IMPACT OF DIGITAL TRANSFORMATION ON IT JOBS. A SECTORIAL APPROACH.

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Abstract: *Technology is changing at an exponential rate. As a result, it does have a disruptive life on society and our lives. It changes our personal lives, socialization, and interaction with people and businesses. Technology has changed and does continue to change the way we work. Along with the four industrial revolutions, many jobs have disappeared, more jobs have been created, and almost every job was transformed by automation. The 4th industrial revolution leading to Industry 4.0 is powered by artificial intelligence, robotics, and the Internet of things. The Information Technology (IT) industry and professionals primarily drive this transformation. While information technology specialists contribute with the technology they build to change their world, technology is transforming the profession responsible for this transformation. The paper looks at how digital transformation impacts the transformation of IT jobs, how government policies and managerial strategies impact the transformation of IT jobs, and how employees and organizations are responding with investment in skills development. The research relies on a questionnaire-based survey with 132 Romanian IT professionals, students, and computer science professors representing small and large organizations. The data supported seven of the nine hypotheses, confirming that digital transformation impacts the transformation of jobs, particularly IT jobs. This drives the need to build new technical and soft skills.*

Keywords: *Information Technology (IT); transformation of IT jobs; skills development; work automation.*

Introduction

"We are shaping the world faster than we can change ourselves, and we are applying to the present the habits of the past." (Rowe & Laura, 2011).

We experience an accelerated rate of technological change (Benedikt et al., 2016; Vătămănescu et al., 2018). New technologies are changing all industries (Hapenciuc et al., 2015; Vătămănescu et al., 2016, Piccarozzi et al., 2018). Technology is also changing the way we work, our jobs, and our overall behaviors (Vătămănescu et al., 2018; Păduraru et al., 2016; IMF, 2018). Starting with Industry 1.0, driven by mechanization and steam power, and ending with the hi-tech Industry 4.0, our lives and work have changed significantly. Many occupations we perform now, such as software engineers, big-data specialists, and even virtual-world designers, were not conceived forty years ago. WEF believes that 65% of students entering primary school today will work in occupations that have not yet been created. Some occupations have entirely disappeared. For example, nobody works as a lift operator or lamplighter(*Jobs That Have Disappeared in the 21st Century*, 2020). McKinsey (Manyika et al., 2017) estimates that 250 million jobs will be created by automation by 2030. Since the work of IT personnel contributes to the IT revolution, the question is how their careers will likely be affected.

In the particular situation of Romania's IT industry, Sanandaji, (2020) shows that the share of brain jobs not susceptible to automation is below 4%, putting many jobs at risk. Furthermore, from a digitalization perspective, the European Union Digital Economy and Society Index places Romania as the last country in the EU to integrate into the digital economy (Wilkinson & Barry, 2020a). Furthermore, Romania is the last country in the EU in the rank of people with digital skills (Eurostat, 2019). The country's IT sector is aided by a law that exempts software developers from income tax, preventing brain drain (Manelici & Pantea, 2019a).

Research hypotheses

According to Manyika (2017), the possibility of automation replacing labor is considerable consideration. The change in the workforce results from rising productivity, quality, and GDP growth. Between 0.8 percent and 1.4 percent of global GDP each year, can be added to the global economy's productivity due to automation. This is accomplished through labor cost reduction, operational cost reduction, large-scale customization, and increased speed and scale. "Technological change, especially digital transformation, intensifies the ongoing structural changes on the labor market, sometimes even in a disruptive manner" (Frey et al., 1990, p. 123). In this vein, the first hypotheses infer that:

H1a: Digital transformation positively impacts work automation.
H1b: Work automation positively impacts the transformation of IT jobs.

According to the EU's Digital Enterprise Score Index (DESI), Romania scores relatively low among EU nations (Wilkinson & Barry, 2020b). In terms of human capital, Romania comes second to last. The indicator comprises the proportion of persons with basic digital capabilities and the number of ICT graduates and experts with advanced skills.

