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Investigating Changes in Teachers' Perceptions about Artificial Intelligence after Virtual Professional Development

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Artificial intelligence is impacting society on a very large scale and should be included in K-12 educational content in some capacity to provide meaningful STEM experiences. Computer vision (a field of research that heavily leverages artificial intelligence) was emphasized in professional development for in-service teachers. The teachers received two to three weeks of training across two states (Arizona and Georgia) that emphasized image processing, computer vision, and machine learning using visual media. Personal Construct Theory (Kelly, 1955) was used to map changes in thinking using hierarchical cluster analysis. The research question was: How did in-service teachers' thinking regarding artificial intelligence change after partaking in remote professional development emphasizing computer vision? Dendrograms and descriptive statistics showed changes in thinking for in-service teachers in relation to artificial intelligence. There were four clusters in both the pre- and post-professional development dendrograms, but constructs shifted within clusters. Implications for practice and research are discussed.

Artificial intelligence (AI) is rapidly becoming a household name due to its ubiquitous nature in our cars and our smart devices. We utilize AI in various domains including matching algorithms for dating apps, mortgage lending, web search, and even emerging applications for healthcare and diagnosis. It is critical that students learn about AI technology as it will undoubtedly shape their lives and careers in the future. Educational engagement in AI is easier said than done. While the field of AI continues to grow (Lucci et al., 2022), there are not enough opportunities for teachers and their students to learn through and from AI in educational experiences. There are relatively few research studies that have explored the use of AI with teachers or students, although this field of research has been growing in recent years.

AI integrates knowledge from disciplines ranging from computer science, engineering, and even cognitive neuroscience and psychology, which is well outside the traditional domains taught at the K-12 levels. Further, teachers have little to no direct experience with AI topics in their training, which is the central challenge of incorporating AI into the classroom effectively. Educational initiatives that incorporate AI into the K-12 curriculum are fairly recent. The AI4K12 (AI4K12, n.d.) organization has curated resources including lesson plans and materials for teachers, five "big ideas" in AI to focus curriculum around, and guidelines for teaching AI in public schools. Zimmerman (2018) outlines lesson ideas for AI, and ties the material to design thinking and project-based learning for Science, Technology, Engineering and Mathematics (STEM). However, there is still a need for research for this emerging area.

Our ImageSTEAM program was developed to improve AI experiences for teachers and students at the middle school level. Our program consists of a series of workshops that are offered to in-service teachers while simultaneously being offered to middle school students during the summer. Computer vision was the main theme for learning modules that targeted AI critical skills. The ImageSTEAM project caters to the professional development and learning needs of middle school teachers and students (grades 6-8) from traditionally underserved populations in STEM and AI topics. Alongside researchers in engineering and education; participating teachers co-create technology-infused teaching and learning materials that optimize learning outcomes and foster enduring interests in STEM knowledge and career paths.

These workshops were held at two United States research universities: Arizona State University and University of Georgia. Collaborative research teams from these institutions partnered with their respective local schools and enrolled teachers into the proposed project activities where they developed their knowledge of (i) ImageSTEAM material surrounding computer vision and visual media, and (ii) integrated machine learning and AI with core mathematics/science content necessary to understand these topics; and (iii) adopted educational theory based on STEM and the arts integration to encourage broader participation within learning environments.

For this research, we provided in-service middle school teachers and middle school students with AI experiences that focused on computer vision. Computer vision is a separate domain of research focusing on how computers extract and understand information from images and video, and AI is used extensively throughout computer vision applications. Providing participants with computer vision experiences also provides exposure to AI underlying these technologies. However, it should be noted that AI can be broader than just computer vision with applications to natural language processing, audio processing, and other domains which are not covered in the program.

Middle school teachers in a plethora of fields (e.g. English, science, mathematics, STEM) participated in two to three weeks of professional development. Middle school students participated in one week of a summer camp. Our research focused on the in-service middle school teachers and our research question was the following: What changes in thinking regarding AI occur with in-service middle school teachers after engagement in two to three weeks of professional development in computer vision? The research question was answered using Personal Construct Theory (Kelly, 1955). Participants completed data collection through construct elicitation using pairwise comparisons, completing a repertory grid using a five-point Likert scale. Then, data were entered into SPSS and hierarchical clusters analysis occurred, resulting in dendrograms.

