Neural Syntonicity: A Constructionist Approach to the Development of Image Recognition Tools Used to Teach Students about Powerful Ideas in Artificial Intelligence

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***Abstract*—Although Artificial Intelligence (AI) is already being used in a variety of ways to support creativity and education, there are still limitations when it comes to understanding how AI becomes intelligent, its impacts and how to manipulate, tinker with and explore future uses. This work builds on the idea of "syntonicity" as a cognitive tool where learners benefit from their existing understanding of intelligence while learning about AI. This work presents a learning framework called "Neural Syntonicity" which describes the syntonic relationship between the student's thoughts and reflections while learning how to use and train AI Image Recognition tools. In this project we: 1) developed a series of Machine Learning Image Recognition software tools that students can manipulate and tinker with, 2) developed a "microworld" of activities and learning materials that supports a conducive learning environment for students to learn about Image Recognition, and 3) developed scenarios that allow students to explore their own cognitive labels of visual Image Recognition while using these tools. The research also aims to help students uncover "Powerful Ideas" and learn technical knowledge in Artificial Intelligence like: prediction, data clustering, accuracy, data bias, training and societal impacts. Using a mixed methods approach of Design Based Research, we conducted studies with three different groups of students. Through the analysis, we found that all groups of students gained confidence with using AI, and learned new technical skills in AI. Students were also able to demonstrate through a variety of examples that bias is a factor that can be controlled in AI systems as well as in the human mind.**

***Index Terms*—Artificial intelligence, constructionism, image recognition, machine learning, neural networks, syntonic learning**

I. Introduction

The aim of this research is to discover the relationship between how students learn about Artificial Intelligence (AI) and how they can relate and reflect that information to how their own mind perceives, labels and uses data. For this research, we chose to specifically work with AI Image Recognition tools that are built using a common Machine Learning algorithm [1] focusing on image data. We introduced students to the basics of AI Image Recognition and then designed experiences where students could discover for themselves the limitations of Image Recognition and how data bias affects accuracy [2]. While learning about the technical aspects of AI and data bias, we also developed scenarios in which students could discuss and elaborate on what they had learned, or how the concepts learned related to other areas of AI such as Text Recognition. Through the products of this research, we show how the participating students gained a basic technical understanding of how AI Image Recognition works, learned about how data bias affects the accuracy of AI, and in-turn students learned how the human mind is affected by the same factors.

Machine Learning, a subset of Artificial Intelligence (AI), pertains to neural networks that are trained to recognize patterns based on training data. Unlike traditional programming methods where patterns are defined by human programmers, in Machine Learning, the computer learns and discerns its own patterns through exposure to significant amounts of data using set of rules that are designed to mimic human biological neural networks. Image Recognition is a branch of Machine Learning that specifically deals with image and video data. Image Recognition has a wide spanning application including; medical imagery, facial detection, video analysis, computer vision, pose detection, object tracking, and more [3]. Because of the wide spanning reach of Image Recognition, it is used in many commonly available products and services that people and students are already using. There are also a variety of open source neural network models that engineers, data scientists and programmers can use to build new Image Recognition models and design new ways to explore how to label and classify image data [4].

As early as the late 1970's constructionist education researchers have been developing theories, models and software to explore ways students can learn about and with AI [5]. One main focus of research during that time was to develop microworlds where students could solve problems using AI software which would provide context for solving real world problems, thus laying the foundation for this research and others. In modern times, several researchers have established a variety of software tools, learning resources and curricular resources that have contributed to continued research efforts [6]. Some researchers have focused their attention on how to design AI learning experiences for diverse populations [7]. Others have specifically looked at how to design AI learning materials that focus on ethics [8, 9]. Other education-focused researchers have noted that students tend to attribute a high level of human intelligence to AI agents (tools), AI chatbots and AI assistants, but often lean towards slight skepticism after learning how to use them [10]. In one research study, researchers prompted students to interact with an "AI smart-home assistant" by asking a series of questions that increased in difficulty. Students became

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more aware of the limitations of the smart-home assistant as the answers became less reliable [11]. Similarly, our research goal is to start with a basic AI tool and allow students to discover for themselves how intelligent an AI can be and what might cause it to act more or less intelligently.

