THESISES OF THE DOCTORAL (PhD) DISSERTATION

LABOUR MARKET IMPACTS OF TECHNOLOGICAL DEVELOPMENTS ON THE PREPAREDNESS OF UNIVERSITY STUDENTS

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1. BACKGROUND, OBJECTIVES, AND HYPOTHESES OF THE RESEARCH

The aim of this dissertation is to assess how a specific subgroup of future—and partially current—labor market participants, specifically university students enrolled in economic programs, perceive the labor market impacts of technological advancements. Furthermore, it examines how accurately they can evaluate a topic outside the core curriculum of their labor market knowledge course, namely, the labor market impacts of artificial intelligence. The latter was assessed through a survey linked to the course examination, while the former was implemented through an experimental design. Students' existing knowledge was evaluated by measuring their assessment of wages associated with certain occupations, the perceived automatability of these occupations, and their estimations of the automatability of various skills and competencies. Prior to the re-assessment, respondents randomly divided into two groups received targeted information: one group ("Group A") received labor-market-focused content, while the other ("Group B") received occupation-specific content. By examining self-assessment errors, I aimed to identify and interpret the Dunning–Kruger effect in a higher education context—a novel application of this experimental methodology within the scope of labor market analysis. The Dunning–Kruger effect refers to a widely observed cognitive bias where typically more than 50% of individuals perceive themselves as above average in desirable traits or attributes (KRUGER & DUNNING, 1999). Kruger and Dunning concluded from their findings that individuals with lower competencies in a given area tend to: 1) overestimate their performance, 2) fail to recognize the knowledge levels of others, 3) lack awareness of their limited skills or knowledge, and 4) only recognize these deficits upon receiving targeted training to enhance their skills.

Technological advancement exhibits complex social and economic consequences on the labor market, typically categorized into three primary effects based on empirical research: creative, complementary, and substitutive. Technological innovations may generate new occupations and industries (creative effect), supplement human labor particularly in tasks requiring high-level cognitive and creative skills (complementary effect), and significantly replace human labor in routine, automatable tasks (substitutive effect). For instance, in the United States, nearly 47% of occupations are threatened by automation within the coming decades (FREY & OSBORNE, 2017), whereas this proportion varies between 14% and 28%

in OECD countries (NEDELKOSKA & QUINTINI, 2018; LASSÉBIE & QUINTINI, 2022).

The impact of technological advancement on wages is similarly ambivalent. While highly skilled workers may experience wage increases due to heightened productivity and technological supplementation, low and medium-skilled workers typically face wage reductions and heightened unemployment. In developed countries, robotization in manufacturing positively influences wages; however, this impact varies in less-developed regions, often neutral or negative (GRAETZ & MICHAELS, 2018; DAUTH ET AL., 2021).

The effect of automation is heterogeneous across occupations. Highly exposed fields, such as manufacturing, logistics, and administrative work, face significant disruptions. In contrast, occupations demanding creativity, social interaction, and complex problem-solving are more resistant to automation. Low-skilled occupations are most vulnerable, while social intelligence and high-level decision-making skills remain relatively non-automatable (FREY & OSBORNE, 2017; HOLM & LORENZ, 2021).

Technology has also reshaped work-life balance. Digital tools offer flexibility but blur boundaries between work and leisure, potentially causing stress and burnout. Although technology facilitates better time management, constant connectivity negatively impacts employee well-being (KESHWANI & PATEL, 2023).

The Dunning–Kruger effect is particularly relevant amidst technological change, as inaccurate self-assessment may distort motivation to acquire new skills. Lower-skilled workers often overestimate their competencies, hindering development, whereas highly skilled individuals might underestimate their capabilities (KRUGER & DUNNING, 1999). Systems combining self-assessment and objective feedback can enhance realistic evaluation and skill development, thus supporting effective labor market adaptation.

Principal Research Questions

> **Q1. Does the labor market knowledge course contribute to students' understanding in areas beyond its curriculum, specifically concerning technological change and labor market relations?**
>
> *Q1.1 Are students achieving higher test scores more informed in these extra-curricular areas?*

Q1.2 Does improvement in test scores correlate with enhanced awareness in these areas?

Q2. How do participating students perceive the different labor market impacts of technological change?

Q2.1 Perceived job-creating impact?

Q2.2 Perceived job-destructive impact?

Q2.3 Perceived complementary impact?

Q3. Does targeted, one-time information dissemination influence students' understanding of technological change and labor market relationships?

Q3.1 Labor market-related impacts of technological change?

Q3.2 Occupational content impacts of technological change?

Q3.3 Work-life balance impacts?

Q3.4 Wage levels in various occupations?

Q3.5 Automatability of occupations?

Q3.6 Automatability of various skills and abilities?

Q4. Does the Dunning–Kruger effect manifest among students regarding labor market knowledge and technological change?

Q4.1 Does greater wage knowledge reduce overestimation?

Q4.2 Does greater knowledge of occupational automatability reduce overestimation?

Q4.3 Does greater knowledge of skills and competencies automatability reduce overestimation?

Principal Hypotheses

H1.1 Students with higher course test scores also perform better on extra-curricular technological change and labor market questions.

H1.2 Improved course test scores correlate with improved scores on these extra-curricular questions.

H2.1 Students perceive a job-creating impact more strongly (scale above midpoint of 3).

H2.2 Students perceive a job-destructive impact more strongly (scale above midpoint of 3).

H2.3 Students perceive a complementary impact more strongly (scale above midpoint of 3).

H3.1 Targeted information changes students' perceptions of technological impacts on labor market aspects (job creation, employability, qualifications, wages).

H3.1.1 Changed perceptions for the past five years.

H3.1.2 Changed perceptions for the next 5-10 years.

H3.2 Information changes perceptions on occupational content (task variety, complexity, content, work location).

H3.2.1 Changed perceptions for past five years.

H3.2.2 Changed perceptions for next 5-10 years.

H3.3 Information changes perceptions on work-life balance impacts (work-leisure, work-family, work-health, work-social life).

H3.3.1 Changed perceptions for past five years.

H3.3.2 Changed perceptions for next 5-10 years.

H3.4 Information improves accuracy in wage level estimations.

H3.5 Information improves accuracy in estimating occupational automatability.

H3.6 Information improves accuracy in estimating skills and competencies automatability.

H4.1 Greater wage knowledge reduces overestimation.

H4.2 Greater knowledge of occupational automatability reduces overestimation.

H4.3 Greater knowledge of skills automatability reduces overestimation.

2. DATABASE AND APPLIED METHODS

My research is divided into two phases: the first involves analyzing survey results linked to examinations in the Labor Market Knowledge course, while the second encompasses conducting an experimental study among university students enrolled in economics programs.

2.1. Survey Study – Relationship between knowledge acquired in the Labor Market Knowledge course and perceptions of technological change impacts (Q1)

To establish a foundation for my analysis, I conducted a survey during the spring semester of the 2023/24 academic year within the Labor Market Knowledge course (a mandatory subject in the first semester of the standard curriculum) targeting students in higher vocational training programs (FOSZ). The survey was conducted in collaboration with my supervisor, who is also responsible for teaching this subject. At the end of the written examinations (containing 20 multiple-choice questions), we added 3 supplementary questions related to the impacts of artificial intelligence. A total of 207 students participated in the survey, encompassing all enrolled students completing the course that semester, as passing required only completing the exam. Students answered these 3 questions voluntarily by selecting one option they considered correct from four provided statements. We acknowledged their additional effort by awarding 0.5 points for each correct response, added to their exam scores (with a maximum of 20 points achievable from the main test). Three questions were selected alternately from a set of nine questions related to artificial intelligence, generated using the ChatGPT 4.0 premium version on November 30, 2023, with the following prompt: "I am a university lecturer in economics. Within the Labor Market Knowledge course, I would like to create test questions regarding the potential labor market impacts of Artificial Intelligence. Each question should have four answer options, one of which is correct. Clearly mark the correct answers for me. Generate 12 such test questions."

2.2. Description and Structure of the Experimental Methodology (Q2, Q3, Q4)

A significant portion of my research utilizes experimental methods, an integral part of modern economic research (WEIMANN & BROSIG-KOCH, 2019). Experimental methods are widely adopted in business economics, industrial economics, finance, capital market studies, macroeconomics, health economics, and numerous other fields. The growing sophistication of these methods has significantly enhanced the quality and applicability of laboratory experiments across various contexts. Experiments are used to observe human behavior under controlled conditions, either through carefully designed laboratory or field setups or naturally occurring experiments.

In the second phase of my research, I developed professional descriptions related to the labor market impacts of artificial intelligence, which played a crucial role in the subsequent experiment. These descriptions were further refined based on expert feedback. Following KOLLÁR (2018), I contacted 11 experts via email who had relevant experience across various labor market sectors, including HR managers and university professors.

I created four different versions of professional descriptions (job-focused and labor-market-focused) using the premium version of ChatGPT 4.0. Experts evaluated these descriptions on a scale from 1 to 10 for content professionalism and comprehensibility, submitting their assessments via Google Forms along with qualitative feedback. The highest-rated versions were selected for the experimental research, refined further based on textual feedback with assistance from my supervisor. This stage ensured that materials used in the experiment were both professionally robust and comprehensible to participants.

2.3. Experimental Process and Group Formation

The following section describes the questionnaire designed for the experiment and its structure. *Figure 1* illustrates the experimental process. I sent the pilot call directly to the students of the University of Debrecen with the help of my colleagues at the Faculty of Economics. In order to start the experiment, a link had to be clicked, which randomly (50-50% probability) grouped the participants into groups and presented them with a series of questions in Google Forms. Both groups went through the 12 stages described below, with the exception that in stage 6, the group labelled "Group A" read a labour market-focused job description, while the group labelled "Group B" read a job-focused job description. The experimental design would provide an opportunity to swap the groups in the interpretation of the focus of the resulting description. In each case, I will highlight in the discussion of the results which fillers received information during the question, i.e. they can be called an experimental group from a methodological point of view.

