

FUNCTIONAL AND STRUCTURAL MODELLING OF THE PHARMACIST'S PROFESSIONAL DEVELOPMENT PROCESS IN BUCHAREST FACULTY OF PHARMACY

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Abstract

A functional and structural model of pharmaceutical educational process from Romanian, Bucharest Faculty of Pharmacy, was conceived for comparison of curricula in different faculties for prediction of students' final achievements.

It was looked for a correlation between a marker of the *final result* (the graduation score) and the parameters of the over time students' evolution (admission score, mean grades of the academic years, score at the licence exam).

In the model it was assumed that the effects on the dependent variables (result markers as for example the general mean and/or the licence exam mean) are linear functions of the entrance variables.

Determination of the coefficients defining linear dependence was performed by applying least square models.

The obtained linear system for determination of coefficients was solved using numerical analysis part of statistics software.

It was obtained that the predicted data, by model, were very close to the observed data, the model being applicable for approximate describing dependencies and predicting the final graduate and licence results.

Rezumat

În lucrare a fost conceput un model funcțional și structural al procesului educațional farmaceutic din Facultatea de Farmacie București, în scopul comparării planurilor de învățământ de la diferite facultăți pentru a prezice rezultatele finale obținute de studenți.

În modelul propus s-a căutat o corelație între un marker al rezultatului final (media la absolvire) și parametrii evoluției studenților pe parcursul anilor de studiu (punctajul la admitere, mediile în anii I-V, media la licență).

Modelul presupune că efectele asupra variabilei dependente (markerul de rezultat cum ar fi media generală sau media la licență) sunt funcții liniare ale variabilelor de intrare.

Determinarea coeficienților care definesc dependența liniară s-a realizat prin aplicarea metodei celor mai mici pătrate. Sistemul liniar rezultat, pentru determinarea coeficienților, a fost rezolvat folosind analiza numerică, parte a soft-ului de statistică.

S-a constatat că datele prezise, prin model, au fost suficient de apropiate de datele reale, modelul putând fi aplicat în descrierea aproximativă a dependențelor și prezicerea rezultatelor finale după cinci ani și la examenul de licență.

Keywords: functional and structural predictive model, pharmaceutical analysis education, linear regression, multivariate analysis

Introduction

Structural and functional equation modeling (FSEM) contains a set of statistical techniques used to measure and analyze the relationships of observed and latent variables. It examines linear causal relationships among variables, while simultaneously accounting for measurement error.

Structural and functional equation modeling is a powerful multivariate analysis technique that is widely used in the social sciences [1]. Its applications range from analysis of simple relationships between variables to complex analyses of measurement equivalence for first and higher-order constructs [2]. It provides a flexible framework for developing and analyzing complex relationships among multiple variables that allow researchers to test the validity of theory using empirical models. Although its application has been seen in pharmaceutical research [3,4,5], it has yet to be extensively used in modeling of pharmaceutical education.

There are several integrated analytic techniques within FSEM [6,7]. These include between-groups and within-group variance comparisons, which are typically associated with analysis of variance. It also includes path analysis (regression analysis) whereby equations representing the effect of one or more variables on others can be solved to estimate their relationships. Factor analysis is another special case of FSEM whereby unobserved variables (factors or latent variables) are calculated from measured variables.

Materials and Methods

General Linear Model

General linear model establishes a linear function which connects a dependent variable usually called "response", which is possible to evaluate experimentally, with other dependent variables or "parameters" or "factors".

The parameters involved may be potential variables which would take values in a given interval [8,9,15]. Independent variables can be of three types: continuous variables (mean grades), discrete variables (grades of a given subject) or nominal variables (accepted, rejected, poorly managed etc.).

The estimated response $\hat{y}$ will never be equal with the actual value y , the relationship of dependence being the following [10]: $\hat{y} = y + e$ where e is the error. In this way, $\hat{y}$ would be an estimator for y , because the "true" value is a function of experimental variables x_i :
 $y = f(x_1, x_2, x_3, \dots, x_k)$
 $\hat{y} = f(x_1, x_2, x_3, \dots, x_k) + e$

In order to develop a predictive model regarding performance we used a functional model of multiple multi linear regression which can be written as:

$$y = f(x) = \beta_0 + \beta_1 \cdot x_1 + \beta_2 \cdot x_2 + \beta_3 \cdot x_3 + \dots + \beta_{11} \cdot x_1^2 + \beta_{22} \cdot x_2^2 + \beta_{33} \cdot x_3^2 + \beta_{12} \cdot x_1 \cdot x_2 + \beta_{13} \cdot x_1 \cdot x_3 + \beta_{23} \cdot x_2 \cdot x_3 + \dots$$

where x_i were the values of parameters specified above.