H2: The macro policies positively impact the transformation of IT jobs.

Management practices are constantly changing with new work models being introduced. An example is the gig economy. The movement of permanent employees toward contractual resources (Behrendt & Nguyen, 2019) is a reaction to the accelerated rate of market change, moving toward a gig economy(International Organisation of Employers, 2020). More and more IT firms are embracing the Scrum approach for project delivery. Scrum, is a component of Agile management approaches.

H3a: Digital transformation positively impacts new managerial strategies.
H3b: The macro policies positively impact new managerial strategies.
H3c: The macro policies positively impact work automation.
H3d: New managerial strategies positively impact the transformation of IT jobs.

Bughin et al. (2018) are some of the authors who link the skills gap and the change in abilities required for the job of Industry 4.0 and future jobs. (Zbuchea et al., 2020). By 2024, the number of jobs needing digital skills will increase by 12% (Accenture, 2017). Bughin et al. (2018) also point out that automation accelerates skills shift, and advanced and basic technological skills will substantially increase demand.

H4a: The transformation of IT jobs positively impacts soft skills development.
H4b: The transformation of IT jobs positively impacts technical skills development.

According to the previously described theoretical models and the proposed hypotheses, this paper will address the impact of digital transformation on IT jobs based on the following research model (Figure 1):

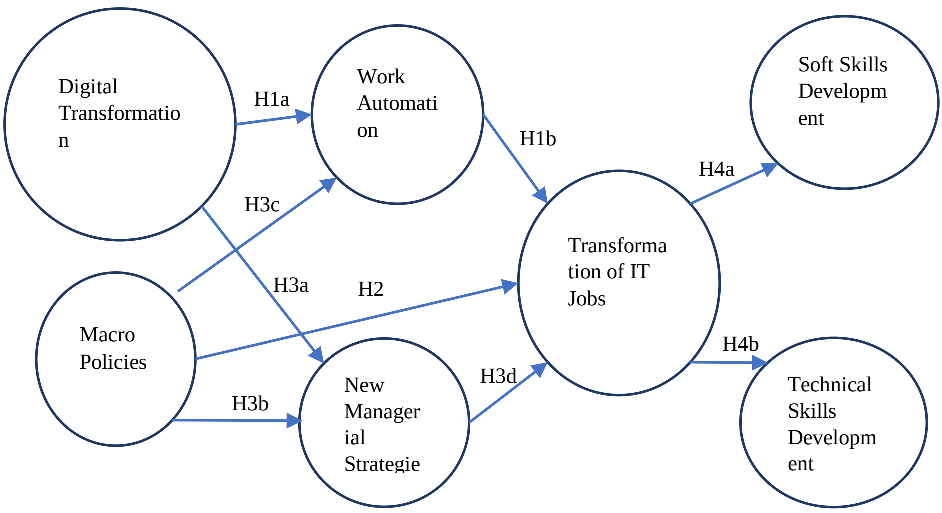

Figure 1. Research model

Material and methods

Research design

The questions addressing the research variables are based on a unipolar Likert scale (Khalid et al., 2012), with a scale of five representing the respondents' agreement with the particular question. This type of answer is based on an ordinal data type. The data will be analyzed in a frequency distribution, mode and median, and range. In ordinal data without normal distribution, only the non-parametric cross-tabulation chi-squared test can be applied (Martin, 2004).

Structural equation modeling (SEM) will also be applied in a multivariate statistical analysis technique to analyze structural relationships. SEM allows a multivariate statistical analysis technique to analyze structural relationships (Stein et al., 2017) SPPS[1] will be used for variable coding and computing the statistical information. SmartPLS[2] is used for structural equation modeling.

Data collection and sample

Sampling is based on a *stratified random* method combined with a snowball technique (Khalid et al., 2012). This method involves splitting the population into subgroups based on the defined independent research variables. This approach enables us to analyze the data from the perspectives of IT professionals. Professionals have significant IT job experience and are most likely impacted by the increasing frequency of technology changes.