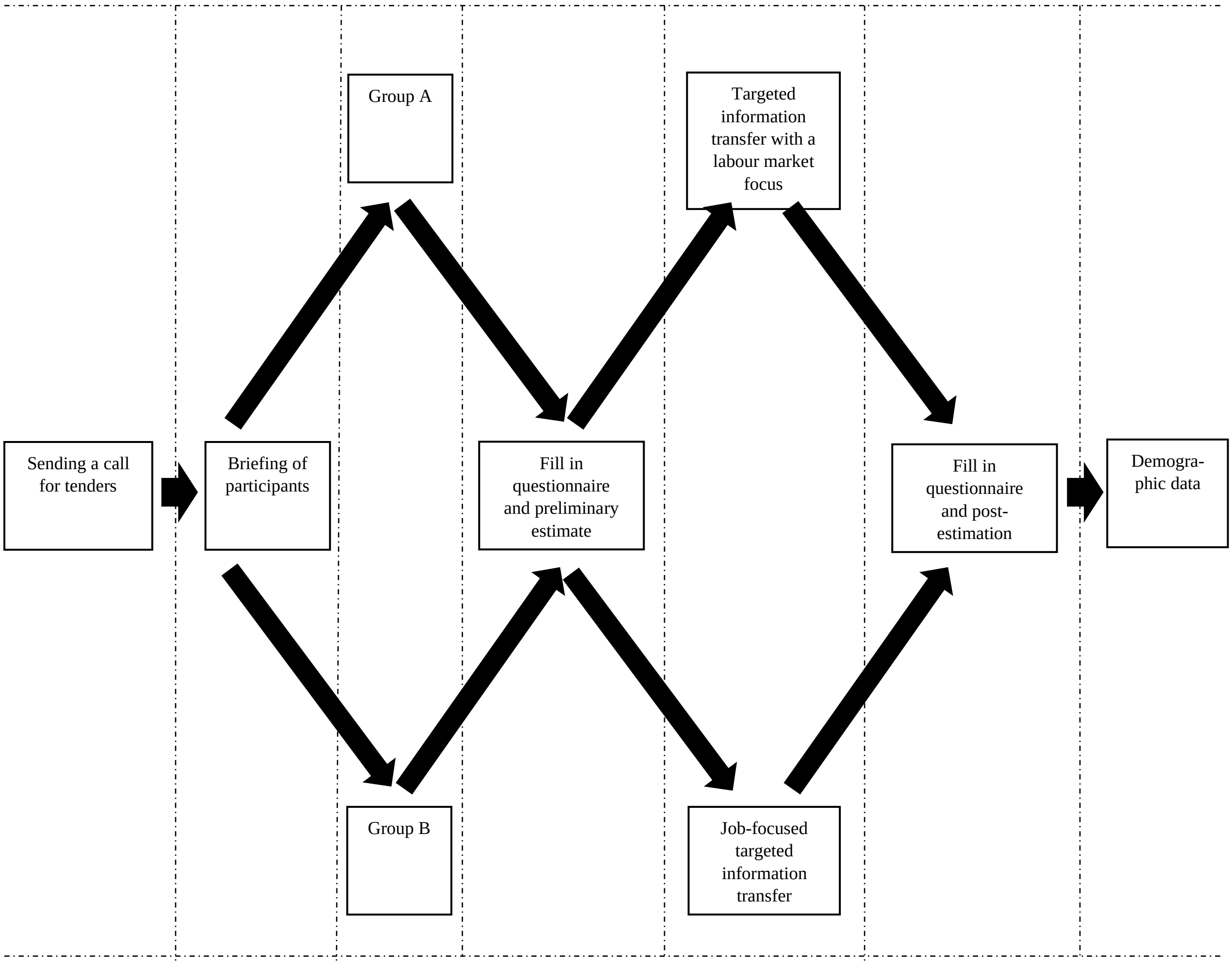

Figure 1: Description of the experimental process

Source: own editing

The set of questions created for the pilot study consisted of 12-12 sections:

- Section 1/12: general knowledge assessment (Q*2.1.*, *Q2.2.*, *Q2.3.*)
- Section 2/12: Impact of technological progress in the 5 years BEFORE (*Q3.1.*, *Q3.2.*, *Q3.3.*)
- Section 3/12: Impact of technological progress in the NEXT 5-10 years (*Q3.1.*, *Q3.2.*, *Q3.3.*)
- Section 4/12: Opinion on the chosen field of expertise
- Section 5/12: Estimation and self-assessment of wage levels and the automatability of occupations and skills (*Q3.4.*, *Q3.5.*, *Q3.6.*)
- Section 6/12: professional description of the topic (labour market and job-related focus)
- Section 7/12: Feedback after writing (*Q2.1.*, *Q2.2.*, *Q2.3.*)

- Section 8/12: Impact of technological progress in the 5 years BEFORE (*Q3.1.*, *Q3.2.*, *Q3.3.*)
- Section 9/12: Impact of technological progress in the NEXT 5-10 years (*Q3.1.*, *Q3.2.*, *Q3.3.*)
- Section 10/12: Opinion on the chosen field of expertise
- Section 11/12: Wages, occupations and skills automatability (*Q3.4., Q3.5., Q3.6.*)
- Section 12/12: demographic data

Section 1 consisted of 3 questions asking respondents to assess 1) their own general awareness of technological progress, 2) the social impact of technological progress and 3) the extent of the impact of technological progress on the labour market. The first two questions were rated on a Likert scale from 1 to 10, while the third question asked to rate the degree of impact of the three impacts (displacing, complementing and creating) on a Likert scale from 1 to 5.

Sections 2, 3, 8 and 9 were scored by completers on the following 12 criteria:

1. pair of statements: job creation
2. pair of statements: simplicity of location
3. pair of statements: ease of obtaining the necessary qualification
4. claim pair: evolution of earning potential
5. pair of statements: variety of job tasks
6. pair of statements: complexity of work tasks
7. claim pair: job content
8. claim pair: place of work
9. statement pair: work-life balance
10. pair of statements: work-family and couple balance
11. pair of statements: work-sport and health balance
12. pair of statements: work-life balance and acquaintances

They had to rate the statements on a Likert scale from 1 to 10, with the endpoints of the scales indicated in text (for example, in the case of statement 1, the respondents could read "It has not led to the creation of more jobs at all" and "It has greatly increased the number of jobs"). Sections 2 and 8 were to be answered in relation to the past 5 years, while sections 3 and 9 were to assess the situation that respondents predicted for the next 5-10 years. Sections 8 and 9 were completed after having consulted the job descriptions, thus providing an opportunity to measure respondents' feedback and to show the impact of knowledge transfer. For the final questions in Sections 3 and 9, respondents were asked to choose a field of specialisation that was most relevant to their future profession.

In the next 2 to 2 stages (stages 4-5 and 10-11), the completers were divided into 3 groups, based on the closest professional content. The guided grouping was different for respondents in that in sections 5 and 11, there were 10 to 10 general occupations (see *Table 7*), along with 10 to 10 different occupations related to their chosen occupation (see *Tables 8 to 10*). An important consideration in the selection of occupations was the inclusion of a level of automatability in the LASSÉBIE & QUINTINI (2022) study and the recording of gross monthly average wages for the same occupation by the Central Statistical Office (CSO) for the testability of subsequent precision estimates.

During Sections 5 and 11, respondents were presented with 20 occupations and 19 skills and abilities (20 skills/abilities were planned to be included, but during the start of the analysis it was noticed that one of the options was not included in the list, and was mistakenly deleted during the editing of the questionnaire). They were asked to estimate occupations based on 2 criteria; 1) average gross earnings (full-time, if employed in Hungary in 2023) and 2) automation capability of occupations. For gross average earnings, I used class intervals of 150,000 HUF, with two endpoints of the scale ranging from 300,000 HUF less to 1,050,000 HUF more. The level of automatability had to be graded on a scale from 0-100%, with intervals of 10-10%. They were able to judge the automatability of skills and abilities by selecting one of the following 7 options (based on those used in the research by LASSÉBIE & QUINTINI, 2022) and coding was performed for subsequent calculations as shown in brackets *in Table 1* on an interval between 0-5 based on LASSÉBIE & QUINTINI (2022):

- No, and this will not be possible in the near future (next 5-20 years) ($x = 0$)
- No, but in the near future it will probably be possible (at least in some contexts) ($0 < x <= 1$)
- Yes, in some cases ($1 < x <= 2$)
- Yes, in some cases ($2 < x <= 3$)
- Yes, in many cases ($3 < x <= 4$)
- Yes, in most cases ($4 < x < 5$)

- Yes, in all cases (x = 5)

After each of the 3 aspects, respondents were asked to estimate the number of times they thought they had accurately marked the interval for each of the 20 professions or skills/abilities (the questionnaire asked for an accurate estimate of skills/abilities between 0-20, the values were standardised in the analysis as there were 19 skills/abilities in the list). To check the accuracy, I used data from KSH (2024) for gross wages, and LASSÉBIE & QUINTINI (2022) for the level of automation for both occupations and skills/abilities.

