Automation fears: drivers and solutions

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Abstract:

New technologies offer employers the ability to replace tasks done by human labour with those done by machines. There are challenges for both employers and employees, as employers look for strategies for the implementation of automation technologies and employees may have concerns about their employment being threatened by automation technologies. In this research, we analyse data of over 500 Bulgarians to learn about how they perceive the automation of their job. The analysis finds that there are segments of the population defined by demographics and attitudes that are more fearful of the automation of their jobs than others. Additionally, we see that attitudes towards the dehumanizing effects of automation, peer-pressure, job automatability, and a person's self-perception of professionalism are the main drivers of the fear of automation. Finally, the paper evaluates respondents' attitudes towards various individual, corporate and social solution to automation fears.

Key words: automation fear, workplace automation, robots, solutions to automation fears, future of work

Highlights:

- The paper discusses the fear of automation
- The sample includes 502 respondents from Bulgaria
- Dehumanizing effects of automation, peer-pressure, job automatability, and professionalism are the drivers of automation fears
- Respondents support mostly individual solutions, followed by corporate and social solutions

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1. Introduction

1.1. Rationale

Automation technologies (ATs) include a wide range of technologies such as industrial robots (Cubero, 2007; Miller & Miller, 2017; Ross, Fardo & Walach, 2018), service and social robots (Bhaumik, 2018; Nørskov, 2016), artificial intelligence (Ertel, 2017; Neapolitan & Jiang, 2018; Russell & Norvig, 2016), vending machines, ATMs, kiosks, chatbots (Singh, Ramasubramanian, & Shivam, 2019), automated trading algorithms (Chan, 2017), and other technologies that allow the production and sale of goods and services with no or minimum human involvement. The technological progress over the last decades has increased the capabilities of ATs and decreased their prices leading to their implementation in various industries (Bhatnagar, 2020; Delgado *et al.*, 2019; Kabugo *et al.*, 2020; Moutsatsou *et al.*, 2019), including agriculture (Driessen & Heutinck, 2015; Slaughter, Giles & Downey, 2008) and services (Huang & Rust, 2018; Ivanov & Webster, 2019a; Wirtz *et al.*, 2018). Automation technologies are used as autonomous vehicles for transporting goods and people (Maurer *et al.*, 2016), in warehousing and supply chain management (Wurman, D'Andrea & Mountz, 2008), in communicating and maintaining relationships with customers through chatbots (Buhalis & Yen, 2020; Hill, Ford & Farreras, 2015), for automated pricing decisions (Tonkova, 2016), for facial recognition and automated border control (del Rio *et al.*, 2016), for provision of legal services (Remus & Levy, 2015), for trading on financial markets (Dunis *et al.*, 2017), and for countless other applications. Driven by their search for greater productivity, competitiveness, profitability, and lower dependency on scarce human talent, companies invest heavily in ATs and replace some of their employees. The International Federation of Robotics (2019) reports that in 2018 alone, the number of newly installed industrial robots was 422,271 to reach a total of 2,439,543 operating industrial robots. There are even instances of American robots losing their jobs to Asian robots (New York Post, 2019).

Every automation technology has both enhancement and substitution effects simultaneously (Decker, Fischer & Ott, 2017; Frey, 2019; Ivanov & Webster, 2019b). The enhancement effect means that the adoption of a new technology allows the employees to perform better at their jobs and increase their productivity. Through the substitution effect the new technology replaces the human workers who were previously doing the same tasks. The massive implementation of automation technologies changes the nature of work human employees

perform (Ernst, Merola, & Samaan, 2019; Webster & Ivanov, 2020) and creates expectations and fear among employees that they may lose their jobs and be replaced (Fiaidhi, Mohammed, & Mohammed, 2018; McClure, 2018; Nam, 2019; Spencer, 2018; Stubbs, 2017). Claims in recent studies that 47% of jobs in the US (Frey & Osborne, 2017) and in other countries (Dengler & Matthes, 2018) are susceptible to computerisation put more fuel into the fear engine that employees will become obsolete in a robonomic society (Ivanov, 2017) and bring back memories from the 19th century Luddite movement (Jones, 2006). Furthermore, the use of ATs raises concerns regarding what individuals, companies, and social institutions should do if the automation fears are materialised into severe technological unemployment (Feldmann, 2013; Postel-Vinay, 2002; Walsh, 2018).

The traditional resistance to new technologies, as per the Luddites, also brings up a deeper philosophical and practical implications in terms of the current technological revolution, as highlighted in discussions of the “ironies of automation.” The “irony” is a discussion regarding how the current wave of automation differs from “classical automation” (Bainbridge, 1983: 778), since it puts human operators in a very different position from the earlier wave of automation. While fears of automation in earlier waves of automation were largely based upon the replacement of human labour for repetitive tasks, the tasks automated under the current wave of automation places greater responsibility upon human operators and leaves the human with little support to deal with the remaining tasks relegated to humans (Baxter et al. 2012; Strauch, 2017). So while early Luddite opposition to AT was largely out of fear of losing jobs, the current resistance to AT may also be influenced by concerns regarding creating difficult and sophisticated situations for humans. Worker resistance to automation may actually be partly based upon resistance to an increasingly complex workplace, since many workplace processes that are not easily automated will be left in the hands of the human operator who is often not given adequate support to handle such tasks [some excellent examples of this are outlined by Baxter et al. (2012)].

This paper addresses the automation fears of employees and the solutions to mitigate them by focusing on a transition economy – Bulgaria, unlike previous studies that are concentrated on major world economies such as USA (McClure, 2018; Nam, 2019), Japan (Morikawa, 2017), or Western Europe (Schlögl *et al.*, 2019). A former Soviet bloc country, Bulgaria, is a member of the European Union since 1st January 2007. With a GDP of approximately 55 billion euros (NSI, 2019a), a population of 7 million (NSI, 2019b), and a GDP per capita of around 8000

euros, Bulgaria is the poorest EU member. At the same time, the severe demographic crisis (low birth rates and emigration) pushes down the unemployment rate to historically low values (3.7% for July-September 2019, NSI, 2019c) and creates a huge deficit of skilled employees (Dimitrova, 2019). Faced with the lack of workers, companies in the country are already forced to use automation technologies in order to decrease the pressure of the current labour market shortages on their operations, hence sowing the seeds of future replacement effect and fear of automation.

1.2. Aims and objectives

In the line of the above discussion, the aims of this paper are: *a)* to assess the level of fear Bulgarians have of losing their jobs due to the introduction of automation technologies; *b)* to identify the factors that have an impact on the fear of automation; *c)* to evaluate the support of Bulgarians to various solutions to mitigate automation fears; and *d)* to identify the factors that have an impact on the solutions to be used to mitigate the fear of automation. The technological, operational and economic aspects of automation, the automatability of specific jobs/tasks, and the political economy of automation go beyond the scope of this paper.

In this paper, we adopt a non-normative approach that looks into how a population views automation and its fears of it, and analyses the data to uncover some of the drivers of automation fears. The rest of the paper is organised as follows. Section 2 provides a focused review of the previous literature on automation fears and develops the research hypotheses. Section 3 elaborates on the methodology. Sections 4 and 5 present and discuss the results, while Section 6 summaries the theoretical contribution, managerial and policy implications of the paper, and concludes the paper.

2. Literature review and hypotheses development

2.1. Fear of automation

The impacts of automation technologies, their social implications, and employees' fear of losing their jobs to ATs are not a new research topic. Back in 1930, Keynes warned about the potential technological unemployment but considered it as a temporary phase of economy maladjustment (Keynes, 1930/1965). In 1958, Cuthbert Hurd elaborated on the new professions and job enhancement (or 'position enlargement' in his terminology) that automation would bring, although there were only a few thousand computers in the USA at that time (Hurd, 1958). Later on in 1965, Louis Rago acknowledged the displacement/substitution effect of automation

technologies but considered that the fears of automation were not justified, because automation created more jobs through lower product prices and the creation of new jobs in areas ‘where the “added” purchasing power generates “new” demand’ (Rago, 1965: 35). Within the next five decades, the growing adoption of automation technologies stimulated automation fears not only among manufacturing workers, but among service employees and farmers as well; giving ground to Stimmer (1984) to ask whether technology is ‘a curse or blessing,’ while Brynjolffson and McAfee (2015) queried whether humans will ‘go the way of horses.’

The fear of automation is stemming from people’s perceptions of losing their jobs to automation and, if they do, how easily they would be able to find a new job in the same or another industry so that they do not find themselves in a financially stressful situation. If automation is not substituting human employees, but in contrast, enhancing them, they would not fear automation and may find it as a tool to achieve higher productivity and greater personal economic wellbeing, unless employees enjoy the specific tasks being replaced. However, the substitution effect of ATs makes human employees uncertain about their future, thus causing fear of losing their jobs. Looking at the broader social effects of automation technologies, Leonhard (2016), Crews (2016), and Barrat, (2013) paint a very grim picture on the impact of robotics and artificial intelligence on employment. From a supply-side perspective, Frey and Osborne (2017), Berg, Buffie, and Zanna (2018), and Autor and Salomons (2018), among others, find that the balance between the enhancement and substitution effects of ATs is definitely on the side of substitution. In a similar vein, DeCanio (2016) shows that the introduction of AI would depress wages of human employees due to the substitution effect. Hence, humans have every reason to fear that they would not only be replaced by technology, but they may face difficulties in finding new jobs in the same or other industries due to widespread automation or lack of skills to work on the newly created jobs.

However, Arntz, Gregory, and Zierahn (2017) consider that the claims about the loss of jobs due to automation are largely exaggerated because of their disregard for the different skills that constitute the jobs. Additionally, Frank *et al.* (2019) warn that it is very difficult to actually measure the impact of automation on jobs due to lack of high-quality data about the nature of work, lack of empirically informed models of key microlevel processes, and insufficient understanding of how cognitive technologies interact with broader economic dynamics and institutional mechanisms. Therefore, the empirical support for the fears of automation may be shaky. Moreover, Walsh (2018) finds that non-experts are more pessimistic than experts in

robotics and artificial intelligence and systematically overstate the risk of automation of jobs. Danaher (2019) goes even further and claims that although automation will substitute human employees in the long-term, people should embrace automation and the elimination of work because work is inherently detrimental and impedes human flourishing and meaningful life. In the same line of thought, Brynjolfsson and McAfee (2014), Drexler (2013), Frank, Roehring, and Pring (2017), LaGrandeur and Hughes (2017), Talwar *et al.* (2017) and others consider that humans should not fear automation technologies because they would have a positive impact on society not only by liberating humans from repetitive, tedious, dangerous, and dirty jobs; but by providing new opportunities for creating value for humans, improving life, and improving the wellbeing of humans in economic, health, and social terms as well. Therefore, although the substitution effect of ATs would be significant in the long-term, it should not be a reasonable basis for automation fears.

From an employee perspective, McClure (2018) found that technophobes in the US who fear automation are fewer in number than non-technophobes. On average, they tend to be older, female, and have lower education. Based on a sample of 10,000 Japanese respondents, Morikawa (2017) concludes that about 30% of respondents are afraid of losing their job to robotics and AI, while gender, age, education, and type of labour contract are influencing the perceived risk of losing their job. Schlögl *et al.* (2019) report that employees fear that they would lose their jobs when mundane repetitive tasks are increasingly replaced by AI tools and technologies. The fear is increased due to the lack of information and knowledge about AI. This is supported by Nam (2019) who reports that people aware of the impacts of automations on the labour market tend to be more optimistic and less sceptic. Milosavljević and Vobič (2019) investigate the fear of ATs of journalists in the United Kingdom, Germany, and the United States. The authors find that the journalists consider the new technologies as liberating rather than subordinating them.

