Título Competencias cognitivas: entrenamiento y claves para comprender su impacto sobre el desempeño

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Autores Cascallar, Eduardo C; Musso, Mariel; Murata, Cecilia; Costa, Diana & Salgado Javier

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UADE

Competencias cognitivas: entrenamiento y claves para comprender su impacto sobre el desempeño

Dra. Mariel F. Musso
Equipo: Lic. Cecilia Murata, Lic. Diana Costa, Lic. Javier Salgado
Alumnos: Paulina Robalino, Heliana Lauria, Pablo González, Cristian Velasco, Javier Taniguchi
Colaboradores: Eduardo C. Cascallar (Universidad de Leuven, Bélgica)

Nuevas tecnologías y automatización de tareas

- Mayor demanda de habilidades de procesamiento de la información y de alto nivel cognitivo
- *"Habilidades clave de procesamiento de la información"* (OECD- PISA-PIAAC)

¿Qué procesos cognitivos hacen posible estas habilidades?

- Memoria de Trabajo: mantenimiento activo y procesamiento ejecutivo de la información disponible en el sistema cognitivo
- Redes atencionales- Atención ejecutiva

Por que?

- Memoria de Trabajo: rol clave en un amplio rango de procesos cognitivos complejos:

- comprensión,
- razonamiento
- resolución de problemas

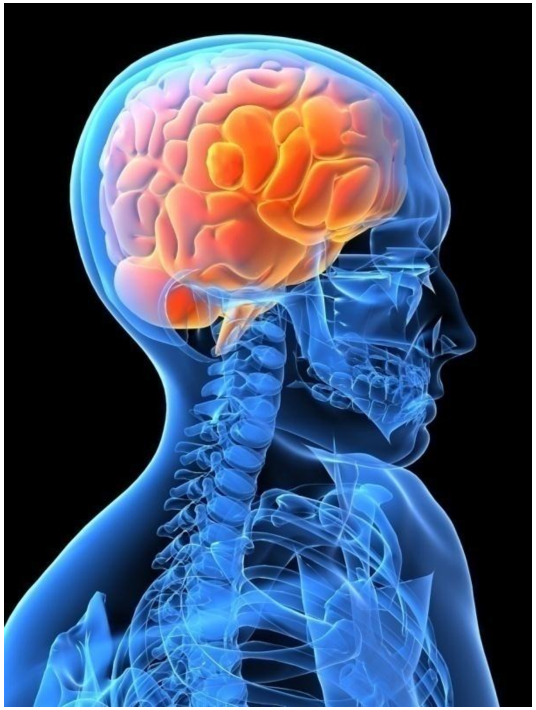
(Engle, 2002; Adams & Hitch, 1997; Ashcraft, 1995; Geary, 1990; Geary & Widaman, 1992; Hitch, 1978; Lemaire, Abdi, & Fayol, 1996; Logie, Gilhooly, & Wynn, 1994; Passolunghi, Cornoldi, & Di Liberto, 1999; Passolunghi & Pazzaglia, 2004; Pickering, 2006; Widaman, Geary, Cormier, & Little, 1989; Cascallar, Boekaerts & Costigan, 2006; Cascallar & Musso, 2008; Musso & Cascallar, 2009ª; Musso & Cascallar, 2009b.).

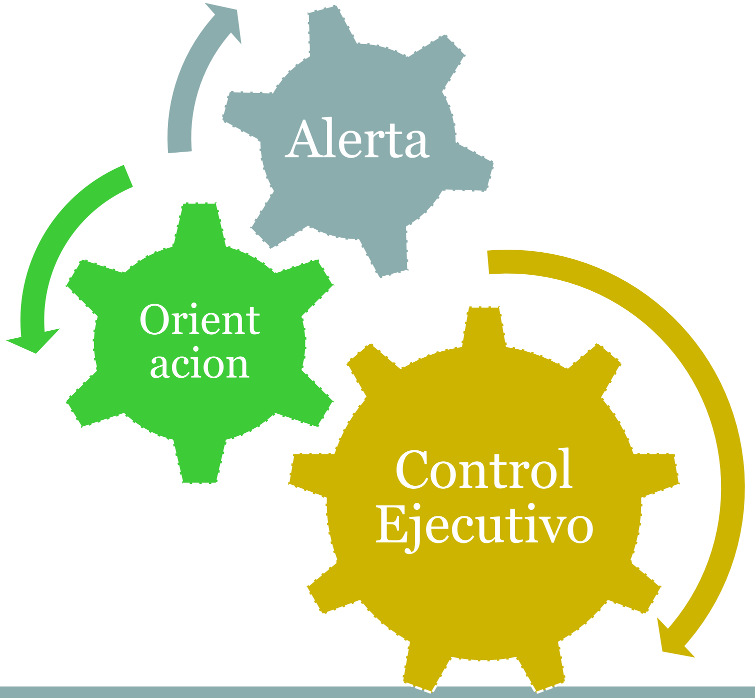
Por qué?

