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Guest Editors' Introduction

BOTSOURCING, ROBOSHORING OR VIRTUAL BACKOFFICE? PERSPECTIVES ON IMPLEMENTING ROBOTIC PROCESS AUTOMATION (RPA) AND ARTIFICIAL INTELLIGENCE (AI)

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Services, the largest component of the world's economy, have significant impact on shaping economic and social relations between organizations and human beings. For many decades, services sector has been cyclically evolving and changing, which has lately accelerated particularly due to the strong influence of emerging technologies. Certain solutions became a thing of the past, some started to transform faster, while others emerged disturbingly, revolutionizing current state of art. The ways and modes services enable humans and technologies to interact and cocreate value have also started to take new, innovative and fascinating forms. Over the past years, global services market got centralized and technologically reshaped influencing lives of us all. Offshoring (global sourcing), enabled by cloud computing, made multiple transnational companies take advantage of migrating some operational processes to different locations ('nearshore' or 'farshore'). Being under constant pressure of competitors' innovativeness, quality and price, organizations explore opportunities offered by the newest technologies and locations to standardize, speed up, simplify, and optimize end-user experiences and quality of service (Piotrowicz & Kedziora, 2018). Cultural and persuasive influence of high-tech made us all observe and experience radical technological changes in modern societies. Solutions based on processing data in a cloud, virtualization of servers, remote workspaces, and large databases of digital footprints, have gradually become completely natural, yet revolutionary and somewhat threatening. Automation with robotic software, advanced analytics, elements of artificial intelligence, recognition of analogue content and human voice, integration of cognitive views, chaining transactions onto blocks, Internet of Things (IoT) and edge computing have already made tremendous impact on the formulation of human-technology relations and experiences.

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Robotic process automation (RPA) technology has recently emerged and accelerated, already gaining status of a disruptive technology that revolutionized global services market. At its many reported implementations, RPA gets integrated with components of artificial intelligence (AI), allowing digital transformations at plethora of organizations, bringing them rapid results with low entry commitment and no radical changes required. This technology has drawn attention both among industry practitioners and academics, promising to sustainably and reliably improve operations and business processes, at the same time transforming human employees' role at the development of organization. RPA aims to release personnel from boredom of performing repetitive and mundane tasks, at the same time allowing them to collaborate with digital teammates, forming 'hybrid workforce' of the future (humans and robots executing activities together). The academic and professional debate has lately started to notice and explore such concepts as 'virtual backoffice', 'botsource', 'roboshore' and even 'aishore'. Firms that managed to successfully adopt and scale intelligent automation (IA) solutions, reported to achieve positive impacts on customer experience, financials, productivity, quality of delivery, strategic goals, and reduction of frustration (Kedziora et al., 2021). It is related to releasing personnel from performing non-value adding tasks that are so manual, time-consuming and monotonous that the more humans execute such, the more frustration they start to feel and more errors they start to make. The implemented use cases have been reported mostly at the business areas of finance, accounting, customer service, procurement and human resources (Agostinelli et al., 2019), but also non-commercial settings of healthcare (Airola & Rasi), in response to COVID-19 pandemic (Kedziora & Smolander, 2022). The emergence of IA, understood as enhancement of RPA and AI, allowed intelligent 'software robots' or 'intelligent bots' to minic actions of humas and process even unstructured data with use of process mining, optical character recognition (OCR), natural language processing (NLP), and machine learning (ML) (Kedziora & Kiviranta, 2018).

In this specific research context, it is essential to explore the successful implementations of RPA and AI from the perspective of novel solutions blending RPA, with elements of AI, particularly from the perspective of cultural, societal, and individual dimensions. The automation of manual work and its perception by human employees have been studied in the manufacturing and humanoid context (Ford, 2015), yet there is still room for extending its practical and theoretical implications on human–technology intersections. Human-technology interactions for the successful implementations of RPA and IA solutions, shall serve as scalable, robust, and well-perceived by the engaged human workers, are to appear as reference for application, evaluation, conceptualization, and advancement of this technology, putting human perception and perspective in its core.

HUMAN-TECH INTERACTIONS FOR RPA AND AI IMPLEMENTATIONS

The RPA and AI technologies quickly scale up due to multiple benefits mentioned in the previous section, yet may be hindered with some risks causing unsuccessful case examples, referred to as Robotic Process Re-Manualization (Modliński et al., 2022). Consequently, as we witness a shifting paradigm from automating basic workflows to applications of more sophisticated products, solutions combining standard RPA with AI elements, there is room for deepening available research on the topic. AI based data algorithms that are increasingly ‘taught’ to generate business rules for the robots, through describing, exploring, and utilizing digital footprints with probabilistic mathematic methods, require large data sets gathered over many years that may bring impressive results for processes done repetitively, massively, yet require high accuracy. As these phenomena can be studied from various perspectives and research dimensions, selected aspects of human-tech interactions for the successful implementations of RPA and AI are to be explored.

As the post-digital era, embracing ongoing advances in AI poses a question whether technology may be deployed to replace roles previously filled by human beings, including job supervisors/bosses. Replacing persons holding managerial positions seems very difficult, if not impossible. With no doubt, the role of technology at organizational development has been transforming, yet it is worth to experimentally consider the boundaries of an ‘AI boss’ adaptation at different types of organizations. Being able to understand which enterprises may adopt and which present strongest resistance to a bot-boss may help reducing such resistance. Hence, trying to navigate across a set of universal features of an ‘AI boss’ that make it acceptance, regardless of employees’ and organization’s culture, shall serve to define ways of controlling and managing hybrid systems in which some form of robo-boss exists. As the responsibility of AI is one of the key concepts studied at modern ethics, it is vital to study how to avoid biases in a hybrid working environment and whether personnel display a sufficient level of non-conformism to address such biases. The decision-making responsibility for the AI boss’s choices, as well as its relation to its creators, employees, and senior managers is still unclear within business ethics and requires further academic investigation.

As it is evident that digital transformation in both business and social contexts require development of specific skills needed to successfully implement and manage emerging technologies. Concepts of Industry 4.0. and “Factory of the Future” (FoF) require building appropriate skills that will be required for the successful design, implementation, and management of AI solutions (Yao et al., 2017). The ongoing debate in industry and academia, emphasizes the need to identify gaps in digital skills, and the technology driven changes in societies and organizations, as it open various opportunities and new types of modes in the value-creation, incl. new roles and competences. Through comparisons of theoretical guidelines with expectations of end-users and employees, it is worth to explore and build a framework for designing training and educating future users, as well as interactors with technology

As already mentioned, automation technologies may go beyond software robotics, with such hardware applications as humanoid robot machines, able to facilitate core living conditions of aging western societies, such as safety, health, and housing. Future smart cities, will be forced to use robotic humanoid workforce for helping elderly at basic duties, improving their quality of life and residential conditions. It is therefore important to study how the design of humanoid robot applications should be conducted, in order to avoid biases and design products of best characteristics, tailored for various age, sex, education and residence place groups of elderly.

The impact of robotic technologies on organizational and economic aspects of enterprises constantly grows and is often being referred to as Robonomics (Ivanov, 2017). The continuous exploration and observation of RPA tools market is of major importance for the future research. The development and validation of research models, as well as practical recommendations on the successful adoption of RPA by companies may give valuable foresight on the future evolution of these technologies. As we can expect further combination and blending of RPA and AI, intelligent robotization will allow companies to achieve results that go beyond financials, but enable quality improvements in services and products, exciting user experience, or advancement in the societal innovations. Hence, researching the assimilation of IA at companies and communities may bring further hyper-automation opportunities, if followed by proper framework.

FUTURE OUTLOOK

The age of RPA and AI has certainly come and will have strong impact on the relations between humans and technology, as well as societies and businesses of tomorrow. The complexity and multidimensional characteristics of this concept created broad opportunities for further exploration and validation of available academic research. Resource and business effort of IA implementations, compensated by quick ROI, stability and numerous value types brought by its digital transformation are on the top of almost every company and community that has either been already robotizing some manual processes or is considering it for the near future. Hence, top provides of RPA solutions have been promoting the concept of 'citizen developer' that enables every office worker to learn basics of RPA programming and start configuring own software robots (Forrester, 2022). Particularly, during the challenging times of COVID-19 pandemic, intelligent automation market has rapidly grown and is most likely going to boost further, as many individuals, communities and organizations embark on the fast-track digital transformation journey with low-code solutions that is relatively easy to adopt. Securing quality and operational excellence in the first place, we will all need to boldly move forward with innovative solutions and initiatives to improve our communities and companies. Possibility of remote deployment and intelligent applications of software robots will allow for promoting Industry 4.0., at the same time minimizing the risk of service discontinuation or re-manualization, resulting from absences and down-breaks of operations. Investments at innovations and digital skills of employees, including RPA and AI shall certainly accelerate the strength and further growth of many societies, making their services more sustainable, disruption resilient and cost effective.

It is of utmost importance to focus on the sustainable transition onto the 'hybrid workforce' of the future, combining manual and digital delivery of work. Continuing exploration on how to successfully integrate software robots onto delivery team and increase acceptance for such technology by collaborative means shall grow as well. Only that will allow us to achieve effective collaboration of people and robots in an integrated way of processing business tasks, forming sustainable future of "humans in the loop". By automating specific work with use of wide technological umbrella, such information systems as RPA, will attempt to replace human actors altogether (Chakraborti, 2020). As it often leads to bias and resentment among human workers who fear losing their jobs, the execution and automation of previously manual tasks by intelligent systems are by no means a replacement of human employees, but rather an augmentation of their way of working (Gerber et al., 2020). Digital transition cannot be successful without proper synergy between all the stakeholders involved, such as automation analysts, maintenance engineers, developers, architects and managers from RPA Teams, as well as process experts and subject matter experts (SMEs) from business teams (Kedziora & Penttinen, 2020). It is therefore important to constantly encourage business communities to innovate, submit automation ideas, communicate the change and recognize their efforts. Going beyond single Proof of Concept (PoC), or ‘pilot project′, while scaling up along the automation journey, requires mutual understanding and orientation around common goals that allows to follow the predefined implementation framework stages and address occurring challenges. It is important to remember that no matter how we name it: botsourcing, roboshoring or virtual backoffice, our horizon for the future digital evolution would make us trust technologies we build and keep our feeling of being a “man-behind-the-wheel”, only if we control and use these solutions for our advantage, as indicated by the French activist of the early XX century, Emile Pouget: “*The worker will only respect the machine the day it becomes your friend, reducing your work, and not like today, who is your enemy, takes jobs and kills workers*”.

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THE EMPOWERMENT OF ARTIFICIAL INTELLIGENCE IN POST-DIGITAL ORGANIZATIONS: EXPLORING HUMAN INTERACTIONS WITH SUPERVISORY AI

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Abstract: *Technology evolves together with humans. Across industrial revolutions, its role has evolved from that of a simple tool used by humans to that of intelligent decision-maker and teammate. In the post-digital era where ongoing advances in artificial intelligence are widely visible, the question arises regarding the extent to which technology will be "upgraded" into roles previously filled by human supervisors, thereby replacing persons in managerial positions. This text aims to delineate how the organizational role of technology has been transformed across decades and the forms that it currently takes within companies, with an eye to the future. We draw on posthuman managerial literature and known cases of organizations where some forms of supervisory artificial intelligence are already used. The text is conceptual-reflective by nature; it seeks to initiate a discussion on the many challenges that humanity will face in connection with the deployment of empowered posthuman agents in companies.*

Keywords: *posthuman management, artificial intelligence, algorithmic management, human-machine interaction.*

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INTRODUCTION

Almost two decades have passed since discussion of the involvement of artificial agents in organizational decision-making processes emerged in the scientific literature, with journals such as Information Technology and Management and Computers in Human Behavior constituting the main centers of reflection in the field. It was Rees and Koehler (2002) who considered genetic algorithms (driven by Darwinian principles) when assessing group decision support systems; while genetic algorithms were previously known, the authors' research largely initiated the scholarly investigation of the impacts of algorithmization and other organizational trends facilitated by artificial intelligence (AI). At almost the same time, Benamati and Lederer (2001) observed the dynamic changes that IT companies faced, as a rapid reshaping of technologies demanded faster decision-making and adaptation to the ever more complex IT environment; as such challenges became increasingly pervasive, some organizations began to involve new kinds of agents (such as algorithms) in making decisions. In turn, Adomavicius et al. (2007) proposed a model for taking technology into account as an equal part of an organization's ecosystem, rather than as an isolated subsystem within the organization. That conceptualization was one of the first in the literature to open the door to a "posthuman" approach in management – one that makes it possible to envision artificial agents as actors that can make decisions and potentially even supervise human workers within an organization. Fairchild (2006), meanwhile, recognized that agents involved in decision management need not be (humanly) embodied, noting that decision-making agents could increasingly be a "something" rather than a "someone"; the author thereby highlighted the possibilities for intelligent software to be adapted for decision-making purposes, to meet organizational needs. More recently, Höddinghaus et al. (2020) have shown that algorithms are already performing leadership functions in organizations. They emphasize, however, that people may view such algorithms in divergent ways. For this reason, it is desirable to formulate models that can suggest what factors may contribute to a higher acceptance of algorithms that perform leadership functions and supervise human beings. The present article seeks to respond to that invitation and the larger discourse developed in such journals across decades, at a time when replacing human managers (or their functions) with AI-facilitated algorithmic systems is no longer just a subject of futurological discussions but already a growing focus of work for technologists and entrepreneurs.

The purpose of the text is to investigate how the position of technology in organizations has changed across industrial revolutions from that of passive support tools for humans to that of active decision-makers and (potentially) supervisors. We thus intend to answer the following research questions:

RQ1: What forms do "human-machine professional interaction" take?

RQ2: How has organizational technology transformed from "simple tools" to "empowered agents"?

RQ3: What forms can (and will) "supervisory technology" take, given the capacities and limitations of human beings and AI-based systems?

We begin our text by referencing the general idea of "empowered technology" that has already appeared in the social space. We then show how artificial intelligence influences the decision-making process and perfoms some supervisory functions in companies. To explain this, we review the evolution of technology and its progressive advance from "teammate" to "supervisor." On this basis, we argue that intelligent technology takes on three main roles in post-digital organizations: the managerial, supervisory, and/or advisory. Finally, we address six challenges for supervisory AI not addressed in earlier research: (1) boundaries, (2) adaptation, (3) self-organization, (4) perspectives, (5) interconnectedness, and (6) dynamics. The main contribution of our article is outlining the evolutionary process of the empowerment of technology, as well as creating a theoretical and reflective foundation for the concept of technology as a supervisor of the human workforce.

REVIEW METHODOLOGY

As this study is conceptual-reflective by nature, we have applied the textual narrative synthesis (TNS) proposed by Popay et al. (2006). TNS offers a solid regime for literature review through adoption of a research protocol, while not imposing quantitative restrictions. Following the suggestions of Xiao and Watson (2017), we constructed our research protocol based on two actions: (1) literature search and evaluation and (2) data extraction and analysis. We describe the details of the protocol in the next subsections.

Keywords Search

In recent years, artificial intelligence and robots have been investigated intensively from multidisciplinary perspectives. On one hand, this helps juxtapose various perspectives, but on the other hand, it limits the possibility of reviewing all papers with such a wide-ranging research protocol. We have thus applied a complex keywords search (by introducing "AND" and "OR") and provided criteria for exclusion. The keywords used for this research were: (1) 'AI' AND 'boss', (2) 'artificial intelligence' AND 'boss', (3) 'AI' AND 'transhumanism', (4) 'artificial intelligence' AND 'transhumanism', (5) 'AI' AND 'posthumanism', and (6) 'artificial intelligence' AND 'posthumanism'.

Inclusion/Exclusion Criteria

The protocol is based on branched exclusion criteria. First, we excluded papers that were not peer-reviewed, as their reliability is low. Second, we rejected papers that were not referring to the concept of supervisory technology. Third, we excluded documents that were not written in English. Finally, we have not included in the final analysis papers that focused on technical aspects of supervisory technology. The procedure for excluding papers consisted of two phases. First, we analyzed titles and abstracts, rejecting papers that did not match our criteria. Second, we read the remaining articles in full, repeating the same exclusion procedure. As our article has a conceptual-reflective nature, we have used cross-reading inclusion.

Database Search

As our manuscript is conceptual-reflective, we employed multi-baseline searching for articles in Web of Science and Scopus. The search results are presented in Table 1.

Table 1. The number of articles found according to keywords search.

	Keywords	Number of articles in Web of Science	Number of articles in Scopus
1	'AI' AND 'boss'	66	7
2	'artificial intelligence' AND 'boss'	47	34
3	'AI' AND 'transhumanism'	37	50
4	'artificial intelligence' AND 'transhumanism'	95	112
5	'AI' AND 'posthumanism'	35	36
6	'artificial intelligence' AND 'posthumanism'	73	66
	Total	353	305
	Total number after duplicate articles have been removed	387	

In line with the protocol, in the first phase, a selection was made on the basis of titles and abstracts. In the second phase, the entire articles were read and those that did not contribute to the answers to the research questions were removed from the analysis. While reading entire articles, we wrote down such sources cited by authors that (a) answered our research questions (b) but did not appear in the Scopus / Web of Science databases. In this way, we included an additional 8 papers. The number of articles eliminated in each phase is shown in Table 2.

Table 2. The quantifying process of eliminating articles

	Number of papers removed	Number of papers left for further analysis
Initial number of articles		387
Phase 1: Title and abstract	324	63
Phase 2: Full reading	37	26
Cross-reading inclusion	8	34

After a detailed analysis of the literature texts, we organized our conceptual manuscript in such a way that it chronologically responds to our three questions presented in the Introduction. We have enriched the theoretical considerations with data from industry reports.

NON-SCIENTIFIC INQUIRIES INTO WORKERS' OPENNESS TO AI SUPERVISION

Within many industries, artificially intelligent systems already play key roles in gathering and processing data, making decisions, and acting in a way that informs or guides the activity of human workers, and as the role of artificial AI in the workplace continues to grow, the question arises of how human beings will respond emotionally, socially, intellectually, and operationally to interacting with AI that is no longer a "tool" or "assistant" but a "supervisor" in the full meaning of the word.

Initial non-scientific attempts to explore that question have already been undertaken. Due to their non-academic nature, such studies have limited scientific value, and it would be risky to presume that their findings reflect with a high degree of accuracy and generalizability either human beings' current attitudes toward or likely future responses to supervisory AI. Nevertheless, the fact that such large-scale studies have begun to be undertaken (and that their findings have been reported in popular business media) suggests growing interest in such questions, both in the world of business management and society more broadly. For example, an online survey of 1,080 managers in the United States conducted in 2019 by LEADx, a producer of AI-based leadership coaching apps, reported that 20% of workers would replace their boss with a robot today, if that option were available; the number rose to 30%, if the workers could be guaranteed that their new robot boss would be an android that behaved in a friendly, human-like manner. Younger workers and male workers were the most likely to welcome a robot boss (Kruse 2019). Meanwhile, in an online survey published by Future Workplace and the Oracle software company in 2019 (Oracle 2019a, 2019b) that gathered input from 8,370 managers and employees in 10 countries, 50% of the overall participants reported that they were "currently using some form of AI at work," ranging from a high of 78% of workers surveyed in India to a low of only 29% of surveyed workers in Japan. Of all workers surveyed, 82% thought that "robots can do certain types of work better than their boss can," 64% "would trust a robot more than their manager," and 50% "have asked a robot for advice instead of their boss." Over 80% of respondents in India, China, and Singapore reported that they trust robots more than their human managers, while fewer than 60% said the same in the US, France, and the UK. As potential supervisors, robots were valued especially for their ability to manage work schedules and budgets, solve problems, and offer unbiased information. In contrast, human managers were valued for their empathy and ability to coach employees and create a positive work atmosphere. The survey found significant growth in positive attitudes toward workplace AI over a similar poll conducted by the same organizations in 2018, suggesting the rapid evolution of workers' attitudes in this area.

The Earliest Vision Of The "Robot" As A Supervisor

The fact that robots might come to oversee human workers should perhaps not strike us as something bizarre, when we recall the fact that, from its very inception, such possibilities were built into the concept of the "robot" by the author who invented the term. The idea that robots might someday serve as supervisors of human workers within an organizational context is, quite literally, as old as the word "robot" itself, as the work that introduced that word "robot" to the world – the 1921 play R.U.R.: Rossum's Universal Robots by Czech playwright Karel Čapek – presents in its later scenes a group of robots who have taken over the world and formed their own government and industries, as they struggle to successfully manage one of the last surviving human beings in carrying out work that is essential for the robots' long-term survival (Čapek 2004). As depicted by Čapek in his pioneering drama, robots were not the cold mechanical automata of many later science fiction works; rather, they were biologically engineered beings who shared the same emotions, intellect, and sociality as their makers. Indeed, they were initially created to replace human workers and provide a vast source of cheap labor. However, in the end, they proved to be far too "human-like": they were not only capable of following instructions but also of giving them – of building organizations and managing entire robot workforces for their own ends. A century later, reality has not yet caught up with Čapek's vision, but the picture that he painted no longer seems so far away. Artificially intelligent systems are increasingly providing at least limited oversight and management of human workers, and it is now possible to envision the path by which future robots and AI will come to serve as "supervisors" of human workers in a robust sense of the word.

Considerations In Analyzing The Capacities And Limitations Of “AI”

In analyzing the potential roles available for supervisory AI, it is important to distinguish a number of partially overlapping concepts. For example, the term “artificial intelligence” is used with divergent meanings across diverse scientific disciplines. Scholars writing in technical contexts may make clear distinctions between limited and domain-specific forms of “artificial narrow intelligence”, more flexible and sophisticated forms of human-like “artificial general intelligence”, and forms of “artificial super intelligence” that significantly surpass human beings’ typical cognitive abilities (Saghiri et al. 2022), while more passing references to “artificial intelligence” in the scholarly literature of disciplines outside of computer science may use the term in a more casual sense, without indicating which of the three abovementioned meanings (or which other alternative concept) is being referenced. Given the wide range of phenomena that can be grouped under the broad rubric of “artificial intelligence,” one must be cautious when making (or analyzing) claims that “artificially intelligent” systems for managing human workers either (1) already exist and are in widespread use; (2) exist as prototypes but are not yet widely deployed; (3) do not yet exist but are likely to be developed in the next few years; (4) may or may not ever be developed, depending on whether certain technological, organizational, legal, or economic challenges can be overcome; or (5) are certain never to be developed.

Researchers employing the term “AI” in the sense of “artificial narrow intelligence” may be justified in discussing the countless ways in which “AI” has for years been playing significant roles in managing human workers, either for good or ill (see, e.g., De Stefano 2020a, De Stefano 2020b, Dong et al. 2022), while researchers who employ the term “AI” to refer to something more akin to “artificial general intelligence” may be equally justified in considering how many years it will be before “AI” is introduced into workplaces to begin managing human workers and in investigating the implications that may arise when that occurs (see, e.g., Chamorro-Premuzic and Ahmetoglu 2016, Mélypataki 2019, Mays et al. 2021).

References throughout this text to the capabilities and limitations of potential artificially intelligent supervisors of human workers may generally be taken to relate to forms of AI that are more advanced than currently widespread forms of “artificial narrow intelligence” but which do not require full “artificial general intelligence” – i.e., forms of AI that are capable of performing a significant range of the managerial functions currently performed by human managers, but without needing to be indistinguishable from human managers or to be their equals in every regard.

The AI Boss As An “Entity” Rather Than An “Approach” Or “Process”

This text seeks to analyze potential organizational roles of the “AI boss” understood as a particular sort of entity which – while not an “entity” in the same sense as a human being – is nevertheless more than simply a “process” or a particular technologically savvy “approach” to organizational management. The fact that an AI boss will be popularly perceived by human workers as an entity (see, e.g., Chamorro-Premuzic and Ahmetoglu 2016, Captain 2017, Kruse 2019, Mélypataki 2019, Mays et al. 2021) is not simply an effect of human cognitive biases but a reflection of the AI boss’s nature, which differentiates it from workplace processes like digitization, digitalization, and algorithmization which – while emerging during roughly the same time period – are conceptually distinct from AI.