The model took into account interactions between factors such as restraint or autoinduction between the terms of squares of variables [11,12, 14-16]. The X_i variables corresponding to nominal parameters, can be 0 or 1 in the following possible cases: accepted or rejected, dwelling in Bucharest or coming from outside, male or female etc.

Application of the model leads to the estimation of the values and confidence intervals for β coefficients. The full application of the model is very difficult that is why, the number of variables is reduced by determining the critical factors and neglecting others.

The coefficients are the ones that minimize the sum of square errors.

$$SS(\beta_0, \beta_1, \beta_2 \dots) = \sum_{i=1}^n (y_i^{obs} - y_i^{estim})^2 = \sum_{i=1}^n (y_i^{obs} - \hat{y}_i)^2, \text{ where}$$

SS - Sum of squares; y_i^{obs} - observed values; $y_i^{estim} = \hat{y}_i$ - estimated values;
 i- subject index (student).

The results are between the solutions of the equations:

$$\frac{\partial f}{\partial \beta_j} = 0 \quad \text{for } j = 0, 1, 2, \dots, n$$

The aim of the present work was to develop a predictive model regarding students' performance in order to establish determinant factors for human resource training at the Faculty of Pharmacy in Bucharest, Romania.

Selected parameters for pharmaceutical education were the admission score, the mean grades (general, at the licence exam, for each of the five

years of study), the students' grades at certain courses. Data were provided by the Faculty Secretary.

General linear structural and functional pharmaceutical education model

Methods and mathematical models have been conceived in order to estimate a subset of parameters that determines the estimated final result (general mean, licence exam mean etc.) of the Faculty's graduates that can be written:

End result = f (admission score, annual mean grades, grades at different groups of disciplines etc.)

For example it can be a linear function:

$$y = \beta_0 + \beta_1 ADM + \beta_2 M1 + \beta_3 M2 + \beta_4 M3 + \beta_5 M4 + \beta_6 M5 + \beta_7 MG + \beta_8 ML + \dots$$

where ADM – admission score; M1-M5 – average grade of the academic years I-V; ML – the average grade at the licence exam.

Particular two dimensional models

Particular models were considered for a calibration of the general models. One case was that where a response variable was determined essentially by two dependent variables.

Case I: the number of independent variables is 2 and the plan determined by the least square method passes through the origin.

The model has the following definition: $y_{final} = \alpha x_1 + \beta x_2$

In this case we found α and β as solutions which minimise the error function

$$f(\alpha, \beta) = SS_{er} = \sum_{i=1}^n (y_i - \alpha x_1 - \beta x_2)^2$$

The solution was obtained as solution of the equations:

$$\frac{\partial f}{\partial \alpha} = 0 \text{ and } \frac{\partial f}{\partial \beta} = 0 \quad \alpha = \frac{\sum x_1 y \sum x_2^2 - \sum x_2 y \sum x_1 x_2}{\sum x_1^2 \sum x_2^2 - (\sum x_1 x_2)^2}$$

$$\beta = \frac{\sum x_2 y \sum x_1^2 - \sum x_1 x_2 \sum x_1 y}{\sum x_1^2 \sum x_2^2 - (\sum x_1 x_2)^2}$$

We applied the model to find out the dependency of the licence exam score to the admission score and the general mean: $ML = \alpha MA + \beta MG$.

We then tried to optimise the model by introducing the restriction that the sum of the coefficients should be 1: $\sum_{i=1}^n \beta_i = 1$

Case II: the sum of the coefficients is 1.

In this particular case we had the following relation:

$$ML = \alpha MA + (1 - \alpha)MG$$

We deduced the formula to calculate α by the same **rule, the least square method**. Using the more general notations of x and y we had to minimise the following function:

$$f(\alpha) = \left[\sum (y - \alpha x_1 - (1 - \alpha)x_2) \right]^2$$

The solution of the problem is

$$\alpha = \frac{\sum y(x_1 - x_2) - \sum x_2(x_1 - x_2)}{\sum (x_1 - x_2)^2} = \frac{\sum (y - x_2)(x_1 - x_2)}{\sum (x_1 - x_2)^2}$$

A more general case:

The factorial analysis of the linear dependency between the general mean (MG) and the independent variables: admission score (MA), licence written exam (MLS), mean grades in academic years I-V (M1-M5)

In this case:

$$MG = \alpha_0 + \beta_{MLS}MLS + \beta_1M_1 + \beta_2M_2 + \beta_3M_3 + \beta_4M_4 + \beta_5M_5,$$

where MG – general mean; MLS – licence written exam; M₁-M₅ – mean grades from the five years of faculty.