Table 1: Average level of automatability of skills and abilities tested in the experiment (0-5)

Memorization (~4,5)	Judgement and decision-making (~1,80)
Concentration, focused attention (~4.1)	System level analysis (~1,45)
Reaction time (~3,8)	Critical thinking (~1,10)
Stamina (~3,51)	Consultation and advice (~1,05)
Organising information (~3,50)	Originality, creativity (~0,92)
Schedule of works and activities (~2,91)	Technology and equipment design (~0,60)
Dexterity (~2,70)	Helping and caring for others (~0,53)
Visualization (~2,20)	Negotiation (~0,48)
Oral comprehension (~2,18)	Complex problem solving (~0,48)
Reading comprehension (~1,97)	

Source: own editing based on LASSÉBIE & QUINTINI (2022)

2.1. Experience of the pilot experiment

Prior to sharing the pilot questionnaire, I also conducted a pilot survey among students of the Faculty of Economics, MA in Human Resource Counselling, in the context of the seminar Social Research Methodology, Quantitative, Qualitative Methods. The feedback and constructive comments of the 11 participating students helped the experiment to take its final form. The feedback pointed out that, for the 12 pairs of statements, it would help traceability and interpretation if, for example, the content of the pair of statements were indicated instead of the name "statement 1". Following this suggestion, for example, I replaced the term "Statement 1" with "Statement 1 - Job Creation" and logically added the other 11 statements in the final version. Other comments included that when duplicating blocks in the question set, the row number of one section of the post-measurement was incorrectly listed with the row number of the pre-measurement, I have also corrected this inaccuracy and re-checked the row number of each section. In addition, the pilot group participants noted that there were more than 40 response options in a multiple-choice type question when providing labour market experience, which they felt would have been more practical to provide in a drop-down list type format, similar to the year of birth in the previous questions. The control group interface had previously included this option for this question, which I have modified via the experimental link. In addition, the wording of one of the questions "In which institution do you continue your studies?" was described as ambiguous, as some respondents understood the question to refer to future continuation. In the final version, this question was worded as follows; "In which institution are you pursuing your studies?".

3. MAIN FINDINGS OF THE THESIS

In the survey study related to the Labour Market Skills examination, 184 of the 207 students who took the examination could be included, as in 23 cases, they did not take advantage of the optional labour market questions related to AI.

To evaluate the results, I conducted a bivariate correlation analysis of the total score for the subject and the total score for the optional extra questions. Pearson's bivariate correlation results showed no significant correlation ($r = 0.111$, $p = 0.135$), however, when comparing scores standardised by exam scales, a weak positive correlation was observed at a 10% significance level ($r = 0.134$, $p = 0.070$). The latter suggests that students with higher test scores (i.e. more informed, better prepared) score slightly higher on a process assessment outside the subject matter of the course but related to the actual process. However, in Spearman's rank correlation analysis of the above comparison, no correlation, even weak, is observed either for actual scores ($\rho = 0.088$, $p = 0.234$) or for standardised scores ($\rho = 0.114$, $p = 0.124$). If we exclude students who did not take the test for the first time from the analysis, we find that for 149 individuals, neither Pearson's bivariate correlation (actual score values; $r = 0.104$, $p = 0.206$, nor the standardized score values; $r = 0.119$, $p = 0.148$), nor the Spearman rank correlation (actual score values; $\rho = 0.081$, $p = 0.324$, nor the standardized score values; $\rho = 0.103$, $p = 0.213$) showed significant correlation. I also examined the correlations using multivariate regression analysis for the total standardised scores obtained with the extra questions, including the standardised examination score, the gender of the examinees, the number of retakes, the students' degree and the training programme. As can be seen *from Table 1,* significant results were only found for the training type ($p=0.043$) and at a 10% significance level for the second repeated examination ($p=0.066$) and the standardised examination score ($p=0.088$). Running the test on the adjusted scores showed that the F value was 5.068 and the adjusted R^2 was 0.042. Since only the correspondence training regime ($p=0.012$) and the second exam ($p=0.029$) showed a significant relationship for the study, which carry so much information that correspondence students can expect to gain minimally more extra points ($B=0.386$), while second exam takers (who took the exam a second time due to unpreparedness) can expect to gain even fewer extra points ($B=-0.391$)

Table 1: Examination of the standardised value of extra scores on the Labour Market Skills test using multivariate regression analysis

	B	*Beta*	*t*	*p*
Constans	0,006		0,036	0,971
Z Item	0,131	0,131	1,716	0,088
Female	-0,168	-0,085	-1,118	0,265
Second exam	-0,373	-0,140	-1,851	0,066
Third exam	0,059	0,011	0,141	0,888
Profession KM	-0,109	-0,033	-0,328	0,743
Profession PSZ	0,065	0,028	0,322	0,748
Sak TV	0,225	0,088	1,005	0,316
Profession MÉN	0,057	0,016	0,202	0,840
Sect MEZ	-0,005	-0,002	-0,021	0,983
Correspondent	0,481	0,204	2,043	0,043
F	1,520			0,136
corr R^2	0,028			
N	184			

Source: own results (2024)

No correlation was found between scores on extra-curricular questions designed to investigate the impact of technological change on the labour market and labour market knowledge.

H1.1 Higher scorers on the subject test also score higher on questions outside the subject area on the relationship between technological change and the labour market. Contrary to AUTOR's (2015) article, those who scored higher on the test related to the Labour Market Knowledge course did not score higher on the test, so I do not accept this hypothesis.

H1.2 The increase in subject test scores also means an increase in scores on questions outside the subject area on the relationship between technological change and the labour market. The study by ACEMOGLU & RESTREPO (2018) stressed the importance of studying technological change in education and that the knowledge gained in education contributes to a better understanding of technological and labour market issues, but although the students' test scores increased in the above mentioned exam, this was not significantly associated with the extra points they gained on the additional questions. Therefore, I do not accept this hypothesis.

The presentation of the experimental results will start with a description and interpretation of the descriptive statistical results. I then deal specifically with the demonstration of the experimental effect, followed by a statistical analysis of the differences between the experimental and control groups. Within the subsections, I will treat as separate units the presentation of general awareness and knowledge of the labour market, the results on wages, and the results on the automability of occupations and skills and abilities. The experiment involved 520 students from the Faculty of Economics at the University of Debrecen.

In assessing the impact of technological developments on the labour market, three dimensions were examined: displacement, complementarity and creation. Each of these offers different perspectives for understanding labour market transformation.

Displacement effect: the mean (3.160) and median (3.0) indicate that respondents take a neutral position. This indicates that the crowding-out effects of technological development are not perceived by respondents as being overwhelmingly dominant, but are not considered insignificant either. The low standard deviation (0.86) suggests a more consistent perception on this dimension.

Complementarity: this dimension is the most positively rated, with both mean (3.862) and median (4.0) indicating that respondents believe that technological developments tend to help labour market processes, for example by complementing jobs and skills. Again, the standard deviation (0.86) is low, indicating that opinions are close.

Creative effect: The mean (3.327) and median (3.0) indicate that the perception of the creative effect is less positive than that of the complementary effect, but also falls in the neutral to slightly positive range. The higher standard deviation (1.07), however, indicates that there is a greater divergence of opinion between respondents on this dimension.

In the initial phase of the survey, the general awareness of respondents and their perception of the social impact of technological development reflect optimism, while the assessment of the impact on the labour market is dominated by neutral and slightly positive opinions. The heterogeneity of self-assessments and perceptions is particularly significant in the dimensions of general awareness and creative effects, suggesting that respondents have different experiences and knowledge on the subject.

H2.1 Students perceive the job creation effect as more likely than not (above 3 on a 5-point scale). Consistent with BRYNJOLFSSON & MCAFEE (2014), students were positive about the job creation effects of technological change, but only slightly towards a 3 on the degree of effect (*Table 2*). I accept this hypothesis.

Table 2: Respondents' perception of labour market impacts (N=520)

	Displacement effect	Complementary effect	A creative effect
Average	3,160	3,862	3,327
Median	3,00	4,00	3,00
Source	0,86	0,86	1,07
Minimum	1,00	1,00	1,00
Maximum	5,00	5,00	5,00

Source: own results (2024)

H2.2 Students perceive the (job) destructive effect as more prevalent than not (above 3 on a 5-point scale). FREY & OSBORNE (2017) studied the automation of a number of jobs, which is consistent with the perception of students of the destructive effect of technological development. The effect barely exceeded the threshold indicated for value three (*Table 1*), but its prevalence was perceived as more real by students than not, so I accept this hypothesis.

H2.3 Students perceive (human work) to be complementary more than not (above 3 on a 5-point scale). AUTOR & SALOMONS (2018) show that technology often complements human work. In the students' feedback, the complementary effect was the strongest (*Table 1*), so I accept this hypothesis.

I assessed the impact of technological progress over the past 5 years and the next 5-10 years by rating 12-12 pairs of statements on a scale of 1-10. The ratings are based on the experiences and expectations of respondents recorded before and after they had read the job descriptions. In what follows, I analyse the main lessons and trends in the results.

Looking at the impact of the last 5 years, respondents were most positive about the change in where they work. The average score before the description was published was 6.896, which showed a slight increase after the description was published (6.938). This relatively high score indicates that respondents perceived a significant improvement in the opportunities for teleworking and working independently. The perception of educational needs is also positive, with an average of 6.223 before and 6.423 after the description. This suggests that technological developments in recent years have led to higher skill requirements, which respondents recognise. Among the pairs of statements concerning work-life balance, work-life balance was the highest rated dimension (mean: 6.212 before and 6.019 after the job description). Although the impact of the job description has slightly reduced the rating, the results suggest that technological progress has generally helped to achieve this balance. However, the lower ratings for job creation (average: 5.715 before, 5.619 after) and job opportunities (5.308 before, 5.315 after) suggest that respondents did not perceive technological progress as having contributed significantly to increasing labour market opportunities. The variety of tasks and the complexity of the tasks also received medium ratings, with a slight decrease after learning the job description. This may indicate that although respondents have experienced the effects of technological developments, these have not become dominantly positive in recent years.

Expectations for the future were generally more positive than in recent years. Respondents were most optimistic about the future of where they would work. The average before the description was given was 7.702, while afterwards it was 7.610. This high rating shows that respondents are confident that technological developments will continue to facilitate teleworking. Future increases in educational attainment were also rated positively (mean: 6.454 before the description, 6.715 after), suggesting that respondents continue to see the need for higher education as a prerequisite for success in the labour market. Among the areas of work-life balance, work-life balance received a particularly positive rating, especially after learning about the description (mean: 6.454), suggesting that respondents believe that technological advances can help maintain work-life balance in the future. Work-family balance and work-leisure balance also showed an improvement, especially after learning about the specification. The perception of job creation in the future improved significantly after learning about the specification (average: from 5.381 to 5.952), suggesting that the professional information has reinforced respondents' optimism about this aspect of technological development. A similar trend can be observed for job opportunities, where ratings showed one of the largest increases (mean: 5.044 to 5.531). The results show that perceptions of the impact of technological developments are mostly positive, both for the past and for the future, but expectations for the future are more positive. After learning the job descriptions, the average scores improved on several dimensions, especially in terms of job creation and job opportunities, underlining the importance of knowledge transfer. Flexibility in the location of work, increasing educational requirements and improving work-life balance are the areas where respondents perceive or expect the most significant positive changes.