2.2. Potential factors influencing the fear of automation

2.2.1. General perceptions of automation technologies:

People can have both positive and negative perceptions about the role of automation technologies in society. The perceived social benefits of automation technologies usually include benefits such as making the lives of people easier and more convenient, eliminating tedious work for human employees, and improving the standard of living by decreasing the prices of goods and services (Brynjolfsson & McAfee, 2014; Drexler, 2013; Talwar *et al.*,

2017). When automation technologies have high perceived benefits for societies as a whole, companies and public institutions would be inclined to implement them. Although some employees would be displaced, the higher perceived social benefits of automation may (partially) off-set the fear of employees for their jobs due to the positive effect of ATs on society. At the same time, people may fear automation technologies because of the negative dehumanisation effects they may have on society such as damaging human relationships, dehumanisation of the workplace, and deskilling of jobs (Bhattacharyya, & Nair, 2019; Danaher, 2019; Leonhard, 2016). This means that automation technologies would make human employees replaceable and society would need to adjust to automation technologies, not the other way around. Hence, the following two hypotheses are formulated:

H1.1. Perceived social benefits of automation technologies are negatively related to the fear of automation

H1.2. Perceived dehumanisation effect of automation technologies is positively related to the fear of automation

2.2.2. Characteristics of automation technologies as production factors compared to human employees

From an economic point of view, automation technologies are production factors. As such they have both advantages and disadvantages compared to human employees. For example, ATs process information much faster than humans and can provide more accurate information with fewer mistakes, they are more reliable than humans, have higher productivity and greater cost efficiency than human employees. Some of the perceived disadvantages of automation technologies include the lack of creativity, less interactive than humans, and operating mostly in highly structured/standard situations (Ivanov, 2019), among others. When automation technologies have more advantages compared to human employees, companies would prefer to use them instead of human employees, thus nurturing automation fears among their employees. On the opposite, when people perceive that they are more competitive than automation technologies they would feel more secure about their jobs. Hence the following two hypotheses are formulated:

H2.1. Perceived advantages of automation technologies compared to human employees are positively related to the fear of automation technologies

H2.2. Perceived disadvantages of automation technologies compared to human employees are negatively related to the fear of automation technologies

2.2.3. *Self-image of human employees*

Prior studies have indicated that the image people have about themselves is influencing the way they behave (Schiffman *et al.*, 2014), the products they buy (Johe & Bhullar, 2016), and their attitudes towards and acceptance of new technologies (Nikou & Economides, 2017). Within this research we consider three characteristics of human employees – innovativeness, professionalism and technological skills. Innovative people try to find new solutions to existing problems and have creative and original thinking (Wiedmann *et al.*, 2010). Creativity is their competitive advantage over automation technologies. This means that they cannot be easily replaced by technology, but even when faced with a potential threat of substitution they may not be frustrated but will look for new ways to develop and remain competitive. Hence:

H3.1. People who consider themselves as innovative are less afraid of losing their jobs to automation technologies

Professionalism refers to how well a person is prepared for and performs the tasks within his/her job, although there is some literature that struggles to define and conceptualise the term with more precision (see, for example, Bossers *et al.*, 1999). Companies try to attract and keep employees that deliver high quality, effective and efficient work. There is some indication that robots may threaten certain management positions more than others, typically less-skilled managers (Dahlin, 2019). Therefore, people with high self-perception of professionalism may be more confident that they will keep their jobs, will not be replaced or, in case they are replaced, they can find new job relatively easily. Hence:

H3.2. People who consider themselves as professionals are less afraid of losing their jobs to automation technologies

Finally, technological skills refer to how confident human employees are in using various technologies. The likely impact of technological skills on fear of automation is not very straightforward. On the one hand, people who feel comfortable with technology, and are confident that they have the knowledge and skills to use automation technologies, will also be able to use these technologies in their favour – e.g. for being more productive on their job (this

is the enhancement effect of automation). On the other hand, the high level of technological skills means that these people will also have greater knowledge about the capabilities of new technologies and their potential for replacing human employees. Moreover, higher technological skills are associated to low supply of human employees with such skills and higher labour costs for them, thus greater economic pressure for companies to decrease their dependency on such skills. A recent study confirms that due to automation and artificial intelligence, technological skills will be in high demand in the future (Bughin et al., 2018). Balancing on this discussion the following hypothesis is formulated:

H3.3. People with higher technological skills are afraid of losing their jobs to automation technologies

2.2.4. Demographic characteristics of human employees

Demographic characteristics have been found to influence perceptions towards automation technologies such as robots (Ivanov, Webster, & Garenko, 2018; Ivanov, Webster, & Seyyedi, 2018). In regard to fear of automation demographic characteristics of human employees may play a role too. Blue collar jobs, that have historically been ousted by industrial robots, are usually occupied by men. Statistical data by International Labour Organization (ILO, 2019a) show that globally men dominate in manufacturing, construction, and transport and storage, where industrial and warehouse robots and autonomous vehicles would be introduced in the future. Data by Bulgarian National Statistics Institute (NSI, 2019d) reveal the same picture on country level. On the other hand, men also hold more managerial positions than women (ILO, 2019b) which are less automatable than operational level jobs (see section 2.2.5 further in the text). Women dominate in professions where emotional intelligence and social skills are key requirements (e.g. services) which are more difficult to automate than manufacturing jobs (ILO, 2019a). At the same time, despite the antidiscrimination laws, women are often in a disadvantaged position when looking for high-paid managerial jobs (Dencker, 2008; Hultin & Szulkin, 1999). Furthermore, as prior Kral *et al.* (2019) have indicated, automation will have different impact on men and women due to the different levels of automatability of the jobs they usually occupy (see section 2.2.5 as well). Specifically, the authors point out that the job positions occupied by men have greater risk of automation compared to those of women. Therefore, although both genders have their reasons to be afraid of the impacts of automation on their jobs and how easily they can find a new job, the following hypothesis is formulated:

H4.1. Men have higher fear of automation

Younger people are more tech savvy, they are more mobile and more adaptable to changing situations compared to older generations (Kolnhofer-Derecskei, Reicher & Szeghegyi, 2017). When they lose their job younger people may find a new job more easily than older employees due to the skills, adaptability, stress endurance, learning capabilities, and readiness to work for longer hours at lower salaries. At the same time, older people may be more afraid of losing their jobs to automation because they are already looking for their retirement and do not want to change their job or spend a lot of time and/or money to requalify for another unautomated job position. Hence, the hypothesis:

H4.2. Younger people are less afraid of losing their jobs to automation technologies

One of the goals of education is to equip students with skills and make them employable. More educated people are supposed to have more knowledge and skills to perform well on their job and will be more competitive on the labour market. This leads to the hypothesis:

H4.3. More educated people are less afraid of losing their jobs to automation technologies

Higher perceived economic wellbeing means that if a person loses his/her job due to automation, he/she will have sufficient financial resources and may afford a longer search period for a new job. Furthermore, the higher economic wellbeing may be a result of holding job positions at managerial and executive levels that are less likely to be automated. Therefore, the formulated hypothesis is:

H4.4. Perceived economic wellbeing is negatively associated to the fear of automation

People living in metropolitan areas are exposed to more technological innovations because larger cities provide greater economies of scale for the introduction of new technologies. Prior studies have shown that the place of living (city size) was shaping people's attitudes towards technology in a way that people in metropolitan areas have more positive attitudes towards automation technologies (Ivanov, Webster & Garenko, 2018). Furthermore, larger metropolitan areas provide greater job opportunities compared to smaller areas. The limited job opportunities outside metropolitan areas increase the time and efforts that displaced workers would need to

spend to find new jobs. Hence, they may be more afraid of losing their jobs to automation technologies compared to people in metropolitan areas. The formulated hypothesis is:

H4.5. People living outside the metropolitan areas are more afraid of losing their jobs to automation technologies

2.2.5. Job characteristics

The automatability of a job position and its level within the organisational structure of the company determine the probability of a job being automated. Each job consists of a series of tasks. At the current state of technological development some tasks (e.g. routine / repetitive tasks, calculations, information processing, moving objects) are easier to automate than others (e.g. non-routine tasks, or tasks that require emotional intelligence and social skills) through physical or cognitive automation (Ivanov, 2020). When most of the tasks that consist a job position are automatable, then the whole jobs position becomes automatable. This means that if various technologies are introduced to perform the automatable tasks of that job position, the remaining tasks will be too few to justify the existence of the whole job position – it will be eliminated and the remaining unautomated tasks would be transferred to other job positions. Therefore, people whose jobs comprise of predominantly automatable tasks have all the reasons to fear that they would be substituted by automation technologies. Coupe (2019), for example, finds that people whose jobs involve a lot of personal interaction are less afraid of losing their jobs to ATs. Therefore, the following hypothesis is formulated:

H5.1. Job automatability is positively related to automation fear

Each job position has its place in the organisational hierarchy. The job level (operational, supervisory, managerial or executive) determines not only the types of tasks that are included in the job position, but also the involvement of the employee in the decision making process, especially for the introduction of ATs. Higher level job positions (managerial and executive) take the practical decisions to introduce automation technologies in company's operations. People on these levels are also fewer compared to employees on operational and supervisory level, and their job positions include tasks that are not always easy or desirable to automate (e.g. strategic decision making). Therefore, larger impact of automation (in terms of number of eliminated job positions) may be achieved by automating jobs on operational and supervisory

levels whose job positions include tasks that are often standardised and automatable. That is why, the formulated hypothesis is:

H5.2. Lower job positions are associated to higher fear of automation

2.2.6. Work experience

In this paper the work experience is measured in two ways: by the total number of years a person worked, and the number of years a person worked on a particular job position. A person with greater work experience would be more confident that he/she performs well (effectively and efficiently) on the job because of the direct work experience he/she has on that same job or the overall accumulated work experience. Hence he/she may not fear so much of losing his/her job to automation or may use this experience as a competitive advantage to find a new job elsewhere if replaced by technology. Therefore, we hypothesise that a negative relationship would exist between the automation fear and the work experience:

H6.1. Longer work experience is negatively associated to automation fear

H6.2. Number of years on a particular job position is negatively associated to automation fear

2.2.7. Social influence

Social influence (TV news and shows, online media, posts in social media and blogs, conversations with colleagues, friends and relatives, etc.) has been found to have an impact on people's behaviour and opinions about vast range of topics, including automation technology (Madigan *et al.*, 2017). The information people are exposed to at work, at home, with friends, or online, contributes to the formation of specific attitudes towards technologies (positive or negative). The social influence may both increase or decrease the fear of automation. For example, if a person is exposed mostly to information showing that ATs are replacing human employees (e.g. in social media feeds, or a relative lost a job for that reason), he/she might be afraid for his/her job. The opposite is also valid. That is why we cannot hypothesise the exact direction of the impact of social influence but only that such an impact would exist:

H7. Automation fears are shaped by peer pressure

2.3. Solutions to automation fears

The solutions to automation fears are in fact solutions to the threat of and consequences of technological unemployment. They can be divided into three groups, depending on who has the responsibility to implement them, namely: individual, corporate and social solutions.

Individual solutions include all those actions that human employees can undertake in order to mitigate the negative consequences of automation on their employability. These actions can be divided into 3 possible strategies – “fight”, “flight” or “passive”. The “fight” strategy encompasses the action that aim human employees to remain competitive on the labour market by improving their qualification in order to perform on their current jobs better than the automation technologies (i.e. fighting the substitution effect of technology), or by learning how to use automation technology to be more productive on their current jobs (i.e. utilising the enhancement effect of technology). The human employees who have a “flight” strategy look for new jobs that are not going to be automated soon in the same or another industry. Employees with a “passive” strategy avoid proactive behaviour, do nothing, and wait for the automation impacts to unfold.