Results and discussion**1. Two dimensional models**

For a sample of 8 students we processed the licence exam mean (ML), the general mean (MG), the admission score (A), the mean grades from the academic years I-V (M_I – M_V). The processed data are shown in Table I.

By calculating according to the method shown above we got $\alpha = -10.67$, $\beta = 1.55$, and the linear model: $ML = -10.67MA + 1.55MG$

From the acquired results we found a negative contribution of the admission score and a positive contribution of the general average grade. On the other hand, the correlation coefficients were found $r_{ML-MA} = 0.07$ and $r_{ML-MG} = 0.001$.

The weak correlations and the negative coefficient indicate that the reduction of the dependency to just two factors was exaggerated. These factors cannot be considered decisive and the contribution of the other factors cannot be ignored.

Table I
Student mean grades – CASE I

	Stud*. 1	Stud. 2	Stud. 3	Stud. 4	Stud. 5	Stud. 6	Stud. 7	Stud. 8	
ML	9.57	9.48	9.39	9.69	9.21	9.4	9.88	9.58	Σ
MG	7.81	7.22	7.82	7.15	9.43	6.68	9.11	7.68	
A	102	76	90	85	108	45	96	80	
M I	6.31	6.29	7.37	6.81	7.29	5.46	9.43	6.98	
M II	6.85	6.87	7.26	6.46	7.38	5.86	9.54	7.05	
M III	9.08	8.12	7.78	6.96	8.25	6.57	9.21	8.14	
M IV	7.8	6.94	7.92	7.4	7.17	7.74	8.4	8.55	
M V	9.02	7.91	8.8	8.12	8.37	7.79	8.98	7.7	
x_1 (A)	9	6	8	7	9	4	8	7	57
x_2 (MG)	8	7	8	7	9	7	9	8	63
y (ML)	10	9	9	9.69	9.21	9.4	9.88	10	76
x_1x_2 (AG)	66	46	59	51	85	25	73	51	455
x_1y (AL)	81	60	70	69	83	35	79	64	541
x_2y (GL)	75	68	73	69	87	63	90	74	599
x_1^2 (A ²)	72	40	56	50	81	14	64	44	422
x_2^2 (G ²)	61	52	61	51	89	45	83	59	501

*Stud – student

Case II: the sum of the coefficients is 1 ($\alpha + \beta = 1$).

In this case we used the same sample of 8 students. The processed data is shown in Table II. We found the following results: $\alpha = -0.98$ and $\beta = 1.98$.
 $ML = -0.98MA + 1.98MG$

Table II
Student means – CASE II

	Stud*. 1	Stud. 2	Stud. 3	Stud. 4	Stud. 5	Stud. 6	Stud. 7	Stud. 8	
ML	9.57	9.48	9.39	9.69	9.21	9.4	9.88	9.58	Σ
MG	7.81	7.22	7.82	7.15	9.43	6.68	9.11	7.68	
Pctj.A	102	76	90	85	108	45	96	80	
M I	6.31	6.29	7.37	6.81	7.29	5.46	9.43	6.98	
M II	6.85	6.87	7.26	6.46	7.38	5.86	9.54	7.05	
M III	9.08	8.12	7.78	6.96	8.25	6.57	9.21	8.14	
M IV	7.8	6.94	7.92	7.4	7.17	7.74	8.4	8.55	
M V	9.02	7.91	8.8	8.12	8.37	7.79	8.98	7.7	
x_1 (A)	9	6	8	7	9	4	8	7	57
x_2 (G)	8	7	8	7	9	7	9	8	63
y (L)	10	9	9	9.69	9.21	9.4	9.88	10	76
x_1x_2 (AG)	66	46	59	51	85	25	73	51	455
x_1y (AL)	81	60	70	69	83	35	79	64	541
x_2y (GL)	75	68	73	69	87	63	90	74	599
x_1^2 (A ²)	72	40	56	50	81	14	64	44	422
x_2^2 (G ²)	61	52	61	51	89	45	83	59	501
y- x_2	2	2	2	3	0	3	1	2	13
$x_1 - x_2$	0.7	-0.9	-0.3	-0.1	-0.4	-2.9	-1.1	-1	-6
$(x_1 - x_2)^2$	0.48	0.79	0.10	0.0	0.18	8.58	1.23	1.03	12.4
$(y - x_2)(x_1 - x_2)$	1.2	-2	-0.5	-0.2	0.1	-8	-0.9	-1.9	-12.1

*Stud – student

The conclusions were the same as in the first case.