Hallazgos claves:

- Alta correlación entre la MT a los 3 años de edad con la MT de los 18 anos (.85 aproximadamente).
- Déficit nutricional de los 3 primeros años de vida afecta negativamente a la MT (comparando con grupos controles) (Boucher y col., 2011)
- La MT tiene una alta correlación con otras medidas educacionales y laborales.

REDES ATENCIONALES





X Congreso Argentino de Neuropsicología
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Buenos Aires, Argentina

UADE

Dra. Mariel F. Musso marimusso@uade.edu.ar
Universidad Argentina de la Empresa (Argentina)

Dr. Eduardo C. Cascallar cascallar@msn.com
Katholieke Universiteit Leuven (Bélgica)

Lic. Cecilia Murata cmurata@uade.edu.ar
Universidad Argentina de la Empresa (Argentina)

EVALUANDO LA MEMORIA DE TRABAJO Y ATENCIÓN CON PRUEBAS AUTOMATIZADAS: UN ESTUDIO NORMATIVO EN ADULTOS JÓVENES DE NUESTRA REGIÓN

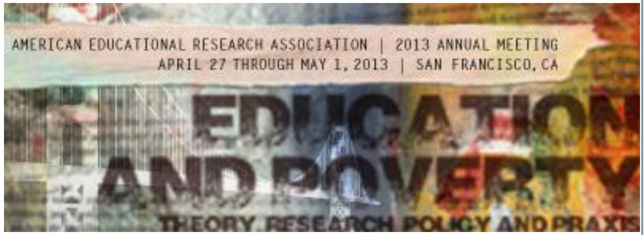
2012 CAPE TOWN ICP
XXX International Congress of Psychology

13:40	Musso Mariel (Argentina) Cascallar Eduardo	The effect of cognitive processes, learning strategies and social context on academic performance
9:40	Musso Mariel (Argentina) Boekaerts Monique, Cascallar Eduardo	Self-regulation working memory and attention: Effects and interactions
13:40	Musso Mariel (Argentina) Cascallar Eduardo	Working memory and attention interactions with complexity and difficulty levels in task performance

ICAP 28th International Congress of Applied Psychology IAAP
From Crisis to sustainable Well-Being
8 - 13 July 2014

•DIV05-OC10005 - Cognitive and non-cognitive predictors of academic retention using Artificial Neural Networks
Mariel Fernanda Musso *(Argentina)*
Eduardo C. Cascallar (Belgium)

AMERICAN EDUCATIONAL RESEARCH ASSOCIATION



PREDICTING GENERAL ACADEMIC PERFORMANCE USING ARTIFICIAL NEURAL NETWORKS: IMPLICATIONS FOR "EARLY-WARNING" DIAGNOSTIC AND PLACEMENT APPLICATIONS

UADE
Universidad Argentina de la Empresa

Mariel Musso
mariel.musso@hotmail.com

Eva Kyndt

Eduardo Cascallar

Katholieke Universiteit Leuven,
Centre for Research on
Teaching and Training

ABSTRACT

The objective of this study is to develop predictive models, using artificial neural networks, to identify patterns of variables that could be used to make accurate predictive classifications for three levels of General Academic Performance (GAP): Low, Middle and High. This is achieved using as inputs variables from basic cognitive processes, learning strategies, and individual background information. Results have important implications for the study of learning processes, and as a tool for the improvement of curriculum design, tutorial systems, and students' academic outcomes. The accurate prediction of student performance helps to identify those students at risk of future low academic achievement and facilitates precise diagnostic work and the implementation of intervention strategies to prevent or mitigate future academic failure.

INTRODUCTION

The prediction of academic performance has been approached using different methodologies.

The most common approaches found in the educational literature involve traditional statistical methods, such as discriminant analysis and multiple linear regressions (Braten & Stromso, 2006; Vandamme, Meskens & Superby, 2007).

These traditional methods do not always result in accurate predictions or classifications, when they are compared with machine learning computing methods (Lykins & Chance, 1992; Weiss & Kulikowski, 1991; Everson, Chance, & Lykins, 1994; Maucieri, 2003).