REVIEW OF THE LITERATURE

AI can be seen and experienced in many facets of society and will be a continued part of STEM development in the upcoming decades. AI has been used in medicine and healthcare (Hamet & Tremblay, 2017; Racine et al., 2019), business and marketing (Babina et al. forthcoming; Verma et al., 2021), and a plethora of other fields (Marr, 2019; Pannu, 2015). The use of AI will continue to impact humans' interactions with technology and society as a whole (Aghion et al., 2018; Lockey et al., 2021; Rahwan & Simari, 2009). With this growth comes a responsibility to offer meaningful activities and lessons to teachers and students so that they can better understand how technology is changing and how curricular activities can support students STEM opportunities emphasizing AI. Researchers and scholars encourage the further development of AI lessons across grade levels to better prepare students for a society infused with AI (Ali et al., 2019; Kandlhofer et al., 2016; Williams et al., 2022).

The topic of AI continues expanding and influencing curricular opportunities, as it is a foundational area of growth in relation to digital technologies (Chassignol et al., 2018; Chikobava & Romeike, 2021; Haseski, 2019). AI has been used fruitfully with elementary teachers leading to improvements of practical knowledge and motivation (Pu et al., 2021). Sanusi et al. (2022) examined AI education in Nigeria with secondary school students (n = 605). They recommended competencies for AI education including: knowledge, team competence, and learning competence. They recommended that AI curriculum include collaboration as a key goal. In a study across eight countries, Yue et al. (2021) examined how AI curriculum is identified and developed. They found that rationale, scope and aims influence AI curriculum at national levels. Zafari et al. (2022) examined AI research through an extensive analysis of publications, AI curriculum continues to grow and advance in relation to students, teachers and institutions across a plethora of countries. There is continued growth in AI across many domains, including K-12 education (Zafari et al., 2022)

While a nascent field, there has been a growing body of literature on the teaching of AI in the K-12 levels. Teacher professional development workshops have been conducted to integrate AI concepts into STEM classes for high school students (Lee & Perret, 2022). For computer science teachers, a technological pedagogical content knowledge (TPACK) framework was introduced by Sun and colleagues (2022) for professional training. Extending beyond STEM classes, Lin and Van Brummelen (2021) conducted teacher professional development workshops where teachers co-designed curriculum that were integrated into English and social studies classes at the middle school level. In particular, AI ethics and literacy have been championed for middle school students with the introduction of MIT's DAILy curriculum (Lee et al., 2021). In addition to teacher professional development, holistic curriculum design for AI education was outlined by Chiu (2021) to contain the four aspects of content, produce, process, and praxis. While most studies focus on middle and high school education, there also has been recent work on elementary school education where AI literacy is advocated through problem-based learning and interactions with basic programming and robotics (Su & Zhong, 2022).

METHODOLOGY

This research explored the impact of computer vision on in-service teachers' thinking in regards to AI after participating in a two to three weeks of professional development entitled ImageSTEAM. The ImageSTEAM program is a set of professional development workshops for middle school teachers to prepare them to introduce topics surrounding computer vision and AI into their classrooms. Similar workshops that have been conducted for the middle school students showed that such experiences can support students' engagement and conceptual learning of AI, shifting attitudes toward AI, and fostering conceptions of future selves as AI-enabled workers (Lee et al., 2021). In-service teachers co-created curriculum with research experts, and tested this new curriculum with middle school students in online classroom settings during the workshop. Technological experiences included using several websites such as Pixlr, Google Colaboratory, and NVIDIA's GauGAN software that is readily accessible to illustrate several computer vision concepts.

Sample Lesson

One lesson for example was the *Predicting Hurricanes with AI and ML* lesson. In this lesson, students built their own machine learning model to predict flood damaged areas due to hurricanes using satellite imagery. Students utilized a real dataset of 10,000 satellite images from after Hurricane Harvey impacted Texas. This lesson used Google's Teachable Machine to train a neural network to perform identification of whether an image had flood damage or not, uploading the real-world image dataset to the website.

