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MULTILAYER PERCEPTRON ARTIFICIAL NEURAL NETWORK MODEL ON ASSESSING EARLY MATHEMATICAL KNOWLEDGE BEHAVIOURS AND TODD-ACTS MOBILE APPLICATION DEVELOPMENT

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ABSTRACT

In modern culture, mathematics is the primary tool for comprehending science, engineering, and economics. Mathematics has historically been viewed as the primary measure of human intellect. Since the early stages, certain industrialised countries have been carefully considering the subject of fostering and generating geniuses among their people. This is because they recognise that individuals learn or remember knowledge the fastest throughout their first four years due to the prefrontal cortex's resiliency. This vital period of human existence needs careful consideration. Previous study has revealed that a person's mathematical skills develop from the day he or she is born. According to science, a person's capacity to acquire math abilities allows them to develop many other talents faster, and infants are no exception. In this study, we looked at the behaviours or modules that contribute to the development of arithmetic skills or capacities in newborns from birth (0 months) to 4 years old (48 months). In this study, a two-layer neural network with tansig transfer function in the first layer and purelin transfer function in the second layer was used. Because many parents and instructors are focused on the programmes offered at childcare facilities, or the so-called nursery, Montessori, or kindergarten, an innovative mobile application called 'Todd-Acts' was created. This mobile application aims to assist parents and teachers with standardised modules that they can practise at home or on their premises, primarily to improve the arithmetic skills of babies in the five critical stages of human life: 0 to 6 months, 6 to 12 months, 12 to 24 months, 24 to 36 months, and 36 to 48 months.

Keywords: Kindergarten, arithmetic skills, artificial neural network, early mathematical knowledge behaviours, mobile application.

INTRODUCTION

Mathematics is a crucial tool in modern civilization for better understanding the world. It is used as a main human intelligence metric. Mathematical prowess among gifted youngsters has been documented on a regular basis in a wide range of domains. However, dyscalculia, which is defined by weak number processing ability, is a frequent mathematics developmental problem that affects 3 to 6 percent of children (Kucian & von Aster, 2015). Childhood mathematical ability has been linked to adults' socioeconomic situation and quality of life (Ritchie & Bates, 2013). Knowing the potential of mathematical talent is an important step in improving children's numeracy abilities and academic achievements, and it may also provide fresh insights into human brain operations. Mathematical ability is a dynamic trait that involves neurological and cognitive development, as well as postnatal instruction and education (Chen et al., 2017).

Every parent and teacher hopes to raise their children to be geniuses. However, the strategy or specific process used at each stage of the infant's growth is unknown. Some industrialised nations conducted study on this topic. The goal of this quantitative study is to find the optimal neural network model for measuring early mathematics understanding behaviours in Malaysian TASKA children. The growth of children's brain capacity and many other personal skill advancements is often influenced by their arithmetic performance. This study is essential in determining the major components that influence children's arithmetic ability. A survey questionnaire and face-to-face interviews with instructors were used to collect data. This research paper's presentation may be broken into six components. The research rationale and introduction are presented in Section One. The second portion goes through relevant literature. The third part goes into further detail on the data background.

RELATED LITERATURE

Preschool children's arithmetic skills and knowledge growth are critical since it caters to their curiosity at such a young age (Campbell, 2005; Sekeris et al., 2021). Curiosity is crucial for knowledge production, even at a young age. It feeds our quest for fresh knowledge about the world, from children's urge to explore their immediate physical surroundings to kindergarteners wondering why the rose is red. Curiosity is both a state and a feature associated with the need for new information and the desire to seek it, and it is the topic of several definitional arguments (Grossnickle, 2016; Kidd & Hayden, 2015).

In their early years, children see and explore mathematical elements of their world. They compare numbers, look for patterns, move about in space, and cope with real-world difficulties like balancing a towering block construction or sharing a bowl of crackers with a playmate. Mathematics assists children in making sense of their surroundings outside of school and in establishing a firm foundation for academic achievement. Children in elementary and middle school require mathematical comprehension and abilities not only in math classes but also in science, social studies, and other areas. Students in high school require mathematical abilities to excel in course work that serves as a stepping stone to technical literacy and further education (Haycock & Huang, 2001; Haycock, 2001; Schoenfeld, 2002). Once out of school, all individuals require a broad variety of fundamental mathematics skills in order to make educated decisions regarding their employment, families, societies, and civic life.

