The Structure of Students' Motivation:

Expectancies and Values in Taking Data Science Course

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Abstract. In this paper we explore motivational structure of students taking a challenging university course. The participants were second-year undergraduate students majoring in Economics, Sociology, Management and Humanities, enrolled in the Data Science minor. Using expectancy-value theory as a framework, we aim (1) to analyze gender differences in motivation; (2) to identify the link between the components of motivation and academic achievement; (3) to estimate the role of the previous academic achievement and educational choices. Two alternative theoretical models are proposed and tested on empirical data. Structural equation modeling (SEM) in MPlus 7.31 was used for analysis. We found that the course is more popular among males students, who also demonstrate higher level of expectancy for success. However, there is no gender difference in academic performance. Students majoring in Sociology and Economics perceive Data Science as more interesting and useful than Management and Humanities students. SEM analysis empirically validated the model in which expectancy of success directly influences academic achievement, and values influence is mediated by expectancies. The final model that includes motivation, gender, student's major, and previous achievement explains 34% of variance in academic performance. We discuss the role of different components of student motivation and practical significance of our results.

Keywords: motivation, expectancy value theory, gender differences, statistics, data science.

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One of the most important practical issues in educational research is how to enhance the academic performance of students. Numerous explanations of low performance typically come down to two major reasons: lack of capabilities and low motivation for learning. Unlike capabilities, which are almost impossible to correct, motivation can be changed—and this generates the ongoing interest of researchers in this field [Hidi, Harackiewicz 2000]. Several theories associating different components of motivation with educational choice and academic performance have been developed over the last 30 years [Bandura 1993; Eccles, Wigfield 1995; Pintrich 2003; Ryan, Deci 2000; Wentzel, Wigfield 2009; Wigfield, Eccles 2000].

This paper analyzes the relationship between motivation and performance using the example of Data Science minor, or optional course, offered to students majoring in different areas, from Economics to Oriental Studies. Minors are obligatory for all students of the St. Petersburg campus of the National Research University Higher School of Economics. A student can pick any of the five minors, regardless of their major. A minor consists of four semester-long courses, each worth five ECTS credits.

We study the motivation of students who chose Data Science as their minor, which includes learning the fundamentals of programming with R for machine learning and related topics, as well as developing data analysis skills. The course developers created the Data Analysis computer system to conduct online surveys, collecting data on students' attitudes and learning behavior (number of code lines written, forum activity, seeking help from peers and teaching assistants), and correlate this information with academic achievements [Musabirov, Sirotkin 2016]. Therefore, research on student course-related behavior becomes integrated in modern learning analytics and educational data mining [Baker, Inventado 2014; Siemens, Baker 2012].

1. Literature Review

1.1. Motivation as a Predictor of Academic Performance

A number of theoretical and applied studies have explored the factors of good academic performance. There is no doubt that cognitive abilities matter, but other student characteristics are significant, too. In higher education, particularly in selective universities, the selection process greatly diminishes the variation of intellectual skills of students [Furnham, Chamorro-Premuzic, McDougall 2002], increasing the role of such personal qualities as character traits, individual learning strategies and motivation as the reasons behind different levels of academic performance [Richardson, Abraham, Bond 2012].

Motivation is understood as a combination of mental processes initiating a specific behavior. Psychologists have developed a great deal of motivation theories, in terms of learning as well [Pintrich 2003]. The modern motivation theories focus on how exactly human behavior is influenced by beliefs, values and goals.

In this paper, we rely on John W. Atkinson's expectancy-value theory [Atkinson 1964], which was expanded by Jacquelynne S. Eccles and Allan Wigfield into the field of education [Eccles, Wigfield 2002;

Wigfield, Eccles 2000]. The theory suggests that motivation involves two factors: expectancies and subjective task values. Expectancies are specific beliefs individuals have regarding their success on certain tasks or activities; task values are incentives, or reasons that stimulate people to do something.