H3.1. After the targeted information transfer, the students' perceptions of the labour market effects of technological development (job creation, job placement, education, earnings) were different. BESSEN (2019) stresses that information and context can change individuals' perceptions of technological development. I found partially consistent results with this, in that in order to be more successful in the labour market, students recognised that higher educational attainment was needed in the last 5 years (*Table 2*) and they expect it to be needed in the next 5-10 years (*Table 3*).

Table 3: Examining the difference between experimental and control groups for changes in labour market focus statements over the past 5 years

	F	t	Average difference	Standard error of the mean difference	95% confidence interval Lower limit	95% confidence interval Upper limit
Job creation	2,213	-0,108	-0,018	0,170	-0,352	0,315
Possibility of location	**6,878****	*1,816**	0,339	0,187	-0,028	0,706
Educational need	**5,359****	**-2,103***	-0,428	0,204	-0,828	-0,028
Earning potential	1,590	0,375	0,064	0,171	-0,272	0,400

**Significant at 5%, *Significant at 10%

Source: own results (2024)

In terms of future expectations, it is thought that in 5-10 years it will be more difficult to find a job due to technological progress (*Table 4*). No significant differences were found for the other aspects, neither for the past nor for the future. Since in some cases I found results consistent with the hypothesis, I cannot reject this hypothesis.

Table 4: Examination of the difference between experimental and control groups for changes in labour market-focused statements over the next 5-10 years

	F	t	Average difference	Standard error of the mean difference	95% confidence interval Lower limit	Upper limit
Job creation	**10,282****	-0,212	-0,040	0,190	-0,413	0,332
Possibility of location	2,531	**2,092****	0,427	0,204	0,026	0,827
Educational need	**10,743****	**-1,975****	-0,421	0,213	-0,839	-0,002
Earning potential	1,433	0,764	0,137	0,179	-0,215	0,489

** Significant at 5%

Source: own results (2024)

H3.2. After the targeted information transfer, students perceived differently the effects of technological development on job content (variety of job tasks, complexity of job tasks, job content and location of work). BESSEN's (2019) research shows how technological development is transforming job content, especially with regard to new tasks and the transformation of existing jobs. The information transfer can help students to recognise these effects. According to BESSEN (2019), technological developments are constantly expanding the content of jobs, with simple routine tasks often being supplemented by more complex and creative tasks. The introduction of new technologies leads to job diversification, for example, in some industries job complexity has increased by 20% in the last decade. Contrary to these results, my experiment did not find significant results in my claims about job content, so I do not accept this hypothesis.

H3.3. After the targeted information transfer, the students' perceptions of the impact of technological developments on work-life balance (work-life balance, work-family and couple balance, work-sports and health balance, work-friends and acquaintances balance) were different. BRYNJOLFSSON & MCAFEE (2014) discuss in detail how technological changes affect work-life balance, with a particular focus on the flexibility brought about by digital tools and the increase in working hours. These authors highlight that the flexibility provided by IT tools has increased the share of working from home by 30%. At the same time, digital working often extends working hours, which has led to a deterioration in work-life balance for 25% of respondents. Based on my experimental results, only a subset of students (members of the control group) perceived the supportive impact of technology on work-family balance over the past 5 years. I did not find significant results in any other respect in either time period, but I cannot reject this hypothesis.

Prior to the description, respondents estimated significant differences in wages for general occupations. The average wage estimates ranged from 354 808 HUF (barman) to 613 558 HUF (electrician). The highest median (675 000 HUF) was for electrician, suggesting that this occupation was considered by a large proportion of respondents to be high paying. The lowest median (375 000 HUF) was found for several occupations, such as hairdresser, secretary and journalist, suggesting that the majority of respondents considered these to be lower income occupations. The largest variance was recorded for train driver (214 507 HUF), indicating a significant difference of opinion between respondents. Once the job description was known, the average wage estimates for general occupations increased. The most significant changes were for train driver (from 485 192 to 544 038 HUF) and electrician (from 613 558 to 636 635 HUF). For most professions there is an increase in average estimates, suggesting that professional information has led to a more positive perception of wages. The variance increased for almost all professions, for example secretary (from 166 465 to 192 521 HUF), indicating a diversification of opinions.

Wage estimates for occupations related to the fields of economics, engineering, information technology and agri-food are given before the job descriptions. The average wage estimates range from 615 789 HUF (surveyor) to 855 668 HUF (application programmer), which covers a considerable range. Perceptions of wages vary among respondents, as reflected in the variation in the standard deviations. Application Programmer (855 668 HUF) and Architect (845 951 HUF) had the highest average wage estimates, suggesting that these occupations were perceived by respondents as high paying. This is confirmed by the medians, which for the architectural engineer were 825 000 HUF and for the application programmer were also high at 825 000 HUF. Land surveyor (615 789 HUF) and HR administrator (632 794 HUF) had the lowest median wage estimates, indicating that these occupations are perceived by respondents as less remunerative. The largest variance was recorded for graphic designer (228 899 HUF), indicating significant differences of opinion. Occupations with relatively smaller variance, such as food engineer (187 231 HUF), suggest that there was greater consensus among respondents for these occupations. The minimum and maximum values also cover a wide range, for example, the salary of an architect ranged from 375 000 HUF to 1 125 000 HUF, reflecting different perceptions of the income potential of the profession.

After the briefing, wage estimates showed slight changes, with several occupations seeing an increase in average estimates, while some occupations showed stability or a slight decrease. The averages range from 646 026 HUF (surveyor) to 851 258 HUF (application programmer). The wage estimates for graphic designer (from 734 211 to 741 398 HUF) and HR administrator (from 632 794 to 666 247 HUF) show a slight increase. The average wage estimate for tax consultant (from 706 883 to 718 763 HUF) and analytical economist (from 693 826 to 721 781 HUF) also improved, indicating that job descriptions had a positive impact on these perceptions. The average estimates for application programmer (from 855 668 to 851 258 HUF) and architect (from 845 951 to 825 604) were stable, which may indicate that respondents were well informed before the information was provided. The standard deviations have generally increased, for example for graphic designer (from 228 899 to 244 388 HUF), which may indicate a diversification of respondents' opinions. The variance for food engineer remained relatively stable, increasing only slightly (from 187 231 to 196 014 HUF), indicating that there is still a relatively uniform opinion in this profession. The maximum values for almost all professions remained at 1 125 000 HUF, indicating that some respondents associate some professions with exceptionally high salaries.

shows the change in accuracy of estimates of wages in general occupations, comparing the experimental and control groups, based on differences in pre- and post-item responses. The results of independent samples t-tests are used to examine the mean differences, their standard errors and the significance of the differences.

When analysing the data, it can be observed that there are significant differences between groups for several occupations. For example, for the firefighting profession, the F value ($F = 6.917$) indicates that there was a significant difference in the variances ($p < 0.05$), but the mean difference was not significant ($t = -1.159$, $p > 0.05$). This indicates that the distribution of responses differed between the two groups, but there was no significant difference in the mean estimation accuracy. A similar significant difference in variance was observed for the counter profession ($F = 4.836$, $p < 0.05$), and here the difference between means was close to significant ($t = -1.725$, $p < 0.10$). The mean difference was -22,284 HUF, suggesting that the experimental group provided more accurate estimates, although the difference did not reach the 5% significance level. An interesting result was observed for the secretary profession, where there was a significant difference between both the standard deviations and the means ($F = 8.578$, $p < 0.05$; $t = -2.206$, $p < 0.05$). The mean difference was -29 605 HUF, suggesting that the experimental group differed significantly from the control group and provided more accurate estimates of the profession's wage. In contrast, for the hairdressing profession, for example, no significant difference was found in either the standard deviations or the means ($F = 0.006$, $t = -1.186$, $p > 0.05$), indicating that there was no significant difference in the accuracy of the estimates between the two groups. A similar result can be seen for the journalism profession, where the mean difference is only -4 610 HUF, and this is not statistically significant ($t = -0.334$, $p > 0.05$). The F values for the tailors and cooks professions ($F = 12.950$ and 4.255) indicate a significant difference in standard deviation, but there is no statistical difference between the means ($t = -1.534$, $p > 0.05$ and $t = -0.903$, $p > 0.05$).

It analyses the change in accuracy of wages in the third occupational group, comparing the responses of the experimental and control groups. Paired-sample t-tests quantify the differences in responses before and after the description, with particular attention to examining the variances and mean differences. The purpose of the table is to explore the extent to which the accuracy of estimating occupational wages has improved as a result of the experimental description.

The results show a significant mean difference for the food engineer profession ($t = -1.822$, $p < 0.10$), where the experimental group's estimates were closer to the real data. The mean difference is -29 066,206 HUF, indicating that the respondents in the experimental group provided more accurate estimates, although the difference did not reach the 5% significance level. This result suggests that the specification supported to some extent the participants' more informed choices in this profession. For the electronics engineer, a significant difference in the standard deviations was observed ($F = 3.196$, $p < 0.10$), but the mean difference did not show significance ($t = 0.363$, $p > 0.10$). This suggests that although the variability of responses was different between the two groups, no statistically detectable difference in accuracy emerged. For other professions, such as land surveyor, tax consultant, analytical economist, and HR administrator, the mean differences were not found to be significant at either the 5% or 10% level. For these professions, the data show that the experimental specification did not result in a significant improvement in accuracy. For example, the mean difference for tax accountant is -7 297 HUF, but this is not statistically significant ($t = -0.427$, $p > 0.10$), suggesting that the estimates of the two groups were at similar levels. Interestingly, for application programmer and graphic designer, no significant differences were observed between the means or variances ($t = -0.186$ and $t = 0.044$, $p > 0.10$). This suggests that participants in these professions provided similar estimates regardless of which group they belonged to.