Curiosity is regarded to be a person-specific (i.e. trait) as well as a situation-specific (i.e. activity-related (state)) construct. Although it is believed that the characteristics of curiosity are highly heritable (Steger et al., 2007), and include an openness to stimuli, a desire for novelty, and a willingness to embrace the unexpected (Kashdan et al., 2009), the expression of curiosity is also thought to be situational (i.e. state) and linked to a person's idiosyncratic desires, which may differ depending on behaviour and background (Kashdan & Fincham, 2004). The first three years of a child's existence are crucial to their total development. In order to grow in a quality parental environment, babies and trainees require a variety of learning experiences at this point (Field et al., 2013). Early childhood reveals a special appreciation of science and mathematics, as well as joy (Cohen & Waite-Stupiansky, 2019). Science helps children comprehend their physical and social contexts, and early childhood is a period when children may use mathematics creatively and rationally (Alvarez, 2019). Good experiences with the application of mathematics to solve problems allow young children to develop auras such as curiosity, creative energy, flexibility, creativity, and stability, which contribute to their potential accomplishment in school (Gold et al., 2020). By providing high-quality daycare, the caregiver or childcare professional plays an important role in the development of future leaders. To ensure the success of the next generation, childcare facilities must strengthen and support quality assurance standards among their employees (Kharuddin et al., 2020). Therefore, the first objective of this research is to identify the theory related to school activities at kindergarten as an independent indicator of children's achievement in mathematics.

DATA BACKGROUND

The initial research and related sampling techniques can be referred in Mustafa et al. (2017). In this research total of 458 (376 registered and 82 unregistered) TASKAs in Malaysia were selected.

Among the 458 centers, only:

i) 13.8 percent (63 centres) focus on providing early childhood educational services for children ages 0 to 6 months (Kharuddin et al., 2018),

ii) 20.7 percent (95 centres) focus on providing early childhood educational services for children ages 6 to 12 months,
iii) 21.8 percent (100 centres) focus on providing early childhood educational services for children ages 12 to 24 months,
iv) 22.3 percent (102 centres) focus on providing early childhood educational services for children ages 24 to 36 months,
v) 22.3 percent (102 facilities) offer education for children to children aged 36 to 48 months.

METHODOLOGY

A sensitivity analysis is carried out, which determines the importance of each predictor in determining the neural network (Al-Imam, 2019). The analysis is based on combined training and testing samples, or simply on training samples if no test samples are available. It generates a table and a map for each factor that displays the value and normalised significance. When there are a high number of predictors or instances, sensitivity analysis is computationally expensive and time intensive. Ibrahim et al. (2020), LaFaro et al. (2015), Mahmoud et al. (2019), Yin et al. (2019), and Zhang et al. (2019) all use a neural network technique (2018).

Table 1

The Variables for Assessing Early Mathematical Knowledge Behaviours

No.	Variable (s)	Parameters	Notation	Type
1.	Dependent	Mean Math	The Mean Value of Early Stages of development of Mathematics and Logical Thinking Items	Continuous
2.		Mean Physical	The Mean Value of Physical Developmental Items	Continuous
3.		Mean SSK	Interpersonal, Socio-Emotional, and Spirituality Development Items' Mean Value	Continuous

(continued)

No.	Variable (s)	Parameters	Notation	Type
4.		Mean BKL	Mean Value of Language Development, Communication, and Emergent Literacy Items	Continuous
5.	Independent	Mean Senses	Mean Value of Sense Development and Understanding of the Environment Items	Continuous
6.		Mean Creativity	Mean Value of Creative thinking and Aesthetics Development Variables	Continuous