The proponents of the theory believe that both expectancies for success and subjective task values directly influence the choice of activity, the persistence in it, and the final result. Besides, the two factors influence each other. These cognitive characteristics may be affected by previous experience (especially in a similar task), gender and other stereotypes, beliefs about one's abilities, etc. In its full form, the expectancy-value theory is described by a complex equation [Eccles, Wigfield 2002:119], all the components of which cannot be possibly covered in one study. Researchers usually focus on proximal to educational outcomes components, i. e. expectancy for success and subjective task value. While developing their theory, Eccles and Wigfield identified four subcategories of task values: intrinsic value (interest), attainment value (importance), utility value (usefulness of the task), and cost.

Intrinsic value reflects the interest in the subject, or the enjoyment an individual gets from performing the activity. Attainment value reflects personal importance of doing well on the task. Utility value means relevance of the task to current or future goals, e. g. a boring and difficult course may be perceived as useful for a future career. Costs reflect negative aspects of engaging in the task: a person believes that participation in a task may limit his/her achievements or impede his/her activity in other fields; it can be time costs, effort costs, or emotional costs.

Most of the empirical studies based on the expectancy-value theory have involved school students. . One important result was that such theoretically different constructs as belief in one's capabilities and expectancy for success turned out to be empirically undistinguishable: in confirmatory factor analysis relevant items always loaded on the same factor. Second, expectancy for success is a domain-specific construct, i. e. a student may be confident about his or her success in humanities, but it does not mean they feel confident in math. Third, school students are good at discriminating between expectancies and values, i. e. between rating their chances of success and estimating how this success is important for them [Eccles, Wigfield 1995; Wigfield, Eccles 2000].

Another essential finding, the most important for our research, is that motivation is a powerful predictor of academic performance (previous experience being controlled for); and expectancies play greater role in performance than values [Meece, Wigfield, Eccles 1990].

Most relevant for our work are studies that have applied Eccles and Wigfield's theory to students learning mathematics, programming and sciences [Abraham, Barker 2015; Hood, Creed, Neumann 2012].

Both teams of researchers demonstrated clearly that the expectancy-value model provided a very good description of empirical data, and that motivation components had a strong positive correlation with efforts applied by students, with their choice of complex courses, and their academic achievements.

The level of motivation, in turn, also depends on a number of factors. Beside gender and cultural stereotypes, previous experience is of great importance, too. Quite naturally, a student who has performed well in math courses so far expects to be successful in a new one [Meece, Wigfield, Eccles 1990; Simpkins et al. 2006]. Therefore, it is very important that a motivation model include variables indicating previous achievements.

1.2. Gender Differences in Motivation and Achievement Patterns in Mathematics

The role of gender stereotypes in achievement motivation has been a topic of research for a long time. Despite different theoretical foundations of research, most researchers agree that gender stereotypes largely affect girls' and boys' beliefs about their capabilities and, as a result, their learning behavior (e. g. courses preferred or the choice of an educational trajectory and later career) [Meece et al. 2006]. Boys are believed to be better at and more inclined towards science and mathematics, while girls are thought to excel at languages and humanities. Gender differences in beliefs about one's capabilities are especially pronounced in primary school and can be leveled out to some extent during the learning process [Jacobs et al. 2004].

Although girls' beliefs about their mathematical capabilities and their expectancies for success in math are always lower than those of boys, the findings based on grades and test scores are less unambiguous. Some researchers reveal that boys score higher, while others find no differences at all [Hedges, Nowell 1995; Lindberge et al. 2010]. The data obtained in international studies (TIMSS, PISA) allow for evaluating gender differences in mathematics across countries and correlating them to such country characteristics as the percentage of women in high-tech fields of science, representation of women in parliament, etc. Paradoxically, the broadest gaps between boys and girls in PISA were revealed in Switzerland, the Netherlands and Germany, whereas PISA scores of Russian school students show no gender-based variations [Else-Quest, Hyde, Linn 2010]. Russian researchers who studied USE (Unified State Exam) scores in mathematics with a very large sample— all graduates from Russian schools who took the USE in 2011 (over 700,000 students)— did not find any differences between girls and boys either [Bessudnov, Makarov 2015].

