Research Trends in Humanities RTH 12 (2025) – ISSN 2284-0184
Sezione BEC Bio-Education & Cognition

Predicting the Impact of Motivational Beliefs of Engineering and Technical Students on Academic Progress in Mathematics Using Neural Networks

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Introduction

From the perspective of psychologists and education professionals, motivational beliefs are a key concept used to explain different levels of performance. In fact, motivational beliefs guide students' actions in terms of planning, organizing, reviewing, decision-making, problem-solving, and evaluation (O'Donnell, 2007).

Numerous studies have emphasized the significance of motivational beliefs and their positive and meaningful correlation with academic performance, demonstrating a strong association between success and academic performance and psychological well-being (Mohammadi et al., 2013). A theoretical framework for conceptualizing students' motivational beliefs aligns with the Expectancy-Value Theory model. This model proposes three motivational components: 1) Expectancy component, 2) Value component, and 3) Affective component (Pintrich & De Groot, 1990). The expectancy component has been conceptualized in various ways, but at its core, it encompasses students' beliefs about their abilities (personal efficacy).

In this sense, the expectancy component includes students' responses to the question: 'Can I perform the task?' Abolghasemi (2003) also believes that high self-efficacy contributes to performance improvement and serves as facilitators, whereas low self-efficacy hinders performance and is considered task inhibitors. The value component of motivation encompasses students' beliefs regarding the importance and interest in tasks, as well as their goals for task completion. While this component has been conceptualized in various ways, fundamentally, it relates to students' rationale for engaging in a task.

In other words, it is the response that students provide to the question: 'Why am I doing this task?' Motivation is the fundamental driving force for all our actions and signifies the dynamism that encompasses our desires and ambitions in life.

The third component pertains to students' emotional and affective responses to the task. It is crucial for students to address the question: 'How do I feel about this task?'

Among the related emotional and affective responses (such as anxiety, fear, anger, and pride), one of the most significant in school learning situations is exam anxiety, including negative emotions, which hinder optimal performance and learning in students (Patrich & SHank, 2007). Exam anxiety is an unpleasant emotional response to an evaluative situation characterized by a mental sense of tension, unease, and arousal of the autonomic nervous system (Guida & Ludlow, 1989). This anxiety, as a prevalent and significant educational phenomenon, has a close relationship with students' performance and academic progress. In fact, it is a global phenomenon and a significant educational issue that affects millions of students worldwide annually (Mehrabizadeh, 2000). This type of anxiety begins at the age of 10-11 and is a global issue observed across all socioeconomic classes (Sarason, 1975). Sarason also regards exam anxiety as a form of cognitive self-occupation characterized by self-doubt about one's abilities and often leads to negative cognitive appraisal, lack of concentration, undesirable physiological responses, and decreased academic performance. It plays a detrimental and inhibitory role in the psychological and educational well-being of students. In the past two decades, the utilization of advanced neuroimaging technologies has significantly enriched researchers' insights into the functioning of the human brain (Gregory & Parry, 2006). Research findings regarding cognition, emotion, motivation, learning, and development have also brought a wave of new insights (Wolfe, 2001), which have to some extent contributed to the reevaluation of existing explanations of social phenomena and issues. This has had the most significant impact in psychology, giving rise to 'cognitive neuroscience' (Gazzaniga, 2002), 'developmental psychology' (Jensen, 2000), and 'social neuroscience'. Today, neuroscience has found wider applications in the field of education compared to other domains (Jensen, 2000), and the understanding of how the brain learns can have a significant impact on education. Recent studies conducted through various imaging techniques have provided us with new insights, enabling educators to gain increasing awareness of the advancements in cognitive neuroscience and apply these findings in the field of education (Hall, 2005). Such that, a nascent field called 'Educational Neuroscience' is emerging, aiming to investigate learning and education issues by combining cognitive neuroscience methods, particularly neuroimaging, with behavioral approaches (Varma et al., 2008).