We tested further, the **correlation** between the licence exam mean, the annual mean grades and grades from disciplines considered to be decisive for the final result, from a sample of 50 students. The processed data and the acquired values for the correlation coefficient r are shown in Table III.

According to Table III we noticed that there was a weak correlation between the license exam mean and the general mean and even negative correlations with some disciplines (Organic Chemistry, Physical Chemistry, Pharmaceutical Chemistry, Pharmaceutical Technology, Toxicology, Drug Control, Marketing and Pharmaceutical Legislation).

Table III
Correlation coefficients of annual results and results of different disciplines

Student Scores	Stud.1	Stud.2	Stud. 3	Stud.4	Stud. 5	Stud.6	Stud.7	Stud.8	r
Licence Mean	9.57	9.48	9.39	9.69	9.21	9.4	9.88	9.58	-
General Average Grade	7.81	7.22	7.82	7.15	9.43	6.68	9.11	7.68	0.001
Admission Score	102	76	90	85	108	45	96	80	-
Year I Average grade	6.31	6.29	7.37	6.81	7.29	5.46	9.43	6.98	0.53
Year II Average grade	6.85	6.87	7.26	6.46	7.38	5.86	9.54	7.05	0.52
Year III Average grade	9.08	8.12	7.78	6.96	8.25	6.57	9.21	8.14	0.33
Year IV Average grade	7.8	6.94	7.92	7.4	7.17	7.74	8.4	8.55	0.52
Year V Average grade	9.02	7.91	8.8	8.12	8.37	7.79	8.98	7.7	0.26
Admission grade	8.5	6.3	7.5	7.1	9	3.8	8.0	6.7	0.07
Mathematics	8	8	8	6	9	5	10	8	0.19
Inorganic Chemistry	5	7	6.5	6.5	7.5	6.5	8	10	0.15
Analytical Chem. 1	5	5	8	8	6	5	7	8	0.32
Analytical Chem. 2	6	7.5	6	5.5	7	5	7.5	10	0.18
Organic Chemistry	6	5	6.5	5.5	7	5	6	9.5	-0.05
Physical Chemistry 1	10	10	10	9	10	8	9	10	-0.25
Physical Chemistry 2	10	10	9	7	10	5	9	9	-0.06
Pharmacognosy 1	10	8	9.5	8.5	8.5	8	9	10	0.24
Pharmaceutical Chem. 1	8.5	7.5	6.5	7	8.5	5.5	7	8.5	-0.06
Pharmaceutical Tech. 1	9	8	7	6	7	5	9	9	0.44
Pharmaceutical Chem. 2	8	6	6	7	5.5	8	8	7.5	0.64
Pharmaceutical Tech. 2	6.5	8	8.5	7	8.5	8	7	9	-0.6
Pharmacology 1	6	5	6	6.5	6	7	6	10	0.1
Pharmacology 2	8	5	7.5	6	6.5	7.5	7.5	9	0.16
Biostatistics	10	10	9	9	8	6	9	9	0.38
Management and Legislation	6	6	9	9	5	8	8	7	0.43
Toxicology 1	7	6	9	7	7	8	7	7	-0.276
Toxicology 2	8	6	9	8	8	8	5	8	-0.59
Drug Control	6.5	8	8	6	7	8	6	10	-0.35
Pharmaceutical Tech. 3	8.5	8	9	6	7	8	8	8	-0.1
Marketing and Leg.	10	10	7	7	8	6	7	9	-0.04
Clinical Pharmacy	6	6	8.5	9.5	9	7.5	8	8	-0.04

We noticed that we didn't have very strong correlations between dependent variables (general mean, mean grades in academic years I-V, grades at certain disciplines) that could prevent the finding of stable linear correlation coefficients.