1.3. Perception of Statistics as a Factor of Academic Performance

It stands to reason that attitude towards a subject affects performance in that subject. Difficult courses like math or statistics often arouse anxiety in students, holding them back [Meece, Wigfield, Eccles 1990; Peng, Hong, Mason 2014; Simzar et al. 2015]. Attempts to solve this problem include the development of the Math Anxiety Scale and the

Statistics Anxiety Scale [Hopko et al. 2003; Schau et al. 1995] as well as research into cognitive and non-cognitive (emotional in particular) factors of teaching statistics effectively [Emmioğlu, Capa-Aydin 2012; Hood, Creed, Neumann 2012]. Meanwhile, there are relatively few studies addressing differences in attitude towards difficult courses among students of different majors. Griffith and his colleagues have established that attitudes of students in different fields of study differed significantly across three parameters: expected utility (for both further education and future career); perception of the course as intellectually challenging; and passion for mathematics. Attitude towards statistics was found to be overall positive among business students, less positive among psychology students, and overall negative among students in forensic science [Griffith et al. 2012].

2. Research Goals, Objectives and Models

The goal of this paper is to explore the motivation of students of different majors in taking the STEM course. We focused our efforts on the following three objectives:

- Find out whether there are gender differences in motivation for the course;
- Identify the structure of the relationship between the motivation components and academic performance;
- Assess the significance of previous academic achievements and educational choices (opting for a specific major).

In empirical testing the expectancy-value theory on various groups of students in different educational contexts, researchers have discovered interrelations between the motivation components and academic performance which were different in their nature. Drawing on the previous research, we constructed two theoretical models describing those interrelations: 1) expectancies and values influence academic performance directly and independently; 2) values influence expectancies (but not academic performance), and expectancies, in their turn, influence academic performance (Fig. 1).

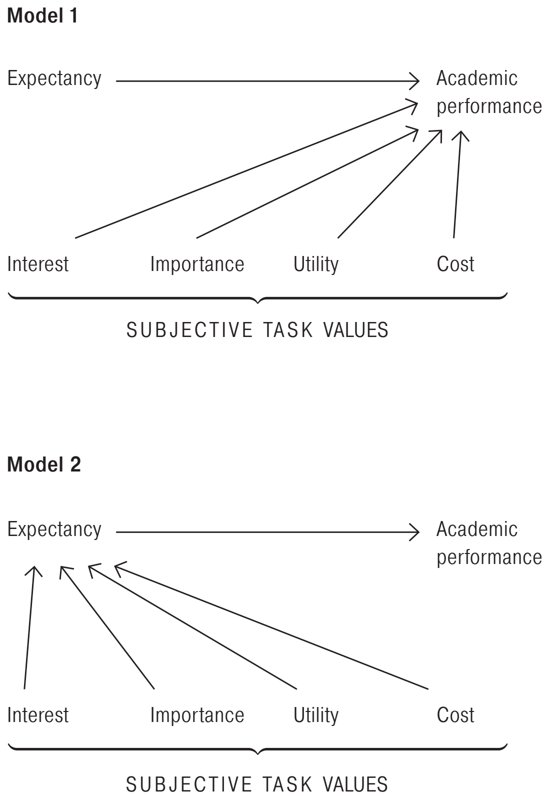
Both models include gender, previous academic achievements, and current major.

3. Data and Methods

3.1. Empirical Basis of Research

Data for the research was gathered through a survey of students who chose Data Science as their minor. A distinctive feature of the Higher School of Economics campus in St. Petersburg is the absence of mathematical and computer science majors, so the minor's target audience consisted of students in economic, management, humanities and social science majors, from Economics to History. The diversity of majors and the differences in training background, primarily in terms of school and university mathematics, determined both the differenc-

Figure 1. **Two alternative models of interrelations between the motivation components and academic performance**



es in motivation for choosing this minor and, presumably, the development of contrasting types of behavior and interaction.

Data Science was most often chosen by students studying Economics and Sociology and most rarely by those in History, Politology and Jurisprudence (Table 1). It was the most popular minor among sociologists, selected by 42% of second-year students in Sociology. The possible reason behind this is that the minor was first introduced as an optional course in the Sociology Department, so it was more familiar to sociologists than to students of other majors.

The survey was conducted at the beginning of the minor's first year (second year of Bachelor's degree) and involved 149 students, which is 94% of all students enrolled in the minor.