II. Background

A. Constructionist Foundations

Our design is based heavily on a Constructionist approach [12] where research suggests that learning is most effective when students are active in making meaningful objects and artifacts and are able to draw their own conclusions through experimentation across multiple media, thus constructing new relationships with knowledge in the process. Three specific elements of Constructionist research were implemented: Syntonic Learning, Powerful Ideas and Microworlds.

B. Syntonic Learning and Neural Syntonicity

Syntonicity was first described by Seymour Papert in his study of how children learn to program computers with the Logo programming language. Papert coined the term "body syntonicity" to describe how a child relates themselves and their physical body to a programming object on the screen [13]. In Logo, students would program an on-screen turtle to move and would relate those movements to how their own bodies could move in space. Syntonic Learning is described as engaging one's body and senses, with the goal to develop a level of self-knowledge through a process of interacting with an agent or learning object [14]. Other researchers have concluded that syntonicity can be observed in a variety of contexts such as ego syntonicity [15], cultural syntonicity [16] and spatial syntonicity [17]. In this project, the term "Neural Syntonicity" is used to describe the relationship between the student's own learning process, formed in a biological neural network that leads to their ability to predict labels of image data and the AI neural network training process that leads to its ability to predict labels of images. While this research focuses on only the Image Classification domain of AI, other domains of AI such as speech recognition could present similar forms of syntonicity.

C. Powerful Ideas

In Constructionism, the term "Powerful Ideas" is used to describe ideas that come from one particular domain that can be applied to other domains. Powerful Ideas are formed through personal cognitive and metacognitive reflection about the idea and the relationships made between the interconnected domains [12]. For example, the idea of "sensors" might first be taught to a student in relation to the five human senses, but then when a student studies electronic sensors in the field of robotics, they will be able to relate the domain knowledge back to the human body. As the student gains more experience with "sensors" the greater the impact the Powerful Idea will have.

In this project we have identified several Powerful Ideas that stem from the field of Artificial Intelligence, that also have further implications in other domains such as: prediction, data clustering, accuracy, data bias, and training. For this research, we focused on the powerful idea of "data bias" and defined three different types of data bias. The learning materials designed for this project were created in such a way as to elicit an understanding of these Powerful Ideas through personal experience instead of teaching students directly. For example, to learn about the data bias of quantity, we invited students to test an image recognition model with five items of data and compare the accuracy to a model that has ten and twenty items of training data. Through personal experience, students found out the need to have a large number of items for a training set.

D. Microworlds

Another Constructionist term popularized by Seymour Papert; Microworlds, are interactive environments that provide learners with a suitable context to delve into specific subjects. An apt illustration of this notion is Papert's assertion that the optimal way to acquire fluency in the French language is through firsthand experience in France, surrounded by native French speakers [18]. In this project, we have developed a Microworld of learning experiences that immerse the learner into a world of using and exploring a variety of AI Image Recognition tools.

III. Software Tools and Activities Developed

Following the previously outlined Constructionist approaches, we developed a series of software tools, activities and scenarios that were designed for students to explore how AI Image Recognition works. The purpose of the activities was to provide basic technical knowledge of how the software works, but also to demonstrate how three different types of data bias affect the accuracy of AI Image Recognition tools and how those same types of data bias might apply to our own human understanding of prediction [19]. We have defined the three different types of data bias as: 1) quantity of data, 2) clarity of data, and 3) diversity of data. A change in any of the three data biases will have an effect on the ability and accuracy of the AI model.