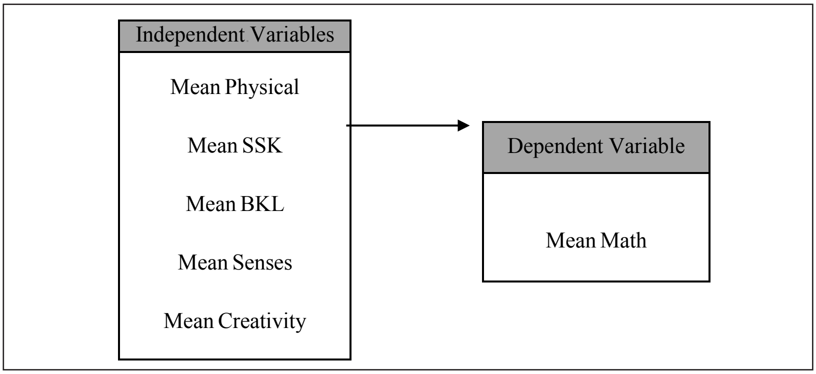
The variables in this study are those proposed by Kharuddin et al (2018). Independent variable importance analysis includes a sensitivity analysis that estimates the relevance of each predictor in determining the neural network. Table 1 depicts the variables employed in this study, while Figure 1 depicts the conceptual framework.

Nonlinear models that consists of more than one independent variables were developed in this research. In this paper, the Artificial Neural Network of Multilayer Perceptron (ANN-MLP) model was applied. The neural network model consists of five independent variables, β_1, β_2, β_3, β_4 and β_5.

$$Y = identity.\left(LW^{2,1}\left(\tan sig.\begin{bmatrix} (IW_1)^{1,1} * \beta_1 + (IW_2)^{1,2} * \beta_2 + (IW_3)^{1,3} * \beta_3 + (IW_4)^{1,4} \\ * \beta_4 + I(W_5)^{1,5} * \beta_5 + \varepsilon^1 \end{bmatrix}\right) + \varepsilon^2 \right) \quad (1)$$

Figure 1

Conceptual Framework



In this study, a two-layer neural network with a tansig transfer function in the first layer and a purelin transfer function in the second layer was utilised. The hidden layer's training function is hyperbolic tangent, and the output layer's identity function is identity, with MSE equal to 0.0 as the criterion function. As a consequence, the neural network model employed in this research is as follows:

$$MeanMath = purelin.\left(LW^{2,1} \left(\tan sig. \begin{bmatrix} (IW_1)^{1,1} * MeanPhysical + (IW_2)^{1,2} * \\ MeanSSK + (IW_3)^{1,3} * MeanBKL \\ + (IW_4)^{1,4} * MeanSenses + (IW_5)^{1,5} * \\ MeanCreativity + b^1 \end{bmatrix} \right) + b^2 \right) \tag{2}$$

Only the important predictors will be included in the final model to explain Mean Math.

There were 5 stages in this research altogether. The stages are as follows,

Stage 1: The finalized questionnaire were distributed and face-to-face interviews were carried out with the teachers at TASKA. The details can be referred in Mustafa et al. (2017).

Stage 2: The data were keyed-in into excel and cleaned.

Stage 3: The data were partitioned into training, testing and validation sets (70%-15%-15%).

Stage 4: The data were analysed using two layer neural network with hyperbolic tangent transfer function in the first layer (from input to hidden layer), and purelin transfer function in the second layer (from hidden layer to output layer).

Stage 5: The results were compiled and integrated into the Todd-Acts Mobile Application. https://play.google.com/store/apps/details?id=com.saadi.ak.toddacts

Figure 2

A Screenshot of the Todd-Acts Mobile Application in Google Play Store

Figure 2 shows a screenshot of the Todd-Acts mobile application in the Google Play store. Readers may install the mobile app to understand the use of the mobile app.

