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Looking into the Antecedents of the Transformation of IT Jobs. A Country-based Perspective

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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, Internet of things. The Information Technology (IT) industry and IT 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. Seven out of the nine hypotheses were supported by the data, confirming that digital transformation impacts the transformation of jobs, particularly IT jobs, and that this drives the need to build new technical and soft skills.

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

Introduction

The future of work is a consequence of a subsequent set of industrial revolutions from Industry 4.0 with steam power's introduction to the implementation of automated and intelligent production representing industry 4.0 (Piccarozzi et al., 2018). The succession of the four industrial revolutions shows the increasing rate of change brought by technology. From the invention of the printing press to the introduction of artificial intelligence (AI), the time between the introduction of paradigm-shifting technologies decreases exponentially (Kurzweil, 2006). Digital transformation is the hallmark of Industry 4.0, following its own exponential curve of processing power (Moore, 2009). According to Manyika et al. (2013), the most important technologies impacting the way we work are the mobile Internet, the Internet of Things (IoT), machine learning (ML), robot process automation (RPA), and cloud computing. There are different views on the impact of these new technologies on work. For example, Frey and Osborne (2017) estimated that 47% of United States jobs would be displaced or transformed by technology. Technology is driving digital transformation by automating repetitive professions. Machine learning has the potential not only to automate repetitive work but to perform highly skilled creative tasks. Besides technology, other factors like globalization, demographics, environment, and urbanization also influence occupations (Thornton & Riviera, 2019).

Information technology employees also see their activities changed by their professions. (Schwab, 2018; Frey & Osborne, 2017). It is expected to see an increase in engineering professions' demand, starting with software developers and new technologies like

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machine learning. However, even software engineers' work is increasingly becoming affected by automation (Frey & Osborne, 2017).

In particular, education and lifelong learning (Nania, Bonella, Restuccia, & Taska, 2019a) represent the employees' solution to keep up with the changes in demand and build new skills. The skills required in the digital economy are the digital skills corresponding to the emerging technologies but also the soft skills of creative problem solving, critical thinking, reason, and logic to assess and analyze problems, entrepreneurial mindset, and adaptation to change in complex environments (Nania, Bonella, Restuccia, & Taska, 2019a). Other types of responses to the rapidly changing industry demand are an increase in work flexibility catachresis by the gig economy (Hines, 2019) and a generally increased adoption of Agile development methodologies (McKenna, 1998) and agile mindset (Nania, Bonella, Restuccia, & Taska, 2019a).

For Romania, Sanandaji (2020) shows that the share of "brain jobs" not susceptible to automation is below 4%, putting many jobs at risk. From a digitalization perspective, the European Union Digital Economy and Society Index places Romania as one of the last countries in the EU to integrate into the digital economy (Wilkinson & Barry, 2020). Romania is the last country in the EU in the rank of people with digital skills (Eurostat, 2019).

In Romania, the IT sector is helped by the software developers' tax exemption from the income tax legislation that succeeded in limiting the brain drain (Manelici & Pantea, 2019a). The industry has a steady growth with a forecasted market volume growth of 25% for the following three years, export volumes having an ascending trend representing 15% of the total county export volumes, and forecasted growth of 22% (ANIS, 2019). Despite the importance of this topic, few studies approach the digital transformation of Romania's IT jobs. The structured search of specialized articles was performed on Google Scholar, Web of Science and Scopus to look for available information on the Romania IT market in an effort to supplement that gap. The search did not retrieve specific results. Still, the structured search on the Web of Science and Scopus has identified a single scientific article (Frey et al., 2008) presenting the development of Romania's IT industry from the 2nd world war until 1998. Google Scholar search returned a result (Manelici & Pantea, 2019a), describing the impact of Romania's tax exemption on the local IT industry (Petcana, 2019).

The SARS-CoV-2 crisis has changed how we work, and its future impact is yet to be determined. From the perspective of the future of work, COVID-19 is accelerating the digitalization of work; it provides more opportunities to work remotely and accelerates the digitalization of the education process (Zahidi et al., 2020). The pandemic forced organizations to accelerate digitalization trends identified in previous research.

Building on these aspects, the study intends to address the antecedents of the IT jobs transformation (i.e., how digital transformation, government policies and managerial strategies impact the transformation of IT jobs and how employees and organizations are responding with investment in skills development). In this sense, a questionnaire-based survey with 132 subjects was conducted during July-August 2022. To thorough tackle these issues, the remainder of the paper brings forward the conceptual background, the methodology used, the research findings and the main implications of the empirical analysis.