In many academic contexts, the terms "digitization" and "digitalization" are used interchangeably (Brennen and Kreiss 2016). Other scholars make explicit distinctions between the two concepts: in these cases, "digitization" may be understood as "the encoding of actions or representations of actions into a digital format (zeros and ones) that can be read, processed, transmitted, and stored by computational technologies" (Leonardi and Treem 2020) or as the concrete computational and "material process of converting analog streams of information into digital bits" (Brennen and Kreiss 2016). A related concept is that of "datafication," which is "the practice of taking an activity, behavior, or process and turning it into meaningful data" (Leonardi and Treem 2020). "Digitalization," meanwhile, can be understood as a higher-order societal process in which "many domains of social life are restructured around digital communication and media infrastructures" (Brennen and Kreiss 2016); as "the ways in which social life is organized through and around digital technologies" (Leonardi and Treem 2020); or as "the integration of multiple technologies into all aspects of daily life that can be digitized," which is manifested in phenomena like "smart homes" and "smart cities" (Gray and Rumpe 2015). The fluidity of the concepts is evidenced, for example, in the work of Kagermann (2015), who references the understanding of "digitization" as "the networking of people and things and the convergence of the real and virtual worlds that is enabled by information and communication technology (ICT)" – a phenomenon which, as indicated by the definitions cited above, other scholars would more readily classify as "digitalization".

"Algorithmization," meanwhile, is often understood as an intentional process by which certain types of decisions that were once made by human beings on the basis of their experience and judgment (insofar as they were made at all) are now made by automated systems using formulas or machine-learning models that have been designed to make such decisions; within the field of HR management, for example, such automated tools for "people analytics" may make decisions in "people-related organizational processes such as hiring, retention, or staffing" (Hüllmann 2022). Other scholarly uses, however, highlight the extent to which (for example) human prejudices or biases may undergo a process of "algorithmization" in which they become assimilated into automated systems to be manifested by machine-learning models or other forms of AI in a manner that was not explicitly intended by the systems' designers (Carrera 2020). With reference to such organizational phenomena, one might say that the AI boss is a particular manifestation, agent, and embodiment of ongoing processes of digitization, digitalization, and algorithmization.

The Ways In Which AI Can Influence Or Control Human Subordinates

Existing theory suggests that there are indeed diverse ways in which an AI boss can potentially control human subordinates and cause them to behave in certain manners. Current forms of AI are better at exercising some forms of control than others; as AI grows in sophistication, the mechanisms of control available for use by AI will grow more diverse. In particular, the ability to engage effectively in social interactions and relations with human workers in order to advance organizational goals is expected to be an essential capacity for robot bosses of the future (Author 2014a).

Raven's (1992) seminal analysis of the bases of social power that allow one intelligent social agent to exercise power over another distinguishes "coercive," "reward," "legitimate," "referent," "expert," and "informational" power. Hou and Jung (2018) note that even an artificially intelligent system that is never officially designated as a "supervisor" (and which lacks "legitimate" power) may, in effect, end up wielding tremendous power over an organization's human workers and influencing their behavior if, for example, it possesses expert knowledge and controls information flow; has the ability to reward or punish workers' actions (e.g., by allocating desirable or undesirable work schedules, tasks, or office space); or possesses human-like charisma and (apparent) personality or values that make human employees want to "please" or to become more like the robot.

While the possibility of robot supervisors relying on their emotional and social intelligence, charisma, and charm to motivate or manipulate human subordinates might seem far-fetched, steady advances are being made in the creation of more emotionally and socially capable robots. For example, much thought has been put into developing facial expressions that robot supervisors could use to offer clear signs of approval or disapproval to neurodiverse human subordinates (see e.g. McKenna et al. 2017). Such advances increasingly open the door to robot supervisors exercising control over human subordinates through referent power and charismatic authority (Author 2014b; Hubner et al. 2019).

"Robot Boss" Or "AI Boss"?

Some authors write about the emerging "robot boss" (McKenna et al., 2017; Hou and Jung, 2018), while others speak of an "AI boss" (Hodson, 2014; Feldman, 2019), which raises the question of whether a substantive difference exists between the two terms. The phrase "robot boss" readily suggests an entity possessing a physical body that allows it to sense and manipulate its environment and to interact socially with human beings, while the term "AI boss" tends to suggest a software-based supervisor that interacts with human beings through apps that are not tied to a specific physical shell (e.g., device-independent cloud-based platforms). However, there is no clear dividing line between a "robot" and "AI": both kinds of entities require physical embodiment, and both rely on some form of software or machine learning to guide their behavior. The difference between the terms relates more to emphasis and appearance than to any underlying reality (see, e.g., the largely interchangeable use of the terms in Ashrafian 2015).

As Rajan and Saffiotti (2017) have noted, the founders of the field of artificial intelligence dealt holistically with the challenge of constructing artificial entities that were capable of "perception, reasoning, and actuation," which required them to draw equally on the fields of electrical and mechanical engineering (for developing a synthetic agent's sensory and motor capacities) and computer science and programming (for developing a synthetic agent's data-processing and decision-making capacities). Over the following decades, the hardware-focused robotics and software-focused AI diverged somewhat; however, they are increasingly becoming theoretically and practically reunified, as the realization grows that every artificial intelligence always manifests itself, in some sense, as a physically embodied robot. Throughout this text, the terms "robot boss" and "AI boss" will thus be used more or less interchangeably.

The AI Boss As A Manifestation Of The "Technological Posthumanization" Of Organizations

The advent of the robot boss is yet another aspect of the ongoing "technological posthumanization" of organizations that has been gathering speed in recent years. Such posthumanization can be understood as the process by which an organization comes to include diverse types of intelligent social actors – beyond just natural biological human beings – who are capable of perceiving, interpreting, and influencing their shared environment and who work together to achieve the organization's goals.

In earlier eras of human civilization, enterprises like farms and military organizations were often "non-technologically posthumanized" through the incorporation of non-human intelligent social actors in the form of animals that collaborated with human workers in order to accomplish certain tasks. In today's organizations, posthumanization is primarily technological in nature. It manifests itself through two complementary forms: (1) the rise of artificially intelligent social actors in the form of workplace robots and AI that introduce non-human agency into an organization and (2) the rise of ubiquitous computing, augmented and virtual reality, online social media, mobile and wearable devices, neuroprostheses, and other technologies that are increasingly modifying and regulating the ways in which human beings exercise agency within organizations (Author 2017; Author 2018a; Author 2018b).

THE HISTORICAL RELATIONSHIP OF AI TECHNOLOGIES TO HUMAN WORKERS

The last seventy years have been characterized by organizations' development and deployment of ever more sophisticated computing technologies, with the result being that many contemporary workplaces already incorporate AI that is capable of exercising partial supervision over limited aspects of human beings' work.

The Computer As A Workplace Tool: Electronic Automation Of The 1950s

Machines capable of semi-automated data-processing and analysis began to be employed in earnest in organizational contexts by the 1950s, as exemplified by the early electronic computers like ENIAC, MANIAC, and UNIVAC, utilized by the US Government. In the beginning, the relationships between such computerized systems and the human beings that operated them were transparent: just like forklifts, timeclocks, elevators, welding equipment, and other devices used to perform particular tasks, such computers were no more than "tools" to be manipulated by their human operators – and even their long-term value as tools was subject to some doubt. For example, in 1959, a Vice President of General Electric (and later president of the Academy of Management) wrote with some skepticism about those seemingly overzealous individuals who were "entranced with the computer as a tool and a mechanism" for use in centralized data-processing within businesses (Smiddy, 1959, p. 25).

Given the limited utility of such automated systems as organizational tools during the early decades of the electronic age, the possibility that computers might someday be capable of filling a role as colleagues, collaborators, or supervisors of human workers was deemed scarcely worthy of serious discussion by scholars – although, as illustrated by Čapek, such visions were already being explored by writers of speculative fiction.

The Rise Of The Robot As A Teammate

Over time, as computers gradually became more compact, portable, and sophisticated, they became integrated into physical systems that – unlike a slide-rule or digital calculator – did not simply perform calculations that were inputted into them by their human operators. Instead, computerized devices were engineered to sense, interpret, and physically manipulate their environment in rich and complex ways. By the end of the 20^{th} century, such semiautonomous embodied *robots* had found diverse applications within organizations – from the robotic lunar probes and Mars landers and rovers that explored distant worlds as part of national space programs to the assembly-line robots that welded parts into place in manufacturing plants, to the self-navigating vehicles that transported materials throughout warehouses and factories. Nevertheless, such machines were from the beginning barred from exercising high-level managerial authority: their decisions had to be approved by one or more human overseers.

Two pivotal incidents significantly undermined faith in fully autonomous machines in certain circles. The first was the case of Vasilii Arkhipov, a Soviet naval officer serving on a submarine during the Cuban Missile Crisis. Upon being subjected to an apparent attack by American ships while submerged, the submarine's three senior officers had to decide unanimously among themselves whether to launch a retaliatory nuclear attack, as they were cut off from communication with their headquarters in Moscow. According to procedures, the crew had the right to counterattack. Out of the three senior officers, only Arkhipov initially rejected the idea of a counterattack; by persuading the other two to agree with him, he prevented further escalation of the clash (Savranskaya, 2005). The second case was that of Petrov and the supposed "American nuclear missiles." While on duty in 1983, Soviet Lt. Col. Stanislav Petrov was informed by a computerized early-warning system that the US had launched several nuclear missiles that were rapidly approaching the Soviet Union. According to procedures, Petrov should have taken steps to initiate a retaliatory nuclear attack. However, Lt. Col. Petrov felt some instinctive doubts, and he failed to take the required actions that, most probably, would have resulted in a nuclear war. His decision was later justified when the system's warning was determined to be a false alarm (Lundgren, 2013). If the Soviet computer system had acted autonomously without a human in the loop, the decision would likely have differed from that made by Petrov – with tragic consequences. Both cases are cited by those who oppose allowing autonomous decision-making by AI, claiming that algorithms lack empathy and moral awareness that may jeopardize individuals, organizations, or even whole countries.

Nevertheless, as computing technologies continued to grow in power and sophistication, new generations of robots and computerized systems began to function with ever greater autonomy from human personnel and to exercise their own agency in analyzing and responding to real-time situations. Such systems were gradually incorporated into various dimensions of organizational life, from cleaning facilities and protecting data and resources to value and product creation. The gradual increase of such machines' autonomy has been described as a process of "techno-empowerment" (Author and Skowroński 2021). By the early 2000s, some taxonomical accounts of human-robot interaction began to recognize the possibility that human workers might potentially fill a role as "teammates" who operate in collaboration with such proactive and independent robots, rather than simply controlling the robots' behavior as their "supervisors" or "operators."[1] Robots were no longer simply confined to the status of a "tool" to be manipulated; they could, in certain circumstances, operate alongside human workers, collaborating on the same organizational plane. Nevertheless, within the field of management studies of the early 2000s, the notion that robotic systems might fill a role as supervisors of human subordinates was still largely deemed unworthy of serious investigation, either because of its supposed theoretical inconceivability or practical unlikelihood. Thus, for example, the taxonomical account of human-robot interaction developed by Yanko and Drury (2004) recognized the possibility that human beings could be "supervisors" or "operators" of robots – or potentially even "teammates" operating in collaboration with such robots – but not subordinates; the relationship of supervision between a human being and a robot could be ordered in only one direction.

From Robots As "Teammates" To Robots As "Supervisors."

It is not surprising that it has proven challenging to develop robots that can function effectively as managers when we are still struggling to develop a comprehensive and accurate theory regarding what it is that makes some human beings (but not others) great managers (see, e.g., Flak 2019). As a result, in recent years, scholars have still largely continued to focus their research on how artificial intelligence is leading to situations in which "employees collaborate with, rather than merely control, the technology in use" (Snow et al. 2017); exploration of how AI might supervise, manage, and control human workers is still in its earliest stages. Nevertheless, some recent systematic accounts have now begun to recognize that robots may indeed fill the role of true "supervisors" of human beings (Hou and Jung 2018).

[1] Robotic "teammates" have – thus far – clearly been of a qualitatively different sort than *human* "teammates." In this regard, such robots are similar, for example, to the specialized breeds of shepherd dogs that had functioned for centuries within the organizational context of large farms: such dogs were not simply "tools" in the way that a plow or hammer was a tool; they were teammates who often operated semi-independently of their human supervisor. Within contemporary organizations and societies, robotic teammates are filling a role similar to (though distinct from) that of the working animals of earlier eras.

THE THIRD WAVE OF BUSINESS TRANSFORMATION AND THE AI BOSS OF THE FUTURE

Numerous contemporary organizations are now attempting to take that next step by pursuing the development of specialized workplace AI whose managerial capacities rival (or surpass) those of the human supervisors whom it may someday replace; such organizations have an optimistic, ambitious vision for the role that AI supervisors can play within organizations and are working hard to bring about that reality. Indeed, in a study that applies Causal Layered Analysis to a discussion of organizational futurists and leaders, Farrow (2020) suggests that the notion of the “AI boss or chief advisor” is a notable element of the “Myth/Metaphor” layer of the organizational “teams of the future.” Such visions are fueled in part by the rise of the “quantifiable workplace” in which vast numbers of key decisions are objectively data-driven, rather than based on intuition, instinct, or emotional intelligence; as organizations become more data-driven, the door is being opened for robot supervisors to take on an increasing range of roles (Sahota and Ashley 2019).

Machines that make such autonomous decisions concerning resources allocation, acceptance of contracts, stock-exchange transactions, or the selection of particular employees have been described as “tertiary intelligent machines” and are perceived to represent the ultimate stage of techno-empowerment (Author and Skowroński 2021). Even if the construction of some such machines is already becoming technically possible, many people seem skeptical about whether they should be used.

AI As A Supervisor Of Human-Robot Collaboration Within Businesses

Following earlier waves of standardization and automation, Daugherty and Wilson (2018) see a dawning “third wave of business transformation” based around organizational adaptation in which human beings and AI systems collaborate; as part of this “emerging symbiosis between man and machine,” robots and AI will increasingly augment human beings’ capabilities and leave human persons to carry out the more complex work of “resolving ambiguous information, exercising judgment in difficult cases, and dealing with dissatisfied customers.” Simultaneously, organizations in many industries are increasingly becoming hybrid “digital-physical” and “cyber-physical” entities in which real-time decision-making is distributed throughout a heterogeneous network of human, robotic, and other agents (Author 2017; Author 2019b). Such visions of ever closer human-robotic interaction raise the question of who is best suited to manage such collaboration within an organization and ensure that tasks are allocated effectively: a human supervisor or robotic supervisor?

Some companies believe that artificially intelligent supervisors have greater potential for filling such roles, and they are working to implement that model. For example, Siemens is engaged in an ongoing effort to develop factories in which an AI supervisor assigns tasks to particular human workers or to robots, based on the AI’s analysis of the actions needed to complete a given task and its knowledge of individual workers’ skills and the robots’ capabilities. The goal is to create a system in which the AI supervisor can draw seamlessly on the unique strengths of human and robotic workers, without assigning either to carry out tasks that are a suboptimal use of their particular abilities (see, e.g., Feldman 2019, and that text’s analysis of Captain 2017).

AI In Other Managerial, Supervisory, Or Advisory Roles

Japanese firms like Hitachi and ORIX have been at the forefront of adapting AI for use in key advisory or decision-making roles. One vision for organizational structures of the future is that "While leaving day-to-day affairs to an artificially intelligent president-cum-chief operating officer, a human chairperson-cum-CEO would make final decisions. It may be only a matter of time before such a corporate governance model emerges" (Nikkei Asian Review 2016). Already, a Hong Kong-based venture capital firm has publicly heralded the fact that it appointed a machine learning program named VITAL to serve as a member of its board. However, it is unclear exactly what such a role might mean from a practical, legal, or organizational perspective (Groome 2014).

Just as human decision-makers choose which forms of artificial intelligence an organization will employ, AI is increasingly playing a role in choosing who *its* human collaborators within an organization will be, by serving as a "gatekeeper" that makes key decisions regarding the hiring of new employees. Experts and practitioners in the field of organizational incentives, rewards, and recognition (IRR) have noted that AI is currently used most extensively in the area of talent acquisition and onboarding (e.g., the algorithmic screening of job applications), with growing roles for AI in predictive analysis for supporting employee retention; facilitating learning by human workers; and motivating employees and managing their performance (Schweyer 2018). In some organizations, artificially intelligent systems also identify those human workers who should be terminated for poor performance (e.g. Lecher 2019).

FURTHER RESEARCH: CHALLENGES OF THE AI BOSS AS PART OF A POSTHUMANIZED HYBRID SYSTEM

The data presented so far demonstrate that the "AI boss" has been evolving from a strictly futurological idea to specific implementations in the form of various types of rational agents that are increasingly becoming incorporated into business organizations. In this way, a previously existing team of employees (in production, services, trade, etc.) is transformed into a hybrid system. Since such changes are not yet widespread, it is an important moment for analyzing and evaluating them scientifically. In practical terms, it remains possible to prevent harmful effects of this type of business experiment, such as in the form of counterproductive behaviors like the boycotting of management decisions or retaliatory behaviors (Robinson and Bennett 1995). On the other hand, an in-depth analysis will make it possible to identify factors that favor the optimization of business processes through delegation of managerial roles to artificial actors. Moreover, within the cognitive dimension, we are dealing with a fascinating area of research into technological posthumanization. The business organization – the environment of the digital transformation processes that interest us – naturally elicits a systemic view of issues of human-computer interaction, broadly understood. In this area, the most important thing is the effectiveness of changes, which is assessed, for example, at the level of economic indicators (e.g., company income or profit) or psycho-social indicators (e.g., job satisfaction or an assessment of positive techno-empowerment). These aspects can be treated as various dimensions of a company's well-being, which – depending on the degree of success in achieving stated goals – are interpreted as “success” or “failure”. Obtaining successful results through the introduction of AI bosses (as part of broader program of digitalization and algorithmization) means that “human-computer interaction” has been successfully transformed into “human-computer satisfaction”.

Recently, Margaret Kern and her colleagues proposed the concept of Systems Informed Positive Psychology (SIPP) (Kern et al. 2020) as a perspective for studying the well-being of social systems, including business organizations. Although the SIPP authors focus on interpersonal systems, this theory is an inspiring perspective for the analysis of hybrid systems which can facilitate the flourishing of organizations. Studying the determinants of shaping positive systems indicated by SIPP is possible thanks to concepts explaining the emergence of beneficial effects of human interaction with intelligent artifacts. Tomas Sander (2011) proposed “Positive Computing” as “the study and development of information and communication technology that is consciously designed to support people’s psychological flourishing in a way that honors individuals’ and communities’ different ideas about the good life” (p. 311). Giuseppe Riva et al. (2012) introduced “Positive Technology” which is “the scientific and applied approach to the use of technology for improving the quality of our personal experience — as a way of framing a suitable object of study in the field of cyberpsychology and human-computer interaction” (p. 70). Recently, Author (2021) suggested the term “Positive Cyberpsychology” to denote the area of research conducted at the interface between cyberpsychology and positive psychology, aimed at defining subjective (e.g., beliefs), objective (e.g., humanoid robots), and contextual (e.g., the employee team) determinants of the optimal functioning of human beings interacting with artificial entities. This approach encourages taking into account the dimension of the individual employee (human well-being), the organization in which he or she operates, and specific, implemented technological innovations.

The SIPP authors propose that research should be guided by the principles derived from systems theory (Bertalanffy 1968). As a starting point for future investigations of the emerging phenomenon of the AI boss, it is possible to outline a number of research areas, along with detailed questions about the posthuman transformation of organizations.

Challenge 1. Boundaries

What are the features of artificial agents that make them capable of being incorporated into an employee system in the role of an AI boss?

A rational agent can cross the boundary of the employee system to become incorporated into it, as long as this has the approval of an organization’s management. The content of expectations, in turn, depends on the real possibilities of designing AI-based systems. When analyzing the boundaries of the hybrid system, attention should thus be paid to the objective determinants of the organizational change – i.e., to its technological foundation. An appropriate basis for such research would be technology adoption models (Venkatesh et al. 2003); concepts such as Experience Design (Hassenzahl 2010), Positive Design (Desmet and Pohlmeyer 2013), Motivation, Engagement and Thriving in User Experience (Peters et al. 2018); and research on algorithm aversion (Dietvorst et al. 2015; Castelo 2019). Thus far, no studies have been carried out that would reveal the social mechanism associated with acceptance of AI as a supervisor; it is therefore necessary to integrate data from studies carried out in the abovementioned paradigms. Another promising path is reference to the relational models theory (Fiske 1992) that postulates that human relations may be based largely on combinations of four relational models: communal sharing, authority ranking, equality matching, and market pricing. Within this concept, the results of studies in which an artificial agent acted as a supervisor can be interpreted (Hinds et al., 2004). It should be anticipated that AI-based innovations will be increasingly capable of performing objective tasks (based on rationality and the application of the rules of logic). In comparison to them, "subjective tasks" require greater use of emotions and intuition (Inbar et al. 2010). This reality significantly limits the potential current scope of an AI boss's managerial activity. However, as previously shown, work is underway to improve such synthetic agents' interpersonal skills (e.g., in the field of emotional expression). Nevertheless, it should be expected that an AI boss will be primarily in demand where precise instruction, control, scheduling, and analysis of indicators (including KPIs) are necessary. Because businesses generally only accept solutions that lead to the desired effects, the real value of an artificial agent will have to be scrutinized by eliminating any anthropomorphizing filter – and thus without projecting skills that do not exist.

Challenge 2. Adaptation

How should artificial units be introduced into the employee system to maximize its well-being?

Introducing an AI boss is a process that – if it is to be successful – should begin by neutralizing negative, irrational attitudes of employees that block progress. The process of disseminating particular types of innovations (which should in principle improve quality of life) can be traced by mapping the years of introduction of the methods of measuring the fears that they arouse: the *Computer Anxiety Scale* (Heinssen et al. 1987), *Internet Anxiety Scale* (Chou 2003), *Robot Anxiety Scale* (Nomura et al. 2006), *Mobile Computer Anxiety Scale* (Wang 2007) and *Artificial Intelligence Anxiety Scale* (Wang and Wang 2019). It can be predicted that if AI bosses are carelessly implemented, there will also be a need to measure the level of fear toward such entities; an appropriate scale should thus be constructed. However, this can be avoided if a process of adaptation to this new type of agency and control is adequately carried out. Three stages can be distinguished: (1) preparation, including necessary antecedents and cognitive, affective, and behavioral readiness (Rafferty, Jimmieson & Armenakis, 2013); (2) action, including explicit reactions and change outcomes (Venkatesh, Morris and Davis 2003); and (3) cognitive, affective, and behavioral acceptance correlated with organizational prosperity, technological functionality, and individual well-being (including job satisfaction). From an individual viewpoint, an employee's well-being is considered from a hedonistic or eudaimonic perspective. In the former case, it is about achieving job satisfaction and the associated emotions from the realm of pride and joy (e.g., Weiss and Brief 2004). The latter is about perceiving the meaning of work and the value of one's personal involvement in it (e.g., Yeoman 2014). Social context refers to the quality of communication that shapes community and understanding of the process of change. People's uncertainty decreases as they gain information about some other party (Berger & Calabrese, 1975), and there is also a strong relationship between information sharing and the quality of team performance, consistency, knowledge integration, and decision satisfaction (Mesmer-Magnus & DeChurch, 2009). Research conducted over many years clearly shows that the manager and the management style that he or she manifests are essential for employees to achieve both dimensions of well-being.