A. Image Recognition Software

We designed five unique but related Machine Learning software tools: 1) a simple web-cam image classifier, 2) an image upload classifier that allows custom training sets of saved images, 3) a web-cam classifier that allows custom training sets from web-cam capture, 4) a web-cam classifier that allows users to adjust accuracy variables, and 5) a web-cam classifier that outputs user generated sounds. All of the Image Recognition tools were designed using the open source Mobilenet neural network [20] using a simple K-nearest Neighbor (KNN) algorithm that is hosted on a platform that stores the necessary HTML, CSS and JavaScript files for access by a web browser. A KNN is a supervised machine learning algorithm that can be used for classification by examining data that is clustered by similarities or neighbors. A KNN model works by finding the relation distances between a query and all the examples in the training data, then votes for the most frequent label based on the K-value (number if items in chosen cluster). Each of the software tools are described further below:

1) Simple web-cam image classifier

Using "mobilenet," a commonly used pre-trained neural network as a base, this web-application prompts students to hold up random objects to their webcam to see what "labels" the pre-trained network will show. This introductory tool is intended to provide a first common experience with Image Recognition and allow students to explore the capabilities and limitations of Image Recognition tools. The interface of the tool provides an accuracy reading from 0% to 100%. For example, if a student holds up a cup, the interface might say "The AI labeled this a coffee mug with a confidence of 68%" (Fig. 1).

Fig. 1. Web-cam image classifier user experience.

2) Image upload classifier

Using "mobilenet" again, and the KNN algorithm, the image upload classifier tool will allow students to upload their own images in up to 3 different classes as a custom training set. After the model has applied the KNN algorithm to any newly supplied image, it will produce a confidence level, indicating similarity between the new image and the original training set. Students can use this tool to tinker with different types, qualities and amounts of image data to see the accuracy result.

3) Web-cam classifier

Using the same methodology as the image upload classifier tool, this web-cam classifier provides the same experience, with the addition of live data inputs from a webcam, providing a more immediate feedback. This allows more room for potential errors in image-background problems commonly associated with web-cam classification, thus giving students an opportunity to debug problems and see directly how some forms of data bias are difficult to account for.

4) Adjustable accuracy web-cam classifier

Expanding on the methods and interface of the web-cam Classifier, this adjustable accuracy web-cam classifier tool allows students to adjust the "k-value" of the KNN algorithm, manipulating the accuracy of the overall performance of the tool. This tool allows students to "break open" the black box of most Machine Learning tools and actually adjust parameters to see the effect. This tool provides opportunities to tinker, play and learn from mistakes while learning how K-clustering affects the results of the tool's accuracy.

5) Web-cam Classifier that Outputs User Generated Sounds

Like the Web-cam Classifier, this tool can be trained on three different classes. Once the training data has been selected and trained, the software triggers a recorded sound upon a correct classification. This tool was designed to show that once the Image Recognition tool has made a prediction, a trigger can cause another action to take place (output), whereas the other tools only display the accuracy. This tool a slows students to record their own sounds and tinker with creative ways to make music or come up with their own ways to combine Image Recognition and sound recordings.

B. Teacher Led Activities

To accompany each of the software tools, we created a series of learning resources and slideshow presentations to share necessary information, background knowledge, examples and discussion points that led the learning process that also provided structure for the overall progression of learning. These resources and slides provided the materials and contexts to support a "Microworld" of learning about and using AI in natural ways. We created five sections of learning resources to go along with the five software tools. Each of the activities are described further below:

1) Introduction to AI

The information presented in the introductory slides provided context, background information and a foundation for understanding the general field of AI. Students were asked to share what they already know about AI and what they thought about AI. Students also learned about the main elements of an AI: sensors, processing and output.

2) How does AI see?

To help students understand the technical aspects of how AI sees an image, students were shown illustrations of basic neural networks with inputs and outputs as well as how a single image is broken down into a pixel matrix of values that a computer can understand, since it cannot be seen in the way that we see with our own eyes. Students learned that images must be converted into data that the AI can understand.