Corporate solutions include the actions that companies can undertake in order to decrease the fear of and the negative impacts of automation on employment. For example, producers of ATs can evaluate and publicly announce the impact of automation technologies on jobs (Stevens & Marchant, 2017). In that way, people and governments would be familiar in advance with the likely effect of these technologies in various industries. Additionally, companies that use ATs can evaluate and publicly announce their impact on jobs before these technologies are being adopted. While the evaluations of the producers of automation technologies would refer to industries as a whole, the evaluations of the corporate users of these technologies would provide more specific light on the exact impacts on particular companies. These two measures do not necessarily mean that the fear of automation would be mitigated (the effect can be even opposite – i.e. increased fear) but at least they can provide an indication about the impact of automation technologies on jobs. Furthermore, when companies have already opted for the introduction of ATs, they could mitigate the fears of their employees by introducing work sharing and reduced working hours (i.e. decreasing slightly the fear of losing a job) (Stevens & Marchant, 2017) and by providing free requalification for displaced employees (i.e. improving the chances of finding a new job). Ultimately, consumers can contribute to the decrease of automation fears by boycotting companies that substitute their employees with ATs. Although not a pure corporate solution, it may have an impact on the decisions of companies about automation.

Social solutions include a set of economic and administrative actions of governments and public institution directed not towards the automation fears of specific persons but to the society as a whole (Ivanov, 2017; Nam, 2019; Stevens & Marchant, 2017). For instance, the government may provide free education to everyone to improve their qualification in order to be more productive and be able to use effectively and efficiently automation technologies (enhancement effect), or it can provide free education only to those who have lost their jobs due to automation (mitigating the negative impacts of displacement). The government may create financial incentives to companies to use human employees rather than ATs (e.g. tax vacations, covering the costs for social security and medical insurance payments) but such measures may turn out to be too costly for governments' budgets. Companies may also have opportunistic behaviour and threaten to automate processes if the government does not provide them with subsidies to keep the human employees. Hence, in the long-term this solution does not seem viable. Government could hire everyone who has lost his/her job due to automation technologies. In that way they would directly decrease or even eliminate the fear of automation, because human employees would know that they have the safety net of government-created employment. If the substitution effect of ATs is massive, the government would not cope with the influx of displaced workers. It will fail not only in creating jobs, but also in financing these jobs, because its budget revenues would suffer due to unemployment-induced drop in income taxes. Thus, although socially pleasing, this option may not be financially feasible. Governments could try to tax automation technologies (Ionescu, 2019). However, this would require very precise legal definition of automation technologies. Once a legal definition is introduced, automation technologies' manufacturers would try to change their products in ways that go beyond the scope of their legal definition, thus making it practically challenging to collect the taxes. Another solution may be the provision of basic income (McDonough & Bustillos Morales, 2020; Sheahan, 2012). It would guarantee that even when left without work-related income, employees would continue to receive some unconditional income from the government (unlike social payments that are usually tight to specific conditions such as disability or have limited duration). Basic income would decrease the fear of employees of being left without financial resources as a result of automation. Strict birth control on populations as a radical measure on fighting technological unemployment has been proposed in the literature too (Ivanov, 2017).

Clearly the different solutions, sketched briefly above, are strongly politically charged. Conservatives and liberals would probably give preference to individual solutions, socialists –

to governmental solutions, while social democrats may reply on all of them with an emphasis on corporate and social. However, it goes beyond the scope of this paper to discuss the role of political ideologies in mitigating the negative impacts of automation on employment, which could be subject of future research.

2.4. Potential factors influencing the support to the solution to automation fears

2.4.1. Demographic characteristics of human employees

If demographic characteristics (age, gender, education, perceived economic wellbeing, and place of living) shape the automation fears (see Section 2.2.4.), it is likely that they also do this regarding the acceptance of the various solutions to automation fears (see also Nam, 2019). Older employees may prefer corporate and social solutions over individual ones because they find it challenging to be proactive and learn new skills to use automation technologies on their workplace. More educated employees may be more confident in their knowledge, skills, and competitiveness on the labour market and may prefer individual solutions. Less affluent employees might focus on corporate and social solutions as a more financially reasonable solution for them personally. While people in metropolitan areas could rely more on their own efforts due to the greater job opportunities compared to non-metropolitan areas. Hence, the following hypotheses are developed.

H8.1. Gender influences the support for the solutions to automation fears

H8.2. Age influences the support for the solutions to automation fears

H8.3. Education influences the support for the solutions to automation fears

H8.4. Perceived economic wellbeing influences the support for the solutions to automation fears

H8.5. Place of living influences the support for the solutions to automation fears

2.4.2. Job level

Corporate solutions directly hit the finances of companies. Therefore, people on managerial and executive levels may not be supportive to such solutions because their bonuses would suffer and may prefer individual and social solutions. At the same time, some of the corporate solutions (e.g. free requalification of employees) are integral part of corporate social responsibility and are likely to be supported by managers. Employees on an operational and supervisory level would expect companies to take care of them if displaced by automation; that is why they may have greater preference about corporate solutions compared to individual ones. The hypothesis is:

H9. Job level influences the support for the solutions to automation fears

2.4.3. Work experience

The influence of work experience on the support for the solutions is not clear cut. On the one hand, as elaborated in 2.2.6 employees with longer work experience are more confident that they would find a job if replaced by automation; hence they may support the individual solutions to automation fears. On the other hand, longer work experience (e.g. 30 years or more) is connected to older age which may weaken the support for individual solutions in favour of corporate and social. Therefore, the hypothesis is:

H10. Work experience influences the support for the solutions to automation fears

3. Methodology

3.1. Data collection procedures

Data were collected during May-June 2019. The link to an online questionnaire was distributed through social media. The authors posted it to different social media groups in order to reach respondents with diverse demographic backgrounds. The administrators of one of the most popular Facebook pages in Bulgaria (“Science and critical thinking”) shared the link to the survey which helped reach a larger audience. Participation in the research was voluntary and entirely anonymous – no personal identifying information was collected. Respondents self-selected to participate in the research. The questionnaire was originally developed in English language and then translated into Bulgarian by the first and second authors who are native speakers. It took about 15 minutes to complete the questionnaire.

3.2. Data collection instrument

The questionnaire consisted of 86 individual questions divided into several blocks. The first block collected demographic data about the respondents. The second block examined the attitudes towards automation technologies (general attitudes, perceived social benefits and negative social impacts of automation technologies, advantages and disadvantages of automation technologies as production factors compared to human employees). The third block included questions related to respondents’ self-perception (technological skills, professionalism, and perceived social influence). The questions in the fourth block related to the possibility to automation of the current job of the respondent and his/her fear of automation

technologies. The final block included various statements related to possible governmental and corporate solutions to automation fears of Bulgarians. The level of agreement to all statements was measured with a 7-point Likert scale (from 1-completely disagree to 7-completely agree). For some statements such as those related to dehumanisation impacts of automation technologies, their disadvantages compared to human employees, the job automatability, and the fear of automation, reverse coding was adopted. The three attitudinal statements were measured on a 7-point scale as well (from 1-extremely negative to 7-extremely positive). Appendix 1 specifies the items in the scales and their sources.

3.3. Data analysis methods

Cluster analysis helped identify segments of respondents on the basis of their fear of automation. The number of respondents in the cluster analysis (502) was 83.7 times higher than the number of variables in the segmentation base (6 statements). Therefore, it exceeded the minimum ratio of 70 recommended by Dolnicar et al. (2014). The Kolmogorov-Smirnov and Shapiro-Wilk tests revealed that for most questions the distribution of responses was statistically different from normal. That is why non-parametric tests were adopted for hypothesis testing. In particular, Mann-Whitney U-test was used to identify differences in respondents' answers on the basis of gender and cluster belongingness, while Kruskal-Wallis χ^2 -test was adopted for analysing the differences on the basis of the age, education, perceived economic wellbeing, work experience, and job level of respondents. Wilcoxon signed ranks test was applied to identify differences in respondents' answers to some questions. Furthermore, factor analysis and regression analysis were used to identify the impacts of various factors on automation fears of respondents.

3.4. Sample's characteristics

The research population included Bulgarian citizens above the age of 18. The authors deliberately looked for respondents not only from Bulgarians living within the country, but for Bulgarian citizens living abroad as well in order to see whether the different cultural and economic environment Bulgarians living abroad face (e.g. in Western European countries, or in the USA) has an impact on the fears of automations. In total 606 respondents completed the survey, but 104 responses had to be removed due to missing answers to numerous questions. The final dataset included 502 respondents. Table 1 presents the demographic characteristics of the sample.

INSERT TABLE 1 AROUND HERE

4. Results

4.1. *The general picture*

In general, the attitude of Bulgarians towards automation is extremely positive ($m=6.17$), with similar positive perceived impacts of automation technologies on society both currently ($m=5.95$) and in the near future ($m=5.94$) (see Table 2). This is further evidenced by the fact that respondents consider that the perceived benefits of automation for society (min $m=4.39$, max $m=6.04$) outweigh the expected negative dehumanisation impacts of automation technologies (min $m=2.70$, max $m=4.37$, reverse coding). In the same vein, the advantages of ATs compared to human employees (min $m=5.30$, max $m=6.19$) are stronger than their disadvantages (min $m=2.58$, max $m=4.77$, reverse coding). Respondents also consider themselves as relatively innovative persons (min $m=4.77$, max $m=5.85$), with very good technological skills (min $m=5.57$, max $m=6.21$) and high level of professionalism (min $m=5.66$, max $m=6.18$). Additionally, they remain generally neutral regarding the automatability of their job positions (min $m=3.46$, max $m=4.44$, reverse coding). Hence, the respondents do not show fear of losing their jobs to automation technologies (min $m=5.61$, max $m=6.00$, reverse coding).

INSERT TABLE 2 AROUND HERE

4.2. *Cluster analysis and hypothesis testing*

A closer look at the data shows that the respondents are not uniform in their answers. The cluster analysis revealed the existence of two large groups of respondents on the basis of their fear of automations (Table 3). The first group ('Confidents') consists of 398 respondents who have a very low level of fear on each of the six statements (min $m=6.03$, max $m=6.37$, reverse coding). The second group ('Neutrals') includes 104 respondents who have generally provided a neutral answer to the statements of fear (min $m=3.77$, max $m=4.57$, reverse coding). Table 3 shows that the two clusters are similar in terms of their demographic characteristics (age, gender, education, and place of living), while the 'Neutrals' have a slightly lower perceived economic wellbeing than the 'Confidents' ($\chi^2=15.764$, $p<0.05$). The differences in the responses of the two groups are mostly statistically significant as the 'Confidents' are systematically more optimistic than the 'Neutrals' (see Table 3). It should be noted that very few respondents actually agreed with the fear statements. As a matter of fact, as low as 29 respondents (or 5.8%) strongly agreed, agreed or somewhat agreed with the statement "I fear I might lose my current

job due to automation technologies within the next 5 years,” while as high as 64 of them (12.7%) strongly agreed, agreed or somewhat agreed with the statement “I fear that the use of automation technologies on my current job will require knowledge and skills that I do not have.”