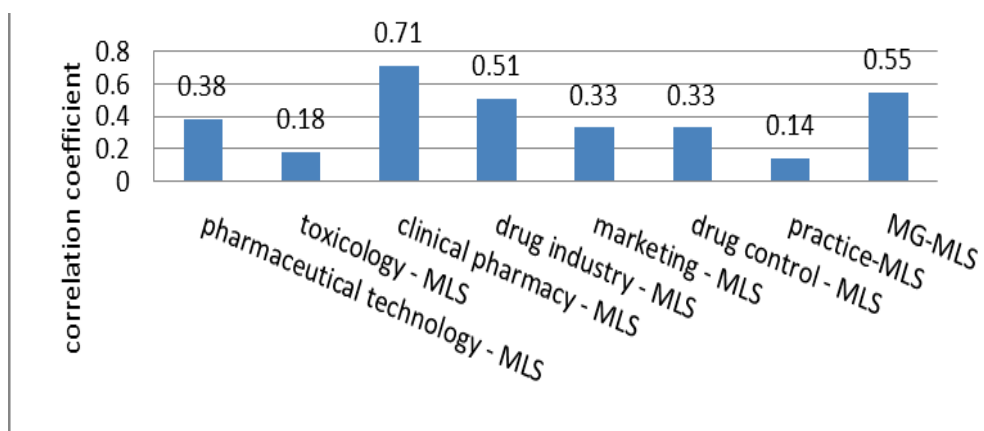


Figure 1

Correlations between written licence grade exam – other results. General mean (MG) licence written exam (MLS).

From figure 1 we notice a very good correlation between the written licence exam mean and disciplines as Clinical Pharmacy, Management and Pharmaceutical Legislation and Drug Industry. Weaker correlations had been found between the written exam at licence and disciplines like Pharmaceutical Technology, Marketing, Drug Control and Toxicology. We had to underline that the negative sign of the correlation coefficient of some disciplines did not mean a negative contribution to the final results. It is rather a sign that disciplines are not dependant, being distributed in different clusters, acting independently on the final result.

We used the STATISTICA software to calculate the correlation coefficients between all variables. The results are shown in table IV.

Table IV

The correlation matrix between the variables licence written exam, grades averages of years I-V and the general grades

Variables n=50	Average p<0.05	Standard Deviation	MLS	M 1	M 2	M 3	M 4	M 5	M G
MLS	8.74	0.85	1.00	0.50	0.46	0.60	0.60	0.45	0.55
M 1	7.09	1.22	0.50	1.00	0.89	0.78	0.69	0.65	0.90
M2	7.11	1.24	0.46	0.88	1.00	0.81	0.72	0.65	0.91
M3	7.62	1.23	0.60	0.78	0.81	1.00	0.86	0.77	0.91
M4	7.47	1.04	0.60	0.69	0.72	0.86	1.00	0.76	0.84
M5	8.05	0.69	0.45	0.65	0.65	0.77	0.76	1.00	0.83
MG	7.44	1.03	0.55	0.89	0.91	0.91	0.84	0.83	1.00

general mean (MG), admission score (MA), licence written exam (MLS), mean grades in academic years I-V (M1-M5)

We noticed that, in general, there were good correlations, a single correlation coefficient being smaller than 0.5 (between licence and general mean). If we looked for the best correlations ($r \geq 0.90$) we observed that the final result (general mean) was better correlated with M 1, M 2, M 3, i.e. basic sciences than with pharmaceutical specific disciplines. The poorest correlation of the general mean was registered for the mean at the written licence exam.

If we consider also the very good correlation between admission and final results, it appears that the general mean (MG) is determined more by intelligence, spontaneity and basic knowledge and less by specific knowledge.

2. Multidimensional models

In the General Case we analyzed the regression, using the STATISTICA software, among six variables. The non-standardized form of the regression line equation was:

$$MG = -0.72 + 0.0006MLS + 0.21M_1 + 0.25M_2 + 0.19M_3 + 0.074M_4 + 0.036M_5$$

Table V

Regression analysis for prediction of the General Mean

N=50	R = 0.98179820; R ² = 0.96392770; R ² Adjusted = 0.95889436; p < 0.0000; F(6,43)=191.51; Estimated standard error 0.20986					
	β	Stand. Err.	B	B Stand. Error	t (43)	p-Level
Intercept			-0.72	0.47	- 1.55	0.13
MLS	0.0005	0.04	0.0006	0.05	0.01	0.99
M 1	0.25	0.07	0.21	0.06	3.73	0.0006
M 2	0.30	0.07	0.25	0.06	4.25	0.0001
M 3	0.22	0.07	0.19	0.06	3.07	0.004
M 4	0.07	0.06	0.07	0.06	1.23	0.22
M 5	0.24	0.05	0.34	0.07	4.93	0.00001

where β – calculated coefficients and B – adjusted coefficients based on the co linearity of some of the predictor variables (licence written exam, mean grades in years I-V).