H3.4. After the targeted information transfer, students will have a more accurate assessment of the level of wages available in the professions studied. AUTOR (2015) analyses how automation and technological progress affect the level and distribution of wages. The transfer of information allows students to better understand the factors affecting wage levels. AUTHOR (2015) highlights that the wages of workers with high technological skills are on average 40% higher compared to non-technological jobs. Low-skilled jobs, however, have seen a 15% drop in wages due to technological automation. In my experiment, I found significant results in accuracy only in the estimation of secretary wages, not for the other 19 occupations. Therefore, I cannot reject this hypothesis.

The professions covered include 10 general professions and 10-10 specific professions in 3 groups. A detailed presentation of the results reveals the perceptions of the threats of automation posed by technological progress and how the participants' estimates have changed as a result of the information provided by the profession.

For the general occupations, respondents' estimates ranged widely (from 5.5% to 95.5%). The results showed significant variation across occupations, indicating that respondents perceived these occupations to be differently automatable. For train drivers (54.73%) and journalists (51.46%), respondents estimated relatively high levels of automation. Lower levels were estimated for hairdresser (16.38%) and firefighter (18.04%), indicating that respondents believe that human labour will remain important in these occupations. The largest variance was observed for journalist (30.76%) and train driver (30.33%), reflecting differences of opinion between respondents. After looking at the job descriptions, estimates of the automation potential of the general professions changed slightly. The estimate for tourist guides decreased (from 46.54% to 42.60%), indicating that the information has corrected the exaggerated perceptions of automatability. For train driver, the estimate also decreased (from 54.73% to 48.50%). There were small increases for fireman (from 18.04% to 19.73%) and electrician (from 24.08% to 24.96%).

Prior to learning the job description, the estimates ranged widely for Group 3, indicating that respondents' knowledge of the automation potential of different occupations varied. For graphic designer (58.56%) and application programmer (51.61%), respondents assumed a relatively high level of automation capability. This suggests that these professions were perceived by respondents as more technology-intensive. Food engineer (33.74%) and electrical engineer (36.27%) were estimated to have lower levels of automation, indicating that these occupations were perceived by respondents as more human skills-based. The largest variance was observed for application programmer (29.49%) and graphic designer (28.92%), reflecting the significant differences in opinion between respondents. Median values (e.g. tax consultant: 35.50%) were lower than average estimates for several professions, indicating that some respondents gave significantly higher estimates, which pulled the average upwards. After the professional briefing, estimates generally decreased, especially for technology- intensive professions. This indicates that the descriptions provided respondents with a more accurate picture of the limitations of automation. Estimates decreased for application programmer (from 51.61% to 47.39%) and graphic designer (from 58.56% to 51.05%), indicating that respondents adjusted downwards as a result of the information, believing that these occupations are less likely to be replaced by technological improvements. Estimates for tax consultant also decreased (from 44.06% to 41.48%). Estimates for food engineer (from 33.74% to 34.90%) and electrical engineer (from 36.27% to 36.20%) were little changed, indicating that respondents' perceptions were stable. In general, the standard deviations decreased, for example for tax expert (from 27.18% to 25.95%), indicating that the differences of opinion between respondents have narrowed. Median values have moved closer to the average estimates for several professions, for example for analytical economist (from 45.50% to 35.50%), indicating that estimates have become more balanced.

I also analysed the variation in the accuracy of estimates of the automation level of general occupations, comparing the results of the experimental and control groups. The results showed that for some occupations the differences in standard deviations were significant, indicating that the experimental specification affected the groups' estimates differently. For example, the F-test value for the barman occupation ($F=10.396$, $p<0.05$) suggests that there was a higher degree of variability in the responses in the experimental group, although the mean difference ($t=1.446$, $p>0.10$) did not reach significance. This suggests that participants responded differently to the description, but the difference in accuracy between the two groups was not statistically significant. A similar trend was also observed for the electrician and tailor occupations, where the differences in standard deviations were significant ($F=6.919$ and $F=8.274$, $p<0.05$), but the mean differences did not show a significant difference. This suggests that the effect of the experimental specification was differential to some extent, but did not necessarily result in a significant improvement in accuracy. Interesting results were observed for the hairdressing and journalism professions. For both professions, the mean difference was in the positive direction ($t=1.289$ and $t=0.750$), suggesting that participants in the experimental group provided slightly more accurate estimates, although this difference did not reach significance. This may suggest that for these occupations, the description may have had a moderate positive effect on the accuracy of the estimates. In contrast, for the secretary and driver occupations, the mean difference was negative ($t=-1.048$ and $t=-0.784$), suggesting that the experimental specification did not lead to an improvement and may even have been a confounding factor. For these occupations, participants' estimates did not become more accurate after the description, and the difference between the two groups was not significant.

Looking at the occupations in occupational group 3, I found that the difference in variance for the food engineer occupation was significant ($F=3.451$, $p<0.10$) and the mean difference showed a negative trend ($t=-1.720$, $p<0.10$), suggesting that participants in the experimental group provided slightly more inaccurate estimates after the description. This finding suggests that the description did not adequately help to provide a more accurate estimate of the level of automatability in this case, and may even have been a confounding factor. The difference in standard deviation was also significant for the tax expert profession ($F=4.467$, $p<0.05$), but the mean difference was in the positive direction ($t=0.503$, $p>0.10$), suggesting that although the variance between the estimates differed, there was no statistically significant difference in mean accuracy between the two groups. This may indicate that the effect of the description was not uniform across participants, but may have been useful for some respondents. The financial analyst profession showed a similar pattern. The difference in standard deviation was significant ($F=3.085$, $p<0.10$), but the mean difference did not reach significance ($t=0.520$, $p>0.10$). This result suggests that the effect of the description was not consistent here either, and that differences between groups may have been due more to differences in respondents' interpretation. For the analytical economist profession, the difference in standard deviation was significant ($F=3.741$, $p<0.10$), but the mean difference was minimal and did not reach significance ($t=0.073$, $p>0.10$). This suggests that the specification did not have a significant effect on the accuracy of the estimates, although there was some variability. In contrast, other professions, such as land surveyor, graphic designer, electrical engineer, and architect-engineer, did not show significant differences in either variances or means. This indicates that the specification in these cases had no detectable effect on the accuracy of the estimates.

H3.5. After the targeted information transfer, students will be able to judge more accurately the level of automation of the professions studied. The study by FREY & OSBORNE (2017) on the automation of professions can help students to form a more realistic picture of the potential and impact of automation. The authors' results show that 47% of occupations fall into the high-risk automation category, especially for jobs involving routine tasks. However, occupations requiring creative and interpersonal skills show low automation rates. I could not support these findings from the literature with my own results, as I did not find any significant results in the accuracy of the automation of occupations in any of the cases, and therefore I reject this hypothesis.

The automation of skills and abilities was assessed in 19 cases, based on numerical codes assigned to different text options. This allowed the estimates to reflect not only quantitative but also qualitative differences. The analysis covered pre- and post-estimation, literature discrepancies and the extent of corrections. The main results and their interpretation are presented in detail below. Pre-job description assessments revealed significant differences in participants' perceptions of the automatability of each skill. The following patterns were observed. Skills such as stamina (mean: 0.996) and originality and creativity (1.110) most often fell into the categories "No, and it will not be possible in the near future (in the next 5-20 years)" or "No, but it will probably be possible in the near future". This indicates that participants perceive these skills as strongly human-driven. Skills such as organising information (3,090) and memorising (2,627) were mostly in the "Yes, in some cases" or "Yes, in many cases" categories. This reflects the participants' perception that these skills can be partially replaced by technology. Judgement and decision-making (1.188) and complex problem-solving (1.663) have mean scores that fall between the categories "No, but will probably be possible in the near future" and "Yes, in some cases", indicating that participants perceive them as moderately substitutable. After learning the job descriptions, a decreasing assessment of automatability is observed for a number of skills. The scores for endurance (0.815) and originality and creativity (0.977) decreased further, confirming that participants preferred the category "No, but will probably be possible in the near future". This suggests that professional information may have biased participants' understanding towards human factors. A smaller but significant decrease was observed for information organisation (2.415) and memorisation (2.144), indicating that participants have slightly reassessed the substitutability of these skills, but still keep them in the category "Yes, in some cases". For Judgment and Decision Making (1.096) and Complex Problem Solving (1.502), the change remained minimal, suggesting that the job descriptions for these skills changed participants' existing perceptions to a lesser extent.

The analysis based on independent samples t-tests found significant differences between the two groups for some skills and abilities, while in other cases the differences were not statistically significant. For the information organization skill, the difference in standard deviation was significant ($F=3.381$, $p<0.10$) and the mean difference was also close to the level of significance ($t=1.704$, $p<0.10$). This indicates that respondents in the experimental group tended to estimate the level of automation more accurately after they had learned the description. This skill is likely to be well delineated in the descriptions, which could support more accurate estimation. For visualization, there was a similarly significant difference in standard deviation ($F=3.487$, $p<0.10$) and a nearly significant difference in mean ($t=1.809$, $p<0.10$). This may suggest that the description helped the experimental group to better understand the level of automaticity of this skill, although the result just reached the threshold of statistical significance. The difference in variance for the scheduling of tasks and activities skill was also significant ($F=8.546$, $p<0.05$), but the mean difference did not reach the level of statistical significance ($t=0.861$, $p>0.10$). This suggests that the description affected the variability of responses, but did not result in an overall difference in accuracy between the two groups. Significant differences in standard deviations were also found for systemic analysis and concentration, focused attention skills ($F=3.456$, $p<0.10$; $F=3.548$, $p<0.10$), but these were not associated with statistically significant mean differences. This indicates that the experimental group's responses were not clearly more accurate, but that the scatter of scores changed as a result of the description. It is an interesting observation that some skills, such as judgement and decision making, originality, creativity, or technology and equipment design, showed no significant difference in either the standard deviation or the mean. This suggests that in these cases the description did not have a noticeable effect on the estimates, or that the participants' existing knowledge was sufficient to make a more accurate assessment.

