The Problem of Missing Data in Structural Modeling of Intellectual and Personal Characteristics of Students

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Abstract

Numerous studies have confirmed that the intellectual indicators of students have the greatest impact on their academic achievements. It is known, however, that personal qualities such as consciousness, emotionality, masculinity, neuroticism, etc. can also indirectly either enhance or weaken the influence of cognitive indicators on learning success. The complexity of the analysis of such indicators based on the test results is gaps in the data, which are objectively explained by the volume and non-simultaneity of passing the tests. This article examines the problem of missing data when building a structural model of a complex system of the interrelation of cognitive and personal indicators, to further analyze their cumulative impact on learning success. One method of multiple imputations (the missForest algorithm), full information maximum likelihood, and some simple techniques like mean imputation and pairwise deletion were investigated. As a result, the mean imputation and FIML methods provide an acceptable quality of the confirmatory factor analysis model.

Keywords 1

Missing data imputation, structural equation modeling, factor analysis, psychometric testing, intelligence, personality

1. Introduction

The study of the factors contributing to academic achievement is one of the most important issues in educational psychology. Numerous studies have shown that the most important predictors of a student's possible achievement are his cognitive abilities since they create the basis for theoretically possible student achievement [1-3]. However, non-cognitive factors such as personality traits and motivational performance can also influence a student's academic performance. These additional characteristics determine how well the student succeeds in converting their intelligence into academic achievement, that is, they can interact with intelligence in predicting academic performance.

So far, however, little attention has been paid to the possible effects of the interaction between personality and intelligence in the formation of academic achievement. In this regard, it is worth mentioning the papers [4-5], which investigate the complex influence of personal and cognitive indicators of students on the performance of students and schoolchildren. Moreover, in [4], the authors investigated whether the study of personality aspects, rather than broader personality factors, in interaction with intelligence, can give more subtle results than the study of common factors alone.

The study of the relationship between the intellectual abilities of students on their characteristics and gender-role stereotypes should take into account possible latent variables that determine the relationship between the observed features (questionnaire items). Therefore, the most applicable analysis methods here would be factor analysis, confirmatory factor analysis, and structural modeling. All these techniques make it possible to process not the original data, but the correlation matrices of features.

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In complex psychological studies of large samples, there are problems with data analysis due to missing values of certain indicators in the collected arrays. Such missingness may be caused by both random factors and peculiarities of the study organization. For example, some characteristics (for example, personality characteristics) are not examined on the entire sample of students, but only on a single group wishing to take this particular test. As a result, some variables have missing values for the same objects. This complicates the analysis and filling of the gaps in the data. However, the correlation matrix can be estimated from pairwise complete observations; in this case, the minimum amount of information is lost. Therefore, latent variable models are often built based on a correlation matrix with pairwise deletion of missing values.

However, such correlation matrices may not have all the properties of a correlation matrix. In particular, they can have a negative determinant, which makes further analysis impossible. In addition, for the correct calculation of the standard errors of the estimates of the model parameters a sample size must be specified. If the original sample size (without deletion of missing values) is specified, then the standard errors will be underestimated. But the sample size after deleting rows with at least one gap may be too small.

This problem can be solved by filling in missing data. In [5], we investigated two methods of filling in missing data, Amelia and missForest, when constructing a regression model of the average score of students, characterizing academic success, on a set of cognitive and personality indicators. As a result, it was revealed that the missForest method is more acceptable in some performance indicators.

However, the analyzed set of explanatory variables (cognitive and personality characteristics) has a more complex structure than the simple linear structure of the regression model, which, together with the problem of missing data, led to unsatisfactory results in terms of their interpretation. Therefore, in this work, we build and investigate a more complex structure of relationships between explanatory variables to understand the relationships of various indicators that characterize the cognitive and personal properties of students.

2. Investigated Methods

The simplest methods of filling in the gaps assume that the gaps are filled separately for each variable, for example, based on the mean. They do not take into account interrelationships between variables and give a significant bias if there are many missing values.

Multiple imputations are more popular [6, 7], but have some disadvantages. They are based on the assumption that data are missing at random (MAR). The latter means that the underlying mechanism of missing data, given the observed data, does not depend on unobservable data. Most of these methods do not yield a determinate result, so latent variable models that differ greatly in structure can be obtained. In addition, a general tendency for multiple imputations to produce underestimates of variances and overestimates of correlations is known [8].