Students found this lesson quite compelling in our workshop, and some students took it as a personal challenge to train all 10,000 images into their machines (which took a significant amount of computational time). The Next Generation Science Standards these lessons aligned with were: MS-ESS3-2: Analyze and interpret data on natural hazards to forecast future catastrophic events and inform the development of technologies to mitigate their effects; and MS-ETS1-3: Analyze data from tests to determine similarities and differences among several design solutions to identify the best characteristics of each that can be combined into new solutions to better meet the criteria for success (National Research Council, 2013).

Participants

Data were gathered from in-service teachers in both states that primarily taught in Title I schools or districts. There were 12 participants total; six in Arizona and six in Georgia. Of those participants, eight completed all survey instruments connected to Personal Construct Theory (Kelly, 1955) data collection procedures. Participants in Arizona participated in construct elicitation through pairwise comparisons. Because of the timeframe of professional development, it was not possible for Georgia participants to complete pairwise comparisons at the same time as the Arizona participants. Data from Arizona were used to create the repertory grid for both states. They completed both the pre-professional development repertory grid and the post-professional development repertory grid. All grids were force complete, so there were no missing data that had to be addressed in our analysis. The reduction in participants (starting with 12 participants and ending with eight participants) was a result of the in- service teachers not starting or completing the data surveys. IRB approval was received and all participants consented to participate in the study.

Data Collection

Data were collected and evaluated following Personal Construct Theory techniques (Beail, 1985; Kelly, 1955) across various elements. In this research, our element was defined as *AI lessons*; more specifically, we phrased our prompt *Artificial intelligence lessons have features that…* The constructs were elicited using pairwise comparisons from only the Arizona participants because their professional development training took place about one month before Georgia's sessions. We wanted the constructs to be the same across both states, so additional constructs were not elicited from the Georgia participants to maintain consistency across the repertory grids.

Arizona participants were asked to answer pairwise prompts in order to elicit the constructs. They were asked questions including: (i) How is computer vision like human vision? How are they different? (ii) How is artificial intelligence like human intelligence? How are they different? And (iii) How are computational cameras like traditional cameras? How are they different? Using the participants' responses to these questions, constructs were identified. The repertory grid was created with exchanges and discussions from two research faculty members. Once a consensus was reached for the constructs, the repertory grid was created and administered. All constructs that were identified by the researchers and used in the repertory grids can be found in Table 1. Constructs were used to create a repertory grid and rated using a five-point Likert scale: (1) strongly disagree; (2) somewhat disagree; (3) unsure/no opinion; (4) somewhat agree; (5) strongly agree.

Data Analysis

The descriptive statistics for each of the constructs (n = 17) were calculated both pre-professional development and post-professional development. Descriptive statistics included the minimum, maximum, mean, standard deviation and cluster membership. The participants completed repertory grids and their data were entered into SPSS. Hierarchal cluster analysis was used to create dendrograms using Ward's Method (1963) for both the pre-professional development and post-professional development repertory grid results. The dendrograms were then interpreted. The number of clusters was determined by visually evaluating the dendrograms for the number of clusters based on the Euclidean distances.

RESULTS

The results showed that the in-service teachers showed some changes in thinking in relation to their perceptions of AI. More importantly, the dendrograms showed shifts in constructs across the clusters. There were four clusters in both the pre- and post-professional development dendrograms. However, there were construct shifts within those clusters.

Pre- and post-professional development descriptive statistics for constructs (n = 17) can be found in Table 1. For the pre-professional development, five constructs had the highest mean of 4.62, including constructs 7, 8, 12, 15 and 16; the construct with the lowest mean of 3.00 was construct 2. The pre-professional development dendrogram can be seen in Figure 1. There were four clusters that contained between three to seven constructs. For the post-professional development, two constructs had the highest mean of 4.88, including constructs 5 and 7; the construct with the lowest mean of 3.13 remained construct 2. The post-professional development dendrogram can be seen in Figure 2. There were four clusters that contained between one to elev-en constructs. To interpret the clusters, "the longest horizontal lines represent the largest differences…[and] 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" (Yim & Ramdeen, 2015, p. 16).