OBJECTIVE

» To identify patterns of variables that will allow a correct predictive classification of three levels of General Academic Performance (GAP)

RESEARCH QUESTIONS

» How accurately can different levels of academic performance in higher education be predicted by working memory capacity, attentional networks, learning strategies and background variables when used as inputs in a neural network model?

» What is the relative importance of the predictor variables and the observed differences for each performance level category?

THEORETICAL FRAMEWORK

» Working memory and academic performance (Unsworth, Heitz, Schrock & Engle, 2005; Heitz, Redick, Hambrick, Kane, Conway & Engle, 2006)
» Attention and academic performance (Posner & Rothbart, 1998; Redick & Engle, 2006; Rueda, Posner & Rothbart, 2004; Riccio, Lee, Romine, Cash & Davis, 2002; Gsanger, Wa, Homack, Siekierski & Riccio, 2002; Kyndt, Musso, Cascallar & Dochy, 2012).
» Learning strategies and academic performance (Weinstein & Mayer, 1986; Weinstein, Palmer & Schulte, 1987; Weinstein, Schulte & Cascallar, 1982).
» Artificial Neural Networks and Performance (Cascallar, Boekaert & Costigan, 2006; PinninghoffJunemann, Salcedo Lagos & Contreras Arriagada, 2007).

METHOD

PARTICIPANTS

» 864 university students,
» Both genders (Females 54.6%),
» Ages between 18 and 25 (M age = 20.38, SD = 3.78),
» Enrolled in the first year in several different disciplines,
» From two private universities in Argentina,
» During the 2009-2011 academic years.

INSTRUMENTS

» **Attention Network Test (ANT) (Fan, McCandliss, Sommer, Raz & Posner, 2002).**
This task provides a measure for each of the three anatomically defined attentional networks: alerting, orienting, and executive attention.

» **Automated Operation Span (Unsworth, Heitz, Schrock & Engle, 2005).**
This is a computer-administered version of the Ospan instrument (Unsworth, Heitz, Schrock & Engle, 2005) that measures working memory capacity. This study reports Absolute Ospan score that is interpreted as the measure of overall working memory capacity, and one Reaction Time score (operations).

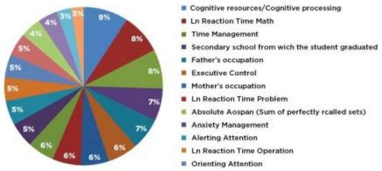
» **Learning Strategies Questionnaire (LASSI, Weinstein, Schulte & Cascallar, 1982; Weinstein, Palmer, & Schulte, 1987).**
A validated version was administered. It is a 77-item questionnaire with 10 scales that assesses the students' awareness about, and use of, learning and study strategies related to skill, will, and self-regulation components of strategic learning.

» **Background information:** basic background information of each student, family system, socio-economic data, level of education and occupation of parents, and other similar variables were collected.

» **Academic Performance** was measured by the GPA at the end of the academic year.

FIGURE 1

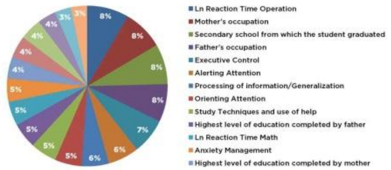
INDIVIDUAL VARIABLE PREDICTIVE WEIGHTS FOR THE PREDICTED LOWEST 33% GROUP OF GENERAL ACADEMIC PERFORMANCE



For the Low performers, several learning strategies related to cognitive resources and processing, reaction time, and time management were most important in attaining a correct classification.

FIGURE 2

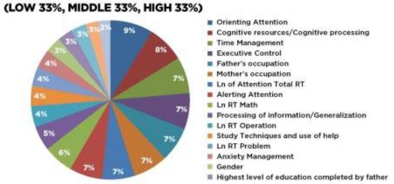
INDIVIDUAL VARIABLE PREDICTIVE WEIGHTS FOR THE PREDICTED HIGHEST 33% GROUP OF GENERAL ACADEMIC PERFORMANCE



For the Highest 33% group, the top four predictors with the most significant participation were reaction time and background variables involving mother and father's occupation, and type of secondary school.

FIGURE 3

INDIVIDUAL VARIABLE PREDICTIVE WEIGHTS FOR THE THREE PREDICTED GROUPS OF GENERAL ACADEMIC PERFORMANCE (LOW 33%, MIDDLE 33%, HIGH 33%)



The most important variables for the prediction of ANN3 were orienting attention, some learning strategies and cognitive resources, time management, and executive control.