For example, Jennifer Chiok Foong Loke’s (2001) research shows that leadership behavior explains 29% of job satisfaction.

Interestingly, employee satisfaction can be generated thanks to leaders representing diverse management styles, including the transactional (Chen 2005), transformational (Shieh, Mills and Waltz 2001), charismatic (Holloway 2012), and authentic (Darvish and Razaei 2011). We also know that supervisors play an essential role in shaping a sense of meaningfulness at work (Pratt and Asghforth 2003). In this case, shaping the community of values and the possibility of meeting the expectations of both sides is of particular importance. The extent to which an AI boss can contribute to the emergence of similar effects is unknown. However, the effects of artificial agents on well-being are already undergoing scientific analysis (Botella et al. 2012). Following different trends in understanding well-being, we can distinguish “hedonic technologies” (which promote an increase in an actor’s pleasure and satisfaction) and “eudaimonic technologies” (supporting the process of his or her self-realization) (Riva et al. 2012). There is a need to investigate the factors that might make a rational agent acting as an AI boss be treated in such ways.

Challenge 3. Self-organization

What factors favor the spontaneous organization of hybrid systems in which an AI boss is included?

Hybrid systems can be formed intentionally or spontaneously. In business, we often deal with the planned incorporation of artificial units into systems. However, human creativity for shaping interactions with artifacts is enormous. In the mental dimension, an example is the anthropomorphization that assigns to (potentially non-human) agents roles such as those of servant, master, or partner (e.g., Aggarwal and McGill 2007). Here we would also like to draw attention to the dimension of education. An AI boss can play the role of an “attractive artifact” in a community of workers, as in the famous series of “hole-in-the-wall” experiments carried out by Sugata Mitra (2012). There the social system centered around the artifact began to live “its own life”. One also finds numerous examples of this on the Internet, where groups of support, interests, and knowledge-sharing are formed spontaneously. The attribute of “attractiveness” is essential, because, from the point of view of the organization's good, the most desirable situation is when employees accept an artificial unit and do not need to be additionally motivated to cooperate with it. Of course, the scope of possible interactions with technological innovation is limited by its structure and functionality. However, under the influence of various types of employees’ interactions, intelligent agents may generate reactions of a new quality. An artificial individual that modifies its reactions thus shapes a stimulating environment in which employees acquire competencies unwittingly and informally (e.g., Marsick and Watkins 2001). It is most often a bottom-up process; it is situational and “immersed” in experience. The AI boss – which is itself subject to evolution – should help release creative potential in employees, which is particularly desirable due to the need to avoid employees getting trapped in suboptimal routines. Thanks to technological posthumanization, the labor system can become a learning system.

Challenge 4. Perspectives

What beliefs of employees are critical to effective functioning within a hybrid system where the artificial rational agent has superior status to them?

The introduction of an artificial unit to the work system in the form of an AI boss undoubtedly gives rise to a wide range of beliefs among employees. Particularly noteworthy is the possibility of granting moral status to such an agent in employees' mental processes (Gray, Gray and Wegner 2007). Research on mental perception shows that people use the so-called two-dimensional *cognitive moral template* when determining the moral status of perceived figures; this model presumes that persons reflect on the extent to which an entity can feel harm (i.e., the entity is a *moral patient*) and whether such an entity can take intentional action (i.e., the entity is a *moral agent*). It has been experimentally proven that various factors can influence how people ascribe such attributes to artificial beings. Here, an important role in the human-likeness of rational agents is played by the physical aspect (e.g., features of the corpus and the way of moving; see Gray and Wegner 2012; Saltik et al. 2021), as well as by the cognitive and emotional attributes (such as creativity; see, e.g., Castelo 2019). A fascinating area of research is the area of anthropomorphizing intentions. Messages in the general form of "AI wants to take jobs" found in pop-culture narratives depict a face of AI that corresponds to *The Dark Triad* of personality, which comprises the socially aversive traits of narcissism, Machiavellianism, and psychopathy (Paulhus and Williams 2002). Assigning these characteristics provokes an automatic assessment of the management style of an artificial system that is closer to the authoritarian style than the genuine or shared leadership preferred by employees (Yukl 2006). Recently, the concept of *The Light Triad* has been developed, including Kantianism (treating people as ends unto themselves), humanism (valuing the dignity and worth of each individual), and faith in humanity (believing in the fundamental goodness of humans) (Kaufman et al. 2019). The factors that can influence the anthropomorphization of rational agents in line with *The Light Triad* and the connections between assigning such attributes with relationships based on official dependence have not yet been determined and scientifically verified.

Challenge 5. Interconnectedness

What is the nature of the relationship between units most favorable for achieve well-being within the system?

The anthropomorphization process supports transforming an interaction into a relationship (Epley, Waytz and Cacioppo 2007). Business organizations promote community and teamwork by strengthening team spirit and shaping relations between employees on a formal and informal level. In the conditions of the COVID-19 pandemic in which working in home office conditions became prevalent, operating within virtual teams has become the norm for many employees. It is presumed that if the activities carried out within such a team are technologically supported, it becomes virtual (Anderson et al. 2007). An indicator of the team's level of virtuality is the degree of use of new technologies: from *semi-virtual* to *pure virtual* (Griffith and Meader 2004). Work during the COVID-19 pandemic has not only transformed employee teams into virtual teams; direct relations between employees have also taken the form of *para-social relations*. Such relationships were initially studied with regard to the psychological determinants of television viewing and the bond generated between the viewer and the image of a person shown by the medium (Horton and Wohl 1956). These new conditions for achieving business goals provide an opportunity to define the similarities and differences between the quality of relationships between employees and their human supervisor (who is, in this case, an image on a computer screen) and between employees and an AI boss (e.g., represented as virtual character). Research on virtual teams indicates the essential role of the boss, which influences an employee's understanding of the meaning of the work performed (Furst 1999) and the coordination of tasks and sense of community (Hertel et al. 2005).

On the other hand, it is necessary to deepen the knowledge of the differences between direct contact with an artificial system (e.g., a robot) and its virtual image. A comparative analysis of twenty-seven studies shows that, in general, participants have a more positive attitude towards rational agents (robots) when watching them in films than when meeting them directly (Naneva et al. 2020). Additionally, it can be concluded that research should distinguish between a positive attitude towards an artificial system, trust in it, and acceptance of it. These variables should be treated as moderators of employees' reactions to an AI boss.

Challenge 6. Dynamics

How do the units of the system in which an AI boss is included interact with each other?

Business is a dynamic reality. With technological progress, new ways of satisfying customer needs emerge, along with the need to modify production, service, logistics processes, etc. Just as employees should be flexible and ready to acquire new competencies, artificial systems cannot be an obstacle to the company's development. The mutual influence of an AI boss and people who play the role of leaders – carrying out managerial tasks that the artificial entity cannot perform – is crucial in this aspect. This requires them to adopt a new style of work in which, for example, they can consult decisions with a synthetic rational agent. In such a situation, the manager resembles a chess player who cooperates with the chess program while playing a match, e.g., at the tournament in Leon. The final decision lies on the manager's side, but the decision-making process itself can be a stressful task for him or her, especially when an agent suggests a different choice. In addition, by analyzing the cooperation of a traditional manager with an AI boss, it will be possible to indicate the area of non-algorithmizable managerial competencies, which are vital from the point of view of the functioning of the team and the expectations of subordinates. Along with the adoption of AI bosses (as part of a broader organizational digitalization and algorithmization process), the notion of the "human capital" of the company changes. It should be expected that it will only include attributes that artificial units are unable to imitate (or can imitate only at a suboptimal level) in the future. This, in turn, will impact the training policy of companies, in which the emphasis will be placed on improving those skills defined as "soft" (i.e., necessary for performing subjective tasks).

DISCUSSION AND LIMITATIONS

The challenges outlined in the previous sections (which overlap in many areas) constitute important research lacunae that should be filled with subsequent research. First, it becomes imperative to identify the boundaries of adaptation to an AI boss for different types of organizations. New technology is linked to stress (Jurek et al., 2021) so the knowledge on how people interact with supervisory AI is crucial to mitigate the risk of refusal. Currently, no studies indicate in which organizations the resistance to the AI boss is strongest and what factors stand behind such resistance. Moreover, it should be investigated whether there is a set of universal features of an AI boss that stand behind its acceptance, regardless of (1) the employees' culture and (2) the organization's culture. If such basic characteristics do exist, their determination becomes essential for practice. Nevertheless, differences in the perceptions of AI bosses in different cultures and organizations also seem worth exploring. For example, do perceptions about the ideal AI boss differ between bank and hospital employees? Moreover, it becomes crucial to define ways of controlling hybrid systems in which some form of AI boss exists. This is especially important in the era when robotic process automation is increasing its influence on companies' performance (Kedziora et al. 2021; Kedziora and Penttinen 2020; Kedziora and Kiviranta 2018). As we pointed out earlier, it is not clear how to avoid biases in a hybrid system or whether people display a sufficient level of non-conformism to oppose such biases. Earlier research shows that people have already problems to adapt to telecommuting where no artificial agents occur (Raišienė et al., 2021). It is not clear yet what kinds of crises may be dominant in a hybrid system. It is thus not known what tools could be used to deal with such crises effectively. Therefore, there is a need for experimental research in the above areas. Another identified research gap for which we found no answer in current theory is that of "deliberate system biasing." Namely, suppose that an AI boss operates on the basis on data collected from the environment that are selected by employees. Might they deliberately manipulate the system to bend and disrupt the organizational reality for their individual ends? Ultimately, it is still unclear who would take responsibility for the decisions made by the AI boss and who would be entitled to question them within the organization. The responsibility of artificial intelligence is one of the most significant emerging issues within contemporary ethics. Within business ethics, various concepts suggest that the responsibility for the decisions of an AI boss rests with its creators, with employees, or with senior managers. As with the other issues discussed above, the question of which of these options for assigning responsibility makes a team most likely to successfully adapt is unclear and requires further investigation (see, e.g., Santoni de Sio and Mecacci 2021).

Although this study is based on presumably reliable literature selected by the research protocol, the topic of techno-empowerment is dynamically evolving; it is probable that since this text has been submitted, new research, case studies, and IT-solutions have already appeared. Moreover, the further research directions are based on literature published in leading databases; we have purposefully omitted journals that are not reported in such databases. Ultimately, we have not included in this analysis more details about the functional capabilities of current IT systems in case of techno-empowerment, for two reasons. First, such capabilities are changing dynamically, and what seemed impossible yesterday may begin to appear in media reports only weeks later. Second, many of the most pioneering, cutting-edge technological advances regarding the functional capabilities of AI technologies (e.g., those occurring in projects developed by DARPA or the Chinese government) are not publicly reported, and it was not our aim to speculate on such unknowns.

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FUTURE-ORIENTED DIGITAL SKILLS FOR PROCESS DESIGN AND AUTOMATION

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Abstract: *The digital transformation in both the social and business fields requires the development of new skills related to the use and implementation of contemporary IT technologies, which provide the basis for Industry 4.0. One of the main concepts of these changes is the automation and robotization of business processes. The design, implementation and use of solutions in this field require appropriate skills. Therefore, it is necessary to identify gaps in digital skills and reduce them with adequate training and development. The main objective of the paper is to identify both current gaps and future needs for digital design skills to support and understand the automation of business processes. A survey was carried out in manufacturing companies from six European countries. Its results have enabled us to create a future-oriented digital design competence framework that addresses the requirements of process design and automation in the Factory of the Future.*

Keywords: *Industry 4.0; Factory of the Future; digital skills; process design, automation.*

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INTRODUCTION

In the contemporary digitalization and robotics world, industries are facing new challenges. The growth of disruptive technologies and, as its consequence, the rise of Industry 4.0 and smart factories will change the traditional role of factory workers. The innovative technologies (artificial intelligence, robotics, automation, big data analytics, cloud computing, Internet of Things, 3D printing), intelligent production system and knowledge workers create a backbone of the "Factory of the Future" (FoF). Unfortunately, availability of adequate digital skills seems to be a challenging issue for the development of FoF.

According to the World Economic Forum (2017, 2020), due to the rapid evolution of the labour market, most people who rely on a single skillset or narrow expertise are unlikely to keep long-term jobs in the digital economy. Moreover, in the next few years newcomers will require new digital, social, emotional, personal development and learning skills. These skills will enable the next generation of employees to achieve the FoF`s objectives and meet new demands of the labour market. Digital skills are considered by many researchers (European Parliament, 2018; Ozkan & Ozen, 2020; van Laar et al. 2020) as one of the strategic pillars and drivers of this transition. It is clear that the deficit of appropriate digital competences, both among the management and employees, causes difficulties for enterprises in implementing digital solutions (McGuinness & Ortiz, 2016; Sari et al., 2020). The European Commission (EC) points out that 15% of EU employers declared a significant digital skills shortage among their employees. This is highly problematic in the context of an increasing automation of processes and digitisation of different areas of our life, according to the EC's experts (Curtarelli et al., 2017). The results of the ongoing analysis and experts' opinions give a clear indication of the need to identify and close the existing digital skills gap in the context of Industry 4.0 challenges. We understand the skills gap as a phenomenon in which the skill level of employees is insufficient to meet the demands of the current job (McGuinness & Ortiz, 2016). That gap may also occur for newcomers, thus reflecting a mismatch between the education system and labour market needs.

Digitalisation and its challenges also affect the education sector. According to the European Strategy for Universities (European Commission, 2022), higher education in Europe needs to address and adapt to variable and ongoing conditions related to climate change, digital and technologies in all activities sectors, demographic change, the COVID-19 pandemic, big crisis situations like war or other not identified yet (Feijao et al., 2021). Students and staff across the EU need to be equipped with the green and digital skills of the future, and the innovative and technological potential of universities needs to be harnessed to address related societal and industry challenges (European Commission, 2022).

As an effect of a digital transformation employment is shifting away from low-skilled jobs and from tasks with a higher routine content, which are easier to automate (Morandini et al., 2020). Whereas tasks requiring experience, intuition, creativity, or the ability to make decisions in the face of uncertainty will remain in the hands of people. Pontes et al. (2021) show that the development of Industry 4.0 fosters several trends (Connectivity, Lower Energy Use, Artificial Intelligence, Big Data and Value of Data) resulting from digitalisation. Sobczak (2021) and Bejaković and Mrnjavac (2020) point out that in addition to technical competence, new technologies including Robotic Process Automation (RPA) also require the development of analytical and cognitive skills. According to a study by Schlegel & Krause (2021), todays' companies looking for RPA professionals expect them to have not only the ability to use certain tools but also domain specific knowledge (business process management, human resources). Employees competence is also seen as a critical factor for the efficiency of Industry 4.0. According to Kumar & Kumar (2019), complexity of an information of FoF production systems makes the cognitive skills of employees and their domain-specific skills, equally important. Digital transformation entails changes in both hard (simulation, programming, machine learning) and soft skills (leadership, teamwork, problem solving). Thus, they should be perceived as a complimentary skill set required by FoF.

Therefore, a need can be observed to develop a digital skills framework that can support serve educators, policy makers, and employers to eliminate a digital competencies gap. Most of existing frameworks are focused on general digital competences (DigComp) and a few consider requirements of Industry 4.0 (Hecklau et al., 2017; Flores et al., 2020; Hernandez-de-Menendez et al., 2020; Oberländer et al., 2020). However, there is a distinct shortage of frameworks that address FoF-specific technologies and fields.

The recommendations of the ongoing debate on the digital transformation challenges stressed the necessity for a deeper understanding of a phenomena. Ras et al. (2017) highlight the need to shape new digital competencies and create a new generation of Industry 4.0 leaders. Margherita and Braccini (2021) point out that while the technical aspects of smart factories are quite widely researched, few studies address the competencies required to manage them. Moreover, existing modes of education may not keep up with employers' demand for digital skills (Feijao et al., 2021). As a result, this leads to inconsistencies between market needs and the education curricula of the future FoF workforce. A variety of studies suggest the necessity of taking initiatives to identify and reduce digital competency gaps. It is indicated that this is one of the main success factors for digital transformation and FoF development (Ras et al., 2017; Florea, 2019; Bejaković and Mrnjavac, 2020).

The literature review findings suggest the following significant research problems: the identification of new digital design competencies, revision of existing frameworks representing the requirements of FoF. There are two main research gaps. First, there are only limited empirical study on the digital competency frameworks for manufacturing industry. Second, there are no empirical study on digital competency supporting process design and automation in the context of Factory of the Future requirements. In the context of the long-running debate on the digital transformation, the following questions arise:

1. What transversal digital competencies supporting process design and automation are required by Factory of the Future employees?
2. What digital skills are required to meet the challenges of process design and automation in a Factory of the Future?

Following this, the main objective of this article is to identify areas of digital skills to support process design and automation in the context of the needs of the Factory of the Future. A general set of digital skills was identified through a literature review. This was the basis for the development of a set of competencies reviewed by representatives of manufacturing companies from six European countries through a survey. The study focuses on the diagnosis of digital transversal competences and digital skills fostering process design and automation from a perspective of a manufacturing sector. The paper also considers the existing digital competency requirements of contemporary enterprises - potential FoF stakeholders which was an additional rationale for proposing a future-oriented digital design competency framework.

The remainder of the paper consists of the following sections: first part reviews the literature on the issues relating to digital competences relating to Industry 4.0 and Factories of the Future and proposed a set of generic set of digital skills and competences Then, the methodology section identifies the relevant research process and methods, and describes the tools and techniques for data acquisition and collection. The empirical data analysis is described in the results section. The literature review and empirical research results served as the basis for the formulation of the future-oriented framework of digital skills supporting process design and automation are included in the following section. Finally, paper summarizes the findings and research contribution and implications for the future research.

DIGITAL DESIGN AND PROCESS AUTOMATION SKILLS IN FACTORY OF THE FUTURE

Today's companies are facing new market challenges driven by, among others, high demand for personalized products, shorter product lifecycle and need to increased productivity, efficiency and energy savings. To cope with these challenges, a wide range of advanced Industry 4.0 technologies (among others: Internet of Things, big data analytics, artificial intelligence, augmented reality systems) have been adopted to improve the capability and effectiveness of manufacturing processes. As a consequence of the changing circumstances, there is need to develop an intelligent, smart manufacturing and cybernetic-physical systems (CPS) as the foundation of Industry 4.0 (Yao et al., 2017). It merges the physical and the virtual worlds in industrial production. Industry 4.0 brings together information technology and factory automation. The new approach to a manufacturing system includes smart design, smart machining, smart monitoring, smart control, smart scheduling (Kumar & Kumar, 2019). This creates opportunities for new ways to automate mundane rules-based business processes using Robotic Process Automation (RPA) tools on information acquired from smart devices (Madakam, Holmukhe & Jaiswal, 2019). Moreover, the joint use of RPA and artificial intelligence, business process management, or natural language processing enables the automation of more complex processes (Kedziora & Kiviranta, 2018; Siderska, 2020). Further, the integration of RPA and cognitive, deep learning results in increased potential and efficiency of process automation (Anagnoste, 2018).

These new and emerging technologies constitute a future-oriented production ecosystem called "Factory of the Future" (FoF). Generally, the term Factory of the Future could be perceived as synonymous with the forthcoming era of digitalisation of industry (DIGIFoF, 2019). The European Commission defines Factories of the Future as a future-oriented manufacturing companies embracing Industry 4.0 opportunities to their full extent. FoF can be considered as an ongoing interconnection in manufacturing systems driven by technology, sustainability, optimization and the need to meet customer demands (Biegler et al., 2018). Lee et al. (2015) conclude that the way to build FoF is to integrate CPS with innovative production, logistics and services practices.

Some scholars argue that a digital transition offers the opportunity to meet not only business objectives (Thames and & Schaefer, 2017; Kedziora et al., 2021) but also enables enhanced human learning through intelligent assistance systems (Müller, Kiel & Voigt, 2018) and helps to face with the challenges of the circular economy and socio-economic sustain development

(Sarc et al., 2019). Since the “digital shift” makes production processes more demanding and complex, the technological development and the implementation of FoF should be considered as a long-term strategic project aimed at: creating smart, closed processes in manufacturing and, and altering the entire value-added chain in manufacturing (Spöttl & Windelband, 2021). KPMG report (2016) suggests that Industry 4.0 is now more of a certain idea than a material entity. At the same time, they draw attention to one fundamental and already topical issue. Industry 4.0 requires products (industry and management software), processes and devices (e.g. Ethernet, sensors, robotics). In turn, FoF equipment requires specialists in ICT and automation technology.

The key challenge of a new digital manufacturing paradigm is the upskilling and reskilling needs required by FoF (KPMG, 2016; Pontes et al., 2021). On the one hand the Industry 4.0 paradigm causes changes in the competences set of FoF's employees while on the other hand creates new jobs. According to recent research (World Economic Forum, 2020) 133 million new jobs will be created over the period 2018-2022. Pouliakas (2018) suggests that around 14% of jobs in the European Union are at high risk of automation. In the medium term, 35 - 40% of workplaces are expected to change in terms of the qualification requirements of employees. This issue is also highlighted by Spöttl & Windelband (2021). They argue that the idea of Industry 4.0 addresses issues related to interdependence of technological and social intelligence as well as the issue of the training and professional development and work design. Development of the required competences and skills plays a significant part in shaping a new ecosystem of FoF, which should not be marginalized. This poses a significant challenge for institutional and national systems of a future oriented competence development (Florea, 2019).

Factory of the Future requires tailored and domain-specific competencies and skills, such as data analytics, IT, software, and human-machine interaction know-how (Müller, Kiel & Voigt, 2018). The leading role of cybernetic-physical systems in FoF requires interdisciplinary and collective competences. Moreover, it calls for the integration of knowledge and skills from the fields of machinery manufacturing, electronics and information-communication technologies (Spöttl & Windelband, 2021). Veile et al. (2020) also argue that future employees of FoF require skills and competencies, such as Information and Communication Technology (ICT) know-how, interdisciplinary competencies and special personality traits. KPMG also suggests that the specificity of FoF requires the integration of different skill sets. Their proposed profile combines three skills areas: theory end expertise (material and production skills, process skills, electrical engineering, software, information and ICT), hardware (mechanical and plant engineering, automation technology, mechatronics, microsystem technology, electronics, IT infrastructure and security) and software (documentation, integration, process mapping, maintenance, trainings and continues professional development).

Leading role of process automation in FoF (KPMG, 2016; Madakam, Holmukhe & Jaiswal, 2019) will have significant consequences on people's professional development (Hirschi, 2018; Pouliakas, 2018). As already emphasised, manual tasks, routine activities and low-skilled jobs will be severely reduced (Morandini et al., 2020). Addressing these challenges requires FoF specific knowledge and skills. Essential technical skills related to RPA include knowledge of this technology, software testing and development, understanding of process design principles (Anagnoste, 2018). Therefore, the digital competence framework referring to FoF requirements should take into account the ability to use specific digital tools and knowledge specific to FoF key development areas (Schlegel & Krause, 2021).

In addition to competences of a technical nature, attention is drawn to the role in digital transformation of 'soft' competences providing, inter alia, creative approaches to analysis and problem solving, communication and networking skills (Hecklau et al., 2017; Flores et al., 2020; Hernandez-de-Menendez et al., 2020; Oberländer et al., 2020). This is very strongly emphasised in the context of implementing RPA solutions. Sobczak (2021) shows the very significant role of organisational, cultural and competence aspects as success factors, not just technological ones. Algorithmic and process thinking skills will play a key role, as well as soft skills not usually associated with RPA. The similar findings were presented by Bejaković and Mrnjavac (2020). The skills and competencies of the team, as well as the culture, ethics and behaviour of people in the organisation, determine the outcome of RPA implementation (Kedziora & Penttinen, 2021; Pramod, 2022). Anagnoste (2018) pointed out that among the non-technical competencies, leadership, communication, team working and problem-solving skills, new technology awareness play an important role in process design and its further automation.