Although in recent years, numerous articles have been published and extensive research has been conducted in support of harnessing the potential of neuroscience to improve educational theory, policy, and practice (for example, Byrnes & Fox, 1998; Eisner, 2005), it seems that a relative consensus has emerged among neuroscientists and educational proponents regarding the necessity and feasibility of establishing a strong link between neuroscience and education (Gonçalves, 2009). However, this clarification of the current position of neuroscience in the field of education, taking into account the criticisms and providing reasoned responses, serves to some extent as a reconciliation and serious engagement between staunch advocates of brain-based education and its critics. Since creating challenges and ample problem-solving opportunities is one of the fundamental principles of brain-compatible education (Caine & Caine, 1990), when students engage in solving real-life problems, they become more interested in learning and value it for themselves. Students appreciate teachers who encourage them to think. They prefer activities that require interpretation, analysis, the manipulation of information, or the application of acquired knowledge and skills, as well as encountering new situations (Fisher, 2003). This is achieved through altering time, presenting new content, providing multiple resources, and engaging students in both individual and group project activities (Jensen, 1998). It involves creating opportunities for active student participation in learning and presenting information in various ways to simultaneously stimulate the neural networks of the brain (Madarzo & Motz, 2005). The aim of data mining is to discover hidden information and patterns within data. To achieve useful results, data must be examined to eliminate low-quality and conflicting data (Yosefi & Gholami, 2012).

Data mining has two methods: predictive and descriptive. The goal of descriptive data mining is to achieve patterns between data so they can be interpreted. Predictive data mining is used for predicting future behaviors (Ghazanfari et al., 2014). "Educational Data Mining (EDM) is the application of data mining techniques to educational data. EDM is a machine learning process used for predicting student performance. The goal of EDM is data analysis and providing solutions to educational problems. EDM is used in the discovery or improvement of structural models in the field of knowledge. Educational data mining employs techniques such as decision trees and neural networks (Kaur et al., 2015). The goals, data, and techniques in educational data mining distinguish it from traditional data mining. Educational data mining, as it deals with various groups such as students, teachers, and administrators, can be analyzed from different perspectives. Ultimately, the obtained information can have practical applications for these groups. For example, the discovery of new learning patterns can assist teachers in their teaching methods (Fernandes et al., 2019). In the discussion of educational data mining, descriptive indicators are useful and facilitate the prediction process.

As part of the above-mentioned research, an investigation was conducted.

In this study, using university data, the performance of students was divided into three clusters using clustering methods, and then the prediction of students' performance within each cluster was addressed." (Alfiani & Wu, 2015)

In another study, data mining was employed to model students' performance with the aim of discovering prior academic knowledge of students for predicting their performance in e-learning and the extent of dropout, using regression analysis." (Burgos et al., 2018).

In a study using data mining methods, it was demonstrated (Asif et al., 2017) that there is a correlation and relationship between a student's performance in their first year of study and their individual performance throughout their academic career. Additionally, factors such as maternal education level, family status, and economic status were identified as significant variables influencing student performance (Koosha et al., 2018).

The recognition of motivational beliefs and their components is important for educational managers, instructors, and counselors in understanding influential factors and directions for students' learning. In this regard, the present research aims to provide evidence for predicting the impact of motivational beliefs on the academic progress of engineering and technical students in mathematics using neural networks.

Methodology

The statistical population included all technical and engineering students, comprising 107 male and female engineering students (majoring in electrical, mechanical, telecommunications, computer, and civil engineering) who were randomly selected. It is worth mentioning that the selected students were from Islamic Azad University, Shahr-e Rey. This research was conducted in the first semester of 2022-2023. Comprehensive explanations regarding the questionnaire were provided to the students. After explaining the research objectives and obtaining participants' consent, the Pentrich Motivation Questionnaires were completed online by the participants. Given that engineering students were experiencing academic declines in mathematics courses and were not paying attention to their coursework, the questions in the questionnaire ('I am confident that I can do my coursework to the best of my ability,' 'Learning the subject matter is important to me,' 'I get so nervous at test time that I forget the things I have learned,' 'I am afraid of taking exams,' 'I think I will get good grades this semester') prompted the researcher to use this questionnaire. The reliability of the entire questionnaire was also examined using Cronbach's alpha, which was estimated at 0.86, indicating good reliability for the questionnaire. The response scale of this questionnaire is a five-point Likert spectrum (Strongly Agree, Agree, Neutral, Disagree, and Strongly Disagree). The research method of this study, in terms of its objective, falls into the category of applied research. To address the complexities of motivation in mathematics education, a neural network approach has been employed.