Another approach is to estimate a latent variable model based on the original data with missing values using the full information maximum likelihood (FIML). It uses all observable features for each sample object (student). As shown in a Monte Carlo simulation [9], the FIML estimation turned out to be better than listwise deletion, pairwise deletion, and similar response pattern imputation. Under ignorable missing data conditions (missing completely at random and missing at random), FIML estimates were unbiased and more efficient than the other methods. In addition, FIML yielded the lowest proportion of convergence failures.

An important feature of building structural models is that assumptions about their structure must be formulated. Incorrect assumptions lead to the fact that the model cannot be estimated, the quality of the constructed model turns out to be unsatisfactory, or the parameter estimates will be insignificant. One popular data-driven approach to model formulation is the use of factor analysis. Factor analysis allows identifying the structure of latent factors underlying the relationship between the observed variables. Assuming the relationship between latent factors, an oblique rotation of the factor loadings matrix can be performed. Based on the revealed structure of latent factors, it is possible to formulate latent variable models. The presence of missing data also complicates factor analysis. Therefore, further methods are investigated that are applicable both for factor analysis and for structural modeling.

2.1. Mean Imputation

One approach to the missing data problem is to make some reasonable assumptions about the values of the missing data and then proceed to conventional analysis of the observed and imputed data. The simplest method to fill in the gaps is to impute an unconditional mean: for each variable with missing values, the mean is computed for the observed cases and the missing data is replaced by it. Unfortunately, this method yields biased estimates of many parameters [8]. Even if bias in parameter estimates can be avoided, all conventional imputation methods tend to underestimate standard errors. The reason is obvious: replacing the missing data with a constant (mean) reduces the real variation of the variables; therefore, the standard errors are also underestimated.

2.2. Pairwise Deletion

A simple alternative to filling the gaps with mean is pairwise deletion, also known as available case analysis. This method is based on the fact that estimates for many linear models, including structural ones, are functions of the first and second moments (i.e., means, variances, and covariances). Under pairwise deletion, each of these moments is estimated using all cases that have data present for each variable or each pair of variables. The resulting moment estimates are then used as input for structural modeling.

If the data satisfies the missing completely at random (MCAR) assumption, pairwise deletion is known to yield parameter estimates that are consistent and therefore approximately unbiased [8]. However, this method also poses some potential problems. First, the pairwise deleted correlation matrix may not be positive definite, which means that the parameters for many linear models cannot be estimated at all. Second, the estimates of the standard errors obtained under pairwise deletion are not consistent estimates of the true standard errors. This casts doubt on the validity of confidence intervals and hypothesis testing [8].

In addition, when building a structural model based on the correlation matrix, it is necessary to specify the sample size. But what sample size should you use for pairwise deletion? The original sample size is too large, leading to underestimates of the standard errors. But the size of the complete-case subsample is too small, which leads to overestimates of the standard errors. Unfortunately, there is no single sample size that gives valid estimates of all the standard errors.

2.3. Multiple Imputations

Multiple imputations are based on the assumption that data are missing at random (MAR). This means that the underlying mechanism of missing data, given the observed data, does not depend on unobservable data.

A sensitivity analysis has been proposed to assess the stability of the results of the multiple imputations concerning model assumptions (MAR) [10]. It also allows comparing the effectiveness of different multiple imputation methods and quantifying the degree of systematic bias caused by the absence of randomness in the missed data.

Article [11] describes the pitfalls that arise when applying multiple imputation methods:

- exclusion of a response variable from the imputation procedure,
- processing non-normally distributed variables,
- plausibility and violation of the assumption of missed data randomness,
- computational problems.

To fill in the gaps, the missForest algorithm was chosen [12], implemented in the R-package. In [5], its effectiveness was shown in comparison with the Amelia algorithm in the problem to determine the contribution of intellectual and personal components to the academic performance of students in the context of a large number of non-random missing data.

The missForest algorithm uses a random forest trained on observable data matrix values to predict missed values. This is a non-parametric method of filling in the gaps, applicable to different types of variables. The non-parametric method makes no explicit assumptions about the functional form.

Instead, it tries to estimate it so that the result appears as close to the data points as possible, but does not seem impractical. It builds a random forest model for each variable. It then uses the model to predict the missing values of the variable with the observed values.