Conceptual background

The industry 4.0 phenomenon was mentioned for the first time in 2011 in Germany during the Hanover Fair (Roblek et al., 2016). Industry 4.0 is a crucial topic in the context of the future of work as transformed by the ongoing digital revolution. It is based on the development of entirely automated and intelligent production capable of communicating autonomously (Piccarozzi et al., 2018). Industry 4.0 focuses on technology topics like IoT, Big Data, Cloud, and Robotics and their impact on economic sustainability, process safety and environment control (Kamble et al., 2018). The discussions stop shorts of addressing the impact of technology and its implications on the work processes. That is a topic picked up later by the future of work research.

While the academic research and cited papers specific to the future of work are somewhat limited, the broader concept of Industry 4.0 has attracted significantly more attention from the scientific community. That is, since Industry 4.0 is a much broader concept involving any type of impact on any industry and not limited to the nature of the jobs (Liao et al., 2017; Madsen, 2019; Mario et al., 2016).

Digitalization is the driving force leading to Industry 4.0 revolution (Madsen, 2019). Digital processes and automation enable industry 4.0 (Piccarozzi et al., 2018) and are responsible for the changes in the number and nature of the jobs (Arntz et al., 2016). Digital transformation is a broad topic with extensive literature dedicated to it, but the relevant ones within the scope of this study relate to the socio-economic and managerial implications for the IT professions (Thomas & Mourad, 2020).

In what concerns the research on Romania's future jobs and on IT data about the country, there is some research done by the management faculties on the topic of digital transformation as a key factor in the future of work research (Bejinaru, 2013; Ionel & Alexandru-Gabriel, 2019). There are also some studies on the IT industry and data from Eurostat and Romania National Statistical Institute. The purpose of the market data is to show the IT sector's evolution until the present day. The studies' role is to provide context on the factors that enabled the IT sector's growth and the factors limiting its growth or long-term sustainability. Moreover, few articles discussing global trends include in their research the Romanian market as well. That is the European Union AI report (Seroz, 2019), the World Bank's The Changing Nature of Work report (Wright, 2018), and The Geography of Europe's Brain Business Jobs: 2020 Index (Sanandaji, 2020) by Nordic Capital presenting the transition from manual repetitive to "brain" creative jobs and readiness in 20 countries including Romania.

The National Bank of Romania published a report (Grigoraș et al., 2016), "Study of the IT sector evolution in Romania", providing an economic perspective of one of the most successful local sectors in terms of growth and profitability. ANIS, the national association of IT employers in Romania, is another relevant source on the topic of IT industry jobs. It publishes a report every year (ANIS, 2019b) with data about the industry growth. It talks about the growth in the number of IT jobs impacting GPD and the digitalization of manual work.

The study of literature on industry 4.0 and the future of work point out several supporting concepts. Those factors are either part of the cause for the disturbance or the solution for the shift in the nature of jobs.

Technology is identified as an enabler of growth but also a source of disruption (IMF, 2018). Artificial intelligence is potentially the technology with the highest potential impact on the future of jobs, leading to a potential future without jobs (Hines, 2019). A short history of AI (Nathan & Scobell, 2012), AI Future of Work (Seroz, 2019), an article describing the impact of the Watson computer on work (Ferrucci et al., 2013), and Google masters Go (Gibney, 2016) have been considered as indicative for this analysis. The exponential growth of technology is captured by Theis and Wong (2017) in "The end of More's Law. Exponential Growth of Technology" (Cassard et al., 2018). City series of "Technology at Work" (Frey et al., 2019) and "Disruptive Innovation" (Ashworth & Barrows, 2018) provide a general overview of the development of technology, including future predictions including but not exclusive to the development of Artificial Intelligence.

Education, in particular continuous education, is identified as the best response to the rapid changes in technology to address the skill gaps forced by technology (Margaryan et al., 2015; Merriam, 2001; Tytler et al., 2019). The *evolution of management models* is also implied as paramount (Bodrožić & Adler, 2018; Nahavandi, 2019). Related subjects like economics, human resources, and projections related to the future of work are also relevant for a thorough approach of current phenomena (Brynjolfsson & McAfee, 2014; Harari, 2015; Kurzweil et al., 2005; Tegmark, 2017).

Current events are obviously influencing the direction of the research. While the pandemic situation and the technological, economic, and impact on jobs are still to be fully understood, we cannot ignore the impact on the work models. For obvious reasons, there is a spike in medical-related academic research. Research started on the macroeconomic situation and specific industries (OECD, 2020). The COVID crisis, for example, has created an increased interest in the future of work subject, but it is still too early for comprehensive research of the crises on the work models, especially as the situation is still evolving.