3) Data bias

After having some experience and understanding of Image Recognition, students then learned about three different types of data bias: 1) quantity of data, 2) clarity of data, and 3) diversity of data. Students were asked to think about how humans obtain training data and if and how any of those same biases have affected human perception and prediction of visual data (Fig. 2).

Fig. 2. Example of teacher led activities.

4) Accuracy

With some experience in understanding how bias affects the results of Image Recognition, we then provided a deeper understanding of the algorithm that defines the accuracy. Using illustrations, the learning materials that we developed describe the function of the KNN algorithm and how data clustering works using graph plots on an X/Y axis.

5) Fun with AI

As a capstone to the experience, we provide students with examples of how AI is currently being used in the entertainment industry, especially to aid in music and performance arts. Students learned about how AI can produce a desired output after the recognition, when a trigger is programmed.

C. Scenarios for Syntonic Learning

To help students connect between the technical learning and the applications of Image Recognition, we developed discussion topics and scenarios to see how students might self-reflect on how their own minds store and retrieve visual data, how the data could be corrupted by bias and how different data sets can affect the different types of data bias. For example, after students participated in several experiences using the Image Recognition tools, we showed the students examples of word clusters from the book "Cat in the Hat" to see if they could predict words that might belong or not belong to the original data set of words from the book. In another scenario, we asked students to imagine creative ways to help a blind person to describe and label images. These scenarios were designed to present an opportunity for students to discuss what they have learned and apply their knowledge to similar situations that require creative thinking and self-identification, which is the main factor in any type of syntonic learning [21]. These scenarios provided an opportunity for students to examine and compare information that they learned about AI and image recognition to what they know about themselves.

IV. Methodology

This qualitative Design Based Research [22] was conducted with students from three different schools in order to evaluate the effectiveness of the research tools and to better understand how constructionist approaches to learning lead towards a personal understanding of concepts as opposed to traditional instructional methods. The choice to collect qualitative data in this research was made so that researchers could focus on identifying indicators of cognitive understanding, using the Design Based Research Methods. Future research on the topic will provide additional quantitative data. The study employed a mixed-methods approach, utilizing surveys and focus group discussions to gather data from the students. The research tools included interactive AI software, online videos, and written materials. Students who participated in the research were asked to provide feedback on their experience using these tools and their perceptions of the effectiveness in improving their understanding of AI concepts by verbally answering questions in whole group and small group discussions.

The software tools and teaching resources were developed during the Summer and Fall of 2021 at the height of the COVID-19 pandemic, so design considerations were shifted so that all of the research materials could be used and taught virtually, following the practices of Design Based Research [22]. From Dec of 2021 to June 2022, we tested the software tools and learning resources at 3 different International Schools.

The research interventions were advertised at the schools as an "Artificial Intelligence after-school enrichment program" lasting five days. Each day contained one hour of learning, though students were given open access to the software tools which they could use any time during and after the enrichment program. Using a video conferencing program, we met with each group of students to conduct the research. For each of the groups, three randomly selected students were invited to participate in two additional focus group discussions lasting about thirty minutes each. The focus group discussions provided time for students to ask questions and for us to ask research questions that would help us better understand the syntonic aspects of what students learned. In total there were nine students that participated in the focus group discussions (see Table I for more participant data).

To prepare for best practices in teaching in virtual environments, we followed suggestions from a variety of research sources about optimal duration and engagement strategies, such as providing time for student-to-student conversation and keeping teacher-led lectures to less than ten minutes [23]. All focus group discussions were recorded and saved for further analysis and coding. Using a process called grounded coding, we reviewed the recordings to carefully listen for patterns and themes that emerged from key vocabulary, identifiers of knowledge and relational understanding of AI [24].