Artificial neural networks leverage the human brain's logic and reasoning through simulation to provide recommendations or make decisions. These artificial neural networks process empirical data, knowledge, or hidden rules beyond the data to create a network structure, a process known as machine learning. In essence, the goal of machine learning is to develop and construct a system capable of learning and self-improvement based on acquired experience, without receiving specific instructions.

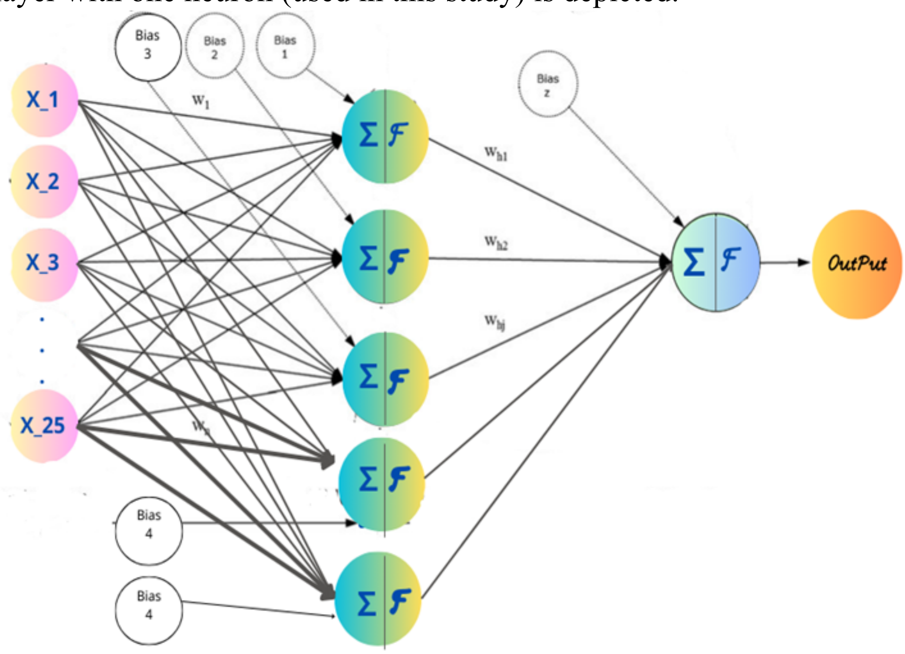
A neural network has a graphical structure in the form of a single-layer or multi-layer network, where each layer contains one or more neurons (nodes), which are, in fact, simplified samples of human brain neurons. Information processing in a neural network is carried out through neurons using a selected mathematical processor called an activation function.

The algorithm of neural networks is designed to take a set of inputs and then process them through neurons in multiple hidden layers, returning a result using an output. This process is called feed forward estimation. Then, by comparing the network's result with the actual output, the output error is calculated. Using the back propagation process, the weights and biases, which significantly affect error reduction, are updated. This way, through repeated training, the output error is minimized to the desired level.

The aim of this research is to utilize a neural network model to investigate the impact of each of the factors present in the questionnaire on the motivation of students to study mathematics.

To use an appropriate statistical method that can confirm the results of neural network testing, it was initially observed, using suitable statistical tests, that the distribution of the identified data follows a normal distribution, and there is also a Spearman correlation coefficient between the variables.

In Figure 1, the structure of a neural network with 25 inputs, one hidden layer with 5 neurons, and one output layer with one neuron (used in this study) is depicted.