The materialisation of the FoF concept entails very extensive changes in the traditional competence structures of employees. Both the type of technical skills and their relationship with soft skills are changing compared to the traditionally structured and non-smart enterprise. Moreover, digital skills gap is crucial challenge of a digital transformation. The gap is a result of the existing structure of the labour market and incomplete identification of FoF needs. This has led to a number of frameworks and maps aimed at developing digital competences and supporting the education and training sector, policy makers and FoF employers and employees in this regard.

COMPETENCY AND DIGITAL SKILLS FRAMEWORKS

The competences and skills required by the Factories of the Future are becoming the determinants of new frameworks and a recommendation made to different sectors of industry, government and academia. Competence models represent the expected social and economic changes and therefore the need for new competences. However, as was discussed in the preceding part, there is a clear need to consider three fundamental skills and competencies: transversal, business and technical. A competency model is a compilation of competencies that, when put together can determine effective performance in a particular job environment. This lists may include different detail levels and also describe relationships between the competencies. Throughout the years, many competency models and frameworks have been developed, including those related to digital skills and competency. The review of digital competency and skills frameworks aims to identify their structure and a core set of digital competencies. Moreover, this has been used to develop a proposal of the future-oriented competency framework reflecting digital design and process automation skills required by FoF.

The Digital Competence Framework for Citizens (DigComp 2.1) covers five key areas of digital competence. These are information and data literacy, communication and collaboration, digital content creation, safety, problem solving (Carretero et al., 2017). DigComp framework provides only general guidance for the development of digital competences of EU citizens. However, it does not refer to specialised competences and skills. Nevertheless, the comprehensiveness and a certain universality of this approach makes it applicable to the identification of basic and transversal digital competences supporting development of FoF.

Oberländer et al. (2020) identified 25 dimensions of digital competences. This research focuses only on white-collar workers with office jobs in Germany and, as the authors themselves point out, cannot be generalised and transferred to other regions and professional groups. Results of the literature studies done by Hecklau et al. (2017) and Flores et al. (2020) identified digital competences needed by Industry 4.0. Smart Factory competence framework proposed by Hecklau et al. (2017) distinguishes four competence areas, i.e. social, methodological, domain-related and personal competencies. Flores et al. (2020), in turn, recognised five sets of competences required by employees in Industry 4.0: soft, hard, cognitive, emotional intelligence, digital. They indicate that the most demanded skills of the digital workforce include programming, cybersecurity, digital networks, cloud computing, databases, web development and also the management of Industry 4.0 technologies. Further research led by Shet & Pereira (2021) focused on managerial competencies for Industry 4.0. They identified 14 groups of managerial competencies for Industry 4.0, including design thinking, problem solving & decision-making, digital intelligence & modelling, robotic process automation. The framework for Industry 4.0 proposed by Shet & Pereira (2021) indicates the need for their comprehensive consideration due to the specificity of FoF competence requirements. As with previous scholars, they do not refer to specialised skills for process design and automation.

On the other hand, report the “Industry 4.0 implications for higher education institutions. State-of-maturity and competence needs” (2019) distinguished two categories of competences supporting the development of Industry 4.0, i.e., discipline-specific competencies and knowledge as well as transferable skills. This framework focuses more on a professional competency that support design then previous works (Hecklau et al., 2017; Flores et al., 2020; Shet & Pereira, 2021). The authors of this study (Universities of the Future, 2019) proposes to classify competences into three categories: technical and engineering, design and innovation, business and management. The development of the technical competences assigned to the first two categories is based, among other things, on the acquisition of skills and knowledge in the field of big data analysis, Artificial Intelligence (AI), robotics, automation advanced simulation and virtual plant modelling, tech-enabled product and service design, human-robot interaction, programming, cyber-physical system development (Universities of the Future, 2019). The main limitations of the research and consequently the framework itself, is the number of respondents (20 respondents) and country representation (Finland, Poland and Portugal).

Unfortunately, presented in the literature frameworks are mostly focused on rather broad digital competences. There is also a lack of a consistent approach to the classification of digital competences among the models analysed. Moreover, these frameworks do not identify skills related to the key area for FoF that is design and automation. The proposed skill sets presented in the literature does not address the needs of the manufacturing sector essential for the development of Factory of the Future.

Considering the limitations identified, we have attempted to develop a set of key digital skills related to process design and automation for the manufacturing sector and FoF. Table 1 shows a proposition of a generic set of digital skills and competences for the Factory of the Future. With regard to the purpose of the study, competences related to process design in the broadest sense were identified. They include design skills understood as the ability to intentionally create a plan or specification for the construction of an object/a service/a system/for the implementation of an activity or process. The scope of these skills involves e.g.: product design, service design, user interaction design, information system design, factory design, production process design, business process design, etc. (DIGIFoF, 2019).

Table 1. Competency framework for Factory of the Future – process design context (Carretero et al., 2017; Shet and Pereira, 2021; Universities of the Future, 2019; DIGIFoF, 2019; Flores et al., 2020; Kunrath et al., 2020).

Transversal competencies and skills	Design competencies and skills	
	Business	Engineering
Information and data literacy	Technology awareness	Big data analysis
Communication	Business analysis	Simulations and virtual plant modelling
Collaboration and networking	Systems analysis	Digital intelligence & modelling
Digital content creation	Process understanding	Cybersecurity/Data security
Safety, data protection	Design thinking	Programming and coding
Problem solving	Anticipatory thinking	Robotic process automation
Teamwork	Cognitive analysis	Process mining
Netiquette	Knowledge management	Cloud computing

Among the competences supporting FoF, we can therefore distinguish their two main groups: transversal and professional (expert/discipline-specific). The first group includes social, methodological and personal competences. According to Fray et al. (2014), they are crucial in shaping young people's career maturity, particularly in terms of perceptions of discipline-specific competency development trainings. Moreover, transversal competences facilitating the transition from professional trainings into employment. It is also worth emphasising that the competences in this group reflect the Digital Competence framework, which provides a reference model to support EU policy-making in this area (Carretero et al., 2017).

Design-specific competences, on the other hand, refer to professional skills and knowledge acquired through formal/vocational education. Among them we can distinguish key competences for the following two areas: business and engineering (Universities of the Future, 2019). They relate to planning, organisation, management, prototyping, testing, implementation and production, among others. These competences are seen as crucial especially for manufacturing sector and industrial processes. (Universities of the Future, 2019; Flores et al., 2020; Kunrath et al., 2020).

RESEARCH METHODOLOGY

The literature review presented in the preceding parts of the paper allow to identify the competency demands of FoF and their role in process design and automation. As was already discussed, a key success factor for the implementation of the idea and development of FoF is the proper background of employees. Therefore, the primary purpose of our study is to identify the key digital skills and competences supporting a development of FoF in the field of design, automation of processes. Results have been used to develop a framework of future-oriented digital design competency. It represents a perspective of a manufacturing sector.

Research Design and Tool

Considering the nature of the research problem, an exploratory and descriptive methods was adopted. The choice of this approach allowed for a better understanding of the research problem and its refinement. Exploratory research enables the discovery of new insights and to see what is happening. Rahi (2017) underlines that it attempts to ask questions and evaluate phenomenon in a new light. The use of the descriptive method in the research has provided information on the current state of the phenomenon. In this research, the results of a quantitative study have been used to identify the key digital skills and competency in the field of design, automation of processes from manufacturing sector perspective. Creswell & Creswell (2018) suggest that survey designs helps to answer three types of questions: descriptive questions; questions about the relationships between, and questions about predictive relationships between variables over time. A survey design provides a quantitative description of opinions of a population by studying a sample of it. Moreover, a quantitative research has the advantage of being an objective representation of reality (Creswell & Creswell, 2018).

The quantitative research consisted of two phases. The first was pilot studies aimed to verify the questionnaire by participants of DIGIFoF project. The pilot study allowed to assess the extent to which the questions were well understood and allow reliable answers to be obtained, thus meeting the aim of the survey. The sequence of questions and the way in which they are presented has been rearranged, descriptions of scales have been clarified and unclear terms and concepts have been improved. The questionnaire was prepared in the appropriate languages of the respondents from each country of the survey. The revised version of the questionnaire consisted of four main sections:

1. General information: includes companies profile.
2. Digital competency needs and demands: includes questions related to the needed design skills and required training for the need of FoF;
3. Designing background: includes questions exploring understanding the companies' attitude towards design concepts, methods and tools;
4. Area of interest and implementations of: questions explore the interest areas to be treated in the FoF training and digital skills development.

The final questionnaire form contains 44 items (points 1-4). It was distributed to respondents and the results were collected and analysed in the second phase of the quantitative research. The paper presents the results of the selected aspects of the whole study which are related to digital skills in design and automation. This part of the study was performed using twelve questions from the second section of the questionnaire form (point 2). They addressed two issues: vocational training needs (form, scope, duration) and the role of digital design competences to support FoF development (digital competency level, digital design skills needs and demands). The questions in this section of the questionnaire were closed (vocational training needs) and multiple choice questions (most important digital competencies of the employee of the Factory of the Future).

Data Collection

The survey was conducted using Computer-Assisted Web Interview (CAWI) and Paper & Pen Personal Interview (PAPI) approach. Both the electronic and paper form were used for gathering information. To collect data, we use convenience sampling (volunteer sample). Convenience sampling involves drawing samples that are both easily accessible and willing to participate in a study (Teddlie & Tashakkori, 2009). Data were collected from 87 representatives of manufacturing companies from six European countries (Italy, Finland, France, Germany, Poland, Romania). The survey was carried out from 14.04 to 27.05.2019 within the DIGIFoF project.

The respondents were primarily employed in large enterprises with 250-4,999 workers (39% respondents) and medium enterprises with 50-249 employees (28% respondents). The representatives of small and micro enterprises constituted respectively 14% and 10% of the sample. The least numerous group were representatives of very large companies (9%).[1]
The respondents mainly represented the following fields:

- development and production of electronic devices for the automotive industry,
- development and testing of software,
- metalworking industry.

The roles of the respondents were as follows:

- engineers involve in product and/or service design,
- IT and enterprise architects,
- strategists and innovators in charge of service/product/business model innovation.

The participation of domain professionals from the above-mentioned areas plays an important role in determining the business-driven digital skills required by the FoF. One third of the respondents were employees who had been working for 1 to 3 years. A relatively significant group were employees with work experience of 5 to 10 years (21% of respondents). A slightly narrower group of participants were those with 3 to 5 years of experience (17% of respondents), as well as those with more than 10 years of work experience (13% of respondents). On the one hand, the roles of respondents fit into the professional profiles of FoF employees, while on the other hand, their knowledge and professional experience can significantly support the verification of needs in terms of digital skills for process design and automation.

RESEARCH RESULTS

In order to answer the research questions, an attempt was made to identify the significance of transversal competencies for the professional activity of the respondents and the enterprise operation. Based on the results of the literature review and opinions of experts cooperating within the DIGIFoF network, a list of 12 transversal digital competencies was defined that entailed: (1) adaptive learning, (2) creativity, (3) critical thinking, (4) complex problem solving, (5) information and data literacy, (6) digital content analysis & creation, (7) digital identity management, (8) data protection, (9) teamwork in a virtual environment, (10) social

[1] It is assumed that very large enterprise employs more than 4,999 people small enterprise from 10 to 49 workers, and micro enterprises not larger than 9 people.

networking, (11) communication and collaboration supported by digital technologies and (12) netiquette. Respondents were asked to indicate the most important transversal digital competences of a Factory of the Future employee that they believe are needed now and those that will be required in 5 years' time. A summary of the relevance to FoF development of the selected competences is shown in Figure 1.

The five most important competences currently on the labour market (70% of indications) are creativity, critical thinking, data protection, adaptive learning and problem solving, respectively. These are also the most frequently co-occurring competences. This set of transversal digital competences was indicated by about 60% of the respondents. They can therefore be seen as the most desirable set of competences for FoF's employees according to the interviewees. Furthermore, about 64% of respondents have indicated that the ability to communicate and collaborate using modern digital technologies is a key skill from the perspective needs of FoF. Among the important competencies information and data literacy and teamwork in a virtual environment were also highlighted. In the opinion of the respondents, competences related to management of digital identity and netiquette are relatively less necessary for the functioning of FoF in the present circumstances (Fig. 1). It is interesting to note that this last competence did not appear in the set of key transversal digital competences in almost 30% of respondents. Besides, about 20% of them did not include in their sets of competences social networking and the previously mentioned digital identity management. These are employees who usually have been with the company for no more than 10 years and who mainly hold management positions (CEO, managing director, manager).

Looking at changes in the perception of particular ones, it is worth noting that some of them are perceived by respondents as indispensable in the context of labour market needs. These include: adaptive learning, creativity, data protection. They were indicated as necessary competences now and in five years by about 10% of respondents. These were usually indicated by respondents with less than 3 years of work experience.

Whereas, in the perspective of 5 years, the set of key competences of a FoF employee indicated above was considered relatively less important. In the opinion of the respondents, competences related to digital content analysis and creation, digital identity management and data protection will increase, although to a relatively small extent (Figure 1). Among the most important transversal digital competences of FoF's employees in five years' time, respondents included:

- digital content analysis & creation,
- digital identity management,
- teamwork in a virtual environment,
- social networking,
- netiquette.

The respondents who indicated these competences are strongly diversified in terms of their professional profile and the positions they hold. They represented both the industrial production sector and software manufacturers. In the majority of them, the length of their work experience in the currently occupied position did not exceed three years. From the perspective of respondents from large companies, a key competence is the ability to teamwork in a virtual environment. They clearly link this with the need to know netiquette rules. Among the five key competences in next five years, there have also pointed out skills connected with social networking. It was most often indicated by the respondents together with competences connected with communication and cooperation using modern digital technologies (35-45%).

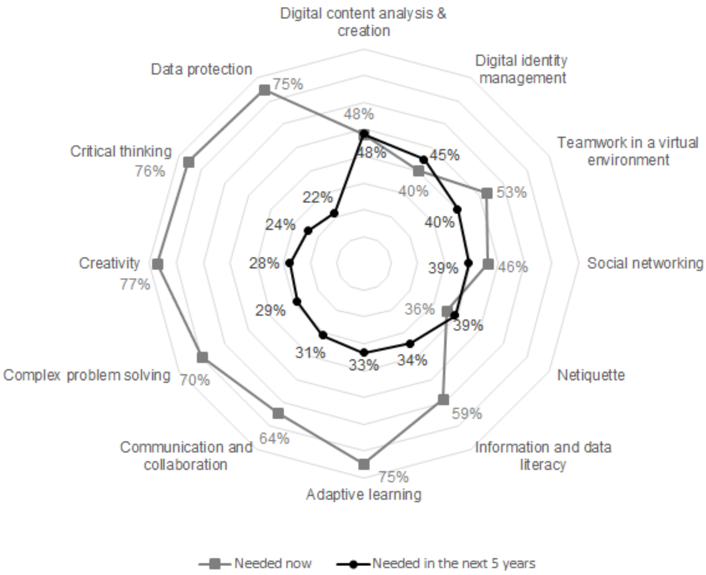

Figure 1. Top transversal digital competences of FoF's employees - present and future needs

A further important issue of the survey was the identification of needs and competence gaps in the design context of digitisation and process automation. Respondents were given a set of 13 key competencies representing both business and engineering areas. It included the following areas of competence: (1) IT infrastructure management, (2) data processing and analysis, (3) data security/cybersecurity, (4) computer programming/coding, (5) internet of things and cyber-physical systems, (6) automation, (7) robotics, (8) additive manufacturing, (9) cloud technologies and big data, (10) product simulation, (11) process design and simulation, (12) service design and engineering and (13) knowledge management. This set was developed based on the results of the literature review and the opinions of experts collaborating within the DIGIFoF network.

Respondents assessed both the level of relevance of competences in a specific area for the company and its current level among their employees. The assessment was made using a five-point scale, where these values in the first area of evaluation mean respectively: 1 – "no relevance", 2 – "low relevance", 3 – "medium relevance", 4 – "high relevance" and 5 – "very high relevance". In the assessment of the current level of digital competence in design, the values of the scale from 1 to 5 were assigned as follows: 1 – "no competencies", 2 – "low competencies", 3 – "medium competencies", 4 – "high competencies" and 5 – "excellent competencies" of the employees of the company in the key fields of the FoF. The results of the survey allowed us to determine the importance of digital design competencies for the surveyed companies and their level among employees. Figure 2 illustrates the respectively diagnosed needs and gaps in digital competences indicated by employees of companies operating in six European Union countries.

The most important and desired competence areas in the surveyed enterprises are related to: data security/cybersecurity, process automation and management of IT infrastructure. The data security/cybersecurity has been perceived as the most important competency by almost

85% of respondents. The group of key competences also includes automation skills and knowledge (75%) and issues related to the development of IT infrastructure (75%).

The very high importance of automation in shaping the development of manufacturing enterprises can be evidenced by the fact that this area was considered extremely important by both managing directors (management board, production, human resource), specialists and also employees directly involved in production. Data processing and analysis/analytics (70%) and process design and simulation (67%) were also in the top five most frequently indicated competence areas by the respondents. The above-mentioned areas are in the group of high and very high relevance digital design competency. In the opinion of the respondents, skills and knowledge of employees in the field of product simulation, knowledge management and robotics are also very important for the development of FoF. The area related to additive manufacturing was considered to be the least important. Respondents considered this to be a low to moderately relevant area of competence needed in their companies (Figure 2). This may suggest that they do not see the potential of 3D printing in industrial manufacturing or rapid prototyping.

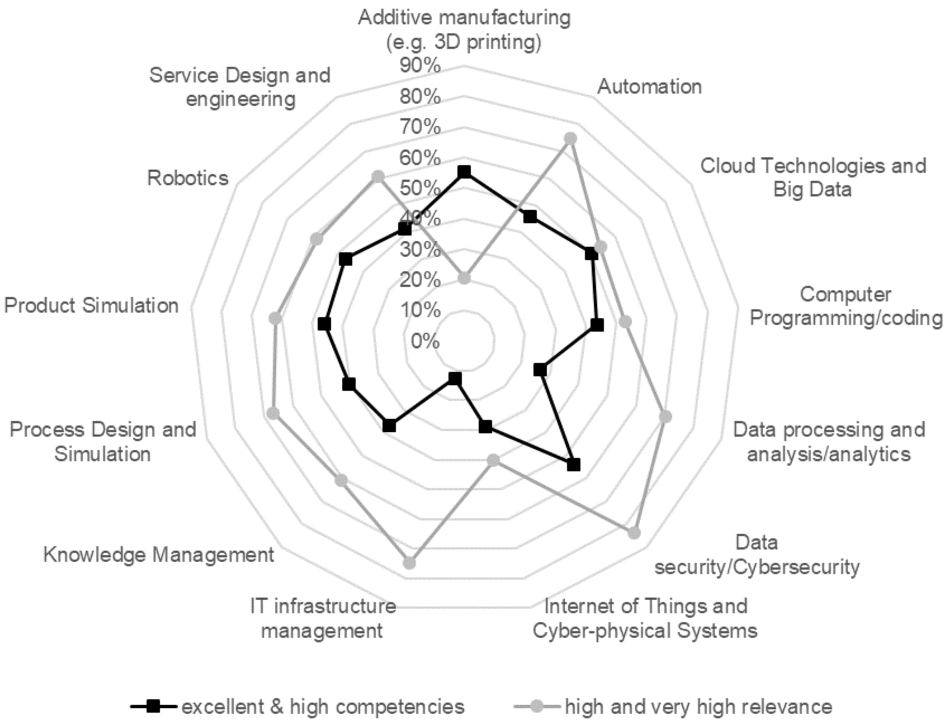

Figure 1. Gaps of digital design competency

The second aspect of the survey was to identify the level of digital competence in design (Figure 2). The performed diagnosis revealed relatively high shortages of competences in this area (no & low competency). The biggest deficiencies of competences concerned the aforementioned area of additive manufacturing. This is reflected in the respondents' relatively low knowledge of computer-aided-design and engineering. About 60% of respondents understand these issues and use them in practice. Almost 50% of respondents indicated that they did not have well established knowledge and skills in service design and engineering. These are the two areas with the relatively largest digital design competency deficits among employees participating in the survey. Furthermore, between 30 and 40% of respondents indicated that they have no or low competencies in the areas of cloud technologies and Big Data, robotics, programming/coding, Internet of Things and cyber-physical systems, product simulation.

By comparing the level of digital design competency indicated by the respondents with the potential needs of enterprises, gaps in individual areas were identified. They are shown in Figure 2 by the differences between the relevance of competences from particular areas in the company's activity (high & very high relevance) and their levels among the surveyed employees (excellent & high competency). The greatest need for improvement is seen in the areas of IT infrastructure management and data processing and analysis. Despite the fact that these competences are very useful in the company's activity, their level among employees is relatively low. High level of skills and knowledge in those areas was declared by only 13% and 26% of employees respectively. Having regard to the needs of enterprises, the shortages are also visible in three areas: automation, knowledge management, process design and simulation.

FUTURE-ORIENTED DIGITAL DESIGN COMPETENCY FRAMEWORK

Considering the increasing role of digital skills, especially in the field of automation, robotization of processes and machine-to-machine communication, an attempt has been made to develop digital competences frameworks. The proposal for a future-oriented digital design competency framework was based on the results of empirical research conducted among employees of companies from six European countries and the results of a literature review. The future digital design competency framework summarises the capabilities that are required of the FoF's employees for process design and automation. It can provide a basis for the development of guidelines and requirements for professional training, as well as for the revision and improvement of curricula for the learning of future FoF employees.

The proposed new approach to the set of competencies takes into account the respondents' opinions on the usefulness of digital competencies from specific areas supporting the Factories of the Future. Therefore, its core part is based on the subjective opinions of professionals from a manufacturing sector. The objectivity of the application of the framework depends on the user's perception and understanding of the essence of the skill sets included. Figure 3 shows a visual illustration of the proposed framework.

In the proposed future-oriented digital design competency framework, two sets of competencies were identified, i.e. digital transversal and digital design competencies. The first group encompasses five key areas: collaboration and networking, digital content creation, safety & data protection, teamwork and netiquette. It responds to requirements specific to European companies in the manufacturing sector. Moreover, the proposed framework reflects the competences identified by the European Parliament (2018) as key to lifelong learning that every European citizen should possess. Properly fostering entrepreneurial skills, combined with cross-cutting social skills, emotional intelligence, personal development and learning skills, is the way to increase Europe's competitiveness, the European Parliament (2018) underlines.

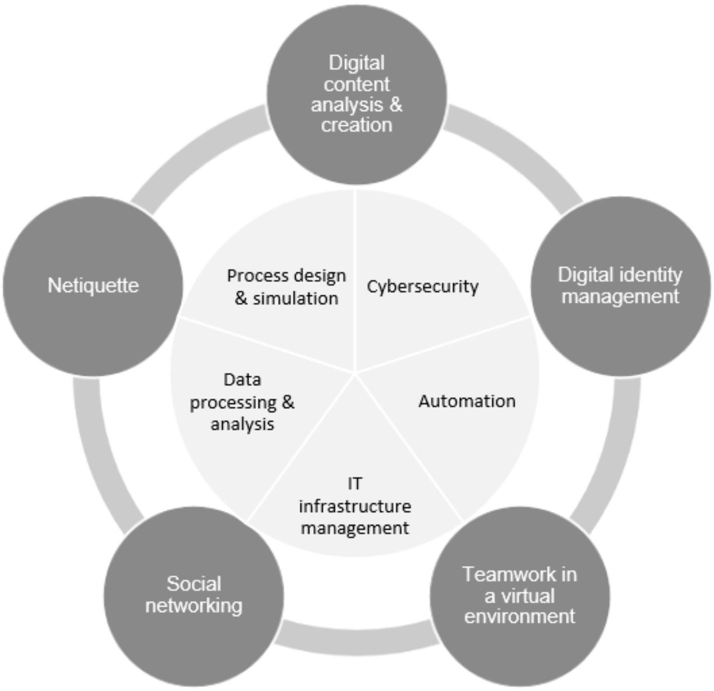

Figure 2. Future-oriented digital design competency framework

The set of expertise competences comprises competences from two areas, i.e. business and engineering. The survey results showed that among the business competencies supporting digital design, knowledge and skills related to understanding enterprise processes and knowledge management are expected to play an important role. The set of subject-related competences includes competences from two areas, i.e. business and engineering. The survey results showed that among the business competencies supporting digital design, knowledge and skills related to understanding enterprise processes and knowledge management are expected to play an important role. However, it is worth noting that relatively the biggest competence shortages were identified in the knowledge management. The recognition of process understanding as a key competence area of the future may stem from the growing need to shift from a functional to process-orientated approach to management. The engineering competency set highlighted three key areas: data analysis, cybersecurity and Robotic Process Automation. According to the surveyed representatives of European companies, these represent the most desirable future set of domain-specific competencies of Factories of the Future employees. This set of competences and skills relates to the area of STEM competences (Science, Technology, Engineering and Mathematics) for lifelong learning for European citizens (European Parliament, 2018). Alongside "cultural awareness and expression" and "digital literacy and language" skills, they are, in the European Parliament's opinion, the cornerstone of the social and economic development of modern Europe.