RESULTS AND DISCUSSION

The results are presented based on the analysis using neural network multilayer perceptron approach to assess the contributing factors of children's mathematical performance at Malaysian TASKA according to the following 5 different stages of a baby's development (refer to appendix 1):

i) 0-6 months (Table 1)
ii) 6-12 months (Table 2)
iii) 12-24 months (Table 3)
iv) 24-36 months (Table 4)
v) 36- 48 months (Table 5)

Table 2

Normalized Importance Among Factors Contributing to Children Mathematical Performance at Malaysian TASKA: 0-6 Months

	Importance	Normalized Importance
MeanPhysical	.283	100.0%
MeanSSK	.082	29.1%
MeanBKL	.246	86.7%
MeanSenses	.248	87.4%
MeanCreativity	.141	49.8%

Table 3

Normalized Importance Among Factors Contributing to Children Mathematical Performance at Malaysian TASKA: 6-12 Months

	Importance	Normalized Importance
MeanPhysical	.085	25.1%
MeanSSK	.084	24.8%
MeanBKL	.204	60.3%
MeanSenses	.290	86.0%
MeanCreativity	.338	100.0%

The normalised importance of each predictor variable is shown in tables 2–6. Normalized importance is a measure of how much the anticipated value of the dependent variable would be altered if a certain independent variable were excluded.

Table 4

Normalized Importance Among Factors Contributing to Children Mathematical Performance at Malaysian TASKA: 12-24 Months

	Importance	Normalized Importance
MeanPhysical	.082	25.8%
MeanSSK	.146	45.7%
MeanBKL	.289	90.3%
MeanSenses	.163	51.0%
MeanCreativity	.320	100.0%

Table 5

Normalized Importance Among Factors Contributing to Children Mathematical Performance at Malaysian TASKA: 24-36 Months

	Importance	Normalized Importance
MeanPhysical	.076	19.0%
MeanSSK	.095	23.8%
MeanBKL	.362	90.1%
MeanSenses	.402	100.0%
MeanCreativity	.065	16.1%

Table 6

Normalized Importance Among Factors Contributing to Children Mathematical Performance at Malaysian TASKA: 36-48 Months

	Importance	Normalized Importance
MeanPhysical	.118	31.6%
MeanSSK	.136	36.3%
MeanBKL	.374	100.0%
MeanSenses	.264	70.7%
MeanCreativity	.108	28.9%

Table 2 indicates that the normalized importance of physical development is highest whereas personality, socio-emotional and spirituality development has least normalized importance for newborn to 6-month-old babies.

Based on Table 3, the normalized importance of creativity development is highest, whereas personality, socio-emotional and spirituality development have least normalized importance for 6-month to 12-month old babies.

Moreover, Table 4 shows that the normalized importance of creativity and aesthetics development is highest, whereas physical development has least normalized importance for 12-month to 24-month old toddlers.

Furthermore, Table 5 demonstrates that senses and comprehension of the global environment development have the highest normalised value, whereas creativity and aesthetics development have the lowest normalised importance for 24-month to 36-month old children.

Last but not least, Table 6 shows that language skills, communication, and early literacy development have the highest normalised relevance for 36- to 48-month-old children, whereas creative development has the lowest normalised importance.

Appendix 1 contains all related bar charts of relevance that are ordered in descending order. Appendix 2 contains the parameter estimation tables. In addition, the model configurations used in this study are presented in Appendix 3.

Appendix 4 contains a list of the best neural network architectures used in this study. The two-layer neural network of 5-6-1 configurations with tansig transfer function in the first layer and purelin transfer function in the second layer is the best model.

Parental encouragement and support are explicitly essential in the learning process and childhood development of toddlers. This is because it leads to their interest in learning especially in a study by Mazana et al. (2018) which highlighted that intrinsic and extrinsic motivation played important role in the students liking Mathematics. This is also proven in this current study which involves the use of a digital application with parents' supervision will increase the young learners' Mathematics knowledge.

Apart from that, emotional support from parents and teachers will increase students' self-efficacy in Mathematics and their enjoyment in class as being mentioned by Blazar and Kraft (2017). This is also relevant in this study because the researchers highlighted on the need for the socio-emotional support that is vital in early stages of the childhood that affects or breaks learning.

Good learning materials can increase educational potential and it can be done within the play-based approach. This is significantly highlighted by Vogt et al. (2018) who highlighted that teachers and parents can analyze, structure the learning arrangement and demonstrate tactics for solving the mathematical problems amongst the children. With an application developed in this study, it eases the learning process.