3.2. Indicators

A survey questionnaire was developed. The full achievement motivation equation based on the expectancy-value theory includes over 20 components, so empirical studies only use some of the theoretical constructs according to a specific objective. We selected five: expec-

Table 1. **Distribution of Data Science students across majors**

Major	Number and percentage of students in the minor	Number of respondents and their proportion in the sample
Economics	46 (29%)	41 (28%)
Sociology	36 (23%),	35 (23%)
Management	16 (10%)	15 (10%)
Logistics	25 (16%)	24 (16%)
Oriental Studies	14 (9%)	13 (9%)
History	6 (4%)	5 (3%)
Politology	7 (4%)	7 (5%)
Jurisprudence	5 (3%)	5 (3%)
Public administration	4 (2%)	4 (3%)
Total	159	149 (94%)

Table 2. **Scale reliability coefficients**

Construct	No. of items	Cronbach's α
Expectancy for success	4	0.83
Interest	6	0.86
Importance	4	0.85
Utility	5	0.79
Cost	4	0.67

tancy, interest, utility, importance, and cost. A Russian version of the scale was prepared for each of the constructs based on Eccles and Wigfield's questionnaire for exploring the motivation components in mathematical courses[1] [Eccles, Wigfield 1995]. The scales for individual constructs consisted of 4–6 items with responses on a four-point Likert scale, from 1 (Strongly disagree) to 4 (Strongly agree). Internal consistency of the scales was rather high (Table 2).

The dependent variable in our model was academic performance in Data Science measured as a cumulative score for two tests, in the middle and at the end of the first semester. All of the models consid-

[1] To validate our instrument, we analyzed the factor structure of the questionnaire using confirmatory factor analysis. The resulting model showed a high degree of fit with empirical data. A detailed description of this work is beyond the scope of this paper and is a topic for a separate publication.

ered student's gender, previous academic achievements (GPA for the first year), and current major as important determinants.

Academic performance (dependent variable) was operationalized as the cumulative score for the first semester in the minor and measured as the arithmetic mean of student's scores for two final tests, one at the end of Module 1 and the other at the end of Module 2[2].

Expectancy for success was measured using a four-item scale. Example of an item: "I expect to do well in this course." The level of expectancy was calculated as the arithmetic mean of responses to four items.

Interest was assessed using a six-item scale. Example of an item: "I find the Data Science minor interesting." The degree of interest was calculated as the arithmetic mean of responses to six items.

Importance was measured using a four-item scale. Example of an item: "For me, being good at this course is very important." The importance of being good was calculated as the arithmetic mean of responses to four items.

Utility was assessed using a five-item scale. Example of an item: "What I learn in Data Science will not be useful for me at all when I graduate." Perceived utility was calculated as the arithmetic mean of responses to five items.

Expected *cost* of time and efforts was measured using a four-item scale. Example of an item: "I fear that the minor program will interfere with my other courses." Cronbach's α for this scale was 0.67, which is less than for other scales in this research, yet this degree of reliability is considered a good one. Perceived cost was calculated as the arithmetic mean of responses to four items.

Gender was coded as a binary variable (0 = female and 1 = male). The sample included 102 females (64%) and 57 male students (36%).

GPA for the first year of studies was used as an indicator of previous academic performance. It would be incorrect to compare GPAs of all Data Science participants directly, as they were enrolled in courses of different complexity and assessed by instructors with different levels of requirements within their majors. To make a comparison like that possible, we standardized the variables based on students' majors, i. e. for each student, we calculated the difference between their personal GPA and the mean GPA of all students in their major.

The current *major* was coded as a nominal variable. Some majors were represented by too few students, so it made no sense analyzing them individually. We merged students in History, Politology, Oriental Studies and Jurisprudence into "Humanities". Unlike Economics, Sociology, or Management, the abovementioned majors offered few mathematical and statistical courses; this could be the reason for

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[2] The Higher School of Economics applies a module-based learning system: the first semester consists of Modules 1 and 2, and the second one of Modules 3 and 4. Tests are taken at the end of each module.

students in these majors not opting for Data Science too often. We also merged Management and Logistics students because their majors were very closely related. As a result, the students in our sample were distributed as follows: 47 in Economics, 36 in Sociology, 40 in Management and Logistics, and 36 in Humanities.