DISCUSSION AND GENERAL REMARKS

Changes associated with digital transformation do not have only technological implications but also implications for the structure of a labour market and workforce (Ozkan & Ozen, 2020). Moreover, the way and form of human-machine interaction related to the Factory of the Future is evolving as a result of advancing virtualisation and automation of processes (Kumar & Kumar, 2019; Pontes et al., 2021). The integration of technologies on the FoF platform on the one results in increased potential of process design, automation, control (Yao et al., 2017; Anagnoste, 2018) and on the other required new capabilities. One of the main challenges of implementing the FoF concept therefore becomes the adaptation and development of the knowledge and skills of smart factory`s employees (Florea, 2019). Moreover, as highlighted by Lasi et al. (2014) technology driven changes in manufacturing systems may initiate the appearance of new types of enterprises in the value-creation chain with new roles and competences. To meet these challenges, attempts are being made to identify the competency needs and demands of manufacturing industry (Hecklau et al., 2017; DIGIFoF, 2019) as well as business and education related entities (Ilomäki et al., 2016; Carretero et al., 2017; Oberländer et al., 2020).

The models and frameworks of digital competency presented by the many scholars (Hecklau et al.,2017; Universities of the Future, 2019; Shet & Pereira, 2021) agree that the essential requirement for the development of FoF is the acquisition of transversal skills in problem solving, communication, and collaboration with ICT. They are, according to many researchers, relevant to the need for creative and innovative approaches to process design (DIGIFoF, 2019; Flores et al., 2020; Hernandez-de-Menendez et al., 2020) as well as successful working in distributed and multidisciplinary teams (Veile et al., 2020; Kipper, et al. 2021). As argued by van Laar et al. (2020), the significant role of such competences is a consequence of the mutual diffusion of technology and society development and the fact that they have a strong influence on the way digital technologies are used. So called “digital shift” also very significantly influences the reconfiguration of design skills in terms of both business and technical skills. These are crucial, above all, for building a company's competitive advantage (Müller et al., 2018). Despite some divergence in the perceived rank of individual skills in these areas (Universities of the Future, 2019; Shet & Pereira, 2021), the foundation for building them is, according to many researchers, process understanding, design thinking, digital modelling, robotic process automation as well as data analysis and programming and coding (Anagnoste, 2018; Flores et al., 2020; Spöttl & Windelband, 2021).

CONCLUSIONS

The proposed framework reflects the real needs of the manufacturing sector in Europe and develops existing competency frameworks to some extent. The use of domain-specific models supports the development of adequate carrier paths for employees or job candidates, as well as the design of tailored FoF training for the acquisition of specific digital skills and competences. The proposed framework is a contribution to the ongoing discussion (Flores et al. 2020, Kipper, et al. 2021) on identifying current and future competence needs in the labour market. It reflects the results of a diagnosis of the digital design skills needs and requirements of manufacturing companies from six European countries. Based on critical and cross-sectional literature studies and empirical survey results, we proposed a framework of future-oriented digital design competency. It is formed by two sets of skills and competencies, digital transversal and digital design competencies respectively. Within each of them there are five skills and competences that we expect to remain relevant in the coming years. It expands and complements the theoretical framework previously given in domain literature. Moreover, through its focus on the specifics of the manufacturing sector, it has strong practical implications. Through the confrontation of theoretical guidelines with the expectations of employees and employers, the framework proposed by us may provide a reliable argument in designing training, educational and self-development programmes.

Due to the size and selection of the sample, the results cannot be generalised but could be seen as a set of common guidelines for stakeholders having a significant involvement in the field of training and education. Future research could be focused on assessing the relevance of education paths to the FoF requirements. Furthermore, cross-sectional and longitudinal research to identify skills needs and demands could be a promising avenue for further research, especially concerning the emerging technologies and a new business models.

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ANALYSIS OF THE CONDITIONS INFLUENCING THE ASSIMILATION OF THE ROBOTIC PROCESS AUTOMATION BY ENTERPRISES

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Abstract: *More and more companies are implementing the RPA (Robotic Process Automation) tools that belong to the newly emerging category of IT solutions used to automate business processes and enable the development of the so-called software robots. The term robot has a metaphorical meaning here – it is a special kind of software, not a device. Due to the fact that this is a new product category and many companies do not have extensive experience in this area yet, the use of the RPA tools is associated with many risks. At the same time, due to the increasingly competitive environment, it seems that there is no turning back from the implementation thereof. For this reason, two goals have been set in the article. The first is to build and verify a research model based on the TOE model (Technology-Organization-Environment), allowing for the identification of the determinants (drivers) influencing the assimilation of the robotic process automation by enterprises. The second goal is to develop recommendations for the managers responsible for implementing the RPA tools that will allow for increasing the assimilation of the robotic process automation. The following methods were used to accomplish these goals: literature research, a survey (conducted on 267 Polish enterprises) and statistical analysis (with the use of the structural equation models).*

Keywords: *Robotic Process Automation, TOE model, Assimilation of innovative IT*

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INTRODUCTION

S. Zuboff described in detail the impact of digital technology on employees and their work using an ethnographic approach in his study *In The Age Of The Smart Machine: The Future Of Work And Power* published at the end of the 1980s (Zuboff, 1988). Despite the extremely rapid technological changes that have occurred in recent decades, Zuboff's main observations on the impact that "intelligent machines" have on the way professional work is carried out are still valid today. According to the author, automation means using information technology to perform work faster and more efficiently. In the long run this will result in a profound transformation of the labor market. A few years later, in 1995, J. Rifkin presented the hypothesis according to which "we are entering a new phase of world history in which fewer and fewer workers are needed to produce goods and services for all mankind" (Rifkin, 1995). In his opinion, the declining demand for employees is a consequence of the progressing process automation made possible thanks to the use of more and more sophisticated IT solutions. At the same time, some researchers indicate that, especially in recent years, there has been a tendency in the media to exaggerate the impact of automation on the labor market. This is demonstrated, among others, by the results of the research (Eikebrokk & Olsen, 2020) analyzing the impact of the robotic process automation on the changes in the white collar workers' employment levels. According to the authors, robotic automation at the current stage of its implementation does not result in labor redundancies – most often it leads to the shifting of workers to perform other tasks within the same company.

However, one should be aware of the fact that the robotic process automation solutions (especially in combination with artificial intelligence) will be offering more and more capabilities year by year. The growing interest of enterprises in the use of the RPA (Robotic Process Automation) tools that belong to the newly emerging category of IT solutions in the field of business process automation is already visible. Enterprises interested in the use of software robots most often decide to implement the Robotic Process Automation (RPA) tools. These tools enable a relatively simple and quick development of software robots that perform activities carried out thus far by people and automate all or a part of selected business processes.

A number of benefits can be achieved thanks to the use of the RPA tools – both measurable as well as non-measurable ones. The most important among them include: cutting down the costs of running business processes, increasing the capability to carry out these processes without raising the headcount, improving Employee Experience by relieving employees from performing routine, tedious and mundane activities, improving the quality of products/services provided – thanks to reducing the number of errors made by employees involved in the performance of business processes, or, finally, increasing the number of innovations implemented in the organization by enabling rapid prototyping of new products/services that require an integration of various systems – in addition, without the need to involve internal IT departments.

At the same time, the author's previous research indicates that a significant number of enterprises in Poland have relatively little experience with the implementation of the RPA tools or are examining how to scale up the previously completed deployments (i.e. move from several to several dozen or more software robots developed with the use of the RPA tools). Therefore, it seems crucial for this purpose to identify determinants (drivers) that have an impact upon the assimilation[1] of these technologies by enterprises.

Therefore, the goals of this article include: (G1) building and verifying a research model allowing for the identification of the determinants (drivers) influencing the assimilation of the robotic process automation by enterprises; (G2) developing recommendations for managers responsible for implementing the RPA tools that will allow for increasing the assimilation of the robotic process automation.

In pursuing the above-mentioned goals of the study a diverse set of research tools was used. These include, accordingly: literature research, survey, statistical analysis (with the use of the structural equation models) and creative thinking techniques.

Due to the above presented goals of the article, the following paper structure was adopted. Section two presents the differentiating features of the Robotic Process Automation against the backdrop of the traditional tools used for automating business processes and indicates why these tools should be perceived as IT innovations, and also discusses the issue of the assimilation of innovative IT tools (RPA tools are an example of tools from this category). Section three provides a description of the structural equations model developed for the analysis of the assimilation of the robotic process automation. This section also discusses the hypotheses that were the basis for the development of the model. The next section presents the method used to acquire the research data, the characteristics of the research sample and the results obtained. Section five discusses the research results obtained and outlines the limitations of the research procedure applied. Section six presents research and application implications (including the recommendations for managers which, if applied, would allow for increasing the assimilation of the robotic process automation). In the last section the up to now considerations (conclusions) are summarized and the potential directions of further research are discussed.

THEORETICAL BACKGROUND

Robotic Process Automation Against the Backdrop of Traditional Automation Methods

The starting point for the analysis of the robotic process automation as compared to the traditional automation methods is to define the software robot concept. According to Willcocks and Lacity ((Willcocks & Lacity, 2016) p. 65), it is a piece of software that automates specific human activities (most often reproducing them faithfully) as part of the performance of the whole or a part of a selected business process. Thus, looking from this perspective, the robot is not regarded as a technical device and does not have the locomotive abilities of a human being. Software robots usually operate based on the set algorithm, although more and more often they are enriched with certain elements of artificial intelligence, thanks to which they are able to make more and more complex decisions (including learning from the data provided thereto - both structured and unstructured) (Lacity & Willcocks, 2018), p. 26).

RPA tools are used to build software robots. It is one of the fastest growing categories of the process automation software. Nevertheless, a consistent and universally binding definition of these tools has not yet been developed, especially as these solutions are evolving. The author, based on the literature studies (Lacity & Willcocks, 2018), (Willcocks, Hindle, & Lacity, Becoming Strategic with Robotic Process Automation, 2020), (Agostinelli, Marrella, & Mecella, 2019), (Aguirre & Rodriguez, 2017), (Anagnoste, 2018), (Kedziora & Penttinen, Governance models for robotic process automation: The case of Nordea Bank, 2020) made an attempt to identify the main differentiating features of this class of IT solutions. It can be stated that:

- RPA software allows for developing software robots that usually operate directly on the IT systems' user interface, most often faithfully reproducing (mimicking) the activities performed thus far by an operator (although more and more often they can use APIs and have direct access to databases);
- software robots automate repetitive and mass (high volume) activities - i.e. ones that are carried out many times within the given unit of time – e.g. within a month or a year;
- use of the RPA tools does not require coding in the traditional sense – instead of writing the robot's code the software is created from predefined code components (providing specific functionalities), presented as graphic objects, which are then configured by providing specific parameters or recording actions (e.g. clicks) performed by a human operator (although some RPA tools already available also allow for traditional coding);
- implementation of software robots built with the use of the RPA tools does not require introducing of any changes to the business processes being automated this way (although this is recommended and allows for achieving much better business results);
- RPA tools do not require the development of dedicated programming interfaces to be used for data exchange between the systems being automated (although more and more tools enable the use of ready-made connectors or adding new ones);
- RPA tools use the business logic of the systems being automated – this eliminates the problem of reproducing this logic (as a consequence it is not necessary to have knowledge about the internal structure (design) of the systems, which is important in the case of legacy systems) and results in no need to change the source code or the database of the systems being automated (which is a common problem in the traditional model of IT systems integration).

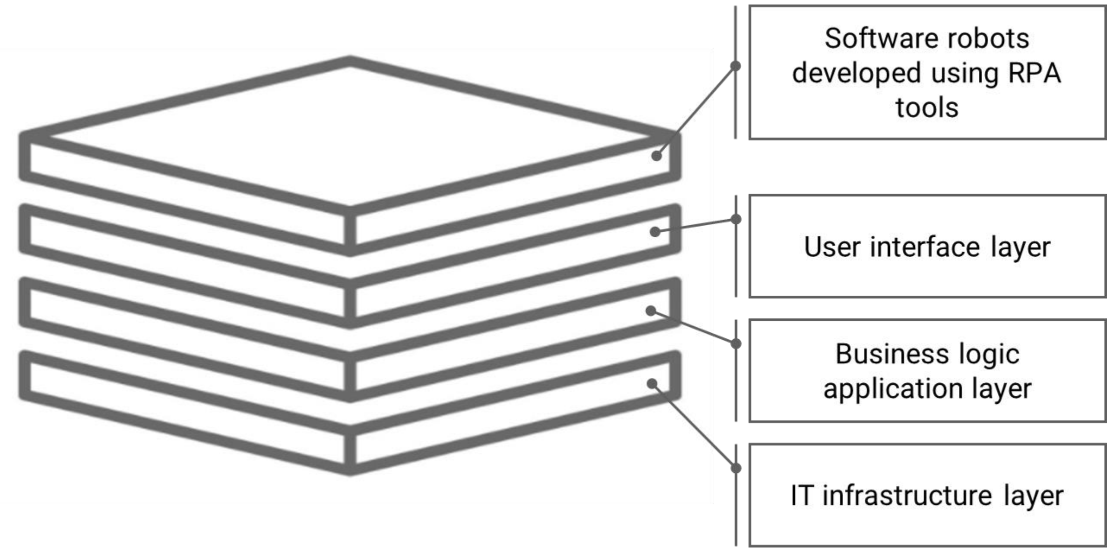

Figure 1. Layered model of process automation using software robots built in the RPA tool.
Source: own study

When comparing the RPA tools with the traditional solutions used to automate business processes – such as workflow systems or the BPMS (Business Process Management System) tools ((Shaw, Ch., Kawalek, Snowdon, & Warboys, 2007), p. 92-94), a single common feature and a number of differences can be identified. As far as the similarity is concerned, the RPA tools and the traditional automation solutions have the same goals – increasing the efficiency of business processes, cutting down the costs of the implementation thereof and ensuring the highest quality of the products of such processes. However, these goals are pursued in different ways.

The deployment of the workflow or BPMS solutions is most often associated with the implementation of complex IT projects, as part of which new components are deployed and the existing ones are altered. That is why such projects are usually carried out by the dedicated IT teams. In addition, this approach to automation assumes a profound alteration (revamping. overhaul) of the existing processes, and the introduction of the changes to these processes after the implementation has been completed results in the need to introduce modifications in the solutions used to automate them (the implementation of which requires time and adequate IT competences).

The RPA tools represent the opposite of the above approach. Their suppliers are striving to make them intuitive to use so that the representatives of business units, not the IT specialists, are able to use them (i.e. so that they are able to develop software robots themselves without or with a minimal support from the IT departments). At a number of companies it is done in the dedicated teams that constitute Centers of Excellence (Anagnoste, Setting Up a Robotic Process Automation Center of Excellence, 2018). Such centers are very frequently placed within the organizational structure of the company on the business side (not IT). The other model used to develop software robots is the distributed model – where people located in typical business units create such solutions (usually in collaboration with the security and IT departments). This approach has a number of advantages – among other things it ensures high speed and scalability of the robot development process and additionally allows for implementing automation based on deep domain knowledge (contained in the minds of the people who create these robots). At the same time, it should be noted that this approach could be dangerous if it were to allow for the occurrence of the phenomenon referred to as the "shadow IT" (i.e. if the robots being developed do not take into account the corporate standards and requirements with respect to security, compliance and IT architecture). Yet another way to acquire software robots is to rent (outsource) them from an external company. In this model the robot acts as a service (Robot as a Service), playing the role of a "digital worker" (Asatiani & Penttinen, 2016). The business department "hires" such a robot to perform a certain task, specifying the requirements for it in advance, and the external company (service provider) delivers and maintains it (in particular introduces changes).

At the same time, when implementing the RPA tools, there is a probability of an occurrence of certain risk factors – some of which are universal (i.e. they also occur in the case of applying the traditional automation methods), but some are specific to the robotic process automation. The most important risk factors – according to the author – that can be indicated include, inter alia, the wrong perception of the robotic process automation by employees (only taking into account the reduction of the costs related to human resources, and not, for example, focusing on improving the employee experience), the risk related to the wrong choice of the approach to the robotic process automation in the given organization (e.g. overly centralized activities related to robotization which will result in a slowdown of these activities), the risk related to the wrong choice of a robotic process automation tool (e.g. a tool that is not adapted to the company's existing IT architecture), the risk related to an inadequate approach to change management in the processes being automated (e.g. robotic automation of the so-called "mess"), the risk related to the resistance of the employees involved in the processes intended to be automated (due to the fear of losing their jobs), the risk of a competence gap (a loss of knowledge of the processes being automated – if robots are developed without adequate documentation) ((Lacity i Willcocks, Robotic Process Automation and Risk Mitigation: The Definitive Guide, 2017), p. 37-42), the lack of up to date and codified knowledge on the actual course of the business processes, in particular with regard to the way of dealing with exceptional situations occurring during their implementation (which may result in underestimating the time and expenditures required to develop the robots) and the lack of the coordination of the changes introduced in the systems as part of which the robot is operating (which usually results in the emergency stopping and downtime of the robotically automated processes).

To sum up, the deployment of the RPA tools can be perceived as one of the ways of implementing digital transformation (understood as a profound alteration (revamping. overhaul) – thanks to the use of technology – of the way an organization operates, leading to the development of a new model of its functioning) and as a digital innovation. Innovations of this type are understood as a) a new type of an IT solution, b) the outcome (result) of using this IT solution, c) the way the processes are implemented using this IT solution, changing the nature, structure or method of delivering products/services or the method of creating value for these customers, which in turn may lead to a transformation of the rules of operation for entire industries (Nambisan, Lyytinen, Majchrzak, & Song, 2017). Based on the presented determinants (drivers) of digital innovation, it can be stated that: (1) RPA tools are classified as innovative IT solutions, (2) software robots (developed with the use of the RPA tools) enable introducing a change in the way a business process is implemented and/or creating of completely new products, (3) use of the RPA tools changes the way entire industries operate – it can be seen most clearly in the banking and investment sector, as well as among the companies providing advanced business services (BPO and SSC) (Fernandez i Aman, 2018) (in the case of this industry it is even referred to as "cannibalization" of the traditional way of doing business ((Hallikainen, Bekkhus i Pan, 2018), p. 50). For this reason, it is so important to develop mechanisms allowing for the effective assimilation of the RPA tools by enterprises and their employees.

As seen from the literature analysis presented above, software robots are a particular type of software that can be used as one of the tools to carry out digital transformation in enterprises. Several existing scientific publications are concerned with identifying the distinguishing features of software robots—on the one hand, against the background of classic, domain-specific IT systems (Lacity & Willcocks, 2018), and, at the same time, against the backdrop of other process automation solutions—in particular, BPMS platforms ((Shaw, Ch., Kawalek, Snowdon, & Warboys, 2007), p. 92-94). The specific features of software robots (e.g. operations mimicking human-operator behavior) allow several benefits to be achieved—both financial (the implementation of Robotic Process Automation—RPA—is a source of significant savings, in particular) and non-financial - concerning, for example, a change in the way and scope of work previously carried out by employees (Willcocks, Hindle, & Lacity, Becoming Strategic with Robotic Process Automation, 2020). On the other hand, implementing RPA solutions may give rise to several risk factors (Lacity i Willcocks, Robotic Process Automation and Risk Mitigation: The Definitive Guide, 2017). These can be divided into elements that are universal to IT projects (i.e., constantly occurring, regardless of the approach or technology used in the project) and those specific to RPA projects. To minimise the likelihood of these risk factors materialising, choosing an appropriate model for implementing RPA and RPA governance solutions is essential (Kedziora & Penttinen, Governance models for robotic process automation: The case of Nordea Bank, 2020). This usually involves the decision to set up a dedicated competence centre, operating in a completely different way from the classic IT department (Anagnoste, Setting Up a Robotic Process Automation Center of Excellence, 2018).

At the same time, the implementation of software robots can be considered a special kind of digital innovation (innovative IT solutions) that requires appropriate approaches and is conditioned by many factors—organisational, technological, human, or related to the external environment (Tornatzky & Fleischer, 1990). Taking this as a starting point for further consideration, the literature analysis carried out by the author indicated that there is a research gap in this area—in particular concerning the identification of approaches to the assimilation of robotic process automation by enterprises (which determines the achievement of the assumed benefits from the robotisation of business processes and allows for its wide dissemination, the so-called scaling up the enterprise).

Models for the Assimilation of Innovative IT Solutions

For at least 30 years now we have been witnessing the development of modern IT solutions that change, on a mass scale, the way organizations operate – starting from the revolution related to the personal computers becoming ubiquitous, through the Internet revolution, the mobile revolution, and up to now, when there are revolutions related to mass robotization and artificial intelligence on the horizon, as well as the introduction of metaverse.

In parallel to the wide spreading of innovative IT solutions, a number of research models have been developed that are used to analyze the factors influencing the assimilation of innovative technologies. Based on these models the creators of digital innovations are able to better adapt the developed solutions to the current market requirements, needs, preferences and trends – which makes them more competitive. It is extremely important – both due to the multitude of technological innovations available today, as well as the ever richer experience of the organizations applying such solutions.

It should be emphasized that the literature on the assimilation models is extremely rich and presents both primary research, meta-analyses as well as the purely model-focused works. For the purpose of the article the author focused on a narrow selection of the topics discussed therein.

Models for the assimilation of digital innovation can be divided into two categories. The first one is related to the technology assimilation models from the perspective of the direct users. In particular, the following models can be identified in this category: TAM (Chuttur, 2009), TAM 2 (Venkatesh & Davis, 2000), UTAUT and UTAUT 2 (Venkatesh, Thong, & Xu, Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology, 2012), (Escobar-Rodríguez & Carvajal-Trujillo, 2014), D&M IS Success (DeLone & McLean, 2002), (DeLone & McLean, The DeLone and McLean Model of Information Systems Success: A Ten-Year Update, 2003). When analyzing these approaches it can be observed that they have been modified a number of times by the researchers. In addition, they have used several methods and/or theories simultaneously, extending one model by adding elements drawn from another. The recommendations developed based on the application of these approaches allow for indicating to the creators of digital innovations the directions of their products' development with respect to providing users with a more ergonomic, reliable and safe way to use their solutions.

The other group of models examines the topic of the assimilation of digital innovations from the organizational perspective. The number of such models is smaller as compared to the first category. The following models can, among others, be included in this group: Strategic Alignment model (Henderson & Venkatraman, 1993) and IT-Enabled Business Transformation frameworks (Venkatraman, 1994), (Agarwal & Brem, 2015). However, the most common model in this area is the TOE (Technology Organization and Environment) model. It was developed by Tornatzky and Fleischer (Tornatzky & Fleischer, 1990). The name of the model comes from three aspects which, according to the authors, affect the process of the organizational adoption and implementation of technological innovations, i.e. the technological, organizational and environmental aspects.