The approach described above gives an estimate of the OOB (out of the bag) imputation error and also provides a high level of control over the imputation process. Moreover, it has options to return the OOB separately (for each variable) instead of aggregation across the entire data matrix. This allows for a closer look at how accurately the model fills in the gaps for each variable.

Since the considered multiple imputation algorithm produces a random result, the problem arises of averaging the results of structural modeling to obtain stable estimates. Let the algorithm be executed to the same dataset m times, then we get m datasets with filled gaps. Using each of them, we can build a model with latent variables.

From the point of view of factor analysis, it was noted in [13] that averaging the eigenvectors of the correlation matrix (factor loadings) ranked in descending order of the eigenvalues of the correlation matrix estimated from each such imputed dataset is likely to lead to incorrect or meaningless results. In addition, it is not guaranteed that each such dataset is required to extract the same number of factors. To overcome these problems, the authors in [14] have averaged the imputed values to obtain a single complete dataset. Another solution to the problem is to estimate the covariance matrix from the imputed datasets using Rubin's rule [15], and then perform the exploratory factor analysis (and structural modeling) to this combined covariance matrix.

Let a correlation matrix be estimated for each of the *m* imputed datasets. Then we have a set of correlation matrices $\hat{\Sigma}^{(1)},\ldots,\hat{\Sigma}^{(m)}$. Using Rubin's rule [15], the multiple imputation estimates $\tilde{\Sigma}$ of the correlation matrix can be obtained as follows:

$$\tilde{\Sigma} = \frac{1}{m}\sum_{i=1}^{m}\hat{\Sigma}^{(i)} .$$

It was this approach that was used further in the study, $m=100$. The estimate $\tilde{\Sigma}$ of the correlation matrix was used as input for exploratory and confirmatory factor analysis and structural modeling.

2.4. Full Information Maximum Likelihood

FIML methods estimate parameters and standard errors using raw data rather than covariance matrix [16]. The FIML approach computes a likelihood function using only those variables that are observed for case i. It is built on the assumption of multivariate normality. A maximum likelihood method that handles missing data is available in the R environment in the Lavaan package [17]. If the data contain missing values, the default behavior of the lavaan package is listwise deletion.

FIML estimation is performed by specifying the argument missing="ml" when calling the fitting function. An unrestricted model will automatically be estimated so that all common fit indices are available. Robust standard errors are available if the data is both incomplete and non-normal. The R-package Umx [18] (function umxEFA) was used to perform exploratory factor analysis by the FIML.

3. Description of the Dataset

The analyzed dataset included normalized measures of general intellect (which was determined using the Amthower Structure of Intelligence test) (IQa), emotional intellect (Barchard test) (IQe), social intelligence (Guilford-Sullivan test) (IQs), creativity (IQc), and practical intelligence (IQp). Personal traits: extroversion (E), neuroticism (N), psychoticism (P) were determined according to the EPQ questionnaire, femininity (F), masculinity (M) - according to the Bem questionnaire (for more information on methods of determining intellectual and personal traits, see Bem's questionnaire) [5].

The total sample size was 466 observations. However, the number of missing values is quite large. The number of missed data for different variables is shown in Figure 1.

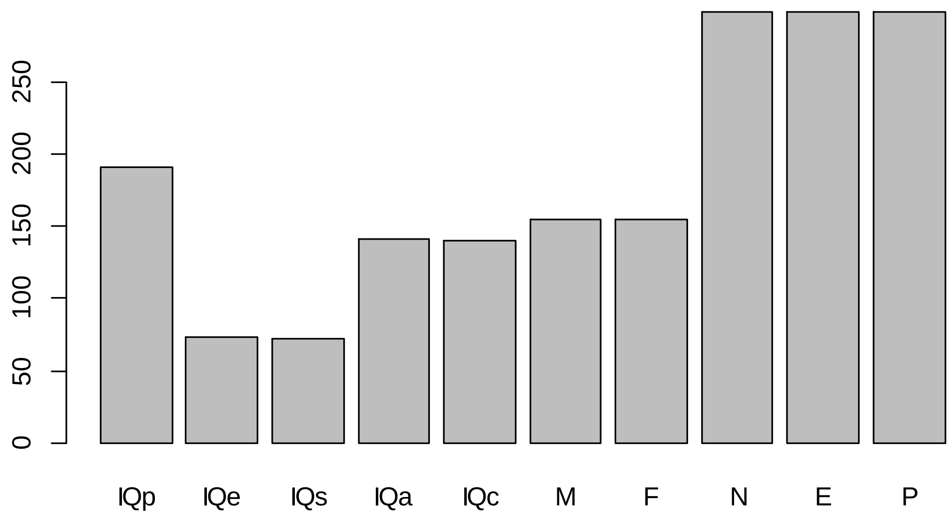

Figure 1: Number of missing values

Groups of variables containing missing values for identical objects can be selected:

- gender stereotypes: masculine (M), feminine (F);
- personal characteristics: neuroticism (N), extroversion (E), psychoticism (P).

For variables of emotional (IQe) and social (IQs) intellectual abilities, about half of the missing values are for the same objects. The same is true for IQa and IQs. For IQp the number of gaps was the highest (almost 200 students). The smallest number of pairwise complete observations is between the IQp variable and personal characteristics, only 59 students. For the remaining pairs of features, the number of pairwise complete observations exceeds 100.

Although there are more than 100 observations for each variable, deleting rows containing at least one missing value (listwise deletion) leaves only 15 valid cases. Therefore, it is necessary to use other methods to deal with missing data.

Mean imputation results in correlations between variables being underestimated compared to pairwise deletion of the missing values. So under mean imputation, the determinant of the correlation matrix is 0.629, and under pairwise deletion is 0.378. Under multiple imputations (missForest), the determinant of the averaged correlation matrix is 0.141, which indicates that the correlations are overestimated in comparison with other methods.

4. Results of Exploratory and Confirmatory Factor Analysis

To formulate the specification of the structural model, exploratory and confirmatory factor analysis was first performed using various methods of handling missing data. At the stage of exploratory factor analysis, four factors were extracted in each case, oblique rotation was performed by the ObiMin method for FIML, and by the ProMax method in all other cases.

Ошибка! Источник ссылки не найден. shows the proportion of explained variance. It is positively related to how strong the correlation between features is, that is, it negatively depends on the determinant of the correlation matrix. For the FIML method, the result is close to the proportion of explained variance obtained by pairwise deletion. Interesting are the results of testing the null hypothesis that four factors are sufficient, according to the chi-square test. At 11 degrees of freedom, the smallest value is obtained by mean imputation. The statistic is 9.29, which indicates that the null hypothesis is not rejected at the 1% significance level. For Pairwise deletion and missForest, the obtained values are 28.62 and 34, which allows us to reject the hypothesis at the 1% significance level.

Based on the matrix of factor loadings, the structure of latent factors was selected. For each method of handling missing data, a different structure was obtained, and their models of latent variables were formulated. On their basis, confirmatory factor analysis was performed. The model was estimated using GLS (for mean imputation, pairwise deletion, missForest) and using FIML. The choice of GLS was justified by the fact that the ML method in some cases did not converge or gave incorrect results.

Table 1 shows the fit indices: Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA). Interestingly, mean imputation provides roughly similar goodness of fit to FIML.

Table 1
Results of exploratory and confirmatory factor analysis

	Mean imputation	Pairwise deletion	missForest	FIML
Proportion of explained variance	0.360	0.392	0.506	0.407
CFI	0.800	0.668	0.682	0.868
RMSEA	0.042	0.083	0.104	0.040
$\overline{z}$	2.094	2.409	4.814	1.512

In addition, the significance of the estimates of the parameters of the models is of interest. To characterize it as a whole according to the model, the average z-statistic was calculated:

$$\overline{z} = \frac{1}{k}\sum_{i=1}^{k}|z_i|,$$

where z_i is the z- statistic for *i*-th estimate, *k* is the number of estimated parameters in latent variable models. If we exclude the fixed coefficients (4 parameters were fixed for 4 latent factors) out of 10 features, only 6 remain, that is $k = 6$. The higher the quality of the estimates corresponds to the higher average z-statistic. The best result is provided by missForest, which is explained by the already mentioned disadvantage of multiple imputations - a decrease in standard errors of parameter estimates. The worst result is given by FIML, for which only one parameter in the models of latent variables is significant at the 5% level. For mean imputation, three parameters turned out to be significant at the 5% level, two at 10%, which makes it possible to better interpret the results obtained.