In this diagram, there are 25 influential factors serving as inputs in generating motivation, and the output layer represents students' grades. The intermediate layer, which acts as a communicative layer between these two layers and is a single layer in this research, describes the way inputs and outputs are interconnected. To this end, using MATLAB software, the results of neural network analysis have been obtained for 50 available samples, which consist of 25 influential factors in motivation, and are presented in Table 1.

Table 1. Results of Neural Network Analysis

Feature	**Value**
Hidden Layers	1
Neurons in Hidden Layer	5
Learning Rate	0.001
Hidden Layer Activation	Soft Plus
Output Layer Activation	Soft Plus
β	1
Minimum Squared Error	9.9839 × 10^(-6)

Therefore, using Table 1, the optimized weights for each variable are obtained using the gradient descent method, and the estimated parameters of the neural network in the hidden layer (a1) and output layer (a2) are obtained with input values derived from the questionnaire as per Table 2.

Table 2. Hidden and Output Layer Variables

hidden lAyer (a^1)					**Output layer (a^2)**	**Sample number**
0.270285	0.128148	0.835022	0.152244	4.068343	14.00000001	1
2.857244	0.10645	1.299477	0.552146	1.116269	13.27666668	2
4.813615	1.090522	3.530394	1.53E-05	7.52E-05	18.75000001	3
0.597618	0.112387	0.146223	0.641292	3.704463	13.33333333	4
6.573011	0.007229	0.922679	0.29119	0.138933	17.50000003	5
4.014137	2.060452	0.00012	9.13E-05	2.375967	17.50000001	6
0.489592	0.00064	0.333408	6.026294	1.517179	18.1666667	7
2.323749	2.164541	1.394666	0.002115	0.730909	11.99999998	8
3.92162	1.031572	1.650611	2.022848	0.001396	17.08333333	9
0.973416	2.167991	0.168653	0.061306	2.642356	11.99999998	10
2.140161	0.000669	1.72618	2.818787	0.396029	15.00000002	11

1.194676	0.164843	0.002581	3.389128	2.029928	15.33333329	12
3.440499	0.235229	0.954086	0.257505	0.006171	10.33333341	13
0.514552	1.288898	0.59042	0.121046	4.040098	15.00000001	14
3.493375	0.639129	1.756825	0.439868	0.683645	14.66666669	15
0.315368	0.424978	0.052146	0.241513	6.101291	18.6666667	16
1.891335	0.393943	0.019537	4.135653	1.078335	16.00000002	17
0.486733	0.028208	0.409665	1.650298	4.458432	17.66666668	18
4.672787	0.210782	0.004943	2.050235	0.011955	14.83333333	19
1.792141	0.013145	0.058451	1.314866	3.188962	15.66666667	20
3.528357	0.035552	2.632411	1.999329	1.8E-05	17.1666666	21
0.011545	0.038079	1.14282	4.292518	2.514863	17.99999999	22
0.114583	0.285195	2.288814	0.682675	3.142285	15.16666667	23
3.528455	0.066135	0.00111	1.477312	2.357599	17.49999999	24
3.327581	1.352429	2.675608	0.68923	0.104254	15.66666668	25
3.430529	0.007169	0.197022	0.593238	2.180969	15.33333335	26
0.000465	0.001078	1.697609	4.46219	2.617841	19.66666666	27
3.636841	2.033717	0.731485	0.030911	0.049659	11.66666667	28
2.782612	0.164038	0.084645	0.518802	2.184072	13.66666667	29
3.25527	1.593385	0.006591	0.002826	2.086868	14.58333335	30
2.71382	1.402958	1.476339	0.001135	2.890984	18.33333334	31
1.984392	0.655598	0.008324	0.000951	3.571255	14.99999999	32
6.232464	0.573697	1.784407	0.001233	0.001986	17.99999995	33
3.715434	0.505479	2.840548	0.269154	0.263874	15.66666668	34
3.342934	1.345242	2.200653	0.146951	0.466476	14.66666667	35
2.82818	0.15381	0.480395	1.046865	1.965106	15.00000002	36
1.30214	0.163158	3.453742	1.497013	0.989149	15.66666669	37
2.309613	1.809575	2.805216	0.001533	1.896404	17.66666665	38
4.165488	1.076591	3.416211	0.133981	5.25E-06	17.33333332	39
0.85792	0.000105	0.005078	4.507993	0.222295	11.66666666	40
3.592652	1.915979	0.939865	3.91E-05	0.118788	11.99999999	41
2.002384	0.001765	1.907033	3.822243	0.007707	16.00000003	42
0.003247	0.804197	3.335599	0.913932	3.884122	19.99999998	43
2.090465	2.349374	4.79478	0.000679	0.000769	16.33333332	44
1.83999	0.001583	1.036379	2.90747	2.679688	19.49999985	45
1.277647	0.036069	2.156485	2.048838	2.050441	17.00000002	46
0.024367	0.004573	0.075782	4.864946	3.516161	19.83333334	47
2.260276	1.544648	0.505409	1.199402	3.02622	18.3333333	48
0.234144	0.003	0.522545	5.014896	1.903461	17.00000004	49
0.158241	0.010568	1.615089	4.112643	0.04505	12.00000001	50