The factors related to the first aspect refer to the technological conditions – both internal (already functioning within the given organization – in particular the technical and organizational compatibility) as well as external (existing outside the organization, but not yet taken into account thereby). It should be noted that in this context the technology can be considered in tangible terms (e.g. hardware), but also in intangible terms (e.g. data and methods applied as well as the positioning of IT within an organization). This aspect is highlighted in the TOE model in order to draw attention to how the attributes related to the technological solutions and the implementation thereof can affect the assimilation of innovative solutions.

The organizational aspect is related to the entities' resources and assets, such as top management support, organizational culture, the complexity of the management structure measured by the degree of centralization and formalization, the quality of human capital, additional resources, process related conditions of the organization's operations. This aspect is highlighted in the TOE model in order to draw attention to how the attributes related to organizational conditions can affect the assimilation of innovative solutions.

Finally, the environmental aspect is related to the environment in which an organization is operating, including competitors and their pressure, technology suppliers, relationships with government entities, social and cultural issues, as well as access to ICT consultants. This aspect is highlighted in the TOE model in order to draw attention to how the attributes related to the nearer and farther environment in which the organization is operating can affect the assimilation of innovative solutions.

Researchers use the TOE model with respect to large organizations, but also more and more parts of it are used to analyze issues related to the assimilation of IT innovations by small and medium-sized enterprises.

The TOE model is widely used for research on the assimilation of innovative IT solutions – it has been applied in such areas as, for example, Cloud Computing (Hiran & Henten, 2020), CRM and eCRM (Cruz-Jesus, Pinheiro, & Oliveira, 2019), Supply Chain (Amelina, Hidayanto, Budi, Sandhyaduhita, & Shihab, 2016), Software-as-a-service (Hwang, Huang, & Wu, 2016), (Valdebenito & Quelopana, 2019), Radio frequency identification (RFID), (Pool, Asadi, & Ansari, 2015) Green IT (Chong & Olesen, 2017), Business Intelligence (Puklavec, Oliveira, & Popovič, 2017), e-commerce (This & Eam, 2011), but also AI (Na, Heo, Han, Shin, & Roh, 2022). The author has also decided to use this model in the research presented further on in the article.

Finally, it should be noted that some researchers believe that the analysis of issues related to the assimilation of digital innovation by enterprises using the TOE model is incomplete without taking into account such constructs as the enthusiasm of the owner and his/her growth (expansion) ambition (Fillis, Johansson, & Wagner, 2004), top management support and productivity of the management (Grandon & Pearson, 2004), differences in the beliefs of managers (Riemenschneider & McKinney, 2002) as well as the competences and characteristics of the CEO.

METHODOLOGY

Rationale for the Selection of the Use of the Structural Equation Modeling by Applying the Partial Least Squares Method (PLS-SEM)

PLS-SEM modeling falls within the scope of multivariate statistical methods known as the so-called second generation methods. The first generation methods (Fornell, 1987) include such analytical approaches as, for example, multiple and logistic regression or Analysis of Variance (ANOVA). In the case of the research problem under consideration, the applied approach (PLS-SEM) allows to overcome the weaknesses of the first generation methods, among others by including immeasurable constructs in the analysis, i.e. unobservable variables and the diagnosis of the relations between them, as well as taking into account measurement errors with respect to the observable variables (Chin, 1998).

An additional advantage of the PLS-SEM approach is the empirical measurement of a latent (hidden) variable, which is performed not only based on several (2-3) indicators, but also taking into account several indicators. As a consequence, the PLS-SEM data modeling process provides a much broader information horizon compared, for example, to the regression analysis, which is based on single observable variables. It is in this context that the structural equation modeling using the partial least squares method (PLS-SEM) proposed in this paper becomes of great importance – due to the range of indicators and the number of latent (hidden) variables as well as the relationships between them. The use of several indicators to measure the given type of a latent (hidden) variable gives this variable a more accurate picture as part of the phenomenon described.

Other advantages of the PLS-SEM approach with respect to data measurement and modeling include a high efficiency of complex model estimations, i.e. the possibility of configuring a research model with a large number of determined paths (relationships, dependencies), while at the same time taking into account a large number of indicators and latent (hidden) variables on the basis of relatively small sizes of the research samples; as in the case of this paper where N = 267 (the detailed information on the research sample is presented further on in the article). From the perspective of mathematical statistics, larger research samples obviously lead to greater precision and significance of the estimated results, however PLS-SEM does not exclude small samples due to an efficient estimation procedure (Hair, Hult, Ringle, & Sarstedt, 2017); (Henseler, Ringle, & Sinkovics, 2009). In this case, the algorithm used, which does not perform calculations on the basis of all dependencies (relationships) in the model simultaneously (as in the case of CB-SEM), but uses an approach based on OLS (least squares regression method), which allows to estimate model relationships in stages, in a partial manner, is important. Thanks to this approach, the PLS-SEM models do not require large samples, as evidenced by the results of empirical studies by a number of authors, such as Chin and Newsted (Chin & Newsted, Structural equation modeling analysis with small samples using partial least squares, 1999), Hui and Wold (Hui & Wold, 1982) as well as Reinartz et al. (Reinartz, Haenlein, & Henseler, 2009). At the same time, the PLS-SEM data modeling process does not require the fulfillment of rigorous assumptions regarding the normality of the distributions of individual observable variables (indicators) from which latent (hidden) variables – theoretical constructs – are created (Cassel, Hackl, & Westlund, 1999); (Wold, 1982); Reinartz et al. (2009); (Ringle & Wilson, 2009).

Theoretical Assumptions for the Design of the PLS-SEM Structural Model

The basis for the specification of the structural model presented in the article and the PLS-SEM analyses carried out in the Smart PLS-SEM statistical program are theoretical assumptions generated on the basis of the previously conducted literature review (presented in the first part of the article). Thus, the design of this model, or more precisely the diagnosis of its measuring elements, does not force the construction of latent (hidden) variables and their indicators from scratch. The author, using the theoretical advancements to date, took into account these constructs (latent variables) based on the analysis of the theory related to both the assimilation of technological innovations as well as the robotic process automation (robotization of business processes), which provided him with the basis for the verification of the theoretical dependencies (relationships) postulated in the Polish research conditions. It is worth emphasizing that one of the key conditions preceding any design of the measurement and structural model (PLS-SEM), taking into account the latent (hidden) variables and indicators associated therewith, is an accurate diagnosis of the current state of affairs based on a review and a critical evaluation of the literature items in the light of the theory under review, as well as the precise definition of latent (hidden) variables and the indicators thereof that the researcher uses to develop models (Węziak-Białowolska, 2011). In an operational sense, this task comes down to checking whether, in theory, there are already clearly defined latent (hidden) variables and whether any relationships between them have already been investigated in the literature on the subject. The researcher may propose an additional, i.e. a new order (configuration) of the relationships analyzed in the structural model, using the same theoretical variables, or he may take into account the same variables, at the same time including new variables in the model, the task of which is to enrich the previous scientific research results. Thus, the decision on what will ultimately be the subject of the PLS-SEM analyses is made by the researcher himself, who reviews the given configurations of sets of latent (hidden) variables in the PLS-SEM structural models in accordance with his own research needs, while using the existing theory to support his efforts.

At the same time, it should be assumed that if the proposed PLS-SEM structural model, and in particular the latent (hidden) variables (theoretical constructs) it contains, reflect a completely new (exploratory) dimension, then these variables must be subjected to a thorough statistical diagnosis from the point of view of the content provided thereby. Since in this study the construction of the model diagnosed with the use of PLS-SEM uses the literature available to date (i.e. the latent (hidden) variables have already been operationalized in the theory using the indicators), hence the overall effort related to the identification thereof has been simplified. Therefore, there is no need to generate a new type of indicators to describe latent (hidden) variables (theoretical constructs), but only to review them and perform a general evaluation with respect to the consistency thereof in accordance with the principles of adaptation of latent (hidden) variables to the given conditions of the social and cultural environment and the specifics of the given issue (in this case, robotic process automation).

Hypotheses Development

For the purpose of conducting research on the determinants of the assimilation of the robotic process automation by enterprises, the assumption was made to transfer and apply the hypotheses related to the implementation of innovative IT solutions previously stated and confirmed in the literature on the subject. The author could not directly use the hypotheses related to the implementation of the robotic process automation, because according to the author's knowledge, at the time of preparing the article, no publications on this topic were available. Therefore, the hypotheses proposed by the author are based on the literature research, but they have been adapted to the specifics of the robotic process automation.

The TOE model presented in the first part of the article is the starting point for the formulation of the research hypotheses. It includes three aspects: technological, organizational and environmental. Having carried out the literature research, the author did not identify articles on the assimilation of the robotic process automation as viewed from the TOE model perspective, and therefore decided to use the research works based on this model conducted in other IT areas.

Six hypotheses (H1-H6) are defined for the technological aspect. The assumptions behind their formulation are presented below.

A rapid increase in the importance of digital technologies has been noticeable over the last few years – both on the micro scale (at the level of the individual enterprises) as well as on the macro scale (at the level of the entire economy). Their wide spread application often leads to a profound transformation of the functioning of not only the individual entities, but even the entire industries. Business decision makers have realized that IT has transitioned from performing a support function to becoming a source of value generation, and they are beginning to appreciate the role of information technology. The literature on the subject repeatedly emphasizes the importance of the provision of benefits by IT technology as a factor having a significant impact on the assimilation of innovative solutions ((Kang & Kim, 2015) (Lai, Sun, & Ren, 2018).

Based on the above considerations the author has defined the H1 hypothesis:

H1: Providing the enterprise with benefits from the use of IT technology has a positive impact on the assimilation of the robotic process automation.

It is a truism to say that "data is the oil of the 21st century." Organizations realize that it is crucial to have data of adequate quality and to make sure that this data is integrated and available without any restrictions. Only then we can talk about the implementation of the "data driven company" concept. The literature on the subject emphasizes that having high quality data and managing integration mechanisms between systems have a positive impact on the assimilation of innovative IT solutions (Park, Kim, & Paik, 2015).

Based on the above considerations the author has defined the H2 hypothesis:

H2: High quality of data and ensuring the integration thereof has a positive impact on the assimilation of the robotic process automation.

Organizations have an ever increasing number of IT solutions that are implemented using diverse technologies and are based on various architectures (at large entities it is usually a combination of a mainframe computer architecture, three-tier architecture, microservice architecture). Organizations that are able to adequately manage the IT architecture and introduce changes thereto in a controlled manner find it much easier to ensure the coherence of the solutions developed (where coherence is understood as a degree to which IT solutions are perceived as compliant with the existing principles, experience and needs of the potential buyers – (Rogers, 1995)). The literature on the subject emphasizes that ensuring IT coherence (and thus effective management of IT architecture) has a positive effect on the assimilation of innovative IT solutions (Verma & Bhattacharyya, 2017). At the same time, in order to ensure the functioning of the tools that are used to robotically automate business processes, it is necessary to provide an ICT infrastructure (which is a part of the company's IT architecture), which must be adequately accessible and scalable. The literature on the subject repeatedly emphasizes the role of the IT infrastructure management as a factor that has a positive impact on the assimilation of innovative IT solutions (Soares-Aguiar & Palma-Dos-Reis, 2008), (Pan & Jang, 2008).

Based on the above considerations the author has defined the H3 hypothesis:

H3: Management of the enterprise's IT architecture and infrastructure has a positive impact on the assimilation of the robotic process automation.

There is a number of different methods of obtaining innovative IT solutions. There are costs associated with each method – such as licensing fees and expenditures related to the implementation. The literature on the subject emphasizes that the cost of innovative IT solutions has an impact on the assimilation thereof – it cannot be too high, as for many organizations it represents a significant barrier to the implementation (Rouhani, Ravasan, & Ashrafi, 2018).

Based on the above considerations the author has defined the H4 hypothesis:

H4: Low cost of the RPA tools has a positive impact on the assimilation of the robotic process automation.

Some of the key factors influencing the assimilation of innovative IT solutions are the features of the implemented solutions – taken into account both from the functional as well as the non-functional side. As described in the literature, in particular, the non-functional issue related to such aspects as stability of operation, ease of use, security, compatibility of the implemented tools with the organization's other, already existing IT solutions, have a positive impact on the assimilation of innovative IT solutions (Janz, Pitts, & Otondo, 2005); (Zailani, Iranmanesh, Nikbin, & Beng, 2015).

Based on the above considerations the author has defined the H5 hypothesis:

H5: Features of the RPA tools have a positive impact on the assimilation of the robotic process automation.

There are specific risks associated with any technological innovation – whether it is related to the choice of the tool or the performance of the implementation itself or, subsequently, the use of the tools acquired. As described in the literature, a high risk (in particular related to security, privacy, ensuring business continuity) is a significant barrier to the implementation of such innovations (Alshamaila, Papagiannidis, & Li, 2013); (Maroufkhani, Tseng, Iranmanesh, & Khairuzzaman, 2020). Therefore, it is necessary to take a number of measures aimed at ensuring continuous management of the risk related to the implementation of innovative IT solutions.

Based on the above considerations the author has defined the H6 hypothesis:

H6: Management of the risk associated with the RPA implementation has a positive impact on the assimilation of the robotic process automation.

Five hypotheses (H7-H11) are defined for the organizational aspect. The assumptions behind their formulation are presented below.

The implementation of innovative IT solutions is not only a technological undertaking. It is, in many cases, a change of the way an enterprise is conducting its business operations. In practice this means that committed management personnel is necessary to carry out and maintain an innovative IT implementation in an organization. As described in the literature, a high level of the decision-makers' awareness of the role of information technology (Boritz, Efendi, & Lim, 2018) and their pro-innovative attitude have a positive impact on the assimilation of innovative IT solutions (Asiaei & Rahim, 2019); (Maroufkhani, Tseng, Iranmanesh, & Khairuzzaman, 2020).

Based on the above considerations the author has defined the H7 hypothesis:

H7: Pro-innovative attitude and awareness of the management personnel have a positive impact on the assimilation of the robotic process automation.

The literature on the subject repeatedly emphasizes that it is the organizational culture in place at an enterprise that determines the speed and effectiveness of implementing innovations – including also the digital innovations. In particular, the role of the employees' trust in the company is highlighted in this respect as well as an organizational culture focused on openness and sharing of knowledge. Such an environment has a positive impact on the assimilation of innovative IT solutions (Veiga, Floyd, & Dechant, 2001).

Based on the above considerations the author has defined the H8 hypothesis:

H8: Company's pro-innovative organizational culture has a positive impact on the assimilation of the robotic process automation.

The implementation of innovative IT solutions entails the need for an organization to have human resources with adequate competences available. Paradoxically – with the growing role of IT at companies – more and more often the division of competences between the representatives of IT and business departments is blurred. This means that the IT specialists should have business competences, and the business people – both process competences as well as digital transformation related competences. As described in the literature, having employees with adequate competences available and being willing to develop them has a positive impact on the assimilation of innovative IT solutions (Cooper & Molla, 2014).

Based on the above considerations the author has defined the H9 hypothesis:

H9: Employees' competences and knowledge have a positive impact on the assimilation of the robotic process automation.

One of the key success factors for the digital transformation is the implementation of a process based approach. Organizations are moving away from a point-based view of the performance of the individual activities and turning towards a holistic view of the processes implemented. Only such an approach allows for improving the Customer Experience or ensuring the actual implementation of the multi-channel customer service concept. As described in the literature, the use of the process-based management by enterprises on a large scale and the ability to manage such processes (in particular, standardization and minimization of the complexity of the processes) have a positive impact on the assimilation of digital innovations (Van Looy, 2017)

Based on the above considerations the author has defined the H10 hypothesis:

H10: Implementation of the process-based approach in an organization has a positive impact on the assimilation of the robotic process automation.

The experience of recent years demonstrates that the organizational structure in place at companies has a significant impact on the success of implementing innovative IT solutions. According to the literature the role of a flat organizational structure in which decisions can be made quickly is indicated as a factor of particular importance for the assimilation of digital innovations (Ali, Shrestha, Osmanaj, & Muhammed, 2020); (Nkhoma & Dang, 2013). A similarly important role is attributed to the departure from the centralized decision-making process and moving towards the distributed decision-making process, which improves the flexibility of this process (Oliveira, Thomas, & Espadanal, 2014); (Yu & Tao, 2009).

Based on the above considerations the author has defined the H11 hypothesis:

H11: Flat organizational structure and the flexible decision making process have a positive impact on the assimilation of the robotic process automation.

Four hypotheses (H12-H15) are defined for the environmental aspect. The assumptions behind their formulation are presented below.

Organizations are increasingly operating not only in a turbulent environment, but also in an environment that is characterized by a growing degree of competitiveness. This competition – as an environmental context – may induce companies to implement innovative solutions in order to maintain or build a competitive advantage (Rouhani, Ravasan, & Ashrafi, 2018). As it is emphasized in the paper (Zhu, Kraemer, & Xu, 2006) companies operating in the competitive environments are more likely to use IT to achieve a competitive advantage.

Based on the above considerations the author has defined the H12 hypothesis:

H12: Competitive pressure has a positive impact on the assimilation of the robotic process automation.

Organizations are operating in an increasingly volatile environment. These changes may be caused by a number of factors, such as - a global pandemic (e.g. Covid-19), military situations (e.g. the war in Ukraine) or changes in the regulations at the level of the entire European Union (e.g. the Data Act). This translates into the behaviors displayed by both other, competing companies, as well as the consumers themselves. In order to survive in such a volatile environment organizations are undertaking a number of projects – involving both organizational as well as technological changes. As described in the literature, the volatility of the environment is regarded as a catalyst for specific projects inside the organization and has a positive impact on the assimilation of innovative IT solutions (Hsing Wu, Kao, & Lin, 2013).

Based on the above considerations the author has defined the H13 hypothesis:

H13: Volatility of the environment has a positive impact on the assimilation of the robotic process automation.

Successive generations of customers expect an ever higher quality of service from the product suppliers and service providers. At the same time, more and more organizations emphasize the role of customer-centricity in their business strategies, believing that this way they will build a competitive advantage. As described in the literature, the pressure exerted by customers regarding the implementation of new technologies by companies has a positive impact on the assimilation of innovative IT solutions (Chatzoglou & Chatzoudes, 2016) (Nugroho, Susilo, Fajar, & Rahmawati, 2017).

Based on the above considerations the author has defined the H14 hypothesis:

H14: Customer pressure has a positive impact on the assimilation of the robotic process automation.

As it has already been mentioned several times in the article, the role of IT at enterprises is growing. At the same time, IT companies – suppliers of these IT technologies – are becoming important partners in the activities carried out by their customers. In order to provide an effective service for their customers, IT companies are building complex, multi-level ecosystems of partners and are investing in consultants who provide the required knowledge and carry out complex implementations of the products supplied. In addition, the IT suppliers support the development of the community of the end users of their solutions. As described in the literature, such activities have a positive impact on the assimilation of innovative IT solutions (Premkumar & Roberts, 1999)

Based on the above considerations the author has defined the H15 hypothesis:

H15: Suppliers of the robotic process automation technology, and the ecosystem of partners and communities they have built, have a positive impact on the assimilation of the robotic process automation.

The author has also formulated four hypotheses (H16-H19) regarding the effects of the assimilation of the robotic process automation by enterprises (Stjepić, Ivančić, & Vugec, 2020).

The implementation of innovative IT solutions is the basis for the way enterprises are operating. In particular, it enables changing the way business processes are carried out at these companies. According to the literature, the determinant (driver) of a successful digital transformation is, inter alia, the redesigning of the existing or even creating new business processes dedicated to the digital channels (Stjepić, Ivančić, & Vugec, 2020).

Based on the above considerations the author has defined the H16 hypothesis:

H16: Assimilation of the robotic process automation enables introducing an innovative change in the way business processes are implemented in the company.

At present organizations have less and less opportunity to build a competitive advantage by applying an approach based on optimizing the use of the existing resources and processes. It is believed that innovations will be the source of the competitive advantage – including, in particular, product innovations. As described in the literature, innovative IT solutions are increasingly becoming the basis for the introduction of such product innovations (Kedziora, Leivonen, Piotrowicz, & Öörni, 2021).

Based on the above considerations the author has defined the H17 hypothesis:

H17: Assimilation of the robotic process automation enables introducing a change to the existing products or launching of new products.

The use of innovative IT solutions directly or indirectly contributes in many cases to an improvement of the Customer Experience. In the case of a direct improvement of the Customer Experience, it is related to the fact that IT solutions enable the introduction of omnichannel services, personalization of products or services, or the introduction of mechanisms supporting the so-called "Voice of Customer" (Foroudi, Gupta, Sivarajah, & Broderick, 2018). In the case of an indirect improvement of the Customer Experience, it stems from the fact that, thanks to innovative IT solutions, not only employee efficiency is often improved, but also the level of satisfaction with the work they are performing goes up (as a consequence of getting rid of monotonous activities). A more satisfied employee will definitely be implementing customer service processes better (Kedziora & Kiviranta, Digital Business Value Creation with Robotic Process Automation (RPA) in Northern and Central Europe, 2018).

Based on the above considerations the author has defined the H18 hypothesis:

H18: Assimilation of the robotic process automation enables improving of the Customer Experience.

The introduction of innovative IT solutions allows, in many cases, to alter (revamp, overhaul) the existing business model of an enterprise (Pateli & Giaglis, 2005). The business model is understood as: a description of the values that the enterprise is offering for its customers, as well as the structure of the company and the network of partners for creating, transferring and delivering of these values in order to generate a profit and sustainable revenue streams (Osterwalder, Pigneur, & Tucci, 2005). The growth of the role of IT can be seen very well on the example of the Business Model Canvas ((Osterwalder & Pigneur, Business Model Generation: A Handbook for Visionaries, Game Changers, and Challengers, 2010) an approach that has become a de-facto standard when it comes to documenting business models. In this approach IT solutions become a key asset of an enterprise. These solutions very often allow for delivering a new type of a business value or reaching a new customer (Bican & Brem, 2020).

Based on the above considerations the author has defined the H19 hypothesis:

H19: Assimilation of the robotic process automation enables introducing a change to the enterprise's business models.

Specification of Theoretical Constructs (Latent Variables) and the PLS-SEM Model

As part of the design of the PLS-SEM structural model, sets of indicators available in the literature were used to define individual types of latent (hidden) (theoretical) variables that constituted individual measurement elements. The configuration of latent (hidden) variables, i.e. the sequence of dependencies (relationships), stemmed from the theoretical foundations (based on the TOE model and the previously formulated hypotheses), logical premises and practical experiences observed by the researcher (in particular, the specifics of the implementation of the projects related to the robotic process automation were taken into account). In a practical sense, this sequence involves placing the independent (so-called exogenous) latent (hidden) variables on the left hand side of the structural model, and the dependent latent (hidden) (endogenous) variables on the right hand side. Thus, the exogenous variables must precede the endogenous variables. Taking these guidelines into account, the following constructs were the independent (exogenous) latent (hidden) variables: "Technology" (T), "Organization" (O), "Environment" (E). On the other hand, the construct defined as "Assimilation of the Robotic Process Automation" (AR) was classified as the dependent (endogenous) latent (hidden) variable placed on the right hand side of the structural model. The relationships between the constructs taken into consideration are shown in Figure 2. Overall, as part of the structural equation model and its measurement models, a total of four types of latent (hidden) variables (theoretical constructs) were used, which were made up of 19 sub-areas:

- a construct defined as "Technology" (T), composed of 6 sub-areas;
- a theoretical construct "Organization" (O), defined based on 5 sub-areas;
- a diagnostic construct "Environment" (E), composed of 4 sub-areas;
- a construct defined as "Assimilation of the Robotic Process Automation by an Enterprise" (AR), including 4 elements.