Research hypotheses formulation

The fourth industrial revolution was driven by "a completely automated and intelligent production, capable of communicating autonomously" (Piccarozzi et al., 2018). Since the printing press creation, the exponential rise in processor performance reduced prices per transistor, and a similar pattern has applied to all types of information technology and will continue. Since the printing press's creation, the exponential rise in processor performance reduced prices per transistor, and a similar pattern has applied to all types of information technology and will continue (Kurzweil, 2006). 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, 2020). Particularly, 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 ICT experts with advanced skills. While 64 percent of major corporations and 56 percent of small and medium-sized businesses in the European Union reported a lack of ICT professionals, more than 80 percent of organizations in Romania reported difficulty finding ICT specialists (European Commission, 2020). Even under these circumstances, adult involvement in continuous learning is the lowest in Europe, at 0.9%, compared to the EU average of 11.1% (Eurostat, 2020). In 2001, the Romanian government passed legislation (Emergency Ordinance No. 7/2001, 2001) allowing software engineers who graduated from an IT institution to be free from paying taxes. Grigoraș et al. (2016) support the positive economic impact of tax exemption. More students are pursuing IT jobs due to the growth in job openings and earnings substantially above the national average (Grigoraș et al., 2016). Building on this, we infer that:
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). According to Schwab (2018), between half and three-quarters of the firms are anticipated to move to contingent labor and freelancer jobs to overcome the skills gap. Another example of change in management practices in the IT industry is adopting Agile project management. More and more IT firms are embracing the Scrum approach for project delivery. Scrum, a component of Agile management approaches, encourages continuous improvement, integrated teams, and rapid failure, giving higher productivity (McKenna, 1998).

The COVID-19 pandemic forced organizations to adopt new practices at an accelerated pace compared to what was envisaged before 2020. The most prevalent change was the wide adoption of remote work, a practice already in place, before 2020, in the IT industry. In the IT sector, there is no hard need for a physical presence in the office. That allows management to with permanent full-time employees or in a hybrid model (Volini & Schwartz, 2020). This leads to the following hypotheses:
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 the jobs of the future. By 2024, the number of jobs needing digital skills will increase by 12% (Acenture, 2017). Bughin et al. (2018) also points out that automation accelerates skills shift, and advanced and basic technological skills will substantially increase demand. The demand will not only be for technical skills, but also soft skills like social, emotional, and cognitive skills will become increasingly important. As a result, competition for high-skills workers will increase. Consequently, it may be inferred that:
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 the digital transformation on IT jobs based on the following research model (Figure 1):