INSERT TABLE 3 AROUND HERE

The Mann-Whitney U-test and Kruskal-Wallis χ^2 -test showed that gender, education, perceived economic wellbeing, and job level have no or marginal effect on fear of automation (Table 2) (Hypotheses H4.1, H4.3, H4.4, H5.2). Age seems to condition the fear of automation as younger respondents (18-30) are less afraid of automation compared to middle aged (41-50 and 51-60) respondents – they are less afraid to lose their jobs within the next five years ($\chi^2=16.675$, $p<0.01$), or that they will not be able to find a new job in the same ($\chi^2=13.767$, $p<0.01$) or in another industry ($\chi^2=17.836$, $p<0.001$) (Hypothesis H4.2). This might be a result of the demographic crisis that Bulgaria is currently experiencing which gives more bargaining power to the younger employees who are fewer, but more educated and mobile compared to the previous generations. Additionally, respondents with longer work experience (21-30 years) are more afraid than less experienced ones (0-10 and 11-20 years) that if they lose their job due to automation, they might not be able to find a new job in the same ($\chi^2=14.944$, $p<0.01$) or another industry ($\chi^2=16.453$, $p<0.001$) (Hypothesis H6.1). These results; however, might not be related so much to the actual work experience of respondents than to their plans and expectations about the upcoming retirement age. Hence, in their eyes, if they lose their jobs to ATs, they might not be able to requalify to gain new job skills and their age might be a hindrance to being hired by another company in the same or another industry. In any case, the data do not allow us to confirm or refute this conjecture. Unsurprisingly, respondents from Sofia (the capital of Bulgaria, its most developed city, and the only city in the country with over one million inhabitants) have more positive attitude towards automation technologies and consider that they will make life easier ($\chi^2=11.114$, $p<0.01$), more convenient ($\chi^2=10.483$, $p<0.01$), and will eliminate tedious work ($\chi^2=11.907$, $p<0.01$). They are also less afraid of the deskilling effect of automation technologies on their jobs ($\chi^2=8.248$, $p<0.05$). However, the effect of place of living on automation fears remains marginal (Hypothesis H4.5).

Looking at the other statements on Table 2 some additional conclusions can be made. In terms of gender, men evaluate the benefits of automation technologies for society and their advantages compared to human employees much higher than women do (most $p<0.001$). Part of the

explanation for this result might be the greater confidence male respondents reported to have compared to females in regard to the use of computers ($U=23161.5$, $p<0.001$) and electronic devices ($U=24436.5$, $p<0.001$), and in their knowledge and skills to use automation technologies ($U=22267$, $p<0.001$). Respondents with higher perceived economic wellbeing agree more with the statements that ATs improve the standard of living ($\chi^2=15.015$, $p<0.001$) and make our life more convenient ($\chi^2=13.187$, $p<0.001$) compared to respondents with average and lower perceived economic wellbeing. Moreover, they have more positive perceptions about the current ($\chi^2=20.840$, $p<0.001$) and future ($\chi^2=15.223$, $p<0.001$) impacts of automation technologies on their lives. It seems that a person's economic comfort gives the individual the sense of security that undermines the fears of automation. Thus, economic vulnerability may actually be the construct that makes respondents wary of technological threats to whatever wealth that they have in life.

4.3. Factor analysis

Table 4 presents the results of the factor analysis. As evident from the values of Cronbach alpha (above 0.7) and composite reliability (above 0.8), all constructs have high convergent reliability. For one of the factors ('Disadvantages' of automation technologies compared to human employees) the Cronbach alpha is just below the acceptable value ($\alpha=0.691$) but the respective composite reliability value ($CR=0.801$) is sufficiently high. Two of the items in the 'Dehumanisation' factor, and one in 'Technological skills' were deleted due to low factor loadings. The average extracted variance (AVE) ranges from 39.412% ('Disadvantages') to 66.577% ('Professionalism'). Table 5 compares the square root of AVE of the constructs (on the diagonal) with the inter-construct bivariate Pearson correlations (below the diagonal). The results confirm the discriminant validity of the factors because the square root of AVE of each construct is higher than the bivariate Pearson correlations with the other constructs, hence the factors are sufficiently distinct from each other and can be used in regression analysis as independent variables.

INSERT TABLE 4 AROUND HERE

INSERT TABLE 5 AROUND HERE

4.4. Regression analysis

Table 6 presents the regression analysis results. Two models were developed. Model 1 considers only the constructs, while Model 2 includes other control variables as well. The values

of the VIF and tolerance statistics indicate that there is no multicollinearity. The models have good predictive power, explaining 28.8% (Model 1) and 29.7% (Model 2) of the variation of the dependent variable. The findings reveal that the fear of automation is stimulated by the perceptions of dehumanisation impacts of automation technologies on society as whole (Model 1: $t=4.196$, $p<0.001$; Model 2: $t=4.023$, $p<0.001$) (Hypothesis H1.2), the automatability of a person's job (Model 1: $t=7.083$, $p<0.001$; Model 2: $t=7.203$, $p<0.001$) (Hypothesis H5.1), and social influence (Model 1: $t=-3.380$, $p<0.001$; Model 2: $t=-3.130$, $p<0.001$ – note that fear, unlike social influence, is a reverse coded variable, thus a minus sign indicates a positive relationship) (Hypothesis H7). At the same time, higher self-image of professionalism decreases the fear of automation (Model 1: $t=3.591$, $p<0.001$; Model 2: $t=3.884$, $p<0.001$ – due to the coding of fear statements, the positive sign here indicates a negative relationship) (Hypothesis H3.2). Put in other words, the fear of automation is nurtured by a respondent's generally negative opinion about the impacts of automation technology on society, the characteristics of his/her job and how easily it can be automated, and the peer pressure. On the other hand, confidence in the preparedness to work at the current (most recent) job, good work performance, and staying up to date with the latest developments in the field, decrease the fear of respondents of losing their jobs due to automation. All other variables ('Perceived benefits' /H1.1/, 'Advantages' of automation technologies compared to human employees /H2.1/, 'Innovative personality' /H3.1/, 'Technological skills' /H3.3/, work experience /H6.1/, years on the job /H6.2/, job level /H5.2/, education /H4.3/, age /H4.2/, and gender /H4.1/) do not seem to be related to the fear of automation.

INSERT TABLE 6 AROUND HERE

Figure 1 summarises the factors that influence the fear of automation.

INSERT FIGURE 1 AROUND HERE

4.5. *Solutions to automation fears*

Table 7 presents the findings about individual and social solutions that can be implemented by the respondents themselves, by the governments or corporations in order to decrease the fear of automation. Results clearly indicate that respondents prefer individual solutions such as to learn how to utilise automation technologies and be more productive on their current jobs ($m=6.01$) and improve their qualifications ($m=5.43$), and the differences with the average responses to

the statements for the other solutions are statistically significant (all Wilcoxon signed ranks test values significant at $p < 0.001$). Furthermore, corporate solutions such as free qualification for displaced employees ($m=4.99$), work sharing and reduced working hours ($m=4.69$), evaluation of the impacts of ATs on jobs by manufacturers ($m=4.49$), and users of technologies ($m=4.48$) find some support among Bulgarians. However, social solutions that require the involvements of the government such as taxing automation technologies ($m=3.14$), provision of basic income guarantee ($m=3.07$) or hiring people displaced by automation ($m=2.53$) are generally rejected, with the exception of the provision of free education ($m=4.71$). Therefore, we may conclude that respondents consider that solutions to automation fears lie first in the hands of the employees, then the corporations, and, finally – the government; i.e., those most affected by automation have the responsibility to cope with its consequences.

INSERT TABLE 7 AROUND HERE

The Mann-Whitney U-test and Kruskal-Wallis χ^2 -test showed that age (Hypothesis H8.2), education (H8.3), work experience (H10), and job level (H9) have no or negligible effect on respondents' support for the solutions to automation fears (Table 7). Female respondents seem more socially engaged than males and provide more support to social solutions such as basic income for displaced workers ($U=22231.5$, $p < 0.001$), taxing automation technologies ($U=25301.5$, $p < 0.001$), government obligation to hire all displaced workers ($U=23604.5$, $p < 0.001$), and financial incentives to companies to use human employees instead of ATs ($U=23604.5$, $p < 0.001$) (Hypothesis H8.1). However, both females and males have generally very low support to government-regulated social solutions. The 'Confidants' are more eager to learn how to use automation technologies ($U=15781$, $p < 0.001$) and improve their qualification ($U=17695$, $p < 0.05$), while the 'Neutrals' prefer to search for a new job in the same ($U=16134$, $p < 0.001$) or another industry ($U=14329$, $p < 0.001$). Metaphorically, we can say that the 'Confidants' prefer to fight, with the 'Neutrals' – to flight. Furthermore, the 'Neutral' provide much greater support to the social and corporate solutions than the 'Confidants', hence transferring the responsibility of finding a solution from themselves to the companies and, especially, the government. Additionally, respondents with a perceived economic wellbeing lower than the average for the country are more supportive of free education ($\chi^2=10.217$, $p < 0.01$), taxing automation technologies ($\chi^2=11.134$, $p < 0.01$), and evaluation of the impact of automation technologies by their producers ($\chi^2=12.794$, $p < 0.01$) and users ($\chi^2=14.786$, $p < 0.001$) (Hypothesis H8.4). Finally, respondents living in the capital city are much less

inclined to accept government-created jobs ($\chi^2=11.257$, $p<0.01$) or financial support to companies for job creation ($\chi^2=10.004$, $p<0.01$) (Hypothesis H8.5).

INSERT TABLE 8 AROUND HERE

The exploratory factor analysis of the solutions statements (see Table 8) extracted five factors which we named ‘Economic solutions,’ ‘Targeted solutions,’ ‘Socialist solutions,’ ‘Escapism,’ and ‘Self-improvement’ with relatively high composite reliability values (excluding for ‘Targeted solutions’) that explain 60.695% of the variance in respondents’ answers. The first group, ‘Economic solutions’ (CR=0.867, VE=27.671%), includes solutions to automation fears that require AT manufacturers and users to evaluate the impact of these technologies on jobs, involve the government through taxes on automation technologies and financial incentives for companies to use human employees, and customers’ boycott of companies that substitute employees with automation technologies. All these solutions are strong economic mechanisms of managing the impacts of ATs on jobs, hence the name of the group. The second group, ‘Targeted solutions’ (CR=0.641, VE=10.224%), includes mostly actions targeted to those human workers who have lost their jobs due to automation, namely free education, government employment, and basic income. The third group, ‘Socialist solutions’ (CR=0.726, VE=8.682%), includes mostly actions that are mostly directed to all employees such as work sharing and reduced working hours, free education, and basic income for all citizens. The fourth group, ‘Escapism’ (CR=0.922, VE=7.394%), includes individual actions related to looking for a new unautomatable job in the same or another industry, while the last fifth group, ‘Self-improvement’ (CR=0.878, VE=6.724%) includes two individual proactive solutions related to increasing the qualification and learning to use automation technologies in order to be more productive.

Table 9 provides the summary results for the hypotheses.

INSERT TABLE 9 AROUND HERE

5. Discussion

The findings illustrate a great deal about how people approach the challenges of automation in the workplace and their preferred solutions to problems introduced by automation. The data show that there are demographic and attitudinal segmentations of the population that give

analytical insight into understanding how people approach automation and the policy solutions they prefer with regards to the challenges of the automation of the workplace. From the most descriptive of statistics from the data, we see that the Bulgarian sample is consistent with McClure's (2018) findings of a US sample – technophobes are a minority. We see that respondents have few fears of being replaced by automation in the workplace (as Table 2 shows), illustrating that the respondents are not particularly concerned about automation technologies in the workplace. These data also show that respondents generally are of the mindset that technologies are not likely to be substitutes for human labour. So it seems that from a broad perspective, the respondents do not fear going “the way of the horse,” something speculated that would happen to humans in an economy with substantial automation (Brynjolffson & McAfee; 2015). Thus, the general sentiments of these Bulgarian respondents on ATs runs counter to what others (Autor & Salomons 2018; Frey & Osborn, 2017; Berg, Buffie & Zanna, 2018) in academic literature have speculated. While those academics argue technologies are more likely to replace human labour than enhance it, the respondents in this sample understand the automation in a different way, either not fearing it will replace them or considering it as something enhancing them in the workplace. This finding from the Bulgarian sample runs counter to Walsh's (2018) expectation that people would overestimate the substitutability of automation for human labour.