Finally, in times of pandemic, it is a favorable option to adopt learning via applications as compared to learning face-to-face to reduce the risks of contracting the deadly virus. It is timely that gadgets can assist in the learning process of children at any ages with strict and constant monitoring and supervision of parents and teachers. Papadakis et al. (2018) agreed that special attention should be offered to the teacher to assist learning through this media, along with emphasis on entertainment. This is parallel with what the researchers have done in this study where the application developed helps learning on both the children on the content and the teachers on the system.

CONCLUSION

The research objective has been successfully achieved. The results are expected to assist parents and teachers in identifying the right process of nurturing the children with respect to their ages at home and TASKAs. Priority is to be given on the arithmetic skills development first. Arithmetic development among babies starts on the first they were born. In that sense, the mobile application “Todd-Act” is expected to assist parents and teachers in identifying the activities of priority to enhance their children’s arithmetic skills according to their age. The research will be expanded in the near future to cover all unregistered TASKA throughout Malaysia, and a fair comparison to registered facilities will be made.

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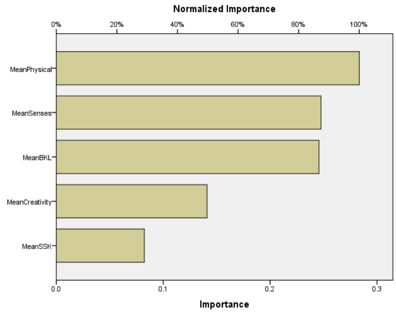
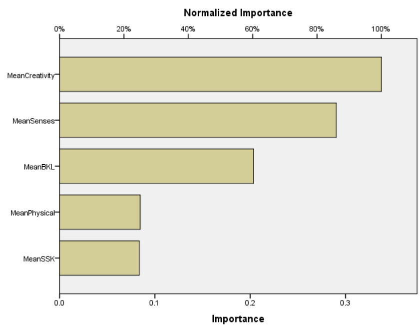
APPENDIX 1

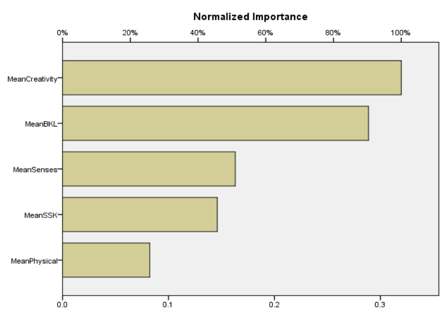
Normalized Importance of Contributing Factors of Children Mathematical Performance at Malaysian TASKA: 0-6 Months



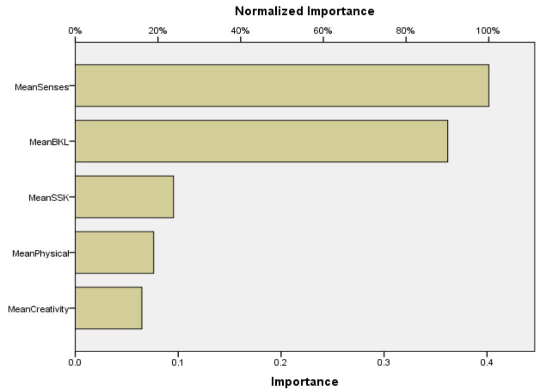
Normalized Importance of Contributing Factors of Children Mathematical Performance at Malaysian TASKA: 6-12 Months



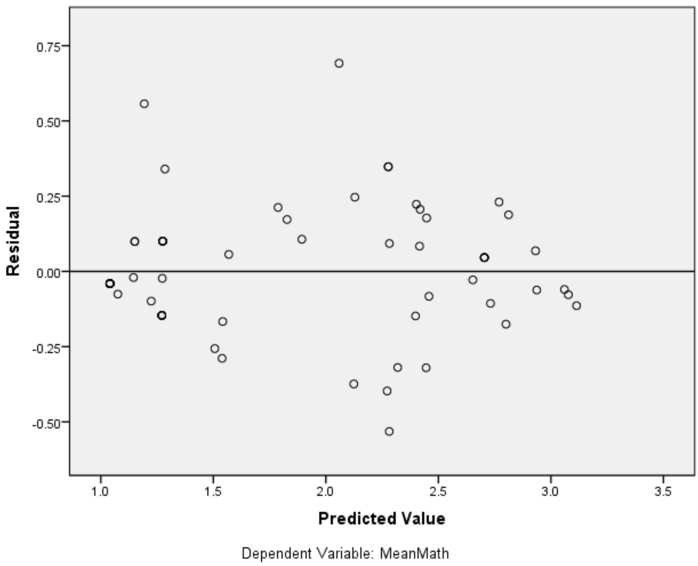
Normalized Importance of Contributing Factors of Children Mathematical Performance at Malaysian TASKA: 12-24 Months