H3.6 After the targeted information transfer, students will be able to judge more accurately the level of automatability of the skills and abilities tested. The studies by ARNTZ ET AL. (2016) and LASSÉBIE & QUINTINI (2022) detail the extent to which different skills and abilities can be automated, and the transfer of information can help students make more informed judgements about this. ARNTZ ET AL. (2016) highlight that 9% of workers in OECD countries work in positions where 70% of tasks can be automated. Skills that require interpersonal communication, problem solving and creativity are less automatable, with an automation risk of only 5-10% in these cases. Based on the results of the students who participated in the experiment, I found no significant results in the accuracy of the automation of skills and abilities, and therefore reject this hypothesis.

H4.1. Students who are more aware of the wages available in the professions are less likely to overestimate their knowledge of these wages. The OECD (2019) report discusses in detail the relationship between labour market wages and knowledge, which supported the hypothesis testing. The application of the Dunning-Kruger effect visualisation tool clearly revealed differences in wage estimates, with less knowledgeable students tending to overestimate their knowledge, while the degree of overestimation decreased steadily as accuracy improved, with the highest performers even underestimating their own knowledge (*Figure 1*). Hence, I accept this hypothesis.

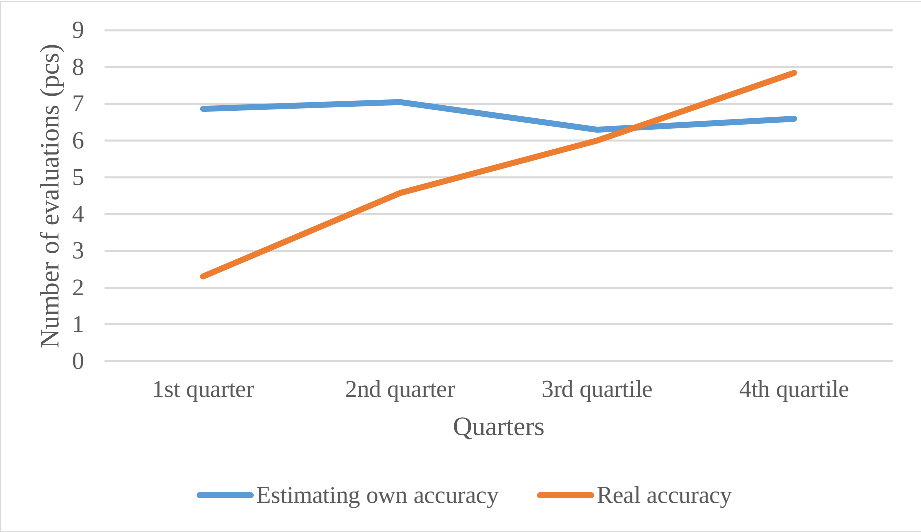

Figure 1: Accuracy of preliminary wage estimates

Source: own results (2024)

H4.2. Students who are more aware of the automation of professions are less likely to overestimate their knowledge in this area. A study by FREY & OSBORNE (2017) investigating the automation of different professions showed that accurate knowledge about automation can help individuals to form a more realistic picture of their own knowledge, thus reducing the chances of overestimating their knowledge. Considering the results of the experiment, the hypothesized situation emerges, i.e., the most prepared are the most prone to overestimate this knowledge (*Figure 2*). Consequently, I accept this hypothesis.

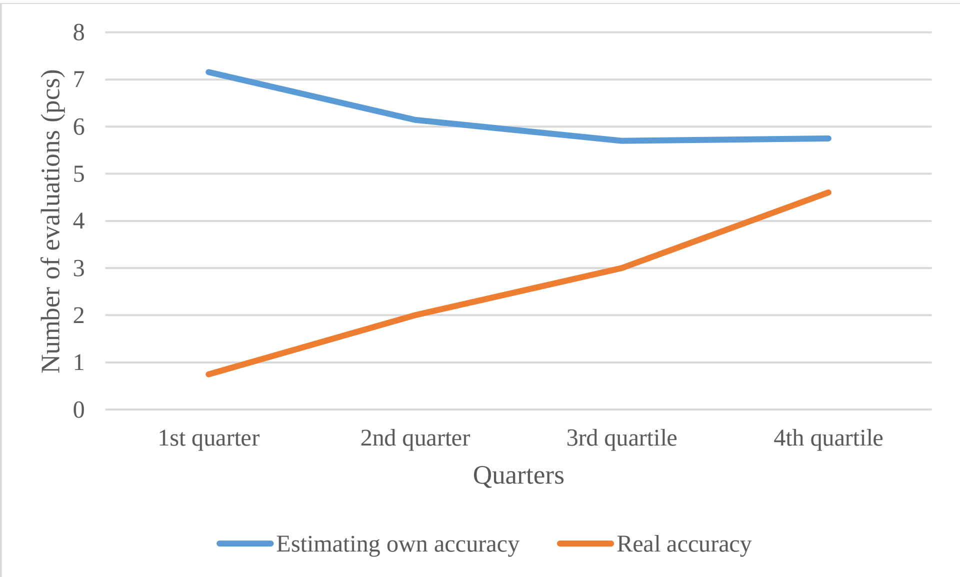

Figure 2: Estimation accuracy of the automation of occupations

Source: own results (2024)

H4.3. Students who are more aware of the automatability of skills and abilities are less likely to overestimate their knowledge in this area. The studies by ARNTZ ET AL. (2016) and LASSÉBIE & QUINTINI (2022) analyse in detail the extent to which different skills and abilities can be replaced by automation. Based on this, gaining accurate knowledge can help individuals to develop a more realistic picture of the value and applicability of specific skills. The overestimation of the students in the experiment was characterized by the fact that the highest overestimation was given by the least prepared, while the rate of overestimation decreased as accuracy increased (Figure 3). Based on my results, I accept this hypothesis.

4. NEW OR NOVEL RESULTS OF THE THESIS

Thesis 1 - "Students' optimism towards technological change": on average, students are more positive about the labour market effects of technological change, as they perceive the destructive effect as slightly less than the creative effect, while the complementary effect is perceived as the most positive. In summary, students expect technological change to be a tool in the workplace, while they do not think it will make a substantial difference in the workplace, and if it does, it will have a more creative effect.

Thesis 2 - "The importance of targeted information transfer": a subject providing general labour market knowledge cannot increase knowledge on the relationship between the labour market and technological development if it is not included in the subject topics. This can be seen both directly through the increase in exam scores and extra points and through the increase in exam scores and extra points. However, the targeted transfer of information has the potential to make students more aware of the role of the need for higher education in adapting to technological developments over the last 5 years and the next 5-10 years.

Thesis 3 - "Limitations of targeted information transfer": targeted information transfer has not been found to be able to influence their perceptions of earnings opportunities and job creation effects, both past and future. Ease of finding a job in the past 5 years was also not influenced, but they became more pessimistic in this respect for the next 5-10 years. Furthermore, students did not have a better understanding of the impact of technological developments on job content (variety of job tasks, complexity of job tasks, job content and location of jobs), neither for the past 5 years nor for the next 5-10 years. In addition, the targeted information transfer did not improve the accuracy of students' estimation of the wages available in the occupations studied (except for secretary, where it improved it and at the same time increased the perception of secretary wages), the accuracy of estimation of the automation of the occupations studied and the accuracy of estimation of the automation of the skills and abilities studied.

Thesis 4 - "The emergence of the Dunning-Kruger effect in understanding the impact of technological change on the labour market": students who are more aware of the wages available in the professions are less likely to overestimate and more likely to overestimate their knowledge of them. Furthermore, students who are more aware of the automation of occupations are less likely to overestimate and more likely to overestimate their knowledge of it. In addition, students who are more aware of the automation of skills and abilities are less likely to overestimate and more likely to overestimate their knowledge of these skills and abilities.

Thesis 5 - "The relationship between work-life balance and technological change": no information on work-life balance was provided to the groups, yet other information on the labour market effects of technological change improved perceptions of work-family and work-sport balance in group B, both for the past 5 years and for the next 5-10 years. For the past 5 years, work-life balance worsened within group A. The descriptions provided for Group B included information on telework and hybrid work, while Group A did not. This transfer of information may have an impact on positive perceptions of changes in work-life balance.

5. THE PRACTICAL USE OF THE RESULTS

The results suggest that students seem to be less likely to think that technological progress would change the structure of jobs, as the participants' answers on the displacement and creation effects were slightly below the medium rating, but they seem to see technological innovation as a tool, as the average scores for the additional effect of technological progress were the highest. Hence, I suggest that it is worth emphasising this impact and its potential uses in job-related subjects and other related subjects.

On the other hand, I would like to draw attention to the fact that excessive disregard for the crowding-out and creative effect can lead to a misperception of reality in students, and it is worthwhile to make up for their lack of knowledge by providing them with targeted information. This lack of knowledge is reflected in the underestimation of the level of automation of many professions, skills and abilities

The misjudgements are presumably due to the fact that the potential impact of technological development is not formally presented in any university course. Due to the lack of information transfer from education, individuals would only be able to infer changes indirectly, but my studies suggest that they are unable to do so effectively. However, after a short period of targeted information transfer, I have been able to show positive changes in the required qualifications, which may justify the strengthening of these efforts.

The Dunning-Kruger effect seems to exist for all the aspects considered (estimation of wages, estimation of the level of automation of occupations and skills and abilities), i.e. those who have a less realistic view of the real labour market situation, are subject to a double curse, so that they must be directly confronted with the risks of not being well informed and of being left behind, which they will not be able to perceive and prepare for in the event of a technological transformation.