There are clear segments of the Bulgarian sample who are more concerned about their job security and how new technologies threaten their sense of job security but the segments are not demographically defined. The analysis generally shows that simple demographic variables have little value in terms of explaining variations in fears of automation. This is very true of the “usual suspect” in social science analysis, gender. There is no substantial evidence to suggest that gender influences automation fears among those in the sample, despite the very different jobs that males and females do in the economy. So, while there may be an objective difference in how automation will impact men and women in the workplace (Kral et al., 2019), the findings do not show that gender has an impact upon automation fears. While a great deal of research with regards to automation and perceptions of robots highlights that females and males perceive robots and other technologies differently (see, for example, Hudson et al., 2017; Reick-Stieber & Eyssel, 2015; Pochwatko et al., 2015; Katz & Halpern, 2014), there is little or no evidence that females and males experience automation fears differently. However, gender seems to influence so much of the responses in the data analysed apart from automation fears, which

makes the findings consistent with other research on attitudes towards automation and gender influences (Ivanov, Webster, & Garenko, 2018; Ivanov, Webster, & Seyyedi, 2018).

However, there is evidence that the age of respondents impacts upon perceptions towards technology, as speculated by Kolnhofer-Derecskei, Reicher & Szeghegyi (2017). Indeed, of all the demographic variables investigated to look into what impacts upon the automation fears of this sample, only the age of the respondents seems to influence how respondents perceive issues linked with their job security and career trajectory in a consistent manner. The data show that younger people are more hopeful and flexible, while older people are less flexible and less willing to invest time in retooling themselves for the workplace. So there seems to be evidence that the human life cycle influences how a human looks upon the threat of automation in the workplace.

The other demographic variables are failures in terms of their conditioning of the automation fears of the respondents. For respondents, it seems that their wealth, education, or whether they are urban or rural plays little or no role in influencing how they perceive the threats to their jobs because of automation. While there is evidence that people in urban centres have a different approach to some questions asked of the sample, there is little evidence that whether a person lives in a rural setting or big city that this will influence automation fears. So while the findings of some of the views on automation seem to be occasionally influenced by whether a person lives in an urban or rural environment, something consistent with the findings of other (Ivanov, Webster, and Garenko, 2018; Hudson *et al.*, 2017), it seems that this plays little or no role in how a person fears that automation may threaten jobs/careers. And this is even more true for education levels, as it seems that there is no evidence that the education level of a respondent would influence her/his fears with regards to automation of the workplace. The lack of a relationship of attitudes with the education level of respondents echoes the findings of Ivanov, Webster, and Garenko (2018), showing that education, even if used as lone indicator, shows no important relationship with attitudes towards automation in workplaces.

While demographics, apart from the age of a respondent, fail to explain automation fears, there are some attitudes and characteristics that have some predictive ability to explain automation fears. In terms of attitudes, the findings show that respondents who perceive that automation dehumanizes the world are more likely to have automation fears. These data suggest that those who have concerns that technologies will dehumanize the world, also fear for the impact of

such technologies in the workplace. Thus, the data suggest that the respondents who fear automation in the workplace may actually fear a world in which the human is replaced by machines, meaning the world will be designed around machines, rather than people. This mindset is consistent with what other authors have speculated about (see, for example; Bhattacharyya, & Nair, 2019; Danaher, 2019; Leonhard, 2016) and others have found empirical evidence for (Tussyadiah, Zach & Wang, 2017). Also, it seems that those who consider themselves to be professional are less likely to fear automation, supporting the findings of others (Nikou & Economides, 2017) to show that self-perception plays a role in influencing acceptance and fears of new technologies. That peer-pressure plays a role in influencing fears of automation is consistent with previous research (Madigan et al., 2017), showing that peer-pressure is a factor influencing perceptions of technologies. The findings also show that a key characteristic of a person's job can influence a person's fear of automation, something consistent with the findings of Coupe (2019).

In terms of solutions to automation of the workplace, this work adds to the previous literature (Ivanov, 2017; Nam, 2019; Stevens & Marchant, 2017) by illustrating that there are different levels of support for different types of solutions among the public. First, there is strong evidence that gender plays a role in influencing preferences for solutions to the challenges of automation of the workplace. Females seem much more engaged in various solutions to the challenges of automation, supporting improving of their qualifications (individual solution), various corporate solutions, and more governmental intervention via training, taxation, and other methods to cushion workers from the impact of automation of the workplace. This finding is consistent with the findings of Nam (2019), suggesting that gender plays a noteworthy role in terms of preferences for policies to deal with the incorporation of new technologies into the workplace. Unsurprisingly, those who are less wealthy seem to be more in favour of government/intervention than others. However, there is some indication that those in the capital city are less likely to support solutions that involve the government creating jobs or subsidizing companies for creating jobs.

The paradox of the findings is that gender plays little or no role in terms of conditioning a fear of automation but is useful in terms of explaining preferences for solutions to automation. This is one of the interesting findings, since while it seems that gender plays a significant role in terms of how one experiences the workplace, it seems to play little or no role in terms of how an individual processes the threat of automation in the workplace. However, when faced with

policy choices with regards to how automation of the workplace should be dealt with, males and females seem to have very different opinions of which policies should be followed. What is also interesting or enigmatic about the findings with regards to gender is that the data show that males and females generally have a statistically different view on many questions with regards to automation in the workplace, except when it comes to automation fears. So, the data seem to show that gender seems to matter in most things tested for, except automation fears.

6. Conclusion

6.1. Contribution

This paper aimed at evaluating the drivers and the solutions to automation fears by using Bulgaria as a case study country. Its theoretical contributions are several. First, the automation fears are assessed for a transition economy (Bulgaria), unlike the previous studies that concentrated on developed countries. Hence, our research extends the cultural and geographic scope of studies on automation fears. Second, the paper elaborates on seven groups of factors that (may) influence the automation fears, namely: *general perceptions of automation technologies* (perceived benefits and dehumanization), the *characteristics of automation technologies as production factors* compared to human employees (perceived advantages and disadvantages), *demographic characteristics* of respondents (education, age, gender, place of living, and perceived economic well-being), their *self-perception* (innovativeness, technological skills, and professionalism), *job characteristics* (job automatability and job level), *work experience* of respondents (number of years on a particular job position and total work experience), and *social influence*. Therefore, the paper considers factors that are associated to human employees, to automation technologies, to job positions, and to external social pressure. The findings revealed that the automation fear was positively associated to the perceived dehumanisation effect of automation on society, job automatability, and social influence, and negatively associated to the professionalism. Third, the paper discusses respondents' support to various solutions to automation fears on individual, corporate and social level, and identifies the factors that shape it, namely gender, perceived economic wellbeing, and place of living.

6.2. Managerial implications

From a managerial point of view, findings reveal that respondents have very low fear of automation (Table 2) that is shaped mostly by perceived dehumanisation effect of automation technologies, social influence, perceived professionalism, and job automatability (Table 6).

However, that result should not lead managers to adopt a false sense of complacency and they should be responsible to their employees. They should organise meetings with employees in the case that automation technologies are to be introduced in their companies in order to address their potential fears of losing their jobs. They need to emphasise the positive impacts of automation on eliminating operational bottlenecks and providing more time to human employees to focus on creative and revenue generating activities (Schlögl *et al.*, 2019). Managers should realize that their employees are not blank slates and there is evidence that citizens have preferences for solutions to the challenges of automation (Nam, 2019).

Companies need to pay special attention to those workers who are most at risk of being replaced by automation by providing them free requalification programs (Hancock, 2015; Harayama, 2017). They could also introduce work sharing and reduced working hours in order to keep some of the displaced human employees (Table 7). It is important, that managers keep their workers informed about strategic decisions and plans about investing in robots, artificial intelligence and automation technologies, and involve them into the decision-making process because workers should be prepared in advance about their professional future in the current company. Employees should support the decisions regarding the adoption of ATs, because otherwise they may boycott their introduction and effective and efficient usage. Managers need to explain benefits that automation technologies provide and how they eliminate a lot of tedious work with real examples and demonstration with the manufacturer of these automation equipment. Meetings could be organized between companies already using ATs to exchange experience on how to work with employees who are potentially at risk of replacement. Additionally, companies should enrich the job positions with tasks that are more difficult to automate but also more meaningful to human employees, hence indirectly decreasing the fear of employees of losing their jobs due to automation technologies.

In terms of communications, the findings suggest that the attitudes towards the dehumanisation effect of automation technologies play a large role in shaping a person's automation fears rather than demographics. Therefore, the messages to make it easier to promote ATs need not be gendered or crafted for a specific demographic group but should be used to communicate to a group defined by attitudes. Companies that produce and implement ATs need to emphasize on the social benefits of automation as a way to mitigate the perceived dehumanization effect of ATs, which may contribute to decreased automation fears as well.

In addition, there are engineering implications, since the philosophical concepts with regards to the “ironies of automation,” (Bainbridge 1983) are still relevant. While many employees may not really fear being replaced by automation, they may actually fear having more responsibilities and less support, since the concern for the human may take a backseat to concerns with the simple automation of a process. So, while the findings indicate that there are clusters of respondents with different levels of fear of automation, some to the fear may be based on that fact that those human jobs remaining may be much more complicated and have less support than a job that is less automated. Therefore, AT producers need to make their products understandable to the employees who use them in order to address their concerns (Bhargava, Bester & Bolton, 2020) – e.g. hotel revenue managers have to understand how an automated pricing system produces a demand forecast. Obviously, the information about the exact way the ATs operate is a trade secret, but users may need to be familiar with their general principles of their operation. Furthermore, AT producers have to provide training and technical support to adopters of their products. Collaboration between AT producers and users in the design of ATs may be beneficial as well.

6.3. Policy implications

Research findings indicate that Bulgarians support mostly individual solutions to automation fears, rather than social ones – they would prefer to improve their qualification in order to perform on their current jobs better than automation technologies, or to learn how to use them more productively rather than relying on some social benefits provided by the government (Table 7). However, confronting automation fear is the destiny of the government, but the tools in their arsenal have different efficiency. Policy makers need to invest in education in order to prepare human employees to work in a robonomic society where most of goods and services are provided through ATs (Ivanov, 2017). They should also require that companies evaluate and publicly announce the impact of automation technologies on jobs. Taxing ATs, although a politically correct strategy that may attract large populist vote, will not be a viable strategy for mitigating automation fears, due to difficulties in providing a workable legal definition of such technologies. Additionally, despite the fact that basic income does not seem to be supported by respondents at the moment, probably due to the low unemployment rate in the country (3.7% for July-September 2019, NSI, 2019c), this option might be on the table in a decade or so when the impacts of automation technologies on the labour market are stronger, especially if newer more sophisticated autonomous robots cause massive technological unemployment. Therefore, the advances in automation technologies, their improved technical capabilities, lower costs, and

wide adoption by manufacturing and service companies in the future may force governments to search for creative solutions to mitigate not only automation fears, but actual technological unemployment as well.

6.4. Limitations

This paper is not without limitations. First, the sample includes only respondents from Bulgaria; hence, the results are generalisable for this cultural context only. Second, despite authors' efforts in distributing the link to social media groups with potential respondents with various demographic characteristics, the shares of respondents with low level of education and incomes, and above 60 years old remained low. Third, data were collected before the COVID-19 pandemic and it is possible that the perceptions of respondents towards automation technologies have changed.

6.5. Future research directions

Future research may focus on overcoming some of the limitations of this paper, e.g. by replicating the study in other cultural and geographic context. More specifically, a global longitudinal study on automation fears may be implemented that would allow the comparison of automation fears across cultures and their changes in time. Additionally, research can investigate the role of some other job characteristics (e.g. emotional, intellectual, of physical labour dominating in the job position) in respondents' fear of automation, since demographics seems to have limited explanatory power in the analysis. Furthermore, future research may shed insights on the perspectives on employers and policy makers at local, national, and international levels in regard to the solutions to automation fears, so that more can be known about how employees, employers, and government views solutions to automation fears. Research can also investigate whether the official government policies reflect the automation fears of local populations and the role of political ideologies in mitigating the negative impacts of automation. Finally, research can be directed on the ways to finances and evaluation of the efficiency of the various strategies to mitigate automation fears.