The quantitative research was performed by sending the Google Forms questionnaire to 150 IT specialists, students, and teachers. The convenience sample focused on colleagues at work, industry partners, members of the IT professional organization, and projects the author is involved in. As a result, 132 people responded to the questionnaire, yielding a response rate of 88% from the persons.

Measures

The questionnaire items focused on views and attitudes about the impact of digital transformation and macro policies on IT job transformation, as they were previously conceptualized. Questions are divided into major categories corresponding to the model's multi-item structures (as presented in Table 1).

[1] https://www.ibm.com/ro-en/products/spss-statistics
[2] https://www.smartpls.com/

Table 1. Constructs and items

Construct	Variable	Item	References
Digital Transformation		*Please rate the following technology items in terms of impact on society's digital transformation:*	(Schwab et al., 2020)
	DTA1	3D printing	
	DTA2	Augmented and Virtual Reality	
	DTA7	Machine Learning	
	DTA8	Quantum Computing	
	DTA9	Robotic Process Automation	
IT Jobs Transformation		*Please rate the degree to which the following technologies are likely to impact IT jobs:*	(Manyika et al., 2017)
	DTI5	Internet of Things	
	DTI6	Machine Learning	
	DTI7	Quantum Computing	
	DTI8	Robotic Process Automation	
	PUR1	Income	
	PUR2	Meaning	
	SCEN1	Augment jobs	
	SCEN2	Replace jobs	
	SCEN3	Create new jobs	
Work Automation		*Which is the technology most likely to replace your current job?*	
	REP1	Machine Learning	
	REP2	Robotic Process Automation	
	REP3	DevOps automation	
Soft Skills Development		Please rate the degree to which the following soft skills are important for your future career	(Nania et al., 2019) (Tytler et al., 2019) (Schwab, 2018) (Stanescu et al., 2020)
	SKL2	Agility	
	SKL3	Creativity	
	SKL4	Cultural Awareness	
	SKL6	Emotional intelligence	
	SKL7	Leadership	
	SKL10	Empathy	
Technical Skills Development		*Please rate the degree to which the following technical skills are important for your future career*	(Nania et al., 2019b)
	TKL10	Java/Software Development	
	TKL5	Big Data	
	TKL7	RPA (Robotic Process Automation)	
	TKL9	Quantum Computing	

Construct	Variable	Item	References
Macro Policies		*Please rate the impact to which the following policies may support the future of the IT industry in Romania*	(ANIS, 2022)
	POL1	Building digital skills	
	POL2	Continuous learning	
	POL3	Education reform	
New Managerial Strategies		*Please rate the degree to which the following managerial strategies may support the future of the IT industry in Romania*	(Hess et al., 2016) (Schwab et al., 2020) (Nania et al., 2019) (Soto-Acosta et al., 2016) (Oztemel & Gursev, 2018) (Hargitai et al., 2021)
	MAN1	Develop human resources strategies for enhancing the employees' soft skills	
	MAN2	Develop human resources strategies for enhancing the employees' technical skills	
	MAN5	Develop strategies for working with project and platform workers	
	MAN6	Develop strategies for long-term digital transformation	
	MAN7	Develop social and environmental sustainability strategies	
	MAN8	Invest in IT infrastructure and re-technologization	

The age of the people responding to the questions covers multiple age groups. 15% are in the 18-24 range, covering the students, junior engineers, and graduate hires. 23% are in the 25-34 range. The largest category is in the 35-44-year-old range. 20% are between 45 and 54 years old. That matches the age demographic of the IT industry.

Results

The exploratory aspect of PLS-SEM (SmartPLS in this case) was favored (Bharati et al., 2015). By using loadings and cross-loadings of the indicators on their reflective constructs, average variance extracted (AVE), composite reliability (CR), and reliability (Cronbach alpha), the author evaluated the convergent validity. The reflected item factor loadings were significant and more considerable than 0.65, and the AVE values were more significant than 0.60, as shown in table 2.