Table 1

Pre-Professional Development Construct Descriptive Statistics

	Construct	Pre-Professional Development						Post-Professional Development				
	Artificial intelligence lessons have features that…	*n*	Min.	Max.	Mean	Std. Dev.	CM*	Min.	Max.	Mean	Std. Dev.	CM*
Q3_1	Acquire knowledge through experience in the form of past data	8	2	5	3.87	.835	4	3	5	4.38	.744	2
Q3_2	Are biased	8	2	4	3.00	.756	4	2	4	3.13	.835	4
Q3_3	Can adapt and learn just like a human can	8	2	4	3.50	.756	3	4	5	4.13	.354	3
Q3_4	Can be integrated into science and mathemat-ics	8	4	5	4.38	.518	1	4	5	4.50	.535	1
Q3_5	Can be used to enrich the lives of students	8	4	5	4.50	.535	1	4	5	4.88	.354	1
Q3_6	Can be used to person-alize a student's learning experience	8	4	5	4.25	.463	2	4	5	4.62	.518	1
Q3_7	Connect to real world issues	8	4	5	4.62	.518	1	4	5	4.88	.354	1
Q3_8	Emphasize problem solving	8	4	5	4.62	.518	1	4	5	4.75	.463	1
Q3_9	Empower students to learn via experiments	8	3	5	4.25	.707	2	4	5	4.63	.518	1
Q3_10	Encourage collaboration among schools and others	8	4	5	4.38	.518	2	4	5	4.63	.518	1
Q3_11	Encourage students to develop their creative and intellectual potential	8	4	5	4.25	.463	2	4	5	4.63	.518	1

	Construct		Pre-Professional Development					Post-Professional Development				
	Artificial intelligence lessons have features that…	n	Min.	Max.	Mean	Std. Dev.	CM*	Min.	Max.	Mean	Std. Dev.	CM*
Q3_12	Engage students	8	4	5	4.62	.518	1	4	5	4.75	.463	1
Q3_13	Identify errors that are analyzed and corrected	8	3	4	3.75	.463	3	3	5	4.13	.641	3
Q3_14	Include gray areas with lots of subjective opinions	8	3	5	4.00	.756	2	2	5	4.00	1.069	3
Q3_15	Incorporate computer use/computer programming	8	4	5	4.62	.518	1	4	5	4.75	.463	1
Q3_16	Involve critical thinking	8	4	5	4.62	.518	1	4	5	4.75	.463	1
Q3_17	Will only do what a programmer tells it to do	8	2	4	3.13	.641	4	3	5	4.25	.707	2

*Cluster Membership (CM)

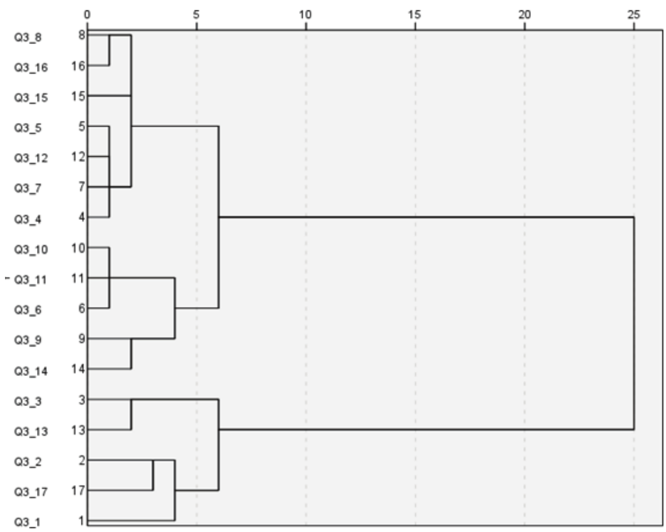

Figure 1. Pre-Professional Development Dendrogram.