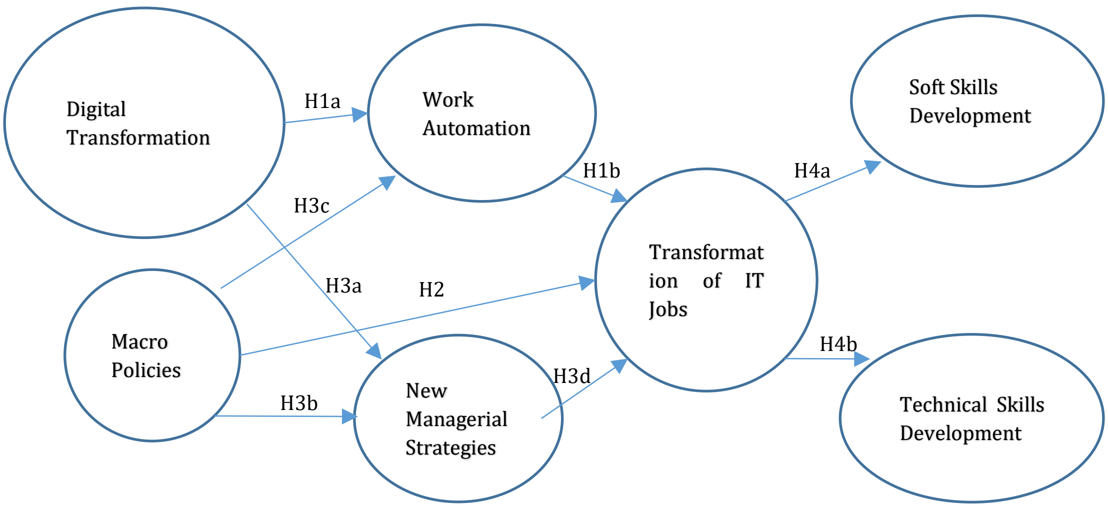

Figure 1. Research model

Material and methods

Research design

The survey outcomes must be valid and trustworthy. Validity is the degree to which the results accurately reflect what they are meant to measure. Internal validity assures that the causal relationship under investigation is reliable and unaffected by other situations or factors. External validity is the extent to which the conclusions of a study may be transferred to other situations, persons, or events. The extent to which a measurement is devoid of random error and generates consistent findings reliable (Khalid et al., 2012). The quality of the research will depend on the sample preparation, sample size, and measuring techniques.

The survey is based on a Google Forms[1] questionnaire and distributed via email and social media platforms like Facebook and LinkedIn. The questions are single-answer multiple options for the items establishing demographic and professional issues. These questions will enable the researcher to analyze the results for different segments like IT professionals' perceptions across company types or genders. 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[2] will be used for variable coding and computing the statistical information. SmartPLS[3] is used for structural equations 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. Therefore, the sampling will be based on *convenience*, including the people most accessible to the researcher, combined with *snowball* sampling, where participants can recruit other participants in their professional group.

The *sample size* must be large enough to approximate the studied population's actual distribution and validate test results. To achieve internal and external reliability, the sample size in quantitative research must be much larger than the qualitative research (Khalid et al., 2012). In management research, the typical confidence level is 95% (Taherdoost, 2020). The research measures the perceptions from multiple perspectives of IT professionals and people working in small, medium and large organizations.

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, projects the author is involved in. The Snowball method is also applied, with several contacts offering to cascade the questionnaire in their network. The questionnaire was also posted on social media, LinkedIn, and Facebook. Social media has helped with the awareness of the research topic but has only helped with a low response rate. Most social media contacts have only responded after being asked to answer the questionnaire. As a result, 132 people responded to the questionnaire, yielding a response rate of 88% from the persons I have directly engaged with. Considering a population of 100.000 IT employees in Romania (ANIS, 2019a), it will result in a 10% margin of error (Taherdoost, 2020).

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

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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)

All respondents have confirmed that they are either working in IT organizations, are students, or teachers in a computer science faculty. That is important because the research is specific to Romania's IT industry. For example, 82% of the respondents work as IT professionals, 3% are computer science students, and 1% are teachers. The rest, 14%, hold jobs in IT organizations like human resources, project management, and public affairs.

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. That correlates with the number of years of professional experience, with 64% having more than ten years of employment. 11% are between 6 and 10 years. Twenty-two responses are from people with up to 2 years of working experience, representing the category more interested in their future work, compared to people that are much closer to the end of their careers.

Regarding gender, 69% are male and 40% female, matching the IT industry demographics. 40% of the responses are from people with bachelor's degrees, roughly similar to the number of people with a master. 13 of the respondents have a Ph.D. This study assumes that students may have a different perspective about their future jobs compete with people already employed. 86% of responses are from people working in large organizations with more than 250 employees. That is consistent with the percentage of large corporations in Romania (ANIS, 2019b). On the other hand, micro, small and medium employees represent between 4% and 6 % of the responses.

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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., 2019a, 2019b) (Tytler et al., 2019) (Schwab, 2018)
	SKL2	Agility	
	SKL3	Creativity	
	SKL4	Cultural Awareness	

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	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	
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., 2019a, 2019b) (Soto-Acosta et al., 2016) (Oztemel & Gursev, 2018)
	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	

Findings: measurement and structural model assessment

The measurement and structural models (Hair et al., 2014) were evaluated using component-based partial least squares (PLS), a rigorous statistical instrument. The method is suggested by Henseler et al. (2014) and Hair et al. (2014).

The exploratory aspect of PLS-SEM (SmartPLS in this case) was favored (Bharati et al., 2015). Table 2 presents the psychometric features of the constructs examined in this study. As stated by Thompson and Barclay (1995), the needed measures are relevant for examining measurement models' convergent validity, individual item reliability, composite reliability, and discriminant validity. 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 the table.