3.3. Analysis Methods

We used structural equation modeling (SEM) realized in the MPlus version 7.31 statistical package as the basic analysis method [Muthén, Muthén 1998]. This method allows for testing associations between variables, including latent factors. The structural model represented a system of regression equations describing correlations between the dependent and independent variables.

Structural equation modeling is used to construct theoretical models and test their goodness of fit, i. e. how well they fit data observed in research. We used three measures of goodness of fit recommended by the majority of modern SEM guidebooks: CFI (Comparative Fit Index), acceptable CFI values $\geqslant 0.90$; RMSEA (Root Mean Square Error of Approximation), acceptable RMSEA values $\leqslant 0.05$; and SRMR (Standardized Root Mean Square Residual), acceptable SRMR values $\leqslant 0.08$. These are indicators of differences between the original covariance matrix and the matrix of covariances of the model, which allow the researcher to measure the goodness of fit of a model to a set of observations [Nasledov 2012: 348–353]. A comparison of fit indices makes it possible to choose the best alternative models.

To compare characteristics of different groups of respondents, we used the t-test (or ANOVA) for normally distributed variables, and the Mann–Whitney U test (or the Kruskal–Wallis test) and the Dunn's test of multiple comparisons for non-normally distributed variables.

4. Findings

4.1. Analysis of Gender- and Major-Related Differences

18% of all females and 26% of all males selected the Data Science minor, which means that the minor was more popular among male students. With a view to finding out whether there were gender differences in motivation and academic achievements, we compared the values of five motivation components (expectancy for success and four subjective task value parameters) and two different measures of academic performance (GPA for the first year and Data Science test scores) (Table 3).

Although girls perform better at university (as the GPA comparison shows), they are less confident about their abilities when it comes to a difficult course involving programming. However, despite the difference in expectancies, males and females show similar levels of academic performance (Data Science test score). Such motivation components as interest, utility, importance and perceived costs also appear to be the same for both genders.

Since students of different majors who chose Data Science as their minor had different backgrounds in university mathematics, one could

Table 3. **Gender-based distribution of the indicators**

Variable	Sample mean (SD) N = 159	Mean (females) N = 102	Mean (males) N = 57	
First-year GPA	7,79 (0,81)	7,92	7,56	***
Data Science test score	6,76 (1,87)	6,68	6,90	
Expectancy for success	3,01 (0,64)	2,91	3,21	**
Interest	3,35 (0,51)	3,34	3,38	
Importance	2,67 (0,80)	2,74	2,54	
Utility	3,39 (0,51)	3,42	3,32	
Cost	2,53 (0,58)	2,58	2,45	

Note: Asterisks indicate statistically significant differences between male and female students: *** $p < 0{,}01$; ** $p < 0{,}05$.

expect that their beliefs about their capabilities, expectations and levels of anxiety associated with the course will differ. Indeed, we found differences in the levels of such motivation components as expectancy for success, intrinsic value and perceived utility (Table 4). Students in Economics showed higher expectancy for success than students in Humanities, while no significant gap was revealed between students in Sociology and Management. Students in Humanities and Management perceived the Data Science minor as less useful than students in Sociology and Economics. In addition, students in Humanities also showed less interest in the course. Average scores were found to be higher among students in Economics than among students in Humanities.

4.2. Relationship Between Motivation and Academic Performance

We constructed path models to explore the relationship between the motivation components and academic performance (Data Science test scores). According to our research plan, we created two models (see Fig. 1) and compared them. It turned out that Model 2 provided a better description of the empirical data, which can be seen from the fit indices (Table 5). Model 1 without control variables fitted the empirical data so badly that it was impossible to estimate the model parameters. Meanwhile, Model 2 described the data well enough even before additional variables were introduced.

The resulting model with control variables is presented in Figure 2. Expectancy for success influences academic performance directly, while interest, utility and cost only correlate with achievements indirectly, via expectancy for success. Importance plays no role at all, showing no direct or even indirect relationship with the real final scores.

Student gender affects expectancy for success, which is lower among girls, but has no effect on other motivation components.