Prediction with Neural Network

Given that all parameters follow a normal distribution, the random model is formulated as follows:

$$dx_t = x_t \mu dt + x_t \sigma dw$$

For each parameter, we consider that $\Delta w_i = \varepsilon_i \sqrt{\Delta t_i}$ and represent _ε_i as a normally distributed random variable with a mean of zero and a variance of one. The analytical solution of the above random model with the Monte Carlo method is as follows.

$$x_{t+1} = x_t \exp(\mu - 0.5\sigma^2) + \sigma\varepsilon$$

Therefore, by performing the prediction for 100 paths and calculating the average values, an acceptable prediction of the parameter is obtained.
Now, to examine the impact of motivation parameters on students' grades, one of the parameters is considered based on the scores.

Table3

Completely Agree	Agree	Neutral	Disagree	Completely Disagree
5	4	3	2	1

Please translate the following text into more professional English, considering the parameters based on the predicted scores obtained using the Monte Carlo random method.

The results of the neural network prediction indicate that among the components of self-efficacy, goal orientation, intrinsic valuation, and anxiety, the most important and effective component in the academic progress of mathematics students is intrinsic valuation. Goal orientation has a less significant influence compared to intrinsic valuation, and self-efficacy has a very minimal impact on motivational beliefs. Additionally, exam anxiety does not have any effect on motivational beliefs.

Discussion and Conclusion

Mathematics is considered a field that relies heavily on abstract reasoning. However, most individuals exhibit strong emotional reactions to mathematics, mathematical thinking, and mathematical learning (Hannula, 2006).

In this regard, Marsh (1998) and Green argue that students with lower confidence in their mathematical abilities and a more negative attitude towards mathematics tend to attribute their failures in learning and problem-solving in mathematics to their perceived incompetence. This leads to a pessimistic outlook on motivation, causing them to believe that success in advanced mathematics is unattainable.

According to Nicolaidou and Philippou (2009), individuals who harbor a positive motivation toward mathematics tend to perform better in this subject. Researchers in the field of mathematics believe in the relationship between motivation and academic performance. When students derive pleasure from what they learn, their learning becomes more effective, and if they have an interest in the subject matter, they make greater progress. Therefore, students who find enjoyment in mathematics experience an increase in their intrinsic motivation for learning, and vice versa.

This study focuses on identifying the influential factors in motivational beliefs related to the academic progress of engineering students in mathematics, utilizing neural networks. To this end, in the first semester of 2022- 2023, 50 engineering students, both male and female, were randomly selected from a pool of 107 students. The results obtained from the neural network prediction reveal that intrinsic valuation, owing to its association with mathematics courses, foundational courses, and prerequisite courses of other academic units, holds particular significance among students, making it the most crucial and effective component.