All students who participated in the research took a pre-test and post-test of general and technical knowledge of AI related concepts to measure growth of technical knowledge. The test consisted of ten questions relating to AI key terms and vocabulary. While our main research focus was concerned with constructionist approaches to learning, we were also interested to see if any technical knowledge was gained. An additional final survey was given to collect feedback and allowed for students to write short form answers.

TABLE I: Participant Data

School Name	Location	Grade Level	Number of Students
School A	Philippines	Grade 7–8	9
School B	Thailand	Grade 6	10
School C	Thailand	Grade 5	18
Total number of students			**37**
Total number of students interviewed			**9**

V. Results and Discussion

Based on the data collected from this research there are three main findings (explored further below). The findings emerged from observational data, survey data, data from the coded analysis of recorded videos and from comparing our findings to other research in similar and analogous areas.

A. Relational Understanding and Syntonicity

During the tasks, when we asked if students could correct a possible data bias in their minds as opposed to correcting data bias in an Image Recognition training set, the student responses were mixed, while some students saw that their minds contained fixed knowledge others saw that their minds could be changed with new data. One example question that we provided to research the relational understanding was: “If we can reduce the data bias of a training set of apples and bananas by providing, clear, diverse and ample images, how could a person reduce a human bias like ageism (discrimination against people because of negative and inaccurate stereotypes of their age)? Through our discussion, we observed that students could understand how bias affects both the human mind and AI Image Recognition tools, though some students weren’t confident that human bias could be easily changed. We consider this to be evidence that students understood that there are Powerful Ideas in AI but there is room for further research to determine the factors that help students see how knowledge is affected by both learned/stored data as well as new data.

Powerful Ideas are concepts that go beyond specific domains and have connections to other areas of knowledge [25]. Through our observations, we found indications that students were developing an understanding of Powerful Ideas related to AI, such as prediction, bias, and training. This was evident from their ability in utilizing the Image Recognition software and their discussions about it.

When asked if they could think of creative ways to use Image Recognition after experiencing the interventions, students proposed ideas such as an “animal species classifier”, a “body height to width ratio calculator”, a “motion detecting security system” and other creative inventions using AI Image Recognition with respect to how those inventions would be affected by data bias. When listening to the students explain their ideas, we asked them to elaborate on how they would specifically address the three types of data bias and noted key words and phrases that demonstrate their understanding. For example, the students who developed the idea of the “body height to width ratio calculator” said that people who use the tool “would get their feelings hurt if the data reported incorrectly” and to keep that from happening, the tool would need “thousands of diverse images for the training process”. Other students reported similar confirmations and understanding of bias in their explanations that seemed reasonably comparable to their peers.

To better understand how the students interpreted what bias is and how it affects data, we let them tinker with six different pre trained data sets that were intentionally biased by at least one of the three types of data bias (created by the researchers) and asked students if they could identify any concerns with the data sets. While students examined the data sets in small groups of 2–3, we recorded and listened for evidence of verbal understanding and keywords to determine if students displayed and understanding of Powerful Ideas or evidence of Syntonicity. The top phrases sorted by frequency were “there isn’t enough clear data here”, “all of the pictures are low resolution”, “these pictures are all the same” and “there isn’t enough diversity”. Based on the phrases heard and the keywords expressed by students, we could observe that students understood how the three types of data bias) affect sets of training images. See Table II for an analysis of the phrases. The table shows an accumulated report for all 37 students that participated. We counted the frequency of phrases heard that demonstrated an understanding of bias for each group of 2-3 students.

TABLE II: RELEVANCE BETWEEN STUDENTS RESPONSE AND THE THREE TYPES OF DATA BIAS

Data Bias Phrases -grouped by themes found in the responses related to the three types of data bias	**Frequency**	**Discussion**
Theme 1—related to Quantity of Data “There isn’t enough data here” “Why are there so few images?” “This wouldn’t be enough information”	**9**	Students remarked that some data sets would not be useful because they didn’t have enough data.
Theme 2—related to Clarity of Data “All of the pictures are low resolution.” “Some of the pictures are blurry.” “I can’t even tell what this image is”	**7**	Students identified that several data sets contained images that were of poor quality or were difficult to see clearly.
Theme 3—Related to Diversity of Data “These pictures are all the same.” “There isn’t enough diversity.” “Too many of these are repeated”	**7**	Students identified that some data sets contained too many repeats, without enough examples.