PREDICTIVE CONTRIBUTION BY CATEGORIES OF VARIABLES

TABLE 1:

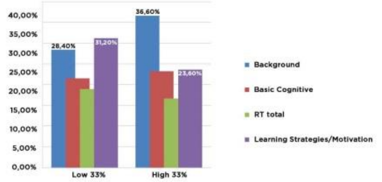
CUMULATIVE PREDICTED WEIGHT FOR EACH VARIABLE SET FOR THE TWO GROUPS OF GENERAL ACADEMIC PERFORMANCE.

	Low 33%	High 33%	Mean Predictive Weight of Each Area
Background	28.40%	36.60%	30.13%
Basic Cognitive	21.50%	23.20%	23.47%
Reaction Time Total	18.90%	16.60%	18.87%
Learning Strategies/Motivation	31.20%	23.60%	27.53%
	100.00%	100.00%	

When comparing the two extreme predicted performance groups: specific patterns involving different variables are evident for Low and High expected academic performance

FIGURE 4

COMPARISON OF PREDICTIVE WEIGHT LEVELS FOR LOW AND HIGH LEVELS OF ACADEMIC PERFORMANCE BY VARIABLE CATEGORY



RESULTS: ARTIFICIAL NEURAL NETWORKS (ANN)

		ANN1 Predicting Lowest 33% Academic Performance Scores	ANN2 Predicting Highest 33% Academic Performance Scores	ANN3 Predicting the Three Levels of Academic Performance Scores (Low 33%-Middle 33%-High 33%)
Training Phase	N	82.4% (n= 632)	77.9% (n= 614)	82.8% (n=710)
	Prediction	81.1%	60.7%	Low= 69.8%, Middle= 14.2% High= 46.3%
Testing Phase	N	17.6% (n=111)	22.1% (n= 136).	17.2% (n=122)
	Prediction	100 %	100%	Low= 87.5% Middle= 100% High= 100%
Precision		1 on a maximum of 1	1 on a maximum of 1	.875 on a maximum of 1
Sensitivity		1 on a maximum of 1	1 on a maximum of 1	1 on a maximum of 1
Specificity		1 on a maximum of 1	1 on a maximum of 1	.50

RESULTS: DISCRIMINANT ANALYSES (DA)

	DA1 Lowest 33% Academic Performance Scores	DA2 Highest 33% Academic Performance Scores	DA3 Three Levels of Academic Performance Scores
Assumption of equality of covariance matrices	It is not violated Box's M = 5.253, F = .871, p= .515	It is not violated Box's M = 11.813, F = .781, p = .700	It is not violated Box's M = 7.522, F = .623, p=.824
Squared canonical correlation (CR^2)	Low Wilk's λ=.896, χ^2=84.786, df=3, p=.001, CR^2=.323	Very low Wilk's λ=.926, χ^2=58.694, df=5, p=.001, CR^2=.271	Very Low Wilk's λ=.998, χ^2=1.791, df=2, p=.408, CR^2=.048
Variables	Gender Working Memory Capacity Cognitive resources learning strategies	Gender Highest level of education of the father Working Memory Capacity Cognitive resources Time management	Gender Cognitive resources within the learning strategies set Working Memory Capacity

For all Discriminant Analyses calculated, although they were able to discriminate between the students in each academic performance group, as the ANN, the explained variance was very low.

DISCUSSION and CONCLUSION

» This methodology (ANN) was chosen as it is extremely effective for use with very complex and large data sets in which a large number of variables interacts in various complex and not very well understood patterns.

» ANN models are able to model nonlinear and complex relationships among variables.

» When we compare the Discriminant Analyses DA results with the NNs analysed in this study, it can be concluded that NNs are more robust and perform significantly better than other classical techniques, as prior studies have indicated (i.e., Everson, Chance & Lykins, 1994).

» The use of ANN together with other methods as cluster analyses and Kohonen networks could contribute to the study of the specific patterns of those variables which influence the learning process for each level of performance.

» A major observation resulting from the data in this study is that variables contribute to the prediction in relative small proportions, and it is the joint effect of many contributing variables that could cause significant changes in performance.

» This methodology could have major impact for the improvement of evaluation procedures and the planning of remedial interventions.

» Implications for the application of these methods in educational research and in the implementation of diagnostic "early-warning" programs in educational settings, as well as informing cognitive theory and the development of automated tutoring and learning systems.

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Predicting general academic performance and identifying the differential contribution of participating variables using artificial neural networks

Mariel F. Musso[ab], Eva Kyndt[ac], Eduardo C. Cascallar[ad], Filip Dochy[a]

V CONGRESO INTERNACIONAL DE INVESTIGACIÓN Y PRÁCTICA PROFESIONAL EN PSICOLOGÍA
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UADE

Dra. Mariel Musso
marimusso@uade.edu.ar
Lic. Cecilia Murata
cmurata@uade.edu.ar
Lic. Javier Salgado
jasalgado@uade.edu.ar

ESTADO DEL ARTE: ENTRENAMIENTO COGNITIVO

CONCLUSIONES

Los efectos de los entrenamientos son contradictorios y variables.