It is recommended that the identified impacts are further broken down by curricular areas to identify those parts that are more likely to develop students' preparedness for the labour market impacts of technological change.

The assessment and potential exploration of this phenomenon in the workplace environment can provide useful information for the design and identification of the content and need for organisational training and development programmes, thereby optimising costs and increasing the effectiveness of improvements.

6. LITERATURE USED IN THE THESIS

DAUTH, W. - FINDEISEN, S. - SUEDEKUM, J. - WOESSNER, N. (2021): The Adjustment of Labor Markets to Robots. Journal of the European Economic Association, 19(6), pp. 1-50.

GRAETZ, G. - MICHAELS, G. (2018): Robots at work, Review of Economics and Statistics, 100(5), pp. 753-768.

FREY, C. B. - OSBORNE, M. A. (2017): The future of employment: How susceptible are jobs to computerisation?. Technological Forecasting and Social Change. 114(48), pp. 254-280.

HOLM, J. - LORENZ, E. (2021): The impact of artificial intelligence on skills at work in Denmark. New Technology, Work and Employment, 37(1), pp. 79-101

KESHWANI, P. - PATEL, S. (2023): The impact of technology on work life balance, Iconic Research and Engineering Journals, 6(12), pp. 1142-1150

KOLLÁR, CS. (2018): A szakértővé válás, illetve a szakértők kiválasztásának és megkérdezésének módszertani kihívásai. Vezetéstudomány, 49(2), pp. 63-75.

KRUGER, J. - DUNNING, D. (1999): Unskilled and unaware of it: How difficulties in recognizing one's own incompetence lead to inflated self-assessments, Journal of Personality and Social Psychology, 77(6), 1121-1134.

LASSÉBIE, J. - QUINTINI, G. (2022): What skills and abilities can automation technologies replicate and what does it mean for workers - New evidence. OECD Social, Employment and Migration Working Papers 13 December 2022

NEDELKOSKA, L. - QUINTINI, G. (2018): Automation, skills use and training. OECD Social, Employment and Migration Working Papers, No. 202, OECD Publishing, Paris.

WEIMANN, J. - BROSIG-KOCH, J. (2019): Methods in Experimental Economics - An Introduction. Springer Cham, 307 p. ISBN 9783319933627

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Subject: PhD Publication List

Candidate: József Boros
Doctoral School: Doctoral School of Management and Business
MTMT ID: 10071195

List of publications related to the dissertation

Articles, studies (10)

1. **Boros, J.**, Dajnoki, K.: A chatbotok alkalmazásának lehetőségei a business coachingban: szisztematikus szakirodalom-elemzés.
   Új Munkaügyi Szemle. 6 (1), 15-25, 2025. ISSN: 2677-1306.
   DOI: http://dx.doi.org/10.58269/umsz.2025.1.2
2. Máthé, I. A., **Boros, J.**: A mesterséges intelligencia alkalmazása az emberi erőforrás-menedzsment területén.
   Új Munkaügyi Szemle. 6 (1), 56-65, 2025. EISSN: 2677-1306.
   DOI: http://dx.doi.org/10.58269/umsz.2025.1.6
3. **Boros, J.**: Jövőbiztos készségek: Várhatóan mire lesz szükség a jövő munkahelyein?
   Régiókutatás Szemle. 8 (2), 36-45, 2024. EISSN: 2559-9941.
   DOI: http://dx.doi.org/10.30716/RSZ/23/2/4
4. **Boros, J.**: Labour Economics: A technológiai fejlődés oldaláról.
   International Journal of Engineering and Management Sciences. 9 (3), 98-108, 2024. EISSN: 2498-700X.
   DOI: http://dx.doi.org/10.21791/IJEMS.2024.022
5. Kun, A. I., Kotsis, Á., **Boros, J.**: Hallgatóink felkészültsége: Hogyan látják ők, és mit mutatnak az eredmények? A Dunning-Kruger-hatás mérése proszemináriumi zárthelyi dolgozatok alapján. In: Tanulmányok Berde Csaba tiszteletére : tanulmánykötet. Szerk.: Dajnoki Krisztina, Boros József, Debreceni Egyetem Gazdaságtudományi Kar Vezetés- és Szervezéstudományi Intézet, Debrecen, 208-2017, 2022.
6. Kun, A. I., **Boros, J.**, Kotsis, Á.: Tudják-e a hallgatók, hogy mennyit (nem) tudnak?: a Dunning-Kruger-hatás vizsgálata üzleti szakokon tanuló felsőoktatási szakképzéses hallgatók körében.
   Marketing & Menedzsment. 56 (3), 7-20, 2022. ISSN: 1219-0349.
   DOI: http://dx.doi.org/10.15170/MM.2022.56.03.01

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7. **Boros, J.**: A technológiai fejlődés lehetséges munkahelyteremtő-, és romboló hatásai.
   International Journal of Engineering and Management Sciences. 5 (1), 1-9, 2020. EISSN: 2498-700X.
   DOI: http://dx.doi.org/10.21791/IJEMS.2020.1.5

8. **Boros, J.**: Egy új korszak határán: Mit tartogat a jövő a szakmák világában?
   Metszetek. 9 (1), 84-90, 2020. EISSN: 2063-6415.
   DOI: http://dx.doi.org/10.18392/metsz/2020/1/5

9. **Boros, J.**, Kovács, É. K., Kun, A. I., Török, P.: Hallgatói önértékelés-vizsgálat a Debreceni Egyetem Természettudományi és Technológia Karán.
   Taylor. 9 (1), 130-138, 2017. ISSN: 2064-4361.

10. Kun, A. I., Kovács, É. K., **Boros, J.**: A comparison of self-assessment tendencies of full-time and part-time university students.
    Annals of the University of Oradea Economic Science. 25 (1), 538-547, 2016. ISSN: 1222-569X.

<u>Conference presentations</u> (9)

11. **Boros, J.**, Kun, A. I.: A mesterséges intelligencia munkaerőpiaci hatásainak megítélése egyetemista hallgatók körében.
    In: 4th Ferenc Farkas International Scientific Conference: "Inspiring Change: Visions for the Future": Abstract Book = 4. Farkas Ferenc Nemzetközi Tudományos Konferencia: "Inspiráló változások, jövőképek": Absztraktkötet. Szerk.: Benke Mariann, Schmuck Roland, Riedelmayer Bernadett, Pécsi Tudományegyetem, Pécs, 144-145, 2024, (VSZI kötetek, ISSN 2786-3891 ; 6) ISBN: 27863891

12. Khateeb, F. R., **Boros, J.**, Kun, A. I., Mándy, Z., Dajnoki, K.: Empirical Evidences on Work-Life-Study Balance of Ph.D. Students.
    In: The 5th International Conference on Future of Education 2022 (Future of Education 2022) : Book of Abstracts. Ed.: Beitzel Brian D, International Institute of Knowledge Management, Colombo, Srí Lanka, 15, 2022. ISBN: 9786245746194

13. Kun, A. I., Kotsis, Á., **Boros, J.**: Tudják-e a hallgatók, hogy mennyit (nem) tudnak?: a Dunning-Kruger-hatás vizsgálata menedzsment szakokon tanuló felsőoktatási szakképzéses hallgatók körében.
    In: 3. Farkas Ferenc Nemzetközi Tudományos Konferencia: "Menedzsment forradalmak": Absztraktkötet. Szerk.: Benke Mariann, Schmuck Roland, Riedelmayer Bernadett, Pécsi Tudományegyetem Közgazdaságtudományi Kar Vezetés- és Szervezéstudományi Intézet, Pécs, 89-90, 2022, (VSZI kötetek, ISSN 2786-3891) ISBN: 9789634299806

14. Kun, A. I., Kotsis, Á., **Boros, J.**: A Dunning-Kruger-hatás a felsőoktatási szakképzésben: online feleletválasztós tesztek vizsgálata.
 In: XXI. Országos Neveléstudományi Konferencia: A neveléstudomány válaszai a jövő kihívásaira : Absztraktkötet. Szerk.: Molnár Gyöngyvér, Tóth Edit, MTA Pedagógia Tudományos Bizottsága; SZTE Neveléstudományi Intézet, Szeged, 636-636, 2021. ISBN: 9789633068335

15. Kun, A. I., Mándy, Z., **Boros, J.**: A munka-magánélet egyensúly fontossága a phd-tanulmányok választásában: egy kérdőíves felmérés eredményei.
 In: XXI. Országos Neveléstudományi Konferencia: A neveléstudomány válaszai a jövő kihívásaira : Absztraktkötet. Szerk.: Molnár Gyöngyvér, Tóth Edit, MTA Pedagógia Tudományos Bizottsága; SZTE Neveléstudományi Intézet, Szeged, 628-628, 2021. ISBN: 9789633068335

16. **Boros, J.**: Az átalakuló munkakörök menedzselése banki példán keresztül.
 In: Farkas Ferenc II. Nemzetközi Tudományos Konferencia 2020. Szerk.: Balogh Gábor, László Gyula, Sipos Norbert, Pécsi Tudományegyetem Közgazdaságtudományi Kar Vezetés- és Szervezéstudományi Intézet, Pécs, 21-33, 2020. ISBN: 9789634295860

17. **Boros, J.**: A munka-magánélet egyensúly szerepe a kutatói pálya választásában.
 In: InterTalent Unideb. Szerk.: Mándy Zsuzsanna, Debreceni Egyetem, Debrecen, 25-27, 2017. ISBN: 9789634739531

18. **Boros, J.**: Hallgatói önértékelés vizsgálata a Debreceni Egyetem két karán.
 In: InterTalent Unideb. Szerk.: Mándy Zsuzsanna, Debreceni Egyetem, Debrecen, 41-49, 2017. ISBN: 9789634739531