In one of the Scenarios for Syntonic Learning activities (discussed in Section III.C), we asked students to imagine that a person had lost all their memory and had to re-learn the names of items that they saw. In the scenario, we said it would be the student’s job to help this person learn the names of items with regard to how the three types of data bias would affect the results. Students then brainstormed methods and procedures in small groups.

In another scenario, students were able to make connections between how text data (words from the book “Cat in the Hat”—Section III.C) and image data are both stored and used similarly in our own minds and that predictions are based on prior understandings, similar to how an AI makes predictions based on training data. When students analyzed a word bank of words that combined words from the “Cat in the Hat” book with other random words, students were able to verbally describe for example why the word “*extracurricular*” would not be found in the text of the book, but words like “cup and fish”, were more likely to be words from the book. These observations lead us to understand that Powerful Ideas learned about Image Recognition correlate to Text Recognition as well, giving further evidence to the notion that Powerful Ideas, like prediction and training transcend more than one domain.

In the focus group discussions, when asked how there might be similarities between how our own minds are similar to AI, all students were able to describe varying ways in which there are similarities. For example, one student said that much of our formal and informal “education is like training data for our minds” so that we “can predict words, images and patterns in life similar to how an AI system recognizes patterns and makes predictions”. Students also demonstrated through verbal discussion that human training data is fallible to bias in the same ways that AI systems are fallible to data bias. For example, some students stated that "AI makes mistakes just like we do". Eight out of nine of the students who participated in the focus group discussion were able to articulate and describe in their own words about similarities between how AI uses and perceives training data compared to how human minds use and perceive training data. One student said, "without training data, we wouldn't know what anything is… learning to read the alphabet is like training data for reading". Another student said that "AI is like a baby that knows nothing, we have to provide the data". We understood these discussions as showing a correlation to the idea that syntonicity between the student's own faculties of Image Recognition and the AI Image Recognition process is present, observable and identifiable.

Other researchers have identified similar forms of syntonicity by observing how students relate their mind or body to new modalities. For example, one researcher describes a form of syntonicity that students experienced when weaving textiles to concepts in computational thinking and reasoning [26]. Seymour Papert describes body syntonicity by suggesting that learning emerges as students reflect on their experience of being a person in a body moving in the world and imagining their own bodies in place of or in relation to the object they are manipulating like a programmable object on a computer screen [27]. Through our research, we have observed a similar form of syntonicity emerging between the students' conceptual understanding of how AI "sees" and how humans see, giving confidence to the idea that there is a syntonic relationship between how humans and AI both learn through training data and are both corruptible to data bias.

B. Performance on AI Image Recognition Tasks to Reduce Bias

After the students examined how bias originates in the training data, we then gave students opportunities to design training data that would potentially contain less bias. Through this process, students began to realize how much human control is involved in organizing training data. For example, we asked students to design a training set of images for the Image Upload Classifier tool (discussed in Section III-A-2) that could identify apples and bananas with a greater than 80% accuracy. Students tinkered with training sets of fewer images and then with more images to see the result. Then they experimented with images that had greater diversity and finally they tinkered with data sets that were noisy and clear (noisy: relating to backgrounds and noise in the image). Once students had experience with how different types of bias affect the AI, we asked them to design a new (training) data set for any two items of their choice. Students used their laptop webcams to collect training data for the items and worked in teams to discuss best ways to collect training data that was potentially free of bias. We observed that through trial and error, students realized that they needed to take photos in an environment with less noise, like with a whiteboard behind the images. Students tinkered with different ways to take photos, such as using a box as a background, or aiming the camera at a clean wall space in order to keep the image data clean and free of bias.