Because composite reliability is regarded to be more accurate than Cronbach's alpha (Henseler et al., 2009), we also employed it to overcome shortcomings by considering the loadings of the different indicators. Nevertheless, 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)*

Using the SmartPLS approach, the discriminant validity of the measurement model was examined by comparing the square roots of the AVEs to other correlation scores in the correlation matrix. None of the construct correlations (non-diagonal entries) surpassed the relevant square root of AVE, as seen in table 4(diagonal entries). The data support the criterion provided by Fornell and Larcker (1981), specifically that the measures of each construct were more closely linked with their items than with items representing other constructs. Therefore, the overall measuring items comply with the reliability adequacy, and the discriminant validity of the study model's components was validated. Within the SMART PLS application, the Fornell and Larcker criteria emerge as the essential exploratory model validity measure (Fornell & Larcker, 1981).

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Table 3. Cross loadings

	Digital Transformation	Transformation of IT jobs	New Managerial Strategies	Macro Policies	Soft Skills Development	Technical Skills Development	Work Automation
DTA1	0.730	0.307	0.245	0.166	0.174	0.256	0.277
DTA2	0.761	0.423	0.317	0.257	0.212	0.283	0.320
DTA7	0.715	0.335	0.386	0.163	0.172	0.130	0.172
DTA8	0.805	0.617	0.454	0.315	0.263	0.369	0.284
DTA9	0.834	0.528	0.388	0.155	0.222	0.280	0.217
DTI5	0.301	0.713	0.353	0.329	0.438	0.271	0.115
DTI6	0.531	0.806	0.391	0.231	0.219	0.338	0.273
DTI7	0.551	0.862	0.454	0.358	0.346	0.459	0.282
DTI8	0.508	0.850	0.488	0.329	0.379	0.504	0.316
MAN1	0.434	0.458	0.737	0.460	0.262	0.261	0.117
MAN2	0.263	0.286	0.678	0.451	0.301	0.164	0.042
MAN5	0.322	0.410	0.778	0.486	0.483	0.289	0.108
MAN6	0.321	0.419	0.723	0.442	0.389	0.330	0.179
MAN7	0.326	0.293	0.770	0.429	0.352	0.165	0.060
MAN8	0.400	0.417	0.711	0.362	0.361	0.449	0.323
POL1	0.143	0.264	0.297	0.757	0.234	0.077	-0.016
POL2	0.325	0.364	0.611	0.862	0.522	0.266	0.126
POL3	0.130	0.261	0.400	0.733	0.403	0.114	0.016
REP1	0.306	0.212	0.146	0.011	0.055	0.396	0.863
REP2	0.305	0.349	0.169	0.071	0.091	0.411	0.921
REP3	0.273	0.265	0.217	0.125	0.115	0.335	0.893
SKL10	0.133	0.299	0.405	0.399	0.782	0.342	0.086
SKL2	0.244	0.346	0.359	0.447	0.648	0.362	0.165

SKL3	0.194	0.372	0.332	0.315	0.696	0.211	0.028
SKL4	0.139	0.298	0.180	0.251	0.701	0.186	0.064
SKL6	0.283	0.296	0.425	0.473	0.811	0.207	0.028
SKL7	0.182	0.253	0.383	0.362	0.709	0.259	0.054
TKL10	0.311	0.555	0.381	0.201	0.278	0.876	0.354
TKL5	0.180	0.240	0.283	0.128	0.299	0.715	0.228
TKL7	0.338	0.383	0.334	0.220	0.284	0.866	0.443
TKL9	0.288	0.398	0.266	0.165	0.361	0.820	0.352

Table 4. Discriminant validity of measurement model*

	Digital Transformation	Transformation of IT jobs	New Managerial Strategies	Macro Policies	Soft Skills Development	Technical Skills Development	Work Automation
Digital Transformation	0.771						
Transformation of IT jobs	0.590	0.810					
New Managerial Strategies	0.473	0.527	0.734				
Macro Policies	0.282	0.388	0.597	0.786			
Soft Skills Development	0.275	0.428	0.493	0.527	0.727		
Technical Skills Development	0.349	0.499	0.388	0.222	0.365	0.822	
Work Automation	0.331	0.312	0.197	0.076	0.097	0.428	0.893

**The diagonals represent the square root of the extracted average variance, whereas the off diagonals represent correlations between constructs.*

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Using a variance inflation factor, the degree of multicollinearity between components was assessed (VIF). According to Diamantopoulos and Siguaw (2006), VIF values less than 3.3 indicate a lack of multicollinearity. As revealed by the computations, the VIF scores varied from 1.21 to 2.50 (below the threshold value of 3.3), indicating that multicollinearity was unlikely to be a problem with the data. Harman's one-factor test was used to quantify the extent of standard method bias, with all constructs subjected to an unrotated principal component factor analysis. Given that no one factor accounted for more than 50 percent of variation (Harman, 1976), the standard method bias was deemed inapplicable to this study.