The components of each construct are the derivatives of the previously defined detailed hypotheses.

"Technology" (T) construct includes 6 sub-areas:

T1 – *The benefits of using IT*, described by the indicator:

- T1a: Providing the company with benefits resulting from the use of RPA tools

T2 – *Data quality and their integration* described by the indicators:

- T2a. High intensity of information exchange between the departments of the enterprise
- T2b. High quality of the data processed by the enterprise's IT systems
- T2c. High level degree of integration between the enterprise's IT systems
- T2d. Openness of the enterprise's IT systems from the perspective of the ease of data exchange between them

T3 – *Technical architecture of the enterprise and IT Infrastructure* described by the indicators:

- T3a. Minimizing the complexity of the company's IT infrastructure
- T3b. Preparedness (readiness) of the IT infrastructure for the implementation of the robotic process automation

T4 – *Costs of acquiring the robotic process automation tools* described by the indicator:

- T4a. Low cost of purchasing a license and implementing the RPA tools

T5 – *Features of the robotic process automation tools* described by the indicators:

- T5a. Stability of the RPA tools' operation
- T5b. Ease of use of the RPA tools
- T5c. Security mechanisms provided by the RPA tools
- T5d. Compatibility of the RPA tools with the company's other IT solutions

T6 – *Risk related to the robotic process automation* described by the indicator:

- T6a. Risk management related to the implementation of the robotic process automation

Theoretical construct "Organization" (O) is defined based on 5 sub-areas:

O1 – *Attitudes and awareness of the management personnel* described by the indicators:

- O1a. Support from the management personnel in implementing the robotic process automation
- O1b. Pro-innovative attitude of the management board
- O1c. High level of awareness of the company's management board of the role of information technology

O2 – *Organizational culture of the company* is described by the indicators:

- O2a. Employees' trust in the company
- O2b. Company's organizational culture is focused on openness and sharing of the knowledge

O3 – *Employees' competences and knowledge* described by the indicators:

- O3a. Business competences of the IT personnel
- O3b. Process related competences of the business departments' staff
- O3c. Digital competences of the business departments' staff

O4 – *Process based approach in the organization* described by the indicators:

- O4a. Minimizing the complexity of implemented processes / tasks
- O4b. Application of the process approach in the company

O5 – *Organizational structure and decision making process* described by the indicators:

- O5a. Flat organizational structure of the company
- O5b. Decentralized way of making decisions in the company
- O5c. Distributed way of making decisions in the company

Diagnostic construct "Environment" (E) is composed of 4 sub-areas:
E1 – *Pressure from the competition* described by the indicator:
- E1a. Pressure from the competition

E2 – *Volatility of the environment* described by the indicator:
- E2a. Speed of changes (technological, economic, legal) taking place in the company's environment

E3 – *Customer pressure* described by the indicators:
- E3a. Customers in the industry in which the company is operating are constantly looking for new, innovative products/services
- E3b. Customers in the industry in which the company is operating expect a very high quality of products/services

E4 – *Suppliers of the robotic process automation technologies and their ecosystem* described by the indicators:
- E4a. RPA tool supplier's reputation
- E4b. Access to the community of the RPA tool users
- E4c. Ecosystem of partners, training and certifications built by the RPA tool provider
- E4d. Ensuring support from the RPA tool provider or its partners
- E5e. Ensuring support from external consultants in implementing the RPA tools

The construct defined as "Assimilation of the Robotic Process Automation by an Enterprise" (AR) includes the following elements:
AR1 – Change in the way processes are implemented thanks to the robotic process automation described by the indicator:
- AR1a. Robotic process automation enables innovative changes to the way business processes are implemented in a company

AR2 – Changed / new products / services thanks to the robotic process automation described by the indicator:
- AR2a. Robotic process automation enables a significant improvement of the already provided products / services or an introduction (launching) of new products / services

AR3 – Improving Customer Experience thanks to the robotic process automation described by the indicator:
- AR3a. Robotic process automation enables an improvement of the quality of customer service (Customer Experience)

AR4 – Change of the enterprise's business model thanks to the robotic process automation described by the indicator:
- AR4a. Robotic process automation enables changing of at least one component of the company's business model (e.g. implementation of the key activities, cost / revenue structure, customer contact methods, etc.)

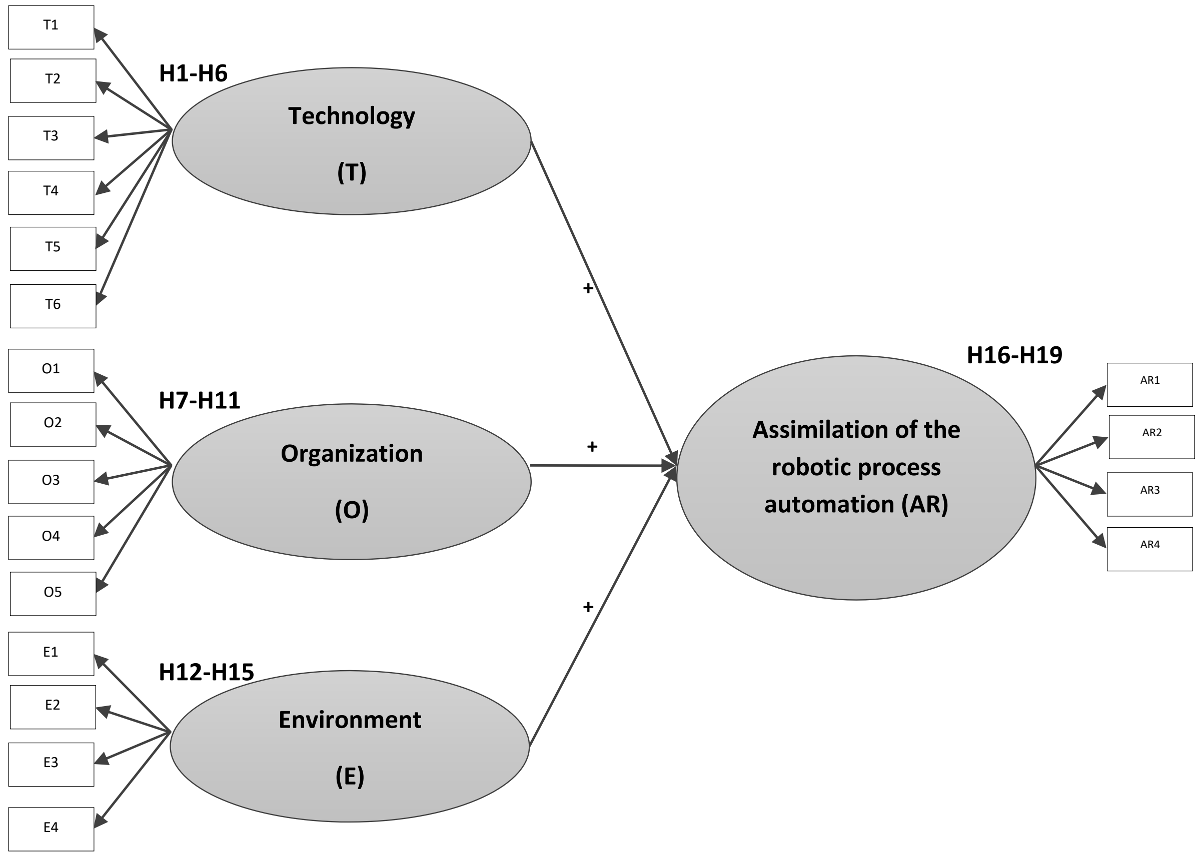

Figure 2. PLS-SEM structural model to diagnose the theoretical relationships with respect to the independent and dependent latent (hidden) variables.
Source: own study

Key: Arrows connecting the latent (hidden) variables (measurement elements of the PLS-SEM model) define the postulated (positive) directions of the PLS-SEM model relationships. Arrows placed between the latent (hidden) variables and the indicators (marked with squares) represent the factor loadings. The oval shape represents the latent (hidden) variable, and the square represents the indicator as part of the latent (hidden) variable.

THE METHOD OF CONDUCTING THE SURVEY AND THE CHARACTERISTICS OF THE SURVEY SAMPLE STRUCTURE

In order to verify the developed research PLS-SEM model, the author prepared and conducted a survey in the time frame from October 2020 to January 2021, which was composed of two stages – a pilot survey and the full scale research. A survey questionnaire related to the determinants (drivers) of the assimilation of the robotic process automation was created and verified during the pilot project. The prepared research questionnaire was verified in the form of a pilot survey conducted among 10 enterprises representing industries that were planned to be included in the full scale research. As part of the verification process the respondents' understanding of the questions included in the questionnaire was assessed, as well as the completeness thereof. As a result of the pilot surveys completed, modifications were introduced in the survey questionnaire itself – three questions were significantly reformulated, and in four questions the wording was made more precise. Due to the changes in the questionnaire the research material collected during the pilot survey was not used in the full scale research procedure. As part the next stage of the research procedure, the key – from the perspective of the verification of the developed research PLS-SEM model – survey was conducted. The selection of enterprises included in the survey was deliberate – each company had to declare the production implementation (deployment) of at least one software robot (developed with the use of the RPA, RDA or C-RPA class tools).

The CAWI (Computer Assisted Web-Interviews) technique was used to carry out the survey, where a respondent completed the electronic version of the questionnaire available online. It is currently one of the most frequently used survey techniques. As Smith and Kim point out, CAWI is a part of the Computer Assisted Survey Information Collection (CASIC) group, which is a part of a wider group of Computer Assisted Data Collection (CADAC) techniques (Smith & Kim, 2015). The author's choice of this survey technique was dictated by several factors. First of all, the main reasons for the use of the questionnaire in an electronic form included: obtaining the largest possible number of surveys collected (the survey was addressed to a specific group of respondents for whom online tools are a natural working environment), shortening the time of conducting the survey, enabling respondents to respond at a convenient time for them and reducing the costs of performing the research work while maintaining a high level of completeness and quality of the responses (possible to achieve thanks to the introduction of the validation rules for the individual fields of the questionnaire and the validation between the individual fields). Significant arguments in favor of choosing the CAWI technique also included the ease and convenience of filling in the questionnaires by the respondents, as well as reducing the influence of the interviewer on the answers given by the respondents (such an influence might occur during a survey using the direct interview technique). The final argument for the choice of the research technique was the coincidence of the timing of conducting the survey with the pandemic situation and the resulting limitations of the direct communication with respondents.

The responses obtained were subjected to an additional verification, going beyond checking the filling of all of the mandatory fields in the questionnaire. In the case of ambiguity or inconsistency in the answers provided, the respondent was contacted by e-mail (the prerequisite for including the given questionnaire in the research pool was the provision of the business e-mail address of the person completing the questionnaire), and asked for explanations to be provided by e-mail, or if there were more ambiguities – a telephone conversation was arranged or teleconferencing tools – Zoom and MS Teams – were used.

The author consciously decided not to engage a survey company to conduct the research. It is true that such a method of conducting a survey has many benefits (including the possibility of the direct clarification of ambiguities that the respondents experienced when filling in the questionnaire, increased motivation of the respondent to fill in the questionnaire, which translates into a higher rate of survey returns), but it also has a number of limitations. First of all, it significantly extends the time and costs of conducting a survey, and also generates the risk of a diversified training of interviewers, which translates into the possibility of inconsistencies in the explanations provided to the respondents. The direct interview research is useful in the case of questionnaires containing a large number of open-ended questions (which was not the case with the questionnaire used by the author, as practically all of the questions were closed-ended) and in the event it is necessary to take actions aimed at forcing answers to all questions (this was not the case with the questionnaire used by the author as the system applied to develop the questionnaire enabled imposing the necessity to provide an answer by the respondent).

Finally, a total of 267 questionnaires were qualified for the analysis, each of which met the following set of conditions:

- a questionnaire was completed by a representative of the enterprise from the industry included in the survey;
- all of the mandatory fields were filled (all questionnaires met this condition); this way the author wanted to avoid the averaging of the respondents' answers, which was a typical procedure in the event this type of situation occurred;
- all validation rules were met;
- all doubts regarding the completion of the questionnaire were clarified by the author by e-mail or during an interview.

The questionnaire used in the survey included basic questions and a respondent’s particulars part (demographics, personal information). A number of questions were included in the questionnaire as control variables. They were related to such issues as:

- size of the enterprise measured by the number of employees,
- industry of the enterprise.

In addition, a filtering question was introduced – its purpose was to separate enterprises with at least one software robot implemented in the production environment from enterprises that could not demonstrate such an implementation (in such a case their answers were not included in the research pool).

A 5-point Likert scale was used to measure the individual indicators in the study. Despite the fact that this scale assumes the ordinal nature of the response, in special cases it approaches the properties of a stronger quasi-interval scale (see (Mooi & Sarstedt, 2011)), as long as the adequate design rules are maintained. Special attention should, however, be paid, as part of the process of preparing questions and statements for the scale, to the coding of the responses and the fulfillment of the so-called condition of equal distance between the response categories on the scale. The use of a 5-point scale in the research presented, with categories such as: (1) strongly disagree, (2) disagree, (3) neither agree nor disagree, (4) agree and (5) strongly agree, allowed for expressing equal "distances" between categories 1 and 2 as well as between categories 3 and 4.

The companies from the following industries were included in the survey: banking and insurance, other finance (excluding banking and insurance), professional business services (split into: Business Process Outsourcing (BPO) and Shared Services Centers (SSC)), e-commerce, retail, logistics, media, advertising and entertainment, health care (including pharma), manufacturing, telecommunications, utilities (including power, gas, district heating). The respondents mainly included the representatives of banking and insurance, manufacturing industry and Shared Services Centers – see Figure 3. Companies from these industries are the leaders of the robotic process automation in Poland.

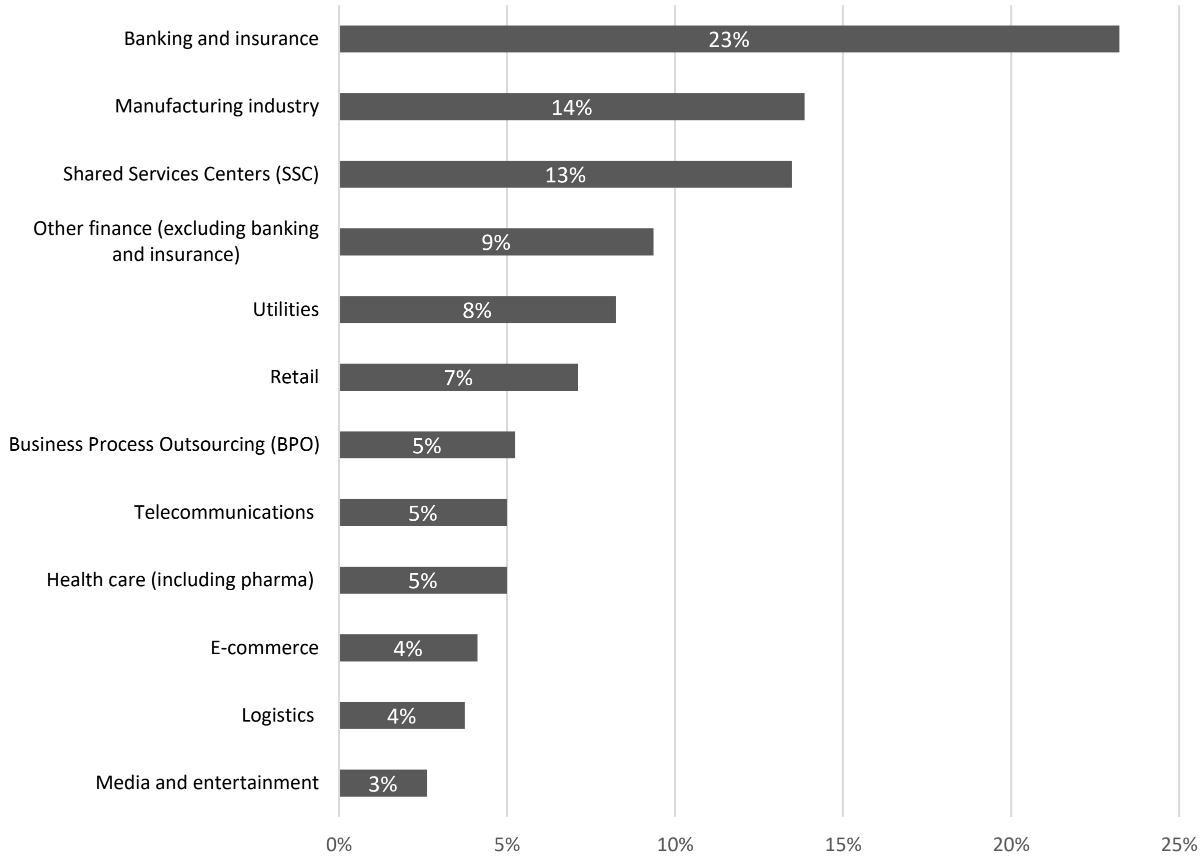

Figure 3. Industries included in the research [N = 267].
Source: own research

Companies from the IT industry (including the RPA tool suppliers) and consulting companies were not included in the study on purpose, as the range of topics covered by the survey concerned mainly intra-organizational issues related to the assimilation of the robotic process automation. The research also did not cover public administration units, as these entities have not yet started to use the robotic process automation on a larger scale. The author is monitoring the progress of the robotic process automation project implementations in the Polish public sector entities (Sobczak, 2021). At the time of conducting the survey only three municipal offices in Poland disclosed information on the implementation of the robotic process automation solutions, and a few more were just getting ready; also in the literature on the subject, there are few references to the implementations at such units – see for example (Nauwerck & Cajander, 2019).

As mentioned earlier, 267 enterprises from all over Poland participated in the survey. When analyzing the structure of the respondents (see Figure 4), it can be observed that large enterprises (i.e. with more than 250 employees) dominated the sample – there were over 70% of them in the group surveyed. Small and medium-sized enterprises, i.e. those employing up to 250 people, were a definite minority.

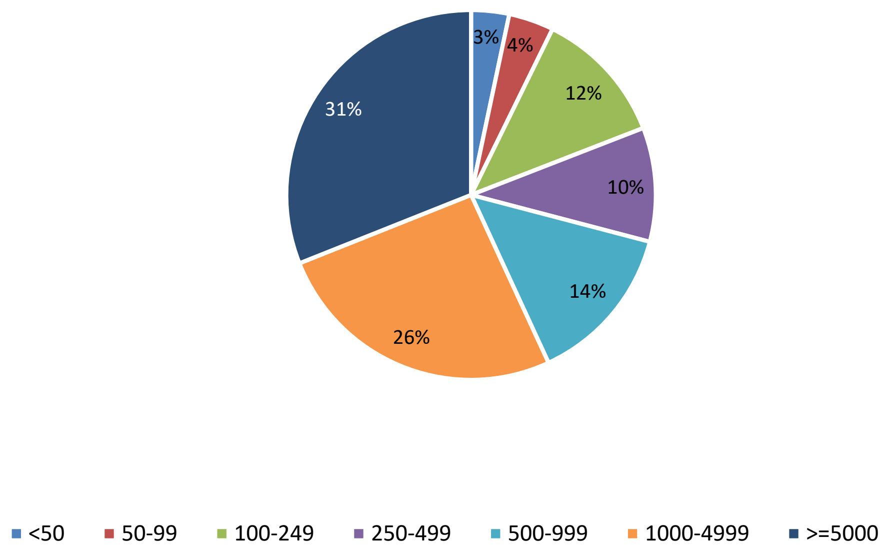

Figure 4. The size of the enterprises participating in the survey [N =267].
Source: own research

As the results of the survey indicate (Figure 5), at most of the enterprises the robotic process automation is a new or a relatively new topic. – 58% of the respondents have been implementing such solutions for no longer than two years. Companies implementing the robotic process automation for more than 3 years (23%) are a minority. According to the author, these results indicate a relatively early stage of the implementation of the robotic process automation at the entities surveyed.

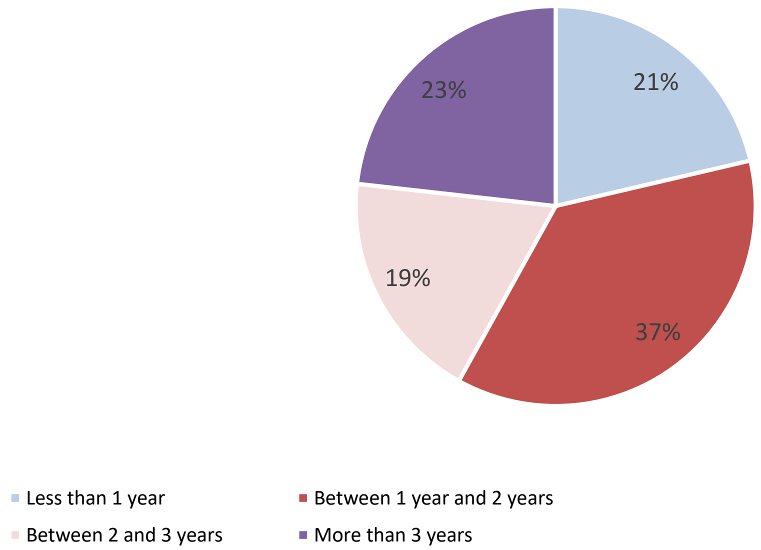

Figure 5. The period of implementing the robotic process automation at the enterprises [N = 267]
Source: own research

The initial stage of implementing the robotic process automation is also confirmed by the number of robots deployed at the companies surveyed. Based on Figure 6 it can be observed that at the overwhelming majority of the companies surveyed (43%) the number of robots deployed ranges between 1 and 4. At the same time, nearly 15% of the enterprises already have more than 100 robots in place.

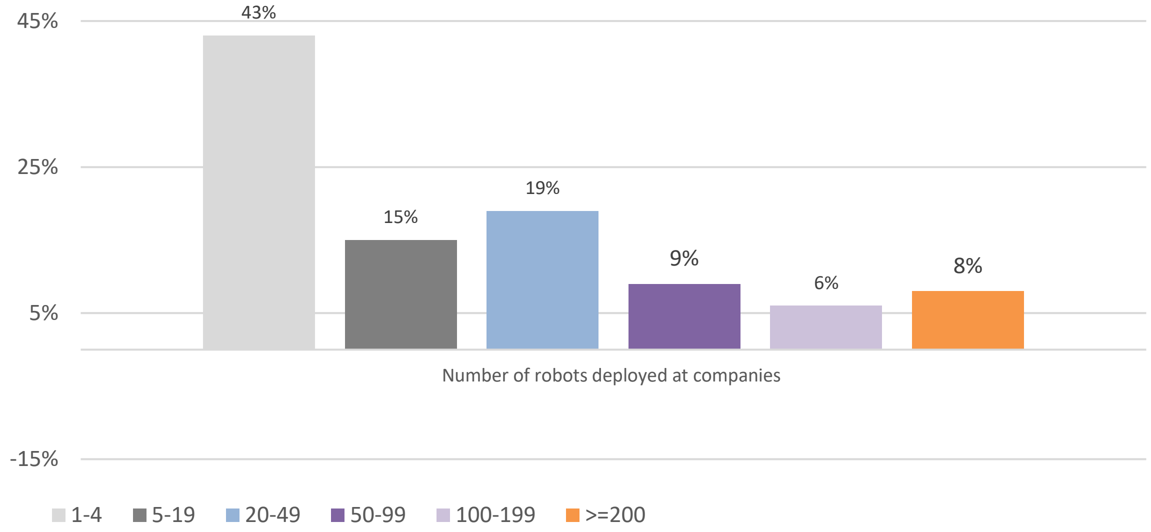

Figure 6. Number of robots deployed at companies [N = 267].
Source: own research

Finally, it is worth noting that the respondents were mainly managers of the units / leaders of the teams responsible for the robotic process automation – 39%. Among the remaining respondents, a large group were project managers who were responsible for the implementation of the robotic process automation – 29% (see Figure 7).