Based on our coded analysis of the focus group discussions, students seemed to have a better understanding of how AI works in general after performing all of the tasks related to the Image Recognition Software as opposed to self-identifying as having little understanding of how Image Recognition works before the performance tasks. All students who participated in the focus group discussions could verbally describe how AI Image Recognition works with technical vocabulary and could verbally explain how data bias affects Image Recognition training sets.

Table III shown the themes of knowledge and understanding that emerged from the coding process that we used to analyze the student discussions. Through the coding process, we identified two major themes in what students discussed.

TABLE III: ANALYSIS OF FOCUS GROUP DISCUSSIONS

Themes	**Ability to describe how bias affects AI**	**Knowledge of key AI ideas and understanding**
Indicators	Students can reiterate what bias is in their own words.	Students can explain concepts to other students.
	Students can describe other forms of bias, such as psychological bias.	Students can articulate areas that are uncertain by asking questions.
	Students can describe in their own words the negative effects of bias in training data.	Students can perform the tasks with little guidance intervention or instruction

C. Confidence and Knowledge of How AI Works

Scores on the post-test of technical knowledge showed somewhat of an increase, where students, on average, answered 6/10 questions correctly on the pre-test and on average correctly answered 8/10 questions on the post-test. These were mostly vocabulary-based questions where students were tested on the correct definition of terms like algorithm, k-value, training data, neural network, etc. After completion of the activities, on a final survey, 92% of students reported having a greater understanding of how AI Image Recognition works. 84% of students identified that they could easily explain how AI Image Recognition works to peers or parents. In a final survey, 80% of students said that they felt comfortable designing training data that accounts for the three types of data bias. From the analysis of this information, we see that students showed some increases in operational knowledge of AI vocabulary, but this is not statistically significant. We did, however, see that students showed an increase in their overall confidence to describe AI and to design training data that was perceived to be free of bias. We attribute the increase in confidence to the active learning style of constructionism, where students are provided with opportunities to learn in a microworld with other learners and through hands-on projects. Constructionist researchers have shown that microworlds, when designed purposefully, allow for ownership and confidence in the learning process [28].

VI. CONCLUSIONS

We have shown that syntonicity between a learner and an AI Image Recognition tool is observable and our findings compare similarly to how other forms of syntonicity have been described by other researchers. This observable relationship that we are calling Neural Syntonicity has been demonstrated through this research with Image Recognition and through our understanding of Powerful Ideas. We believe that a syntonic relationship would transpire with other aspects of AI as well, though further research would be needed to verify and expand our understanding of the reaches of Neural Syntonicity. This research has shown that students can understand a variety of similarities between human visual perception and AI Image Recognition and that students can even use this knowledge to spur creative and analytical thinking about how to solve problems of data bias both in AI systems and in their own thinking and reasoning.

In future research, the link between fixed knowledge and variable knowledge might be explored, especially in how it relates to AI models that use live responsive data sets that allow for responsive learning (self-driving car) vs. an AI model that is trained once on a fixed data set (AI that can tell the difference between apples and bananas). While this research attempted to draw conclusions that point towards a syntonic connection between the human mind and AI, we only explored this relationship using Image Recognition. Other domains of AI such as text generation, image generation, speech recognition or pose detection could equally result in similar forms of syntonicity.

This research also adds to a growing body of knowledge in the educational approach of constructionism that builds on decades of contributions showing that "Powerful Ideas", "Microworlds", and "Syntonic Learning" are useful ways to teach and explore ideas and applications in learning for students that allow for creativity, agency and self-expression.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

MWB conducted the research, analyzed the data and wrote the paper; AS supervised the research and confirmed the results; PB advised the research and conclusions; all authors had approved the final version.

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