Cronbach's alpha values of all indicators surpassed the acceptable level of 0.6 (Nunnally & Bernstein, 1994), and the reflective construct measure loadings were over the recommended threshold of 0.70 for composite reliability following the recommendations offered by (Yi & Davis, 2003) In this study, CR values varied from 0.83 to 0.92, but AVE values ranged from 0.60 to 0.80.

Table 2. Psychometric properties of reflective constructs

	Cronbach's alpha	Composite reliability*	Average variance extracted (AVE)
Macro Policies	0.710	0.828	0.618
Soft Skills Development	0.820	0.870	0.528
New Managerial Strategies	0.828	0.875	0.538
Digital Transformation	0.829	0.879	0.594
Transformation of IT jobs	0.824	0.883	0.656
Technical Skills Development	0.840	0.892	0.676
Work Automation	0.872	0.922	0.797

**Composite reliability (CR) = (square of the summation of the factor loadings)/[(square of the summation of the factor loadings) + (square of the summation of the error variances)]; AVE = (summation of squared factor loadings)/(summation of squared factor loadings) (summation of error variances)*

To further evaluate the advanced structural model following (Hair et al., 2022), we have estimated the R2, beta, and t-values. In this regard, adopting a bootstrapping approach with 5000 resamples enabled us to provide a more comprehensive analysis of the results, including reporting on effect sizes (f2) and predictive significance (Q2). Following Fornell and Larcker (1981), the reported value (0.263) demonstrates that the model has a moderate to substantial predictive significance for the hypothesized endogenous component.

Table 5. R Square

	R-square	R-square adjusted
Transformation of IT jobs	0.334	0.318
New Managerial Strategies	0.453	0.445
Soft Skills Development	0.191	0.184
Technical Skills Development	0.334	0.324
Work Automation	0.110	0.096

As seen in table R2, it exceeds the 0.35 threshold (Cohen, 1977)only for technical skills development with 0.35 and for the new managerial strategies with 0.46.

Table 6. Results of the structural model analysis (hypotheses testing)

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics* (|O/STDEV|)	P values	Decision
Digital Transformation -> New Managerial Strategies	0.335	0.337	0.072	4.668	0.000*	Supported
Digital Transformation -> Work Automation	0.336	0.346	0.076	4.439	0.000*	Supported
Transformation of IT jobs -> Soft Skills Development	0.250	0.250	0.099	2.534	0.011*	Supported
Transformation of IT jobs -> Technical Skills Development	0.322	0.324	0.076	4.231	0.000	Supported
New Managerial Strategies -> Transformation of IT jobs	0.405	0.418	0.121	3.352	0.001*	Supported
Macro Policies -> Transformation of IT jobs	0.132	0.123	0.117	1.127	0.258	Not supported
Macro Policies -> New Managerial Strategies	0.496	0.498	0.068	7.276	0.000*	Supported
Macro Policies -> Work Automation	-0.021	-0.022	0.078	0.264	0.810	Not supported
Work Automation -> Transformation of IT jobs	0.222	0.218	0.069	3.229	0.001*	Supported

***p< 0.01, *p< 0.05.*

We performed the analysis considering R2 showing that two exogenous dimensions are extracted from the proposed model. In addition, table 6 shows that 2 out of 9 relationships reject the null hypothesis. One has a small effect of 0.06, while three have a large effect with an f squared off of more than 1.6 (Cohen, 1977) (Table 7).

Table 7. f square

	Transformation of IT jobs	New Managerial Strategies	Soft Skills Development	Technical Skills Development	Work Automation
Digital Transformation		0.189			0.117
Transformation of IT jobs			0.236	0.349	
New Managerial Strategies	0.155				

Macro Policies	0.017	0.415			0.000
Soft Skills Development					
Work Automation	0.071				

Discussion of the findings

Figure 2 shows the PLS structural model applied in the context of digital transformations and macro policies impacting work automation. New managerial strategies are changing the future of IT jobs and how we prepare for these changes by building technical and soft skills.