The results of neural network predictions indicate that among the components of self-efficacy, goal orientation, intrinsic valuation, and absence of anxiety, intrinsic valuation is the most important and influential component in the academic progress of mathematics students. Goal orientation has a lesser impact compared to intrinsic valuation, and self-efficacy has a very minimal effect on motivational beliefs. Additionally, exam anxiety does not have any significant impact on motivational beliefs.

According to the obtained results, the most influential factor on students' motivation is intrinsic valuation. The significant impact of mathematics courses on the selection of academic majors in high school and university, coupled with the importance that society, family, and school attribute to mathematics, has led to this subject acquiring a special and crucial position among students. As a result, intrinsic valuation is fostered. The next influential factor on students' motivation is goal orientation. Since foundational math courses serve as prerequisites for many technical and engineering subjects, goal orientation strengthens students' academic behaviors. It propels them towards activities and plans that lead to their academic progress.

Another factor, self-efficacy, has a very minimal impact on motivation. This is because the weak foundation of students in math courses and the lower performance in math assignments compared to other subjects result in students having lower self-efficacy beliefs in math compared to other subjects. As a result, self-efficacy will have a lesser influence on students' academic performance. Ultimately, exam anxiety has no significant impact on students' motivation. Since goal orientation plays a considerable role in motivation, students who possess self-sufficiency and strong beliefs in internal control are capable of managing exam anxiety. Emphasizing the learning outcomes, they encourage themselves to strive for completing their academic tasks in mathematics.

The following studies (Alfiani, 2015), Burgos et al., 2018), (Asif et al., 2017), (Koosha et al., 2018) are in line with the aforementioned research.

It is recommended that by using both qualitative and quantitative data available at the university, the discovery of relationships between these data can provide some of the necessary information for improving the quality of engineering education activities. The information and relationships discovered among the data, besides being beneficial for administrators, can also be of effective assistance to students in their academic success. This information assists in providing solutions to enhance the engineering education process, preventing wastage of time and resources.

References

Abolghasemi, A. (2003). *Exam anxiety, diagnosis, causes and treatment based on research,* Ardabil, Nik A. Publications.

Amiri Moghadam, M., Gadimi, K., & Afshar (2017). Presenting a fuzzy neural network model to predict the general health of women through the relationship between the influential components of sports participation motivation and body culture. *Examining Iran's social issues* 8(1), 233-251.

Alfiani A., Wulandari F. (2015). Mapping student's performance based on data mining approach (a case study). *The 2014 International Conference on Agro-industry (ICoA): Competitive and sustainable Agro-industry for Human Welfare* 3, 173-177.

Cacioppo, J.T. (2005). *Social neuroscience: Key readings.* Psychology Press.

Caine, R.N., Caine, G. (1997). *Unleashing the power of perceptual change: The potential of brain-based teaching.* Alexandria, VA: Association for Supervision and Curriculum Development.

Eisner, E.W. (1995). *The educational imagination*. New York: Macmillan College Publishing Company.

Fisher, R. (2003). *Teaching thinking: Philosophical enquiry in the classroom*. London: Continuum.

Fernandes E., Holanda M., Victorino M., Borges V., Carvalho R., & Van Erven G. (2019). Educational data mining: Predictive analysis of academic performance of public school students in the capital of Brazil, *Iranian Journal of Business Research*, 94, 335-343.

Gazzaniga, M.S. (2002). *Cognitive Neuroscience: The Biology of the Mind*. Psychology. Publisher, Norton.

Gonçalves, T.N. (2009). Complex systems and plastic brains. A trans-disciplinary approach to education and the cognitive sciences. In M. Karanika-Murray & R. Wiesemes (Eds.), *Exploring avenues to interdisciplinary research: From cross- to multi- to interdisciplinary research* (pp. 9-24). UK: Nottingham University Press.

Green. B.A. (1999). *Goal, values and beliefs as predictors of achievement and effort in high school mathematics classes.* Retrieved from http://www.findarticles.com

Gregory, G.H., Parry, T. (2006). *Designing brain compatible learning.* Thousand Oaks, CA: Corwin Press.