The linear regression coefficients indicated that the means from years I, II, III but also V have approximately equal contributions in the general mean (MG). The result was in a good correlation with that suggested by correlation coefficients. The dependence between the general mean and IVth year mean was surprisingly low. Also, the mean at written licence exam had a very small influence to general mean.

In conclusion, the correlation between the two final result indicators (general mean and written licence exam) was very low, even if they depended of the same partial indicators.

Examining the multidimensional matrix of the correlation coefficients and the graphical representation of individual results we observed that distribution of these results is far from normal in the first two years and at the written licence exam.

In the first years the grades were biased to the lower limit of interval. On the contrary, at written licence exam the grades were biased to the upper limit of interval.



Figure 2

The Correlation Matrix between the variables Licence Written Grade Exam, Mean Grades years I-V and General Grade Mean

Concerning deviations from linear correlation, these were large for written licence exam – partial results lines. On the contrary, fairly linear correlations appeared in case of general mean.

As a general rule it seems that the accuracy of linear fit increased continuously from the beginning to the ending phases of the educational process.

Model validation

Comparing the true values and the regression equation predicted values we obtained figure 3.

We noticed that predicted data are very similar to the real data, therefore the model is acceptable for describing dependencies and predicting the final result.

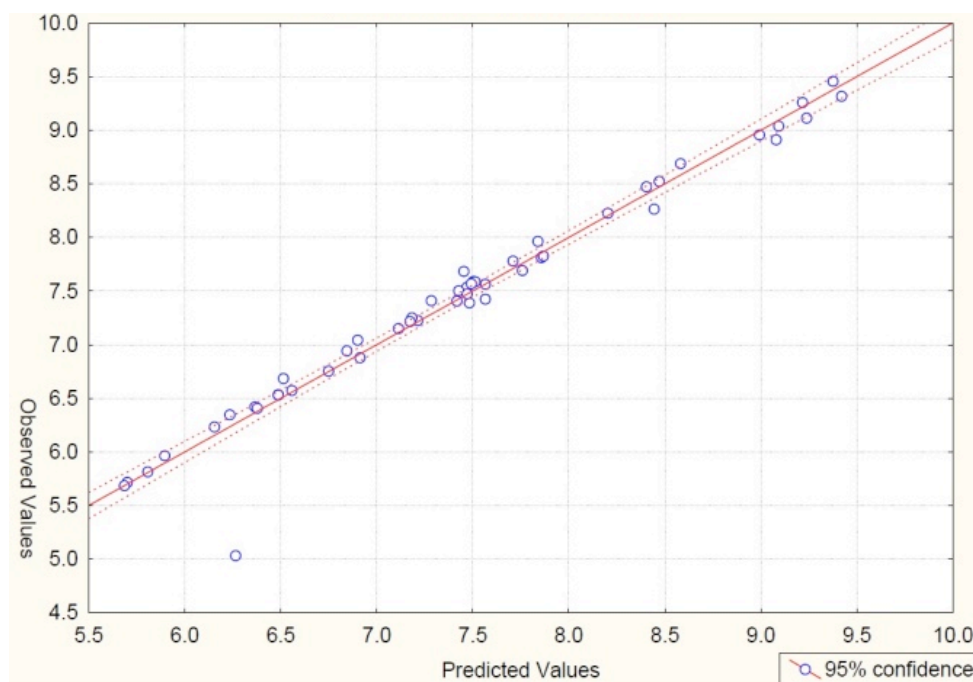


Figure 3
Predicted vs. Observed values
Dependent variable: General mean

Conclusions

The data processing clearly indicated that a linear regression model could be applied in order to predict final indicators (students' achievements) from partial result parameters associated with different stages in

professional development (admission, mean grades at different disciplines, grades during the training period).

Given the way the theoretical licence exam was conducted (multiple choice test) it was obtained a correlation with the admission, both being conducted by multiple choice questionnaires.

The two dimensional linear regression function assumed in estimating the importance of each discipline in the final grades (the general mean, the written licence exam mean), proved a poor correlation between dependent and independent variables suggesting the need of more complex models, including more than two independent variables.

Results suggest that the license is less dependent on the knowledge level being rather a test of intelligence.

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