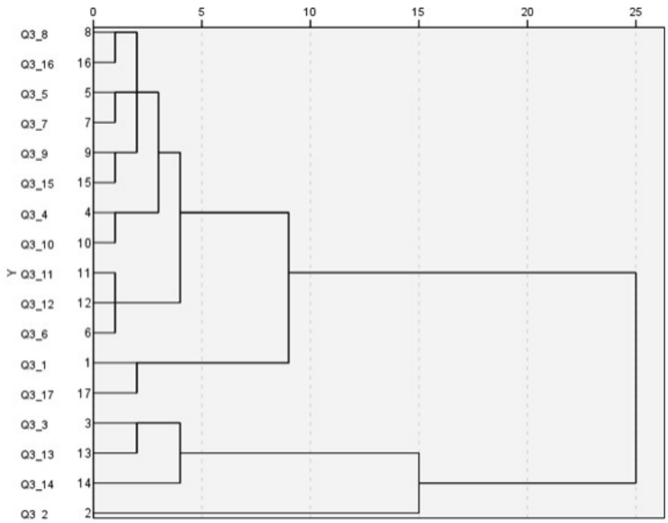

Figure 2. Post-Professional Development Dendrogram.

PRE- TO POST-PROFESSIONAL DEVELOPMENT CHANGES

The pre- and post-professional development dendrograms both had four different clusters. The cluster means increased across three of the four clusters. Standard deviations increased in three of the four clusters, indicating more instability in the cluster means. The differences in cluster constructs, means and standard deviations can be seen in Table 2. There were some changes in constructs within the clusters. While Cluster 1 was the cluster with the highest mean among the four clusters both pre- and post-professional development, there were changes amongst the constructs. There were several constructs that migrated into Cluster 1, making it larger in the post-professional development compared to the pre-professional development. If constructs are contained in the same cluster, they can be thought of as simi-lar according to the participants' perspectives. (Tan & Hunter, 2002).

Table 2
Pre- and Post-Professional Development Dendrogram Cluster Findings

	Pre-Professional Development Constructs	*M*	*SD*	Post-Professional Development Constructs	*M*	*SD*
Cluster 1	Q3_4, Q3_5, Q3_7, Q3_8, Q3_12, Q3_15, Q3_16	4.57	.520	Q3_4, Q3_5, Q3_6, Q3_7, Q3_8, Q3_9, Q3_10, Q3_11,	4.71	.470
Cluster 2	Q3_6, Q3_9, Q3_10, Q3_11	4.23	.581	Q3_12Q3_15, Q3_16, Q3_1, Q3_17	4.32	.726
Cluster 3	Q3_14, Q3_3, Q3_13	3.63	.610	Q3_3, Q3_13, Q3_14	4.09	.688
Cluster 4	Q3_1, Q3_2, Q3_17	3.33	.744	Q3_2	3.13	.835

DISCUSSION

Our research set out to discover what changes in thinking regarding AI occurred with in-service middle school teachers after engaging in two to three weeks of professional development focusing on computer vision, a research and application area which leverages AI heavily in its methods. Through the use of Personal Construct Theory (Kelly, 1955), we found primarily more positive perspectives of AI. Most of the constructs (n = 16) showed improvements from the pre- to post-professional development and no constructs decreased. The shifting of constructs showed that there were changes in thinking that occurred after the professional development experiences.

Our results showed that there were changes in thinking in relation to cluster membership. Cluster membership movement helps to map changes in perspective (Liu & Graham, 2019). When a construct changes from one cluster to another, it simply means that there were changes in perspective regarding that construct. To show changes in thinking pre- and post-professional development dendrograms would need to be different; dendrograms would change. The change in constructs among clusters help show how the participants' think about and interpret AI lessons at the middle school lev-el. In relation to the changes in the dendrograms, the participants' cluster means all rose, and most of the standard deviations became smaller. This indicates more agreement with the constructs within the clusters describing AI lessons. In other words, they more strongly agreed with the constructs contained within each of the clusters.

IMPLICATIONS FOR PRACTICE

The broader implications of this research can positively benefit both the ImageSTEAM program as well as future teacher professional development in the field of AI. It is clear that teachers experienced a positive shift in their attitudes and competencies surrounding AI. More technology-based workshops can potentially lower the barrier for middle school teachers to incorporate the material into their classrooms. However, there are still challenges including alignment with state-standards and how AI instruction can be made equitable particularly for schools and populations that are underprivileged and do not have adequate resources. Yet it is crucial for the leaders, scholars and educators in the twenty-first century to prioritize AI education in primary and secondary schools to maintain our technological edge in the global world in the future.