Normalized Importance of Contributing Factors of Children Mathematical Performance at Malaysian TASKA: 24-36 Months



Normalized Importance of Contributing Factors of Children Mathematical Performance at Malaysian TASKA: 36-48 Months

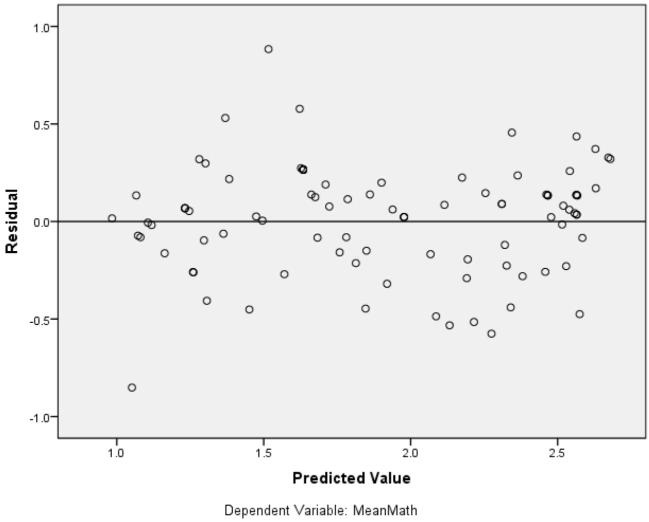


APPENDIX 2

0-6 Months

Parameter Estimates

Predictor		Predicted						
		Hidden Layer 1						Output Layer
		H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(1:5)	H(1:6)	MeanMath
Input Layer	(Bias)	-.791	.337	.274	.284	-.148	-.434	
	MeanPhysical	.127	.358	-.602	-.067	-.262	.419	
	MeanSSK	-.328	.340	.143	.129	-.014	.285	
	MeanBKL	.619	.034	-.081	-.270	-.491	.252	
	MeanSenses	1.134	-.463	.012	-.249	-.172	.458	
	MeanCreativity	-.548	.290	-.450	.063	.125	.446	
Hidden Layer 1	(Bias)							.296
	H(1:1)							.838
	H(1:2)							.496
	H(1:3)							-.654
	H(1:4)							-.196
	H(1:5)							-.030
	H(1:6)							-.271