En general se sostiene la efectividad a corto plazo sobre tareas similares a las entrenadas, pero estos cambios no se transfieren a otras habilidades cognitivas ni al desempeño en otras pruebas de la vida real.

Necesidad de mayor clarificación de modelos teóricos de los procesos involucrados en las tareas de los programas de entrenamiento de la MT.

Futura investigación necesita focalizar sobre estrategias y mecanismos específicos del entrenamiento de la MT y su transferencia a otros aspectos de la cognición en el mundo real.

?

¿Es posible entrenar estos procesos cognitivos básicos?

Objetivo General

Estudiar la efectividad del entrenamiento cognitivo sobre memoria de trabajo y atención, y su alcance de generalización a otras tareas no entrenadas, a fin de contribuir con estrategias adaptadas a situaciones de enseñanza y aprendizaje de la vida universitaria.

Objetivos Específicos

1) Analizar el impacto del entrenamiento de la memoria de trabajo y atención sobre medidas de inteligencia general.

2) Estudiar el impacto diferencial del entrenamiento sobre la memoria de trabajo y redes atencionales, de acuerdo a los perfiles cognitivos del sujeto.

3)Estudiar la transferencia lejana del entrenamiento de la memoria de trabajo y atención a otras tareas no entrenadas.

Hipótesis

- El entrenamiento de la MT no incrementará el desempeño en pruebas de memoria de trabajo
- El entrenamiento de la A tendrá un efecto positivo sobre el desempeño en la prueba de atención.
- El entrenamiento de la MT y de la A incrementará el desempeño en pruebas de atención, pero no en la de MT.
- Los efectos sobre las habilidades entrenadas serán moderados por el perfil cognitivo previo del sujeto.
- El entrenamiento de la MT y de la A no tendrá un efecto significativo sobre medidas de transferencia lejana.

Diseño

- Diseño pre- post, con grupo control activo.
- Se realizarán mediciones antes y después del entrenamiento cognitivo en todos los grupos.

Participantes

- Muestra: estudiantes universitarios asignados al azar.
- El grupo experimental 1 (n= 60) recibirá un entrenamiento de la MT.
- El grupo experimental 2 (n= 60) recibirá un entrenamiento de la A.
- El grupo experimental 3 (n= 60) recibirá un entrenamiento de ambos procesos (MT y redes atencionales).
- El grupo control estará conformado por 60 estudiantes universitarios sin entrenamiento pero realizará una tarea de reconocimiento de información (preguntas multiple-choice).

Medidas cercanas

Automated Operation Span (Unsworth, Heitz, Schrock & Engle, 2005): tarea computarizada que mide la capacidad de memoria de trabajo.

Test de Redes Atencionales (Attention Network Test (ANT) (Fan, et. al., 2002). Esta tarea provee una medida para cada una de las tres redes atencionales anatómicamente definidas: Alerta, Orientación y Ejecutiva.

Medidas lejanas

Test de Matrices Progresivas de Raven (Raven, 1995).

Medidas lejanas

Tarea de matemática básica: 50 items multiple choice del test de matemática (Cortada de Kohan & Macbeth, 2007) distribuidos de acuerdo a su nivel de dificultad y otros parámetros ya analizados de acuerdo a TRI en estudios previos (Musso & Cascallar, inédito), conformando dos versiones equivalentes de la prueba a aplicar antes y después del entrenamiento.

Promedio académico

Entrenamiento MT

Entrenamiento de la MT basado en el paradigma de Chein & Morrison (2010) el cual utiliza una tarea span adaptativa, con estímulos verbales y espaciales, y el paradigma n-back: Brain Scale.

Entrenamiento Atención

Entrenamiento atencional: Tareas del programa Cognifit (https://www.cognifit.com/es) y tareas de atención dividida de Brain HQ que focalicen sobre la atención ejecutiva, conformando sesiones online de 20 minutos cada una, 4 veces por semana (8 semanas).

Grupo control

Tarea de reconocimiento de información (preguntas multiple-choice).

Diseño

Diseño factorial intersujeto de 4 (grupo: 3 experimentales vs control) x 2 (tiempo de evaluación: pre- post), utilizando ANOVA de medidas repetidas sobre las medidas de los test cognitivos y de transferencia

Muchas gracias por su atención…

mariel.musso@hotmail.com