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Figure 1. *Factors influencing the fear of automation*

Note: + positive relationship, - negative relationship

Table 1. *Sample characteristics*

Variable	Value	Number of respondents	Percent
<i>Gender</i>	Female	212	42.2
	Male	288	57.4
	Prefer not to say	2	0.4
<i>Age</i>	18-30	134	26.7
	31-40	218	43.4
	41-50	118	23.5
	51-60	27	5.4
	61+	5	1.0
<i>Education</i>	Secondary / high school or lower	65	12.9
	3-year Bachelor/Specialist	37	7.4
	4-year Bachelor	120	23.9
	Master	251	50.0
	Doctorate	29	5.8
<i>Perceived economic wellbeing</i>	Much less wealthy than the average for the country	3	0.6
	Less wealthy than the average for the country	14	2.8
	Slightly less wealthy than the average for the country	31	6.2
	About the average for the country	147	29.3
	Slightly more wealthy than the average for the country	181	36.1
	More wealthy than the average for the country	107	21.3
	Much more wealthy than the average for the country	19	3.8
<i>Place of living</i>	Sofia	278	55.4
	Living in Bulgaria but outside Sofia, including:	196	39.0
	City with 100 000 – 999 999 inhabitants	125	24.9
	Town with 10 000 – 99 999 inhabitants	58	11.6
	Town with less than 10 000 inhabitants	4	0.8
	Village	9	1.8
	Bulgarian citizens who live abroad	28	5.6
Total		502	100.0

Table 1. *Hypothesis testing*

Statements	Mean	St. dev.	Mann-Whitney <i>U</i> -test		Kruskal-Wallis χ^2 -test					
			<i>Gender</i>	<i>Cluster</i>	<i>Age</i>	<i>Education</i>	<i>Wellbeing</i>	<i>Work experience</i>	<i>Job level</i>	<i>Place of living</i>
Attitude										
What is your personal attitude towards automation technologies in general?	6.17	0.958	25745***	14252.5***	3.198	0.194	5.804	1.201	7.131	7.000*
How do you evaluate the current impact of automation technologies on your life?	5.95	1.112	26806.5*	16726.5***	5.312	2.938	20.840***	1.254	8.345*	3.813
How do you evaluate the impact of automation technologies on your life would be in 5 years?	5.94	1.219	27239*	14387.5***	6.508	4.832	15.223***	1.936	3.813	0.621
Perceived benefits										
Automation technologies are (will be) responsible for many of the good things we enjoy in life	5.04	1.474	23424.5***	17350.5**	0.892	5.516	7.738*	0.237	4.854	2.693
Automation technologies (will) improve our standard of living	5.52	1.368	25286.5***	13602***	2.151	3.511	15.015***	3.233	5.266	6.078*
Automation technologies will bring us a bright future	4.79	1.504	25842**	16267***	19.646***	8.115	9.343**	7.273	1.966	3.208
Life is (will be) easier with automation technologies	5.75	1.203	23536***	13572***	4.316	5.402	4.888	1.905	0.713	11.114**
Automation technologies (will) make our lives more convenient	5.99	1.014	24997***	15100.5***	5.632	4.278	13.187***	2.978	3.832	10.483**
Automation technologies (will) eliminate a lot of tedious work for people	6.04	1.064	25821.5**	16015.5***	11.436*	3.277	4.592	7.545	1.307	11.907**
Automation technologies (will) make people happier	4.39	1.517	25493***	16689.5**	14.131**	3.004	9.023*	3.909	1.739	2.023
Advantages										
Automation technologies (will) provide more accurate information than human employees	5.49	1.341	25343***	18021.5*	7.555	3.467	5.278	6.131	4.491	2.889
Automation technologies (will) make fewer mistakes than human employees	5.66	1.262	23133***	17222.5**	4.608	1.643	4.467	0.936	0.957	10.182**
Automation technologies (will) perform faster than human employees	6.19	0.963	22771.5***	16482***	10.549*	12.959*	10.188**	4.287	0.644	17.042***
Automation technologies are (will be) more reliable than human employees	5.30	1.447	22160.5***	145135***	5.926	0.915	9.074*	4.728	1.574	7.420*
Automation technologies (will) have higher productivity than human employees	6.11	1.024	23865.5***	17007.5**	4.784	8.168	3.656	1.820	3.868	9.725**
Automation technologies are (will be) more cost effective than human employees	5.69	1.289	23816***	18312	3.551	5.109	2.878	3.298	5.821	3.023
Dehumanisation										
Automation technologies (will) hurt our human relationships in society (r)	4.18	1.791	27150.5*	14264***	4.701	3.883	5.405	4.590	4.437	4.777
In the future, automation technologies will dominate society (r)	2.70	1.405	28087	20382	8.306	2.312	1.258	10.003	1.198	1.208

Statements	Mean	St. dev.	Mann-Whitney U-test		Kruskal-Wallis χ^2 -test					
			Gender	Cluster	Age	Education	Wellbeing	Work experience	Job level	Place of living
The overuse of automation technologies may be damaging and harmful to human beings (r)	3.85	1.734	28467.5	14849***	1.816	4.396	5137	0.389	3.606	4.964
The overuse of automation technologies may be damaging and harmful to the society as a whole (r)	4.01	1.798	27162*	14762.5***	1.374	3.332	6.753*	4.856	1.935	2.348
Automation technologies (will) dehumanize the workplace (r)	4.37	1.750	27498.5	13106***	1.218	2.517	5.968	5.267	2.396	5.314
Automation technologies (will) lead to deskilling of jobs (r)	3.63	1.802	30108.5	17833*	7.403	20.841***	0.180	5.877	3.826	0.440
Disadvantages										
Automation technologies are (will be) able to deal with/operate only in standard situations (r)	3.31	1.606	26234**	17465*	2.726	2.243	7.471*	4.698	4.964	2.437
Automation technologies (will) lack the creativity of human employees (r)	2.58	1.532	30133	20413	9.604*	1.400	5.423	5.888	1.353	4.191
Automation technologies are (will be) difficult to operate by their intended users (customers, employees) (r)	4.77	1.519	25440.5***	14095***	1.975	2.519	13.564***	1.290	3.401	13.777***
Service provided by automation technologies are (will be) less interactive than services provided by human employees (r)	4.13	1.617	29747	17859.5*	3.395	4.977	3.988	4.247	1.155	9.048*
People feel frustrated when they need to use automation technologies (r)	4.34	1.538	27285.5*	17352**	0.794	0.652	4.347	1.132	4.737	4.965
People prefer to communicate with human employees rather than with automation technologies (r)	3.34	1.678	29764.5	16848**	6.820	3.403	9.547**	2.751	2.892	4.804
Innovative personality										
I consider myself to be creative and original in my thinking and behaviour	5.19	1.331	30300.5	19206	8.036	19.180***	2.819	12.898**	10.120*	3.568
I seek out new ways to do things	5.85	1.044	26491**	15708***	1.302	3.521	9.444**	4.354	14.793**	1.935
I usually adopt new products before my friends do	5.17	1.329	26908*	17787.5*	5.108	15.068**	7.433*	10.989*	8.354*	0.042
Others see me as an innovative person	4.77	1.304	29679.5	18435	11.073*	5.586	13.247***	16.346***	15.297**	4.477
Social influence										
People who are important to me influence my opinion about automation technologies	3.87	1.657	26027**	18689	5.493	5.817	0.311	0.801	1.456	1.253
Media/social media influence my opinion about automation technologies	3.68	1.700	30037	14299.5***	2.977	1.970	1.000	3.576	1.276	3.173
I trust other people's opinions about automation technologies	4.10	1.476	26284.5**	16574.5***	2.325	0.636	4.174	2.999	2.115	0.500
People who are acquainted to me influence my opinion about automation technologies	3.58	1.626	28763.5	18296.5	3.843	6.691	3.246	1.081	0.715	0.452
Technological skills										
It is not (will not be) hard for me to learn to use automation technologies	5.57	1.756	29014	15704.5***	5.382	8.517	0.804	6.167	11.338**	1.348

Statements	Mean	St. dev.	Mann-Whitney U-test		Kruskal-Wallis χ^2 -test					
			Gender	Cluster	Age	Education	Wellbeing	Work experience	Job level	Place of living
I am confident when I use a computer / computer applications / software packages	6.21	0.922	23161.5***	16804***	5.861	2.837	6.681*	2.645	4.929	7.958*
I am confident when I use electronic devices around the house and at work	6.19	0.855	24436.5***	14633.5***	6.367	2.229	8.373*	3.191	2.655	3.509
I have the knowledge and skills to use automation technologies	5.73	1.188	22267***	16816**	3.745	0.910	25.229***	4.466	6.092	10.857**
Professionalism										
I am (was) well prepared for my current (most recent) job	5.87	1.135	30118.5	15909***	8.142	18.399***	15.165***	14.096**	23.519***	2.654
I perform(ed) very well on my current (most recent) job	6.18	0.801	29173	16906**	5.100	3.402	9.017*	6.994	9.136*	6.947*
I stay(ed) up to date with the latest developments in my field	5.66	1.192	28814.5	14977***	2.976	11.191*	14.845***	5.889	26.640***	3.941
Job automatability										
I think it would be easy to automate most of the activities I currently perform(ed) on my job (r)	4.44	1.919	30347.5	15502***	0.598	2.353	1.625	4.389	1.354	0.131
Provided the opportunity, the managers of the company I currently work(ed) for will substitute the human employees with automation technologies (r)	4.02	1.993	24929.5***	14964.5***	2.330	2.328	7.748*	0.800	4.161	1.324
The company I currently work(ed) for uses (or plans to use) actively automation technologies (r)	3.46	1.883	26845*	18305	4.109	8.656	16.014***	0.565	0.984	16.875***
The other companies in the sector use (or plan to use) actively automation technologies (r)	3.68	1.872	25484***	18474	11.012*	3.359	11.014**	1.665	0.484	0.222
Fear										
I fear I might lose my current job due to automation technologies within the next 5 years (r)	6.00	1.205	29119	6205.5***	16.675**	2.214	2.176	5.117	3.621	3.829
I fear that, if I lose my current job due to automation, I will not be able to find a new job in the same industry (r)	5.80	1.411	28199	2964***	13.767**	1.605	1.753	14.944**	7.933*	1.567
I fear that, if I lose my current job due to automation, I will not be able to find a new job in another industry (r)	5.90	1.299	25850**	5110***	17.836***	1.364	0.801	16.453***	4.081	2.730
I fear that if my salary is increased, my company will have good reason to automate my job (r)	5.59	1.456	29896.5	4612***	10.485*	1.336	2520	5.731	1.713	4.442
I fear that the use of automation technologies will cause deskilling of my current job and the company will hire someone with lower education / skills (r)	5.78	1.350	28574	5103.5***	2.286	0.569	2.582	2.127	8.458*	8.248*
I fear that the use of automation technologies on my current job will require knowledge and skills that I do not have (r)	5.61	1.439	29210	5634.5***	5.341	1.319	1.220	7.366	4.418	7.666*

Notes: 1. Levels of significance: *** p<0.001, ** p<0.01, * p<0.05; 2. All statements measured on a 7-point level of agreement scale (from 1-completely disagree to 7-completely agree), excluding the statements on attitudes which are measured on a 7-point scale between from 1-extremely negative to 7-extremely positive; 3. (r) - reverse coding; 4. Grouping variables: *Gender* (male/female), *Cluster* ('Confidents'/'Neutrals'), *Age* (18-30, 31-40, 41-50, 51-60, 61+), *Education* (Secondary / high school or lower,

3-year Bachelor/Specialist, 4-year Bachelor, Master, Doctorate), *Perceived economic wellbeing* (Lower than average for the country, About the average for the country, Higher than the average for the country), *Work experience* (<10, 11-20, 21-30, 31+ years), *Job level* (No managerial or supervisory responsibilities, Supervisory role, Middle management, Top management), *Place of living* (Sofia, in Bulgaria outside Sofia, abroad).