19. Kun, A. I., **Boros, J.**, Kovács, É. K.: Teljesítmény és önértékelés összefüggésének empirikus vizsgálata alapképzéses hallgatók esetében, feleletválasztásos és igaz-hamis tesztek használatával.
 In: A tanulás új útjai : HUCER 2016 Absztrakt kötet, Magyar Nevelés- és Oktatáskutatók Egyesülete, Budapest, 96, 2016. ISBN: 9786155657009

List of other publications

Books (3)

20. Berde, C., szerk. Dajnoki, K., Juhász, C., **Boros, J.**, Márta, E., Szántó, G.: Emlékek és hagyományok: Gyakorlati Tanszéktől a Vezetés- és Szervezéstudományi Intézetig : 150 éves a vezetés és szervezés oktatása. Center-Print Nyomda, Debrecen, 243 p., 2022. ISBN: 9789634904526

21. Szerk. Dajnoki, K., **Boros, J.**: Tanulmányok Berde Csaba tiszteletére: köszöntők és tanulmányok Berde Csaba professzor úr 70. születésnapja tiszteletére. Debreceni Egyetem Gazdaságtudományi Kar Vezetés- és Szervezéstudományi Intézet, Debrecen, 328 p., 2022. ISBN: 9789634904502

22. Szerk. Poór, J., Balogh, G., Dajnoki, K., Karoliny, M., Kun, A. I., Szabó, S.; Bajnok, A., Balogh, G., Balogh, K., Bencsik, A., **Boros, J.**, Cseh Papp, I., Dajnoki, K., Grotte, J., Hegedüs, H., Horváth, A., Jarjabka, Á., Kajtár, E., Karácsony, P., Karoliny, M., Kálmán, B. G., Király, Z., Bilanics, Á., Kovács, I. É., Kópházi, A., Kőműves, Z. S., Krizbai, J., Kun, A. I., Kunos, I., Majó-Petri, Z., Metszősy, G., Palotai, M., Pató, G. S. B., Poór, J., Princzné Ördögh, K., Szabó, K., Szabó, S., Szabó-Szentgróti, G., Szenes, Z., Szretykó, G., Szüts, I., Tóth, A.: COVID-19: Koronavírus-válság: második fázis kihívások és HR válaszok. Magyarország 2020 augusztus-november. Magyar Agrár- és Élettudományi Egyetem, Gödöllő, 57 p., 2020. ISBN: 9789632699363

Articles, studies (11)

23. Dajnoki, K., **Boros, J.**: "Innovatív HR - Kihívások a XXI. században": Konferencia és Szakmai Fórum - konferencia-beszámoló.
Új Munkaügyi Szemle. 5 (1), 72-73, 2024. EISSN: 2677-1306.

24. Tóbiás Kosár, S., **Boros, J.**, Dajnoki, K.: A háborús válság hatásai a vizsgált országok gazdaságára 2023-ban.
In: , Humán Szakemberek Országos Szövetsége, Budapest, 43-53, 2024. ISBN: 9786150203393

25. Dajnoki, K., Berde, C., **Boros, J.**: Harminc éve a Humán Szakemberek Országos Szövetsége (HSZOSZ) a HR szolgálatában.
Új Munkaügyi Szemle. 5 (2), 70-75, 2024. EISSN: 2677-1306.
DOI: http://dx.doi.org/10.58269/umsz.2024.2.7

26. Szeiner, Z., Szabó, K., Kerekes, K., Zaharie, M., Kálmán, B. G., Tóth, A., Kovács, I. É., Varga, E., Metszősy, G., **Boros, J.**, Poór, J.: A Covid-19 válság kihívásai és HR válaszok Közép és Kelet Európa hat országában elvégzett empirikus kutatás tükrében.
In: "Mérleg és kihívások - Fenntarthatóság": XII. Nemzetközi Tudományos Konferencia: Konferenciakiadvány (12.)(2022.10.12-14.)(Miskolc). Szerk.: Veresné Somosi Mariann, Lipták Katalin, Miskolci Egyetem Gazdaságtudományi Kar, Miskolc, 349-358, 2022. ISBN: 9789633583609

27. Dajnoki, K., Konczosné, S. M., **Boros, J.**: A háborús válság hatásai a magyar gazdaságra 2022-ben.
In: A vállalati-szervezeti stabilitást veszélyeztető tényezők : Gazdálkodás, menedzsment és HR a háború árnyékában (ipar, mezőgazdaság, szolgáltatások, egyéb területek). Szerk.: Poór József, Bruder Emese, Dajnoki Krisztina, Jarjabka Ákos, Kovács Ildikó Éva, Pató Gáborné Szűcs Beáta, Szabó Szilvia, Magyar Agrár- és Élettudományi Egyetem, Gödöllő, 36-44, 2022. ISBN: 9789636230104

28. Dajnoki, K., **Boros, J.**, Ladislav, M., Rahimić, Z.: HR Changes Due to the Crisis.
In: Coronavirus crisis challenges and HR responses in six countries of Central and Eastern Europe. Szerk.: Poór József, Kálmán Botond, Varga Erika, Szeiner Zsuzsanna, Kovács Éva Ildikó, Kerekes Kinga, Tóth Arnold, Beáta Szűcs Pató, Kunos István, Dajnoki Krisztina, Janos Selye University, Komárno, 68-80, 2022. ISBN: 9788081224249

29. Dajnoki, K., **Boros, J.**, Horváth, A., Bilanics, Á., Kun, A. I.: A vizsgált szervezeteknél jellemző általános és HR válságkezelő intézkedések.
In: COVID-19 : koronavírus-válság: harmadik fázis: kihívások és HR-válaszok. Szerk.: Poór József, Balogh Gábor, Dajnoki Krisztina, Karoliny Mártonné, Kőműves Zsolt, Pató Gáborné, Szűcs Beáta, Szabó Szilvia, Magyar Agrár- és Élettudományi Egyetem, Gödöllő, 33-35, 2021.

30. Dajnoki, K., **Boros, J.**, Kun, A. I., Jenei, S.: A vizsgált szervezeteknél jellemző általános és HR válságkezelő intézkedések (első, második és harmadik fázis összehasonlítása).
In: Koronavírus-válság : kihívások és HR-válaszok : első-második-harmadik hullám összehasonlítása. Szerk.: Poór József, Dajnoki Krisztina, Pató Gáborné, Szabó Szilvia, Szabó Katalin, Tóth Arnold, Magyar Agrár- és Élettudományi Egyetem, Gödöllő, 42-50, 2021. ISBN: 9789632699677

31. **Boros, J.**, Khateeb, F. R., Kun, A. I.: Research and development career plans and work-life balance: Evidence from a survey among Hungarian Ph.D. students.
In: Módszertani újítások és kutatások a szakképzés és a felsőoktatás területén : X. Trefort Ágoston Szakképzés- és Felsőoktatás-pedagógiai Konferencia Tanulmánykötet. Szerk.: Simonics István, Holik Ildikó, Tomory Ibolya, Óbuda University, Budapest, 128-140, 2021. ISBN: 9789634492399

32. Dajnoki, K., **Boros, J.**, Kun, A. I.: Válaszadó szervezetek összehasonlító jellemzői az első és a második időszakban.
In: Koronavírus-válság kihívások és HR válaszokelső és második fázis összehasonlítása. Szerk.: Poór József, Dajnoki Krisztina, Pató Gáborné Szűcs Beáta, Szabó Szilvia, Gödöllő : Magyar Agrár- és Élettudományi Egyetem, Budapest, 14-22, 2021. ISBN: 9789632699400

33. **Boros, J.**: Motivációs tényezők vizsgálata a PhD képzésre való jelentkezés esetén.
Gazdálkodástudományi Közlemények. 7 (1), 19-24, 2018. ISSN: 2061-2443.

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Conference presentations (4)

34. **Boros, J.**, Dajnoki, K.: A chatbotok alkalmazásának lehetőségei a business coachingban: szisztematikus szakirodalomelemzés.
In: "Fenntartható Gazdaság - Fenntartható Társadalom" : Nemzetközi Tudományos Konferencia : 30 éves a debreceni közgazdasági és üzleti felsőoktatási képzés = "Sustainable Economy - Sustainable Society" : International Scientific Conference : Celebrating 30 Years of Economics and Business Higher Education in Debrecen. Szerk.: Dajnoki Krisztina, Szenderák János, Erdey László, Fenyves Veronika, Debreceni Egyetem, Debrecen, 45, 2024. ISBN: 9789634906247

35. Kőmíves, P. M., **Boros, J.**: A gyermekvállalásban szerepet játszó tényezők és a családtámogatási formák hatékonyságának elemzése.
In: Magyar Nemzeti Bank - Debreceni Egyetem kutatási konferencia Fenntartható gazdaság Versenyképesség és digitalizáció. Szerk.: Fenyves Veronika, Debreceni Egyetem, Debrecen, 70-91, 2022.

36. Mándy, Z., Kun, A. I., **Boros, J.**, Dajnoki, K.: PhD-hallgatók elégedettsége és a képzésre való jelentkezés motivációs tényezőinek összefüggései.
In: XXI. Országos Neveléstudományi Konferencia: A neveléstudomány válaszai a jövő kihívásaira : Absztraktkötet. Szerk.: Molnár Gyöngyvér, Tóth Edit, MTA Pedagógia Tudományos Bizottsága; SZTE Neveléstudományi Intézet, Szeged, 535-535, 2021. ISBN: 9789633068335

37. Kun, A. I., **Boros, J.**, Gottfried, P.: Tanulási görbék egy űripari magáncégnél: a SpaceX példája.
In: "Kihívások és tanulságok a menedzsment területén. Fókuszban a folyamatmenedzsment : az Ipar 4.0 kihívásai" = "New Trends and Challanges in Management. Special Focus on Process Management and Industry 4.0" : Absztrakt kötet / közreadja a Debrceni Egyetem Műszaki Kar, Debreceni Egyetem Műszaki Kar, Debrecen, 56-56, 2019.

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