Table 4. **Major-based distribution of the indicators**

Variable	Economics N = 47	Sociology N = 36	Management and Logistics N = 40	Humanities N = 36
First-year GPA	7,4 (0,6)**	7,9 (0,7)	8,1 (0,8)	7,9 (1,0)
Data Science test score	7,4 (1,8)	6,6 (2,0)	6,6 (2,0)	6,2 (1,8)***
Expectancy for success	3,20 (0,57)	3,11 (0,71)	2,91 (0,66)	2,81 (0,55)***
Interest	3,45 (0,52)	3,52 (0,44)	3,31 (0,48)	3,12 (0,50)***
Importance	2,68 (0,71)	2,72 (0,83)	2,62 (0,77)	2,67 (0,91)
Utility	3,52 (0,44)	3,57 (0,40)	3,21 (0,55)**	3,24 (0,54)***
Cost	2,39 (0,54)	2,55 (0,58)	2,53 (0,61)	2,69 (0,58)

Note: Asterisks indicate statistically significant differences between majors: *** $p < 0{,}01$; ** $p < 0{,}05$.

Table 5. **Model fit indices**

	CFI	RMSEA	SRMR
Model 1*	—	—	—
Model 1 with control variables	0,806	0,088	0,090
Model 2	0,985	0,051	0,028
Model 2 with control variables	0,995	0,027	0,035

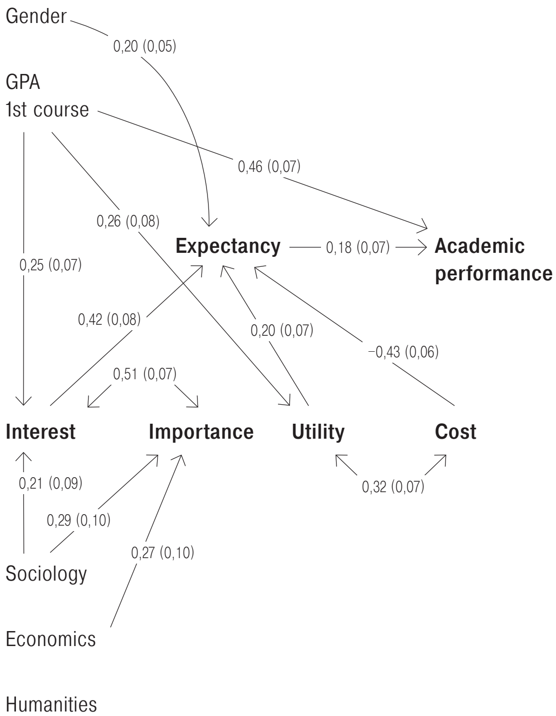
* The model parameters were impossible to estimate.

Neither does it influence academic performance, i. e. the mean final course scores are the same for both male and female students.

First-year GPA correlates positively with academic performance, which is no surprise. Besides, GPA is related with some of the motivation components: the higher the GPA, the more interesting and useful the course appears to a student. At the same time, importance, cost, and expectancy for success show no correlations with GPA.

When we introduced majors into the model, we took Management and Logistics as the reference category. We performed an analysis to find out whether students in different majors had different levels of various motivation components and academic performance. Figure 2 presents the path model (Model 2 with control variables) with significant correlations only. They demonstrate that grades obtained in Data Science had more importance for students in Sociology and Economics than for those in Management and Logistics. In addition, Sociology students displayed more interest in the course than their Management and Logistics peers. By contrast, students in Humanities did not reveal any difference from students in Management.

Figure 2. **Model of relations between the motivation components and academic performance in the Data Science course**



$R^2_{performance} = 0{,}34$
$R^2_{expectancy} = 0{,}49$

Note: Values of unstandardized regression coefficients and their standard errors are specified above the arrows. The basic model variables (expectancy, interest, importance, utility, cost, and academic performance) were regressed on control variables (gender, current major, and first-year GPA). Only statistically significant correlations were left in the figure to make it easier to understand.

The final model (Fig. 2) explains 34% of the variance in academic performance, with interest, utility and perceived costs collectively explaining 49% of the variance in expectancy for success.

5. Discussion

This paper explores how the motivation of students affects their performance in the Data Science course. The course belongs with the group of academic disciplines referred to as STEM (Science, Technology, Engineering and Mathematics) and also with statistics. Both mathematics and statistics are believed to be difficult subjects, and numerous studies have been devoted to mathematical and statistical anxiety, which is also related to gender stereotypes in education [Emmioğlu, Capa-Aydin 2012; Hood, Creed, Neumann 2012]. There are two scientific journals, *Statistics Education Research Journal*and *Journal of Statistics Education*, which specialize in statistical education and publish papers similar to this one. Thus, our work is integrated in research on attitudes and stereotypes that make the learning of many STEM subjects challenging.