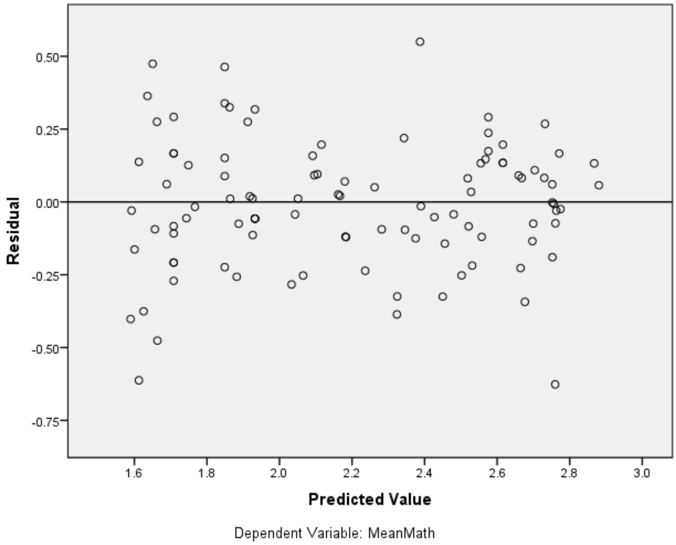


Scattered residuals

6-12 Months

Parameter Estimates

Predictor		Predicted					
		Hidden Layer 1					Output Layer
		H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(1:5)	MeanMath
Input Layer	(Bias)	-.358	.132	-.085	-.173	.195	
	MeanPhysical	-.033	.050	.031	-.345	.103	
	MeanSSK	.213	-.227	.054	-.096	-.188	
	MeanBKL	-.343	.164	-.077	-.237	.444	
	MeanSenses	-.067	.263	-.499	.230	-.408	
	MeanCreativity	-.390	.134	-.410	-.086	-.173	
Hidden Layer 1	(Bias)						-.281
	H(1:1)						-.437
	H(1:2)						.411
	H(1:3)						-.658
	H(1:4)						-.299
	H(1:5)						-.002

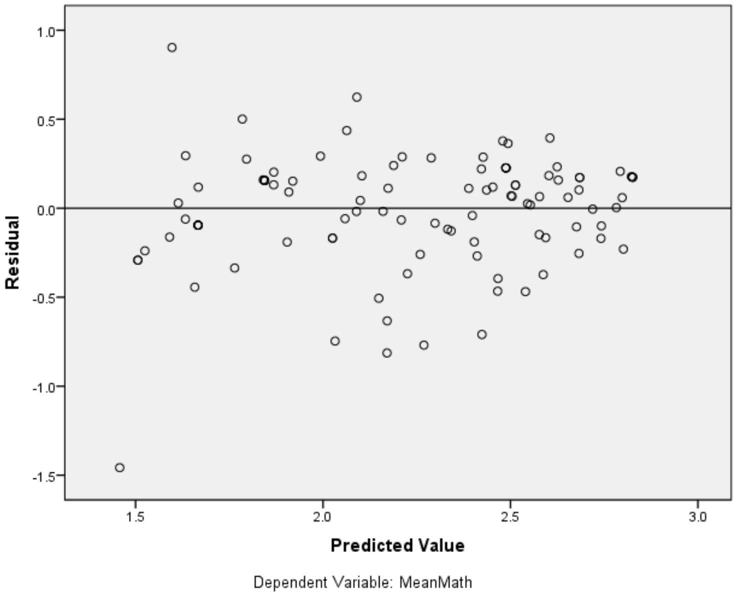


Scattered residuals

12-24 Months

Parameter Estimates

Predictor		Predicted			
		Hidden Layer 1			Output Layer
		H(1:1)	H(1:2)	H(1:3)	MeanMath
Input Layer	(Bias)	-.658	-.094	-.128	
	MeanPhysical	.153	-.383	.051	
	MeanSSK	-.156	.292	.392	
	MeanBKL	.289	.605	-.170	
	MeanSenses	.173	.177	.095	
	MeanCreativity	-.020	.548	.450	
Hidden Layer 1	(Bias)				.411
	H(1:1)				.746
	H(1:2)				.775
	H(1:3)				.363