Our results also highlight the need to emphasize bias in AI education and instruction. AI technologies exhibit bias issues such as low performance on minority groups in the data and the ability to replicate harmful and discriminatory content from data sources (Mehrabi et al., 2021). These issues lead to increased inequality between majority and minority groups, and reinforces existing social division in our algorithmic systems. The in-service teachers in our study maintained a low mean of around 3 (unsure/no opinion about AI bias) from the pre- and post- professional development scores. We would hope that AI bias issues would be recognized by the participants and recommend that professional development emphasize potential for bias in regards to AI.

Finally, we recommend longer professional development experiences for teachers if possible. While we offered professional development experiences for teachers across multiple years, for this research study, we gathered data from one summer. While we did see positive results, we do recommend more professional development in AI because of the multitude of possible experiences in this growing field. We were just able to touch the surface of teaching AI in the middle school classrooms. The participants had very limited AI academic backgrounds at the start of the professional development.

IMPLICATIONS FOR RESEARCH

AI is going to expand and grow, impacting society on a greater scale as time passes (Aghion et al., 2018; Lockey et al., 2021; Rahwan & Simari, 2009). AI experiences for teachers and students are encouraged (Haseski, 2019; Pu et al., 2021; Xia & Zheng, 2020). In order to improve the emphasis on AI, we recommend further AI research, with a particular emphasis on how AI can impact (a) pre- and in-service teachers and (b) K-12 students.

In relation to pre- and in-service teachers, we recommend using AI as a context for STEM lessons while researching the impact with particular focus on efficacy and awareness of STEM practices. For example, many pre- and in-service teachers may feel obligated or required to follow standards and principles provided by school districts (Polikoff, 2021). They may not feel able to introduce STEM unless it is contextualized within a required content area (i.e. science or mathematics). We recommend studying the impact of AI curricular technologies on mathematics-based or science-based K-12 lessons in relation to teachers' knowledge about integrated STEM learning. Furthermore, we recommend that teachers' efficacy and motivation be researched to find out what kinds of AI experiences have a positive impact.

In relation to K-12 students, we recommend expanding AI opportunities through classroom experiences and after school or summer supplementary opportunities, and researching their impact on students. With such limited studies in the field of AI with K-12 students, there are lots of opportunities to contribute to our understanding of the impact of AI curriculum. For example, Chiu (2021) provided a holistic approach to use AI in the K-12 classroom. Chiu's design and approach can be researched to explore the impact of AI lessons on children's thinking, learning, motivation and efficacy. The "big ideas" not only need to be implemented, but need to be researched to show if they can positively impact K-12 students (Michaeli et al., 2022; Touretzky, & Gardner- McCune, 2021).

LIMITATIONS

Ideally, our professional development was designed for face-to-face instruction but due to the pandemic, all professional development and interactions with students occurred in a virtual format. Because of this format, it is likely that there were limitations in learning and interactions with the curriculum.

Another limitation of our study was that the data were gathered across two states with some differing curriculum to meet the diverse needs of the participants. While the curriculum was co-developed with researchers in both states, there was flexibility regarding adjustments to meet the in-service teachers' and students' needs. In addition, in-service teachers participated in two to three weeks of professional development with some differences in time commitment across participants in different states.

Finally, our sample size was relatively small (n = 8) and 33% of our original participants (four out of the original 12) did not complete all of the surveys. A higher completion rate was desired. In addition, we would ideally want to elicit constructs from all participants when creating our repertory grid. However, this was not possible with a one month break between the professional development across the two states. Therefore, constructs only represented the perceptions from Arizona.

CONCLUSION

AI is a growing field in the 21st century (Lucci et al., 2022). The workforce global need for contributors in AI will continue to grow in the upcoming decades (Bughin et al., 2018). In order to meet the national and international workforce needs in AI, it is imperative that a concerted effort be made to prioritize AI education.

Waiting until learners enter college to receive AI instruction may be too late. To address AI needs, experiences in AI should occur as early as possible. Teacher professional development opportunities need to consider not only teachers' and their students' needs, but also societal needs and workforce development considerations. Our research showed that ImageSTEAM yielded improvements in in-service teachers thinking about features of AI lessons. More opportunities on a larger scale should continue to be fostered for teachers and their students. To be competitive, future AI opportunities should be created and offered at both national and international levels to provide meaningful opportunities in this growing field that will continue to impact technology for future generations through the education of teachers.

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