5. Interpretation of Results and Conclusions

Thus, the mean imputation and FIML methods provide an acceptable quality of the confirmatory factor analysis model (RMSEA <0.05). Although the CFI for the model built with the FIML turned out to be higher, nevertheless, the significance of the parameter estimates is significantly lower. To compare the structure of latent factors, Tables 2-3 present factor loadings matrices.

We note right away that the emotional intelligence quotient in both cases fell into a group different from the groups in which other intelligence quotients are located, which is in good agreement with existing studies of the influence of psychometric indicators on the outcome of the educational process. Thus, in [19, 20] the results of studies are presented, showing that the academic performance of schoolchildren and students is influenced not only by cognitive abilities, expressed by different intelligence quotients but also by emotional intelligence IQe. On the other hand, unlike IQ, which is a relatively fixed and constant value throughout life, emotional intelligence can and should be developed.

Some studies have shown that emotional intelligence IQe is associated with academic and professional success, contributes to individual cognitive performance, and it can influence academic performance both in conjunction with other IQ indicators and independently, by itself. Thus, in [19] it was found that seventh-grade pupils with high IQ and high IQe received higher results on the final exam than other children. However, the following was revealed. Boys with high IQ scores and the best overall IQ scores did better in their final exams than their peers. The situation with girls was different, for them, IQe only increased the effect of IQ, but did not affect the indicator of the effectiveness of passing the exam by itself. This confirms our result on the relative independence of the emotional intelligence quotient and other intellectual indicators.

Nevertheless, the results of factor analysis in Table 2, obtained using mean imputation, seem to be more reasonable in terms of the available knowledge about the objectively existing and described in the literature relationships between the analyzed characteristics. In this case, characteristics such as masculinity and neuroticism act as separate factors, that is, they are relatively independent of other variables, and are not included in any groups of correlated features. All IQ indicators, except for emotional intelligence IQe, are combined into one group of interdependent features, subject to the influence of one common latent factor F1. The fourth group includes such indicators as emotional intelligence, femininity, extraversion, psychotic, the relationship between which is due to the influence of one common factor F4.

Table 2
Factor loadings matrix under mean imputation (ProMax rotation)

	F1	F2	F3	F4
IQp	**0.114**			
IQe	-0.110			**0.347**
IQs	**0.370**			
IQa	**0.998**			
IQc	**0.210**			
M		**0.998**		
F			0.101	**0.548**
N			**0.863**	0.100
E		0.118	-0.183	**0.236**
P				**-0.221**

Because of the above, preference in our study is given to the structure of latent variables presented in Table 3. However, it is known that the estimates of the parameters of the structural model after mean imputation can be biased. Therefore, based on the formulated models of latent variables, the structural model was estimated by the FIML method. In this case, the latent variable F1 was set as endogenous, and the influence of exogenous variables M (F2), N (F3), and F4 on it was investigated. It turned out that the influence of neuroticism N is insignificant; therefore, in the final model, only M and F4 were taken into account as exogenous variables that affect the endogenous variable F1. The structural modeling results are shown in Figure 2.

Table 3
Factor loading matrix estimated by the FIML method (ObliMin rotation)

	F1	F2	F3	F4
IQp	-0.186		**-0.192**	
IQe		**0.555**		0.113
IQs	**-0.526**		-0.237	
IQa	**-0.969**			
IQc	-0.245		**0.305**	0.163
M	0.158	-0.253	0.136	**0.508**
F		**0.398**	-0.140	0.262
N	0.153	**0.425**	0.146	-0.250
E		0.111		**0.719**
P			**0.604**	

Estimates of the equation for the relationship of latent variables indicate that both masculinity and the latent factor F4 on the intelligence indicators described by factor F1 are negative. Thus, the more pronounced both male and female traits, the lower on average the level of intelligence (except emotional) can be. As a result, the influence of emotional intelligence on other indicators of intelligence is negative.