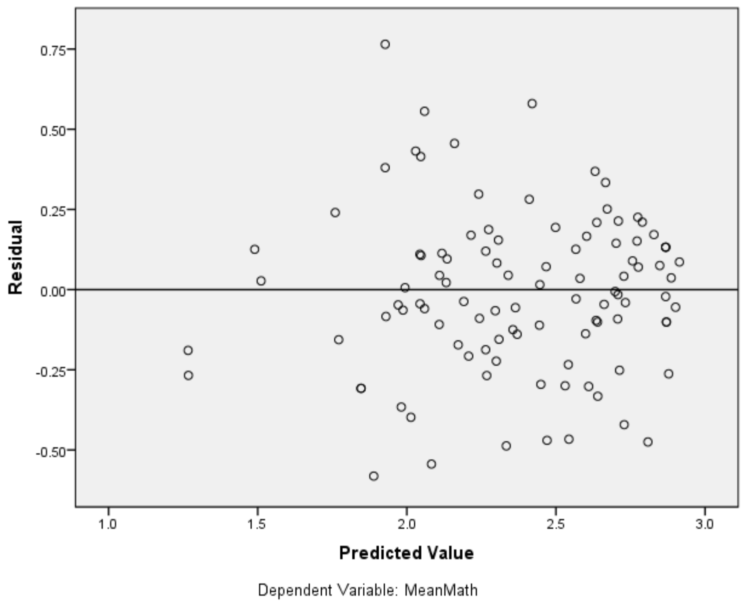


Scattered residuals

24-36 Months

Parameter Estimates

Predictor		Predicted		
		Hidden Layer 1		Output Layer
		H(1:1)	H(1:2)	MeanMath
Input Layer	(Bias)	-.027	-.134	
	MeanPhysical	.413	.265	
	MeanSSK	-.354	-.422	
	MeanBKL	.377	-.319	
	MeanSenses	.500	-.477	
	MeanCreativity	.076	.220	
Hidden Layer 1	(Bias)			-.084
	H(1:1)			.690
	H(1:2)			-.638



Scattered residuals

36-48 Months

Parameter Estimates

Predictor		Predicted					
		Hidden Layer 1					Output Layer
		H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(1:5)	MeanMath
Input Layer	(Bias)	-.677	.306	.717	-.321	-.088	
	MeanPhysical	-.359	.600	.156	-.318	.039	
	MeanSSK	.175	-.057	.318	.199	.282	
	MeanBKL	-.071	-.279	.347	-.191	-.019	
	MeanSenses	-.470	-.390	-.302	-.125	-.320	
	MeanCreativity	.475	-.312	-.214	-.069	.211	
Hidden Layer 1	(Bias)						-.609
	H(1:1)						-.707
	H(1:2)						-1.023
	H(1:3)						.739
	H(1:4)						-.324
	H(1:5)						.328

Scattered residuals

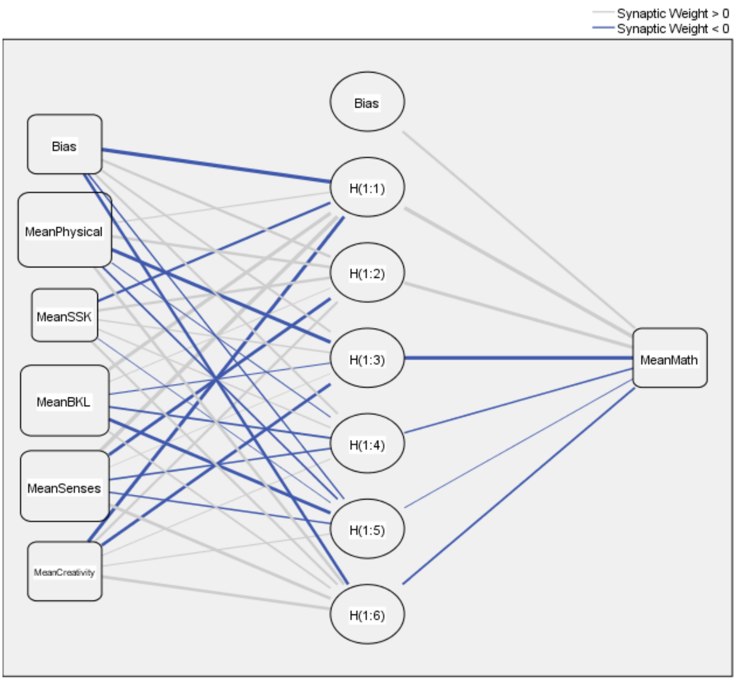
APPENDIX 3

Best Configuration

Group (Month)	Data Partitioning: % (training), % (validation), % (testing)	Configuration	MSE	RMSE
0-6	70, 15, 15	5-6-1	0.049	0.221359
6-12	70, 15, 15	5-5-1	0.317	0.563028
12-24	70, 15, 15	5-3-1	0.244	0.493964
24-36	70, 15, 15	5-2-1	0.318	0.563915
36-48	70, 15, 15	5-5-1	0.220	0.469042

APPENDIX 4

The architecture of the neural network model in this research



Hidden layer activation function: Hyperbolic tangent

Output layer activation function: Identity