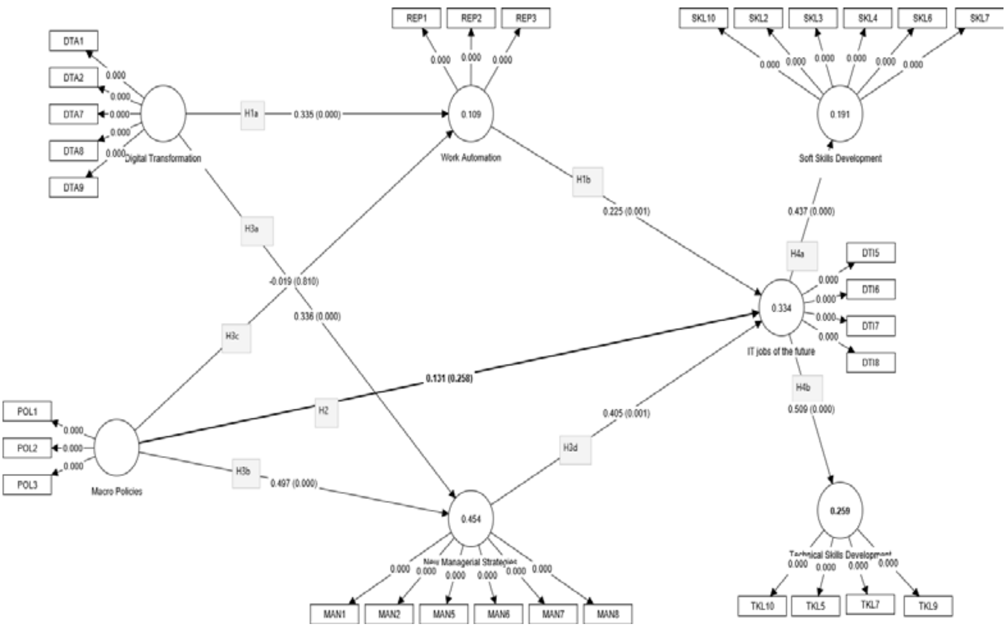

Figure 2. PLS test of the proposed structural model

Testing H1a - *Digital transformation positively impacts work automation* -, the p-value is smaller than 0.0001 and β of 0.34. An f-square of 0.12 shows a small to medium effect size. Although that clearly rejects the null hypothesis, the two independent variables (i.e., Digital transformation and Macro policies) explain 11% of the changes in work automation. That is consistent with the literature review (Cassard et al., 2018), showing that work models are impacted by other factors, such as demographics, globalization, environment, and urbanization. However, the hypothesis is confirmed.

Focusing on H1b - *Work automation positively impacts the transformation of IT jobs -,* the R2 for the dependent variable is 0.334, with the highest effect from work automation with an f-squared of 0.071. The patch coefficient β is 0.22, and a p-value of 0.001 does reject the null hypothesis. Thus, the hypothesis is confirmed. That validates the fundamental assumption of the study that automation developed by IT engineers is impacting the very profession developing that automation. While that is true, the most significant impact on the transformation of IT jobs comes not from work automation but new managerial strategies (H3d).

Regarding H2 – *The macro policies positively impact the transformation of IT jobs* - a p-value of .26 does not reject the null hypothesis. Manelici and Pantea (2019b, p. 28) concluded that the tax exemption policy for software developers effectively supported the IT sector's development. The same is concluded by ANIS (2022, p. 59) The current study removed the tax deduction load factor with only .599 from Macro policies. While in the Melinci and ANIS studies, the tax deduction was considered the main factor positively affecting Romania's IT policy, this may explain the different results. The hypothesis is thus rejected.