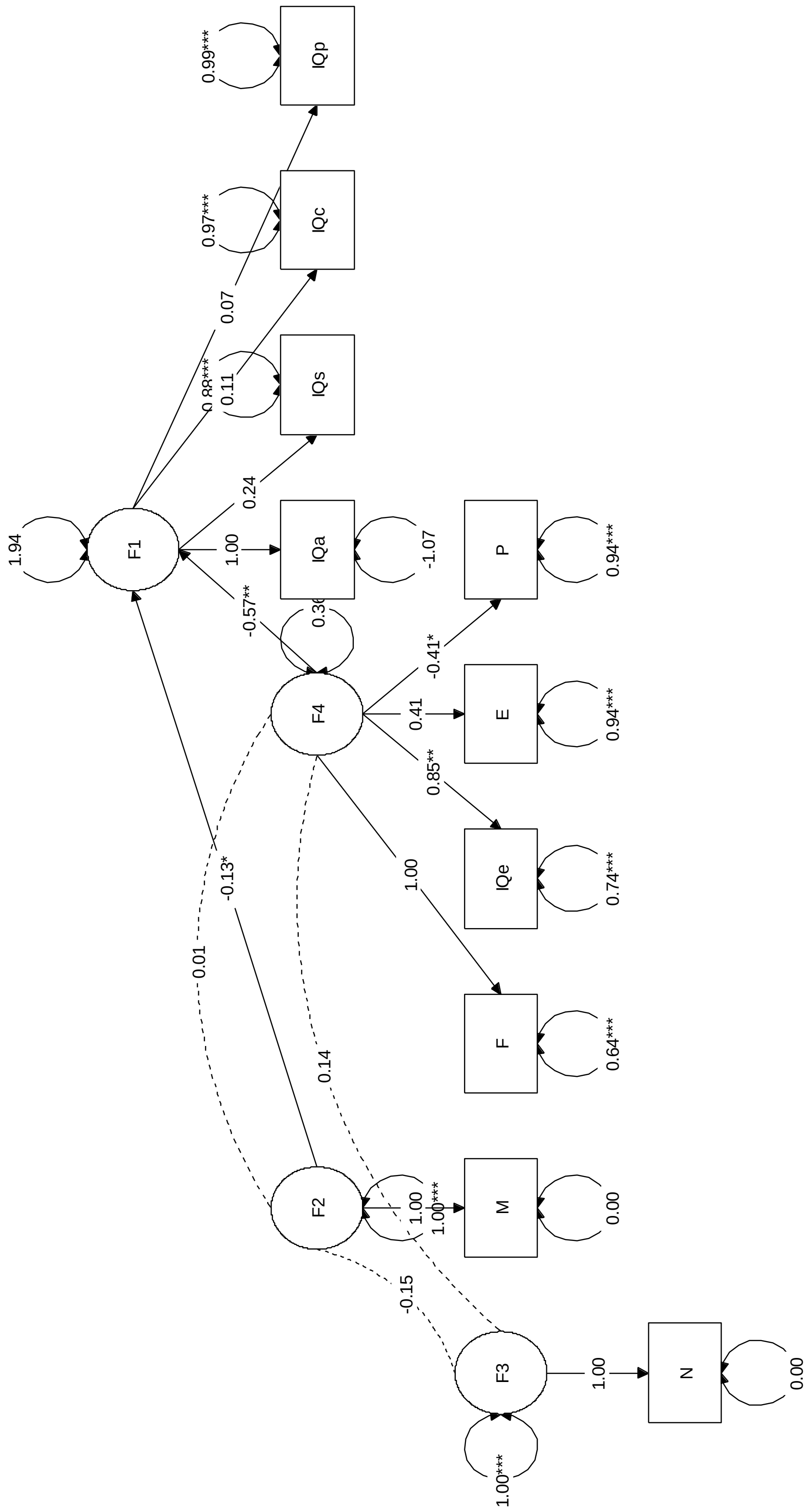

Figure 2: Results of a structural equation modeling

Thus, we have revealed that the system of cognitive and personal indicators that can influence and affect the results of educational activities of students has a rather complex structure, therefore, the use of a linear model of the influence of these indicators on some criteria of learning success (for example, the average score) is ineffective. Since, to build a model of acceptable quality, we will have to discard some of the information contained in the data, simply discarding linearly dependent regressors.

It was shown that in this case the system of the considered indicators could be described using a structural model with acceptable quality indicators. The constructed model shows the hidden relationships that exist between ten different characteristics of students. The next stage of the study is to introduce an additional endogenous variable into the model - an indicator of the quality of learning, and to investigate the influence of personal and cognitive indicators on the success of learning, taking into account their complex systemic relationship.

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