Table 3. *Clusters' characteristics*

Variable	Value	Number of respondents		Chi-square
		<i>Confidants</i>	<i>Neutrals</i>	
<i>Gender</i>	Female	168	44	0.525
	Male	228	60	
	Prefer not to say	2	0	
<i>Age</i>	18-30	112	22	9.441
	31-40	172	46	
	41-50	93	25	
	51-60	16	11	
	61+	5	0	
<i>Education</i>	Secondary / high school or lower	48	17	2.607
	3-year Bachelor/Specialist	32	5	
	4-year Bachelor	96	24	
	Master	200	51	
	Doctorate	22	7	
<i>Perceived economic wellbeing</i>	Much less wealthy than the average for the country	2	1	15.764*
	Less wealthy than the average for the country	10	4	
	Slightly less wealthy than the average for the country	18	13	
	About the average for the country	111	36	
	Slightly more wealthy than the average for the country	151	30	
	More wealthy than the average for the country	92	15	
	Much more wealthy than the average for the country	14	5	
<i>Place of living</i>	Sofia	231	47	9.104
	Living in Bulgaria but outside Sofia, including:	146	50	
	City with 100 000 – 999 999 inhabitants	94	31	
	Town with 10 000 – 99 999 inhabitants	43	15	
	Town with less than 10 000 inhabitants	4	0	
	Village	5	4	
	Bulgarian citizens who live abroad	21	7	
Total		398	104	

Note: * Significant at $p < 0.05$

Table 4. *Factor analysis*

Factors	Factor loading	Cronbach's Alpha	Composite reliability	Eigenvalue	Variance explained	KMO	Bartlett
FACTOR 1: Fear		0.868	0.928	3.641	60.69%	0.888	1292.991***
I fear I might lose my current job due to automation technologies within the next 5 years	0.793						
I fear that, if I lose my current job due to automation, I will not be able to find a new job in the same industry	0.840						
I fear that, if I lose my current job due to automation, I will not be able to find a new job in another industry	0.810						
I fear that if my salary is increased, my company will have good reason to automate my job	0.763						
I fear that the use of automation technologies will cause deskilling of my current job and the company will hire someone with lower education / skills	0.765						
I fear that the use of automation technologies on my current job will require knowledge and skills that I do not have	0.696						
FACTOR 2: Perceived social benefits		0.878	0.932	4.115	58.792%	0.892	1649.591***
Automation technologies are (will be) responsible for many of the good things we enjoy in life	0.744						
Automation technologies (will) improve our standard of living	0.817						
Automation technologies will bring us a bright future	0.799						
Life is (will be) easier with automation technologies	0.800						
Automation technologies (will) make our lives more convenient	0.807						
Automation technologies (will) eliminate a lot of tedious work for people	0.622						
Automation technologies (will) make people happier	0.760						
FACTOR 3: Advantages		0.855	0.926	3.584	59.725%	0.873	1302.878***
Automation technologies (will) provide more accurate information than human employees	0.721						
Automation technologies (will) make fewer mistakes than human employees	0.822						
Automation technologies (will) perform faster than human employees	0.801						
Automation technologies are (will be) more reliable than human employees	0.833						
Automation technologies (will) have higher productivity than human employees	0.821						
Automation technologies are (will be) more cost effective than human employees	0.616						
FACTOR 4: Dehumanization		0.865	0.934	2.993	49.880%	0.816	1047.169***
Automation technologies (will) hurt our human relationships in society	0.835						
The overuse of automation technologies may be damaging and harmful to human beings	0.858						
The overuse of automation technologies may be damaging and harmful to the society as a whole	0.855						

Factors	Factor loading	Cronbach's Alpha	Composite reliability	Eigenvalue	Variance explained	KMO	Bartlett
Automation technologies will dehumanize the workplace	0.788						
FACTOR 5: Disadvantages		0.691	0.801	2.365	39.412%	0.734	453.122***
Automation technologies are (will be) able to deal with/operate only in standard situations	0.653						
Automation technologies (will) lack the creativity of human employees	0.545						
Automation technologies are (will be) difficult to operate by their intended users (customers, employees)	0.654						
Service provided by automation technologies are (will be) less interactive than services provided by human employees	0.692						
People feel frustrated when they need to use automation technologies	0.577						
People prefer to communicate with human employees rather than with automation technologies	0.633						
FACTOR 6: Innovative personality		0.721	0.865	2.200	55.009%	0.699	429.872***
I consider myself to be creative and original in my thinking and behaviour	0.675						
I seek out new ways to do things	0.720						
I usually adopt new products before my friends do	0.734						
Others see me as an innovative person	0.829						
FACTOR 7: Social influence		0.783	0.898	2.440	61.009%	0.756	595.453***
People who are important to me influence my opinion about automation technologies	0.833						
Media/social media influence my opinion about automation technologies	0.686						
I trust other people's opinions about automation technologies	0.748						
People who are acquainted to me influence my opinion about automation technologies	0.846						
FACTOR 8: Technological skills		0.800	0.917	2.352	58.791%	0.735	590.292***
I am confident when I use a computer / computer applications / software packages	0.858						
I am confident when I use electronic devices around the house and at work	0.857						
I have the knowledge and skills to use automation technologies	0.799						
FACTOR 9: Professionalism		0.738	0.899	1.997	66.577%	0.680	352.629***
I am (was) well prepared for my current (most recent) job	0.847						
I perform(ed) very well on my current (most recent) job	0.786						
I stay(ed) up to date with the latest developments in my field	0.814						
FACTOR 10: Job automatability		0.702	0.859	2.147	53.686%	0.696	408.001***
I think it would be easy to automate most of the activities I currently perform(ed) on my job	0.575						
Provided the opportunity, the managers of the company I currently work(ed) for will substitute the human employees with automation technologies	0.694						

Factors	Factor loading	Cronbach's Alpha	Composite reliability	Eigenvalue	Variance explained	KMO	Bartlett
The company I currently work(ed) for uses (or plans to use) actively automation technologies	0.801						
The other companies in the sector use (or plan to use) actively automation technologies	0.833						

Table 5. *Discriminant validity matrix*

Factors	Fear	Perceived social benefits	Advantages	Dehumanisation	Disadvantages	Innovative personality	Social influence	Technological skills	Professionalism	Job automatability
Fear	0.7790									
Perceived social benefits	0.300***	0.7668								
Advantages	0.238***	0.679***	0.7728							
Dehumanisation	0.369***	0.525***	0.342***	0.7063						
Disadvantages	0.255***	0.343***	0.341***	0.574***	0.6278					
Innovative personality	0.176***	0.359***	0.275***	0.129**	0.077	0.7417				
Social influence	-0.221***	0.038	-0.034	-0.076	-0.100*	0.024	0.7811			
Technological skills	0.238***	0.428***	0.368***	0.200***	0.116**	0.521***	-0.097*	0.7668		
Professionalism	0.261***	0.288***	0.280***	0.107*	0.083	0.432***	-0.072	0.412***	0.8159	
Job automatability	0.252***	-0.150***	-0.116**	0.035	-0.025	-0.239***	-0.184***	-0.178***	-0.097*	0.7327

Notes: 1. The diagonal cells indicate the square root of AVE. Bivariate Pearson correlations in the cells below the diagonal. 2. Levels of significance: *** p<0.001, ** p<0.01, * p<0.05;

Table 6. *Regression analysis results*

Independent variables	Model 1								Model 2							
	Unstandardized Coefficients		Standardized Coefficients	t	95% Confidence interval for B		Collinearity Statistics		Unstandardized Coefficients		Standardized Coefficients	t	95% Confidence interval for B		Collinearity Statistics	
	B	Std. Error	Beta		Lower bound	Upper bound	Tolerance	VIF	B	Std. Error	Beta		Lower bound	Upper bound	Tolerance	VIF
<i>Dependent variable: Fear (r)</i>																
(Constant)	-0.001	0.038		-0.022	-0.075	0.073			0.258	0.247		1.045	-0.227	0.744		
Factor: Perceived social benefits	0.102	0.060	0.102	1.685	-0.017	0.220	0.392	2.549	0.091	0.061	0.091	1.488	-0.029	0.211	0.378	2.642
Factor: Dehumanisation (r)	0.218	0.052	0.218	4.196***	0.116	0.320	0.528	1.893	0.211	0.052	0.210	4.023***	0.108	0.314	0.518	1.932
Factor: Advantages	0.012	0.053	0.012	0.232	-0.092	0.117	0.506	1.977	-0.005	0.054	-0.005	-0.091	-0.111	0.101	0.482	2.074
Factor: Disadvantages (r)	0.058	0.047	0.058	1.226	-0.035	0.151	0.636	1.572	0.069	0.047	0.069	1.458	-0.024	0.162	0.628	1.592
Factor: Innovative personality	0.066	0.047	0.066	1.402	-0.027	0.159	0.636	1.572	0.086	0.048	0.086	1.786	-0.009	0.181	0.607	1.646
Factor: Social influence	-0.133	0.039	-0.133	-3.380***	-0.210	-0.056	0.921	1.086	-0.124	0.040	-0.124	-3.130**	-0.202	-0.046	0.896	1.116
Factor: Technological skills	0.079	0.048	0.079	1.631	-0.016	0.173	0.614	1.629	0.061	0.049	0.061	1.255	-0.034	0.156	0.597	1.674
Factor: Professionalism	0.157	0.044	0.157	3.591***	0.071	0.242	0.748	1.337	0.177	0.045	0.177	3.884***	0.087	0.266	0.684	1.462
Factor: Job automatability (r)	0.284	0.040	0.284	7.083***	0.205	0.362	0.888	1.126	0.291	0.040	0.291	7.203***	0.211	0.370	0.868	1.152
Work experience									-0.005	0.009	-0.041	-0.568	-0.022	0.012	0.273	3.664
Job level									0.027	0.038	0.029	0.707	-0.047	0.101	0.826	1.211
Years on the job									-0.014	0.013	-0.048	-1.106	-0.039	0.011	0.750	1.332
Education									0.016	0.036	0.018	0.458	-0.054	0.087	0.876	1.141
Age									-0.009	0.008	-0.079	-1.099	-0.024	0.007	0.276	3.622
Gender									0.068	0.078	0.035	0.879	-0.085	0.221	0.874	1.144
R	0.549								0.564							
R Square	0.301								0.318							
Adjusted R Square	0.288								0.297							
F-statistic	23.492***								14.993***							
Standard Error of the Estimate	0.8445								0.8400							

Note: 1. Levels of significance: *** p<0.001, ** p<0.01; 2. (r) - reverse coding.

