 1955). There were no missing data; all participants completed the pre- and post-repertory grids. IRB approved this study; consent was received from all participants.

Data Collection

Personal Construct Theory (Kelly, 1955) was used to guide our research. First, we defined our element as *computer vision*. Using the element, we elicited constructs by asking two pairwise comparison questions. The questions asked to the in-service teachers in Arizona prior to PD were: (a) How is computer vision similar to human vision?, and (b) How is computer vision different from human vision? Pairwise comparisons yielded 18 constructs that were subsequently used to create the repertory grid. Data from Arizona were used to create the repertory grid for both states because PD took place one month earlier and it was not possible for Georgia participants to complete the pairwise comparisons prior to their PD. We wanted to keep the repertory grid the same for both states, so we did not separately elicit constructs from Arizona and Georgia.

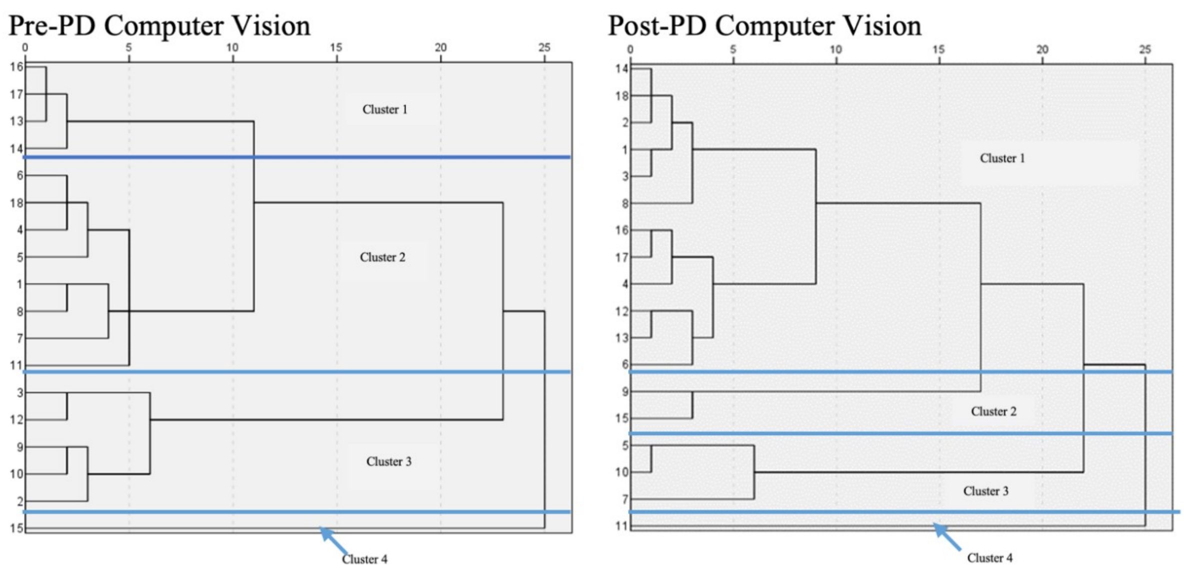
Data Analysis

Descriptive statistics were calculated both pre-PD and post-PD for the element *computer vision*. Descriptive statistics included the minimum, maximum, mean, standard deviation and cluster membership. After the data were entered into SPSS, we performed hierarchical cluster analysis using Ward's Method (1963) and squared Euclidean distances.

Findings

The computer vision pre-PD and post-PD dendrograms can be seen in Figure 1. Within the pre-PD dendrogram, there were four clusters that contained between one to eight constructs. Within the post-PD dendrogram, there were four clusters that contained between one to twelve constructs. Yim and Ramdeen (2015) describe how to interpret the clusters, noting, "the longest horizontal lines represent the largest differences…[and if] the vertical and horizontal lines are close to one another, then this would suggest that the level of homogeneity of the clusters merged at those stages is relatively stable" (p. 16). Visually, there was a difference in clusters and confirmation that Cluster 1 became more detailed and contained more constructs after PD.

Figure 1: *Computer Vision Dendrograms*



The means and standard deviations, along with cluster membership shifts can be seen in Table 1. Cluster 1 had the highest mean and the lowest standard deviation out of all the clusters, both pre-PD and post-PD. A high mean indicates that the participants thought of the cluster as very descriptive of computer vision. The means for all clusters increased post-PD. The pre-PD and post-PD descriptive statistics and cluster membership for computer vision can be seen in Table 2.