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). Considering that the multi-item endogenous variable is reflective, a blindfolding process was used to determine the predictive significance. Blindfolding is a sample reuse strategy that excludes every data point from the endogenous construct's indicators and estimates the parameters using the remaining data points (Hair et al., 2022). 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 5, R^2 exceeds the 0.35 threshold (Cohen, 1977) only for technical skills development with 0.35 and for the new managerial strategies with 0.46.

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 more than 1.6 (Cohen, 1977) (Table 7).

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.*

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				

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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.

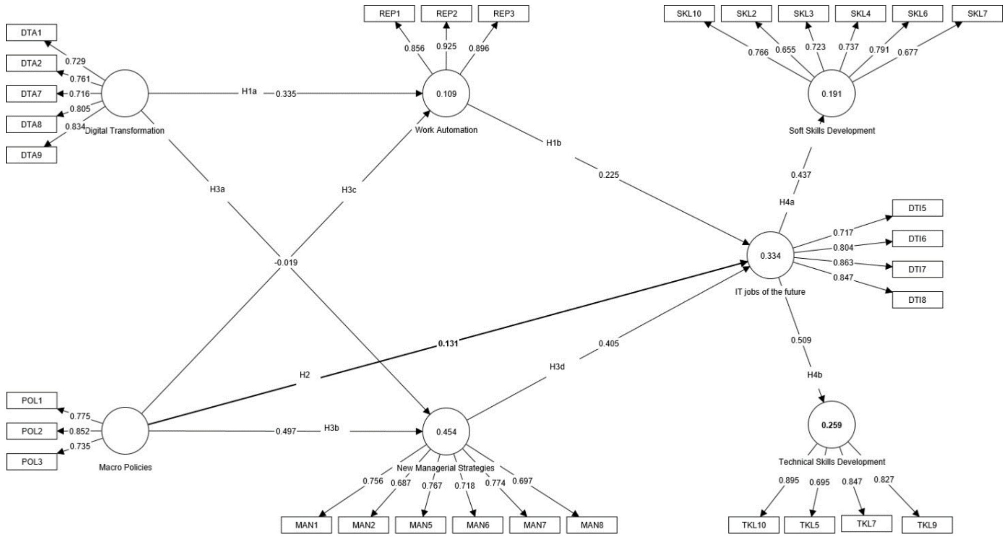

Figure 2. PLS test of the proposed structural model

Testing H1a - *Digital transformation positively impacts work automation* -, the p-value is smaller than 0.0001 and the value of the path coefficient (β) is 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. Given that β is 0.22, and the p-value is 0.001, the null hypothesis is rejected. 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 from 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 the Romania IT policy, this may explain the different results. The hypothesis is thus rejected.

Focusing on H3a – *Digital transformation positively impacts new managerial strategies* - the 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 needs to find new strategies and models to adapt to the increasing rate of technology change and the impact of digitalization. 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 path coefficient (β=0.5) and a large f-square of 0.41 were observed. The hypothesis is thus confirmed. H3c –*The macro policies positively impact work automation* – was not supported, with a p-value of 0.81. 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 and a big β path coefficient of 0.4 are an expected result, in 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 path coefficient for soft skills development is 0.25 and 0.32 for technical skills development. R2 is 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 the 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 that are 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. That covers the impact of digitalization on the future of jobs and the link between the changes like the jobs and the need to re-skill. While we have found statistically significant correlations in both aspects, they are not as strong as in the more prominent global studies like World Economic Forum (WEF) (2013).

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 the macro policies and work automation. While that is a topic of research (Reischauer, 2018; van Dorsser et al., 2018), a significant focus with the World Economic Forum (World Economic Forum (WEF), 2013), OECD countries (OECD, 2019), this is not as much in focus for the Romanian government, and this is visible in the results as well (as also underlined by Sanandaji, 2020). Considering previous studies (ANIS, 2022; Manelici & Pantea, 2019b), the expectation was to find a correlation between the government policies and the future of the IT jobs in Romania. Failing to find an impact may be because the policy is limited to IT tax exemption legislation and missing a holistic strategy. That will have to be further investigated.

Most of the studies do not research specific professions or do it across multiple professions. Instead, 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 the 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) adding other factors influencing work automation to the research. The additional information can help understand why work automation is only influenced with 10% by the digital transformation in the perception of Romania IT professionals; (c) running a qualitative study with selected responders from the qualitative survey to explore the relationship between the future of IT jobs and new skills development in more detail.

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