Focusing on H3a – *Digital transformation positively impacts new managerial strategies* - a p-value of less than 0.0001 β of 0.34, a 0.02 medium f-square value, and a large R2 of .45 show a strong correlation. Therefore, management must find new strategies and models to adapt to the increasing technology change rate and digitalization's impact. For this study, the impact of digitalization on the organization is considered a baseline assumption to research the impact on the jobs. The result is aligned with all the conclusions in the literature (Bejinaru, 2013). The hypothesis is hence confirmed.

Moving to H3b – *The macro policies positively impact new managerial strategies* - a strong positive effect on managerial strategies with a p-value smaller than 0.0001, a high patch coefficient with β of 0.5, and a large f-square of 0.41 was observed. The hypothesis is thus confirmed. H3c –*The macro policies positively impact work automation* – was not supported, with a p-value of 0.81, a negative β of -0.02, and no impact on work automation shown by a 0 f-square. Consequently, Macro policies do not have any impact on work automation. Romania has little influence on global policies and industry trends. Petcana (2019, p. 1) showed how that 600.000 jobs in Romania would be impacted by automation, but we could find no study to show how Romania in any way induces the digitalization trends. The result is consistent with the literature, and the hypothesis is not confirmed. Further, H3d - *New managerial strategies positively impact the transformation of IT jobs* -a p-value of 0.001 rejects the null hypothesis. A medium f-square value of 1.56 shows and a big patch β coefficient of 0.4 is an expected result that management impacts the jobs being created in the IT industry. The hypothesis is therefore confirmed.

Regarding H4a and H4b – *The transformation of IT jobs positively impacts soft skills, respectively technical skills development. B*oth relations are statistically relevant. The p-values for these relationships are lower than 0.01. The β patch coefficient for soft skills development is 0.25 and 0.32 for technical skills development. R2 is low, with 0.19 for soft skills and 0.26 for technical skills development. This is an expected result, consistent with the literature (Little, 2004; Schwab, 2018; Singlehurst et al., 2020), in that changes in job, requirements will impact new skills development. At the same time, people are not only developing new skills to become competitive in the job market. They can learn because they are curious, to develop a hobby, or simply for the pleasure of learning, items not part of this research. Both hypotheses are hereby confirmed.

To conclude, seven out of nine hypotheses were supported, confirming that digital transformation impacts the nature of the jobs, particularly IT jobs, and that this drives the need to build new technical and soft skills. However, the research did not show any positive influence of Romania's government policies on the new managerial strategies and the transformation of IT jobs. The results are consistent with the ones found in the literature, except for the IT impact the Romania tax deduction for IT employees has on the local legislation.

Conclusions

On the one hand, the research results from 132 Romanian IT professionals, students and teachers confirm the results of international studies on the impact of digital transformation in automating the workplace, making jobs redundant, creating new jobs, or changing the nature of existing jobs. While this does not bring new information, with fewer studies done for Romania, it shows that the perception of Romanian IT workers is consistent with what we have seen in more general studies.

The study looks at the specific impact of the Romanian government on work automation, new managerial strategies, and IT jobs. The only statistically significant correlation is the one with the new managerial strategies. That is not a surprise, knowing that government policies are expected to influence management policies. The research did not find a statistically significant relationship between macro policies and work automation. Considering previous studies (ANIS, 2022; Manelici & Pantea, 2019b), the expectation was to find a correlation between government policies and the future of IT jobs in Romania. Failing to find an impact may be because the policy is limited to IT tax exemption legislation and lacks a holistic strategy. That will have to be further investigated.

This paper focuses on understanding the transformation of the jobs responsible for building new technologies. The survey results show that work automation, government policies, and management strategies are responsible for 34% of the factors transforming IT jobs. That is three times more than the impact of the same factors on work automation in general.

Considering the research findings, the study will mainly benefit from the following: a. making a follow-up study on the impact of the local policies on the evolution of the IT professions. The available data for tax exemption loading was too small to be included in the model. At the same time, as discussed by Manelici & Pantea (2019b), this is the single piece of policy supporting the country's IT industry; b. add other factors influencing work automation to the research.

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