Table 1: *Computer Vision Pre- and Post-PD Dendrogram Cluster Membership*

Cluster	Pre-PD Constructs	*M*	*SD*	Post PD Constructs	*M*	*SD*
Cluster 1	13, 14, 16, 17	4.50	.705	1, 2, 3, 4, 6, 8, 12, 13, 14, 16, 17, 18	4.79	.418
Cluster 2	1, 4, 5, 6, 7, 8, 11, 18	4.18	.735	9, 15	4.54	.787
Cluster 3	2, 3, 9, 10, 12	3.95	.779	5, 7, 10	4.53	0.723
Cluster 4	15	3.50	1.000	11	4.50	1.168

Table 2: *Descriptive Statistics for Computer Vision*

		Pre-PD					Post-PD				
	Computer vision can be described as…	Min	Max	*M*	*SD*	CM*	Min	Max	*M*	*SD*	CM*
1.	Able to classify objects and store them in memory	3	5	4.25	.754	2	4	5	4.83	.389	1
2.	Able to detect objects	3	5	4.17	.718	3	4	5	4.92	.289	1
3.	Able to recognize unique features	3	5	3.75	.754	3	4	5	4.83	.389	1
4.	Coordinating with other systems to translate light into images	3	5	4.33	.651	2	4	5	4.75	.452	1
5.	Detecting light patterns	3	5	4.17	.718	2	3	5	4.67	.651	3
6.	Fast and efficient	3	5	4.17	.835	2	4	5	4.58	.515	1
7.	Having clear vision	3	5	4.00	.853	2	2	5	4.25	.866	3
8.	Having the ability to identify, distinguish and classify objects	3	5	4.25	.622	2	4	5	4.75	.452	1
9.	Having the ability to take in their surroundings based on what is physically there	2	5	3.92	.900	3	3	5	4.58	.669	2
10.	Identify objects in its field of vision	2	5	4.00	.853	3	3	5	4.67	.651	3
11.	Identify things that are similar	3	5	3.92	.669	2	1	5	4.50	1.168	4
12.	Interpreting what is shown	3	5	3.92	.669	3	4	5	4.67	.492	1
13.	Programmable	3	5	4.50	.674	1	4	5	4.75	.452	1
14.	Seeing in pixels	3	5	4.50	.798	1	4	5	4.92	.289	1
15.	Sensing the surroundings	1	5	3.50	1.000	4	2	5	4.50	.905	2
16.	Using algorithms	3	5	4.50	.674	1	3	5	4.75	.622	1
17.	Using data	3	5	4.50	.674	1	4	5	4.83	.389	1
18.	Using machine learning techniques	3	5	4.33	.778	2	4	5	4.92	.289	1

*Cluster Membership (CM)

Discussion

After in-service teachers participated in PD that provided training on computer vision, as well as an opportunity to teach a self-developed lesson to middle school students, their perceptions of computer vision changed. The perceptions of computer vision were richer, more developed, and resulted in a more defined understanding of computer vision. The changes in perceptions of computer vision were likely a result of very limited experience with AI or computer vision in the context of education. While AI and computer vision have become the norm in society, teachers may be unaware of the interactions with the technology (Norton, 2022).

In relation to teacher education and computer vision, research sometimes focuses on how computer vision can be used to support teachers' learning of concepts. For example, computer vision algorithms were used with teachers to support intelligent e-learning (Xu & Jin, 2005). This is different than the education our in-service teachers experienced. Computer vision was not used to educate our teachers on some topic; rather, computer vision was the topic of education and was used to teach concepts of artificial intelligence. The change in perspective is likely a result of the intentional use of computer vision as the topic of PD.

Conclusion

Computer vision is expanding due to computer capacity and improved developments. There are emerging techniques that use computer vision including recognition, visual tracking, semantic segmentation, and image restoration (Chai et al., 2021). No doubt, there will be continued advancements in the field of computer vision. In order to stay competitive, it is imperative that a workforce is produced that explores computer vision technologies. Where does the workforce development start? We argue that starting to educate learners in the field of computer vision at the undergraduate level is too late. Exposing learners earlier in their educational careers to computer vision opportunities may pique their interest and motivate them to pursue future studies.

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