Table 7. Solutions to automation fears

Statements	Mean	Standard deviation	Mann-Whitney U-test		Kruskal-Wallis χ^2 -test					
			Gender	Cluster	Age	Education	Wellbeing	Work experience	Job level	Place of living
Individual solutions:										
I will try to improve my qualification in order to perform on my current job better than the automation technologies	5.43	1.528	26361.5**	17695*	0.816	4.383	5.020	3.824	3.212	0.121
I will try to learn how to use automation technology to be more productive on my current job	6.01	1.140	29291	15781***	5.574	1.678	3.680	0.998	2.069	1.778
I will look for a job in the industry I currently work in that is not going to be automated soon	3.80	1.821	29309.5	16134***	7.069	16.070**	0.679	6.759	12.475**	5.432
I will look for a job in a different industry that in not going to be automated soon	3.44	1.808	29585.5	14329***	1.130	11.177*	0.519	3.564	8.687*	7.499*
I will not undertake anything	2.29	1.552	28900.5	16448***	9.405	14.419**	2.855	6.660	0.730	4.040
Corporate solutions:										
Producers of automation technologies should evaluate and publicly announce the impact of automation technologies on jobs	4.49	1.842	25582.5**	16612.5**	6.858	5.139	12.794**	6.269	3.206	5.629
Companies that use automation technologies should evaluate and publicly announce the impact of automation technologies on jobs before these technologies are being adopted by them	4.48	1.836	25411.5***	16479.5***	4.726	3.337	14.786***	4.967	2.481	5.886
Companies should introduce work sharing and reduced working hours for employees	4.69	1.613	29240.5	19812	5.062	5.064	0.770	2.874	2.034	0.862
Companies should provide free requalification for displaced employees	4.99	1.721	24874.5***	16118***	7.238	5.239	4.882	3.134	5.601	1.042
Consumers should boycott companies that substitute their employees with automation technologies	2.20	1.409	24820***	13313.5	4.558	1.834	10.564**	1.117	4.535	13.390***
Social solutions:										
The government should provide free education to everyone to improve their qualification	4.71	1.804	29141.5	19032	2.774	5.745	10.217**	6.267	1.487	1.664
The government should provide free education only to those who have lost their jobs due to automation technologies	3.19	1.832	27132*	17361**	1.513	16.784**	0.576	6.636	0.626	9.300**
The government should provide basic income to every citizen of the country	3.07	2.005	30126	17864*	6.243	6.499	5.728	1.533	8.707*	6.103*
The government should provide basic income only to those who have lost their jobs due to automation technologies	3.07	1.769	22231.5***	14730***	5.635	7.650	5.571	4.000	4.163	4.664
The government should tax automation technologies	3.14	1.907	25301.5***	14360***	7.811	0.589	11.134**	4.743	1.780	4.079
The government should hire everyone who has lost his/her job due to automation technologies	2.53	1.669	23604.5***	15097.5***	3.764	3.382	5.773	0.934	2.506	11.257**

The government should provide financial incentives to companies to use human employees rather than automation technologies	3.18	1.864	24526***	14781.5***	6.446	7.742	6.507*	5.747	2.782	10.004**
The government should impose strict birth control on population	2.47	1.832	27325.5*	18841.5	3.609	4.380	5.260	5.967	4.844	9.561**

Notes: 1. Levels of significance: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$; 2. All statements measured on a 7-point level of agreement scale (from 1-completely disagree to 7-completely agree). 3. Grouping variables: *Gender* (male/female), *Cluster* ('Confidants' / 'Neutrals'), *Age* (18-30, 31-40, 41-50, 51-60, 61+), *Education* (Secondary / high school or lower, 3-year Bachelor/Specialist, 4-year Bachelor, Master, Doctorate), *Perceived economic wellbeing* (Lower than average for the country, About the average for the country, Higher than the average for the country), *Work experience* (<10, 11-20, 21-30, 31+ years), *Job level* (No managerial or supervisory responsibilities, Supervisory role, Middle management, Top management), *Place of living* (Sofia, in Bulgaria outside Sofia, abroad).

Table 8. *Exploratory factor analysis from the solutions items*

Factors	Factor loading	Cronbach's Alpha	Composite reliability	Eigenvalue	Variance explained
FACTOR 1: Economic solutions		0.813	0.867	4.704	27.671%
Producers of automation technologies should evaluate and publicly announce the impact of automation technologies on jobs before these technologies are being introduced by them	0.809				
Companies that use automation technologies should evaluate and publicly announce the impact of automation technologies on jobs before these technologies are being adopted by them	0.793				
The government should provide financial incentives to companies to use human employees rather than automation technologies	0.703				
The government should tax automation technologies	0.629				
Consumers should boycott companies that substitute their employees with automation technologies	0.612				
FACTOR 2: Targeted solutions		0.647	0.641	1.738	10.224%
The government should impose strict birth control on population	0.622				
The government should provide free education only to those who have lost their jobs due to automation technologies	0.614				
The government should hire everyone who has lost his/her job due to automation technologies	0.533				
The government should provide basic income only to those who have lost their jobs due to automation technologies	0.520				
FACTOR 3: Socialist solutions		0.622	0.726	1.476	8.682%
Companies should introduce work sharing and reduced working hours for employees	0.719				
The government should provide free education to everyone to improve their qualification	0.640				
The government should provide basic income to every citizen of the country	0.605				
Companies should provide free requalification for displaced employees	0.519				
FACTOR 4: Escapism		0.771	0.922	1.257	7.394%
I will look for a job in a different industry that is not going to be automated soon	0.887				
I will look for a job in the industry I currently work in that is not going to be automated soon	0.878				
FACTOR 5: Self-improvement		0.592	0.878	1.143	6.724%
I will try to improve my qualification in order to perform on my current job better than the automation technology	0.855				
I will try to learn how to use the automation technology to be more productive on my current job	0.818				
Total variance explained					60.695%

Notes: 1. One item ('I will not undertake anything') excluded due to low factor loading; 2. Coding: 1-completely disagree, 7-completely agree; 3. Extraction method: Principal Component Analysis; Rotation method: Varimax with Kaiser Normalization. Rotation converged in 6 iterations; KMO Measure of Sampling Adequacy=0.805; Bartlett's test of Sphericity: $\chi^2=2507.585$, $df=136$, $p=0.000$; overall Cronbach alpha of all items: $\alpha=0.798$; overall Composite reliability of all items: $CR=0.9543$.

Table 9. *Support for the research hypotheses*

Hypotheses	Result	Note
GROUP 1: Automation fears		
1. General perceptions of automation technologies:		
H1.1. Perceived social benefits of automation technologies are negatively related to the fear of automation	Not supported	
H1.2. Perceived dehumanisation effect of automation technologies is positively related to the fear of automation	Supported	
2. Characteristics of automation technologies as production factors compared to human employees:		
H2.1. Perceived advantages of automation technologies compared to human employees are positively related to the fear of automation technologies	Not supported	
H2.2. Perceived disadvantages of automation technologies compared to human employees are negatively related to the fear of automation technologies	Not supported	
3. Self-perception of human employees:		
H3.1. People who consider themselves as innovative are less afraid of losing their jobs to automation technologies	Not supported	
H3.2. People who consider themselves as professionals are less afraid of losing their jobs to automation technologies	Supported	
H3.3. People with higher technological skills are afraid of losing their jobs to automation technologies	Not supported	
4. Demographic characteristics:		
H4.1. Men have higher fear of automation	Not supported	Supported by the Kruskal-Wallis χ^2 test (Table 2), but not by the regression analysis (Table 6) when all variables are taken into consideration
H4.2. Younger people are less afraid of losing their jobs to automation technologies	Partially supported	
H4.3. More educated people are less afraid of losing their jobs to automation technologies	Not supported	
H4.4. Perceived economic wellbeing is negatively associated to the fear of automation	Not supported	
H4.5. People living outside the metropolitan areas are more afraid of losing their jobs to automation technologies	Not supported	
5. Job characteristics:		
H5.1. Job automatability is positively related to automation fear	Supported	
H5.2. Lower job positions are associated to higher fear of automation	Not supported	
6. Work experience:		
H6.1. Longer work experience is negatively associated to automation fear	Not supported	Work experience increases fear
H6.2. Number of years on a particular job position is negatively associated to automation fear	Not supported	
7. Social influence:		
H7. Automation fears are shaped by peer pressure	Supported	
GROUP 2: Solutions to automation fears		
8. Demographic characteristics:		

H8.1. Gender influences the support for the solutions to automation fears	Supported	Significant differences in the support for 1 individual, 4 corporate and 6 social solutions
H8.2. Age influences the support for the solutions to automation fears	Not supported	
H8.3. Education influences the support for the solutions to automation fears	Not supported	
H8.4. Perceived economic wellbeing influences the support for the solutions to automation fears	Partially supported	Significant differences in the support for 3 corporate and 3 social solutions
H8.5. Place of living influences the support for the solutions to automation fears	Partially supported	Significant differences in the support for 1 individual, 1 corporate and 5 social solutions
<hr/> <i>9. Job level:</i>		
H9. Job level influences the support for the solutions to automation fears	Not supported	
<hr/> <i>10. Work experience:</i>		
H10. Work experience influences the support for the solutions to automation fears	Not supported	

Appendix 1. Sources of scale items

Statements	Source of items
Perceived social benefits Automation technologies are (will be) responsible for many of the good things we enjoy in life Automation technologies (will) improve our standard of living Automation technologies will bring us a bright future Life is (will be) easier with automation technologies Automation technologies (will) make our lives more convenient Automation technologies (will) eliminate a lot of tedious work for people Automation technologies (will) make people happier	Tussyadiah, Zach & Wang (2017) and expanded by the authors
Dehumanisation Automation technologies (will) hurt our human relationships in society (r) In the future, automation technologies will dominate society (r) The overuse of automation technologies may be damaging and harmful to human beings (r) The overuse of automation technologies may be damaging and harmful to the society as a whole (r) Automation technologies (will) dehumanize the workplace (r) Automation technologies (will) lead to deskilling of jobs (r)	Tussyadiah, Zach & Wang (2017) and expanded by the authors
Advantages Automation technologies (will) provide more accurate information than human employees Automation technologies (will) make fewer mistakes than human employees Automation technologies (will) perform faster than human employees Automation technologies are (will be) more reliable than human employees Automation technologies (will) have higher productivity than human employees Automation technologies are (will be) more cost effective than human employees	Ivanov, Webster & Garenko (2018) and expanded by the authors
Disadvantages Automation technologies are (will be) able to deal with/operate only in standard situations (r) Automation technologies (will) lack the creativity of human employees (r) Automation technologies are (will be) difficult to operate by their intended users (customers, employees) (r) Service provided by automation technologies are (will be) less interactive than services provided by human employees (r) People feel frustrated when they need to use automation technologies (r) People prefer to communicate with human employees rather than with automation technologies (r)	Ivanov, Webster & Garenko (2018) and expanded by the authors
Innovative personality I consider myself to be creative and original in my thinking and behaviour I seek out new ways to do things I usually adopt new products before my friends do Others see me as an innovative person	Parasuraman & Colby (2015); Wiedmann <i>et al.</i> (2010)
Social influence	

Statements	Source of items
People who are important to me influence my opinion about automation technologies Media/social media influence my opinion about automation technologies I trust other people's opinions about automation technologies People who are acquainted to me influence my opinion about automation technologies	Venkatesh, Thong & Xu (2012), Chen & Huang (2016) and expanded by the authors
Technological skills It is not (will not be) hard for me to learn to use automation technologies I am confident when I use a computer / computer applications / software packages I am confident when I use electronic devices around the house and at work I have the knowledge and skills to use automation technologies	Developed by the authors on basis of the Effort Expectancy scale by Venkatesh, Thong & Xu (2012)
Professionalism I am (was) well prepared for my current (most recent) job I perform(ed) very well on my current (most recent) job I stay(ed) up to date with the latest developments in my field	Developed by the authors
Job automatability I think it would be easy to automate most of the activities I currently perform(ed) on my job (r) Provided the opportunity, the managers of the company I currently work(ed) for will substitute the human employees with automation technologies (r) The company I currently work(ed) for uses (or plans to use) actively automation technologies (r) The other companies in the sector use (or plan to use) actively automation technologies (r)	Developed by the authors
Fear I fear I might lose my current job due to automation technologies within the next 5 years (r) I fear that, if I lose my current job due to automation, I will not be able to find a new job in the same industry (r) I fear that, if I lose my current job due to automation, I will not be able to find a new job in another industry (r) I fear that if my salary is increased, my company will have good reason to automate my job (r) I fear that the use of automation technologies will cause deskilling of my current job and the company will hire someone with lower education / skills (r) I fear that the use of automation technologies on my current job will require knowledge and skills that I do not have (r)	Developed by the authors