Guida, F.V., Ludlow, LH. (1989). A cross-cultural study of test anxiety. *Journal of Cross-Cultural Psychology* 20, 178-190.

Ghazanfari, M., Alizade, S., Teimori, B. (2014). *Data mining and knowledge discovery*. Tehran: Iran University of Science and Technology Publications [in Persian].

Sarason, I.G. (1975). Anxiety and self- preoccupation. In I.G. Sarason, C.D. Spielberger (Eds.). *Stress and Anxiety* (vol.2). New York: Hemisphere/Hastead.

Hagan, M.T., Demuth, H.B., Beale, M. (1997). *Neural network design*. PWS Publishing Co.

Hall, J. (2005). Neuroscience and education: What can brain science contribute to teaching and learning? *Spotlight*, *92*, SCRE Center, University of Glasgow.

Hannula, M.S. (2006). *Affect in mathematical thinking and learning towards integration of emotion, motivation, and cognition*. Rotterdam: Sense.

Jensen, E. (2000). Brain-based learning: A reality check. *Educational Leadership* 57(7), 76-80.

Jensen, E.P. (1998). *Teaching with the brain in mind*. Alexandria, VA: ASCD Publishing.

Madarzo, G.M., Motz, L.M.L. (2005). Brain research: Implications to diverse learners. *Science Educator* 14(1), 56-60.

Mehrabizadeh, M., Abu Al-Qasimi, A., Najarian, B. (2000). The prevalence of exam anxiety, and the level of self-efficacy and the place of restraint with it according to the variable of intelligence. *Journal of Educational Sciences and Psychology* 3(2,1), 55-72.

Middleton, M.J., Midgley, C. (1997). Avoiding the demonstration of lack of ability: An under explored aspect of goal theory. *Journal of Educational Psychology* 89(4), 710-718.

Mirfakhredini, H., Taheri Demeneh, M., Mansouri, H. (2010). Artificial Neural Networks; A new approach in measuring the quality of university library services. *Librarianship and information 13*(1), 205-225.

Mohammadi, N., Hatami, H., Asadzadeh, H. (2013). Investigating self-regulation strategies (cognitive and metacognitive) on motivational beliefs. High school students. *Journal of Educational Psychology* 27(9), 49-66.

Nicolaidou, M., Philippou, G. (2009). *Attitude towards mathematics, selfefficacy and achievement in problemsolving.* European Research in Mathematics Education III. Retrieved from http://www.dm.unipi.it/diduca/CERME3/Proceedings.

O'Donnell, A.M., D'Amico, M., Schmid, R.F., Reeve, J., Smith, J.K. (2007). *Educational Psychology: Reflection for Action.* USA, Wiley.

Ostovar, S., Hayyer, M. (2004). Mathematics self-efficacy and mathemathics problem-solving. Implications of using defferent self-efficacy forms of assessment. *The Journal of Experimental Education* 65, 213-228.

Pentrich, P.R., Schunk, D.H., (2006). *Motivation and Education. Theories and research strategies*. Tehran, Elam.

Schunk, D.H., Ertmer. P.A. (2000). *Selfefficacy and academic learning: Selfefficacy enhancing interventions*. Handbook of self-Regulation, 631-649.

Varma, S., McCandliss, B.D., & Schwartz, D.L. (2008). Scientific and pragmatic challenges for bridging education and neuroscience. *Educational Researcher,* 37(3), 140-152.

Byrnes, J.P., & Fox, N.A. (1998). The educational relevance of research in cognitive neuroscience. *Educational Psychology Review*, *10*(3)*,* 297-342.

Wolfe, P. (2001). *Brain matters: Translating research into classroom practice*. Alexandria, VA: Association for Supervision and Curriculum Development.

Yosefi, R., Gholami, A. (2012). An overview of data mining concepts. *Iranian Journal of Brought light* 39, 10-15 [in Persian].