It is one of the distinctive features of this case that the course was largely *terra incognita* for all students when they were choosing their minor, and motivations could differ from student to student as well as from major to major. When students move passively through compulsory courses, which is typical for Russian universities, they may have no motivation for learning a specific course. In our case, they were responsible for electing a course that differed from their major, being guided by certain beliefs and expectations—which could later turn out to be false and require corrections in the learning process, and a revaluation of cost and utility. It makes the situation as similar as possible to the practice of elective courses adopted in the Anglo-Saxon education system.

Another distinctive feature of this course is the active integration of computer technology into the learning process: opportunities of out-of-school access to the virtual learning environment, a special forum for online panel discussions on the issues arising when students work independently, access to supplementary materials on the server, etc. Development of online learning and active integration of computer technology into the learning process have a double effect: it increases student involvement and provides individualizes learning, and at the same time makes it possible to obtain information on student engagement and effort [Barba, Kennedy, Ainley 2016].

In this paper, we managed to explore the structure of motivation and fit a model to describe the relationship between the different motivation components in a group of students, heterogeneous in many ways, who started attending the Data Science course. The model explains 34% of the variance in academic performance, proving that motivation significantly contributes to education outcomes.

Meanwhile, our model shows that subjective task values only influence academic performance indirectly, via expectancy for success, which makes it different from the classic model of Jacquelynne S. Eccles, where performance is directly affected by values. In this respect, our findings appear to be closer to Albert Bandura's idea that perceived self-efficacy is a crucial factor affecting academic achievements, being in turn influenced by various contributory factors [Bandura 1993].

Apart from motivation, performance in the minor is also influenced by previous academic achievements, notably first-year GPA. Like many educational researchers [Bretz 1989; Kuncel, Hezlett, Ones 2001], we believe that GPA is an adequate indicator of academic performance that reflects student's cognitive abilities as well as zeal and self-discipline, so new difficult courses are easily mastered by those who performed well during previous years. This observation was true even when majors were controlled in the model, i. e. students in Economics had no advantage over those in Humanities. At the same time, first-year GPA did not affect self-confidence in any way, yet students with better grades expressed more interest in the course and perceived it as more useful for their future career.

The gender effect—which is that girls tend to assess their abilities lower than boys, despite the absence of any meaningful gap in educational outcomes—we explain by gender stereotypes, as in a number of other studies [Abraham, Barker 2015; Meece et al. 2006]. However, there is hope that gender disproportions in expectancy for success will be gradually reduced, given the fact that girls accounted for 64% of the students who registered for the Data Science course, as well the absence of gender-related differences in academic performance.

An important finding is the prevalence of intrinsic value (interest) over attainment value (importance). We believe that this is a distinctive feature of elective courses, which make students feel more responsible than compulsory ones. In this respect, it should be admitted that the practice of introducing minors and allowing students of all majors to choose any available minor proved to be successful.

We revealed no association between major and Data Science test score. Because the curricula of different majors include different amounts of mathematical and logical courses, one could expect that Economics students should be better prepared for the course than students in Humanities, yet no such effect was observed. This can be explained to some extent by self-selection of students in Humanities majors: the low percentage of those opting for Data Science may indicate that only the most prepared registered for the minor.

The relation between academic performance, previous training and motivation that we established in this study deserves close examination, given the widespread prejudice that the "advanced" use of modern data science technology is not available to everyone and is impossible without a solid mathematical background.

Studies similar to ours have a practical importance. Using statistically justified models, they help find ways of assisting students in mastering difficult courses on which they have formed some biased opinions. Our findings demonstrate that motivation, especially self-confidence, is extremely important even when the effect of previous achievements is taken into account. Unlike cognitive abilities, beliefs about oneself and one's own capacities can be corrected. Correction of gender and occupational stereotypes as an integral step towards developing the motivation for learning may be an essential component of university education, providing students in all kinds of majors with the opportunity to master competencies demanded in the modern labor market.

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