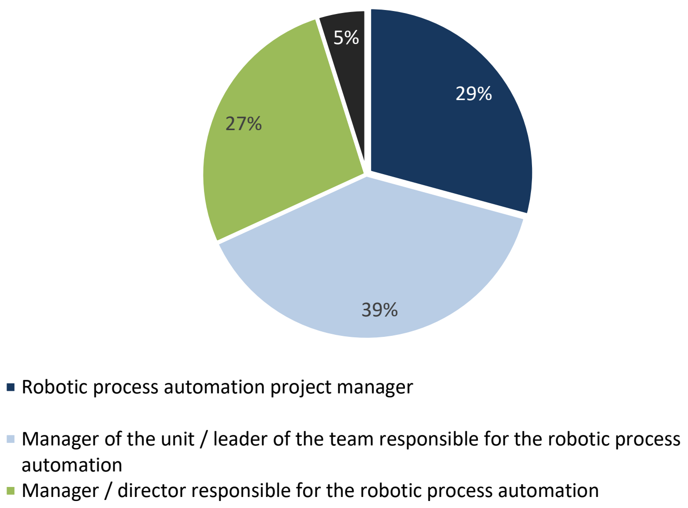

Figure 7. Respondent positions [N = 267].
Source: own research

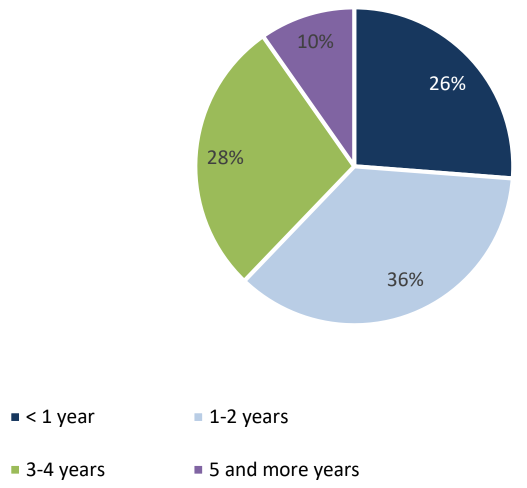

Figure 8. Professional experience of the respondents in the robotic process automation [N = 238].
Source: own research

The respondents were dominated by people with a relatively short experience in the RPA area activities (between 1 and 2 years – there were 36% of them) or with an average experience (between 3 and 4 years – there were 28% of them) (see Figure 8).
Such a structure of people participating in the survey confirms that Polish enterprises already have some experience related to the implementation of the robotic process automation, but it is relatively limited (this is also due to the fact that the robotic process automation in Poland on a larger scale began to be implemented only starting from around 2019).

DISCUSSION OF THE RESULTS OBTAINED

Diagnosis of the Latent (hidden) Variables as the Main Components of the PLS-SEM Structural Model

The key element having an impact on the correctness of the PLS-SEM structural model is the quality of the individual latent (hidden) variables. They must meet the formal and statistical adequacy criteria. The assessment of this adequacy is made on the one hand on the basis of the assessment of the adequacy of the indicators (among others, the size of factor loadings). The higher the factor loading (see Table 1), the stronger the constructive substantive relationship between the given indicator and the corresponding latent (hidden) variable. On the other hand, the second part of the analysis comes down to the assessment of the level of consistency (reliability) of the theoretical construct itself (latent (hidden) variable). However, the reliability of the latent (hidden) variables depends on the properties of the individual indicators, which means that the quality of a single indicator determines the level of the precision of the measurement of the selected latent (hidden) variable.

Therefore, taking into account the above guidelines, the first step in the evaluation of the results was to verify the indicators for the individual latent (hidden) variables used in the PLS-SEM structural equation model. In this case, the indicators were assessed on the basis of the size of their factor loadings. In the light of the theoretical assumptions (see (Thurstone, 1931); (Sztemberg-Lewandowska, 2008); (Spector, 1992)), these values should generally stand at 0.70, which in turn allows the given latent (hidden) variable to explain a significant part (more than 50%) of the variance. Based on table 1 it can be observed that all factor loadings of the indicators under consideration within the range of the latent (hidden) variables selected for the measurement were even higher.

As part of the second stage of the diagnosis, the level of internal consistency of the latent (hidden) variables was assessed. For this purpose, Jöreskog's composite reliability coefficient (1971) was used, where higher values indicate a higher level of reliability of the latent (hidden) variable. The values of this coefficient within the (0.60 - 0.70) range are considered acceptable for the construct (Chin, The partial least squares approach to structural equation modeling, 1998); (Höck & Ringle, 2010), and the values within the (0.70 - 0.90) range indicate a good or even a very good level of reliability.

Taking into account the latent (hidden) variables considered in the study, the values of Jöreskog's coefficients were respectively: 0.91 (for the "Technology - T" construct); 0.89 (for the "Organization - O" construct); 0.88 ("Environment - E") and 0.83 ("Assimilation of the Robotic Process Automation - AR"). Therefore, the figures provided meet the internal consistency requirement.

In addition to the above reliability index, its alternative variant (Cronbach's alpha) was used as well. It is also worth emphasizing that the minimum level of acceptability of the Alpha reliability coefficient is 0.60. This value is a kind of a threshold for the latent (hidden) variables under consideration.

Table 1. Factor loadings of the indicators and the quality of the latent (hidden) variables.

Indicators	**Latent (hidden) Variables and their Indicators Used in the PLS-SEM Structural Model**			
	T	O	E	AR
T1	0.85			
T2	0.73			
T3	0.82			
T4	0.89			
T5	0.83			
T6	0.81			
O1		0.86		
O2		0.85		
O3		0.82		
O4		0.81		
O5		0.79		
E1			0.78	
E2			0.85	
E3			0.79	
E4			0.81	
AR1				0.88
AR2				0.82
AR3				0.74
AR4				0.79
	Reliability and Validity Indicators			
Jöreskog's indicator	0.91	0.89	0.88	0.83
Alpha indicator	0.82	0.86	0.79	0.74
AVE indicator	0.68	0.71	0.65	0.66

Key: T = Technology; O = Organization; E = Environment; AR = Assimilation of the Robotic Process Automation. N = 267
Source: own research

Thus, taking into account the above guidelines, the values of Cronbach's alpha coefficients for the latent (hidden) variables under consideration stood at, respectively: 0.82 (for the "Technology - T" construct); 0.86 ("Organization - O"); 0.79 ("Environment - E") and 0.74 ("Assimilation of the Robotic Process Automation - AR"). Therefore, the values provided (calculated on the basis of the indicators contributing thereto) meet the internal consistency requirement.

At the same time, it is also worth emphasizing that the calculated alpha coefficients came in at lower values, on average, in comparison with Jöreskog's reliability coefficients. This is because Cronbach's alpha is a reliability measure whose items are not weighted. On the other hand, Jöreskog's complex reliability coefficient is determined based on the weighted indicators, i.e. factor loadings.

Finally, the AVE index was used in the study to assess the convergent validity of each of the highlighted latent (hidden) variables. This measure reflects the average level of the total variance explained by the given theoretical construct (latent (hidden) variable) on the basis of its co-creating indicators, and to be more precise, the factor loadings thereof. The lowest acceptable level of AVE in the analyses stands at 0.50 (Chin, 1998) (Höck & Ringle, 2010) and it assumes that the given latent (hidden) variable should explain min. 50% of the variance for all analyzed indicators (items). On the other hand, the value of AVE below the level of 0.50 means that the error variance outweighs the true variance. With these facts in mind, in the case of the data under consideration, we can conclude that all AVE values of the analyzed latent (hidden) variables exceeded the level of 0.50 (see Table 1), thus an acceptable level of convergent validity was obtained.

Assessment of the Quality of the Structural Equation Model in the PLS-SEM Analysis

Having validated the theoretical constructs as the main components (latent (hidden) variables) of the PLS-SEM structural equation model, the PLS-SEM model was assessed as a part of the next phase (see Figure 9). This aspect of the analyses was related, firstly, to the general diagnostics of the predictive capabilities of the models and the diagnosis of the relationships between the theoretical constructs (latent (hidden) variables) in terms of the statistical significance of the results. The evaluation process was carried out in five stages (see Figure 2). Thus, as part of the first stage, the model was verified with respect to the problems of collinearity between the latent (hidden) variables of the structural model. The lack of this type of verification could result in an erroneous estimation of the parameters of the PLS-SEM model's structural paths. Collinearity, similar to the regression models, determines the level of dependence (relationship) between the endogenous variables and their predictors – the exogenous variables. The problems of collinearity in the PLS-SEM models are diagnosed using the so-called collinearity index (VIF – variance inflation factor). In practice, the value of the VIF parameter above 5.0 indicates a significant problem related to the collinearity between the predictors and the estimated parameters of the model (Mason & Perreault, 1991). On the other hand, VIF values in the range between 3.0 and 5.0 are considered acceptable (Hair et al. 2017) (Hair, Hult, Ringle, & Sarstedt, 2017). However, the most desirable VIF values are values below 3.0. According to these premises, based on the observation of the results obtained (see Table 2), we can conclude that in the case of the latent (hidden) variables under consideration, VIF values did not exceed 3, which proved the lack of collinearity between the predictors (exogenous latent (hidden) variables) in the PLS-SEM model.

As part of the second stage, the value of the R^2 determination coefficient of the endogenous latent (hidden) variable (AR) was checked. This coefficient measures the predictive accuracy of the PLS-SEM model and is computed as the square of the correlation between the actual and the predicted values of the given endogenous variable (i.e. the dependent latent (hidden) variable). The value of the R^2 coefficient ranges from 0 to 1, with the higher value reflecting the higher level of predictive accuracy of the exogenous variables. In the literature on the subject the following values of the R^2 coefficient in the PLS-SEM analyses are assumed: 0.75, 0.50 or 0.25, which are assigned the level of explained variance at the following levels: significant, moderate and weak ((Hair, Ringle, & Sarstedt, PLS-SEM: Indeed a silver bullet, 2011); (Henseler, Ringle, & Sinkovics, 2009). Taking these guidelines into account, it can be concluded that the model based on the endogenous variable (AR) in relation to the three exogenous latent (hidden) variables ("Technology" - T, "Organization" - O, "Environment" - E) produced the value equal to 0.63.

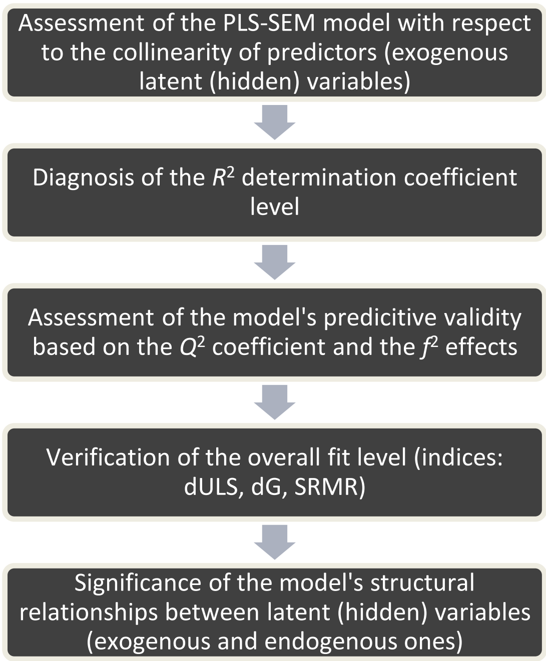

Figure 9. Stages of the PLS-SEM structural models diagnostics process.
Source: own research

Table 2. Diagnostic assessment of the PLS-SEM model based on the selected indicators

Exogenous Latent (hidden) Variables	Endogenous Latent (hidden) Variable (AR)	
	VIF Values	f^2 Values
Technology (T)	2.55	0.22
Organization (O)	1.75	0.42
Environment (E)	2.10	0.36
	Indicators	
R^2	0.63	
Q^2	0.55	
SRMR	0.05	
dULS	0.15*	
dG	0.12*	

Reference values: (*) $p > 0,05$. N = 267
Source: own research.

In addition to the evaluation of the R^2 determination coefficients, in order to verify the predictive relevance of the models, the Stone-Geisser Q_2 predictive quality (relevance) indicator (see (Geisser, 1974); (Stone, 1974)) was also used in the study. This indicator allows to determine the predictive relevance of the given endogenous latent (hidden) variable (taking into account its indicators – AR) along with the simultaneous impact of the exogenous latent (hidden) variables thereupon. The higher this indicator, the more accurate (relevant) the level of prediction is, which also translates into a higher level of the estimated paths in the PLS-SEM model in terms of the relationship between the endogenous latent (hidden) variable and the given exogenous variable under consideration. The interpretation of the Q_2 indicator's value should be as follows; values slightly higher than 0 (after the decimal point) indicate a poor level of prediction, while the values 0.25 and 0.50 reflect the average and high level of prediction of the given path in the PLS-SEM model. In the case of the model under consideration, the value of the predictive quality (relevance) indicator stood at 0.55.

Next, the level of impact of the exogenous latent (hidden) variables on the endogenous latent (hidden) variable was considered. In other words, the effects of the magnitude (f^2) of the relationships under consideration with the endogenous latent (hidden) variable from the perspective of the impact of the individual exogenous latent (hidden) variables were verified, assuming that the given exogenous variable is deliberately omitted from the model in order to estimate its true impact on the endogenous variable. This way the so-called potential effect that is the effect of an exclusion (loss) of an exogenous latent (hidden) variable from the structural model is subjected to verification. Guidelines for the interpretation of the magnitude of this f^2 effect can be found in the following papers (see (Cohen, 1988); (Wong, 2019)). Thus, the f^2 level of 0.02, 0.15 and 0.35 reflects a small, medium, and large effect of removing an exogenous latent (hidden) variable from the dependency (relationship) model. Taking these guidelines into account and the calculated f^2 effects (Tab. 2), we find that among the exogenous variables of the model in question the following constructs had the greatest impact: "Organization" at $f^2 = 0.42$, and then "Environment" at $f^2 = 0.36$. A moderate level of impact is visible in the case of the "Technology" variable with $f^2 = 0.22$.

Finally, the Standardized Root Mean Squared Residual (SRMR) index was used to perform an overall diagnosis of the proposed model (see Figure 2). The value of this index, if it does not exceed the level of 0.08, indicates an adequate level of the model's fit (see

Henseler et al. 2014), while a level equal to or lower than 0.5 means a very good fit level. As part of the alternative measures, two indices: dULS and dG, were also used (Dijkstra & Henseler, 2015), which allowed to diagnose the level of discrepancy between the empirical covariance matrix and the implied covariance matrix by the model. The difference between the matrices should be as small as possible so that it could be possible to obtain the best fit of the PLS-SEM model. In other words, the difference is defined in terms of the statistical insignificance of the result obtained ($p > 0.05$). This means that the discrepancy determined by the dULS and dG indices with respect to the compared matrices should be small enough to be ascribed to a negligible percentage of the impact of random errors. On the other hand, if this discrepancy is considered as significant ($p < 0.05$), then the model's fit in terms of the relationship (dependency) configurations (between exogenous and endogenous variables) postulated by the researcher may raise doubts. In the light of these rules it can be concluded that the value of the calculated SRMR index came in at 0.05. Thus, it did not exceed the model's upper rejection level (0.08); the model is within the range of the theoretical recommendations (Henseler et al., 2014). A similar situation occurs in the case of the dULS index which clocked in at 0.15 with $p > 0.05$. The dG index reflects the adequacy of the model and stands at 0.12 for the case under consideration, with $p > 0.05$.

Diagnosis (assessment) of the Relationships (dependencies) Occurring in the PLS-SEM Structural Model

The acceptance of the quality of the proposed PLS-SEM model allows, as part of the next step, for a closer look at the values of the structural parameters (path coefficients) describing the relationships between the exogenous latent (hidden) variables and the endogenous variable under consideration (see Figure 2).

The first approach applied in the study to estimate the relationships (dependencies) in the model was based on a point diagnosis of the estimated value of the path (relationship, dependency), while an analytical procedure based on "BCa Bootstrapping" was used as part of the second stage. The latter procedure made it possible to obtain a 95% confidence interval with respect to the estimated value – the result for the given path. The size of the samples taken, based on which the confidence interval is finally determined, may be between 1 000 and 10 000 samples. For the purpose of estimating the confidence intervals of the diagnosed structural parameters in the model under consideration, the sampling size was assumed to be 5 000.

The results obtained are presented in Table 3. Their analysis demonstrates unequivocally not only the significance of the three estimated paths at $p < 0.05$; 0.01, but is also in line with the theoretical premises of the model: T → AR ($\beta = 0.39$; $SB = 0.04$, with a 95% confidence interval of BCa from 0.31 to 0.47); O → AR ($\beta = 0.62$; $SB = 0.05$, with 95% of BCa ranging from 0.52 to 0.72); E → AR ($\beta = 0.53$; $SB = 0.06$ with BCa from 0.45 to 0.64).

Table 3. Results of the structural model with respect to the relationships (dependencies) diagnosed.

Structural Parameter	Estimated Statistics			95% Confidence Interval of the Path (BCa)	
	β	SB	*t*	Lower limit	Upper limit
T → AR	0.39	0.04	9.75	0.31	0.47
O → AR	0.62	0.05	12.40	0.52	0.72
E → AR	0.53	0.06	8.83	0.45	0.64

Explanations: T = Technology, O = Organization, E = Environment, AR = Assimilation of the Robotic Process Automation, SB = Standard Error, β = Estimated Path Value. BCa = Estimate based on the deviation correction procedure. All structural parameters are significant at $p < 0.05$; 0.01. N = 267
Source: own research.

Discussion

As can be seen from the analysis presented in the 'Theoretical background' section of this article, at present, the vast majority of research papers focus on the attempt to identify the distinctive features of robotic process automation, the identification of the benefits and risks associated with the implementation of this approach, and the narrowly perceived technological aspects. A distinct minority of studies are dedicated to the strategic positioning of RPA, RPA governance, and the scaling of RPA implementations. Also, there is scarcely any research on the role of the organisational factor in the implementation of RPA (if such studies are conducted, they mainly focus on the issue of the fear of robotisation that can occur among employees). Finally, a significant part of the existing research uses qualitative methods (usually case studies) rather than quantitative research.

The research conducted by the author, with its results presented in this article, attempts to address the issue of assimilation robotic process automation by enterprises as comprehensively as possible. The main goal of the research was to identify factors influencing the assimilation of the RPA by companies. In the author's view, correctly identifying these factors and subsequent action relating to them will ensure the appropriate scaling of RPA and its strategic positioning.

For this purpose, the TOE model was selected as the basis of the research process – following the completion of the literature research presented in the first part of this article. Based on this model, a structural equation model was developed, which was made up of four types of theoretical constructs:

- a construct defined as "Technology" (T) composed of 6 sub-areas;
- a theoretical construct "Organization" (O) defined based on 5 sub-areas;
- a diagnostics construct "Environment" (E) composed of 4 sub-areas;
- a construct defined as "Assimilation of the Robotic Process Automation by an enterprise" (AR), including 4 elements.

and 19 detailed hypotheses were formulated.

In order to validate the model developed, the author used the results of his own quantitative research.

The research procedure completed allowed to come to a conclusion that all of the hypotheses had been confirmed (although with a varying "strength" – see figure 10-12).

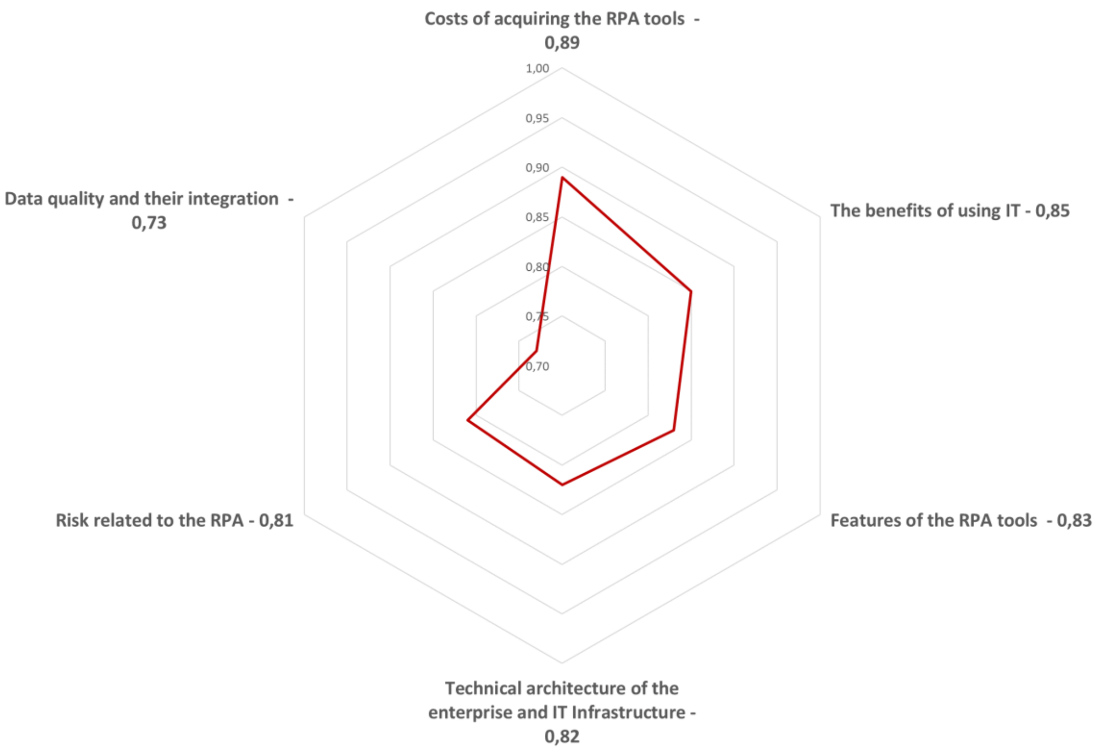

Figure 10. Decomposition a construct defined as "Technology".
Source: own research

With respect to the construct related to the Technology (figure 10), the T4 sub-area, covering the cost of acquiring the RPA tools, obtained the highest value of factor loadings. The issues related to licensing methods and costs of RPA tools have been repeatedly raised in source literature (Willcocks, Hindle, & Lacity, Becoming Strategic with Robotic Process Automation, 2020). As the author's practical experience demonstrates, currently the license fee for the RPA tool from a top supplier can reach several thousand EURO per annum. This may constitute a significant barrier to the spread of the robotic process automation at an enterprise. That is why it is so important to precede the choice of a tool with an in-depth analysis of the RPA solutions available on the market. It may turn out that a tool from a less renowned supplier, albeit definitely a cheaper one, will meet all the expectations of the organization. It is worth noting here that a possible solution to the problem of high costs of acquiring software robots is their implementation in the robot-as-a-service model. According to it, you pay for example for the actual working time of the robot or for the number of transactions made, and not for the license (Lacity i Willcocks, Robotic Process Automation and Risk Mitigation: The Definitive Guide, 2017).

The second Technology related construct's sub-area that obtained a high factor loadings value was the T1 sub-area, covering the provision of benefits thanks to the robotic process automation tools. This is also an important topic from the practical point of view. The issue of assessing the benefits of implementing the robotization of processes – their abilities to identify and estimate the delivered value, also are the subject of many literature studies (Kedziora & Kiviranta, Digital Business Value Creation with Robotic Process Automation (RPA) in Northern and Central Europe, 2018). The authors focus primarily on selecting the appropriate processes for robotization – in particular in the context of any possible savings. Some non-financial aspects are also increasingly emphasized – such as e.g. improving the quality of services provided and creating innovative products (Kedziora, Leivonen, Piotrowicz, & Öörni, 2021), (Willcocks, Hindle, & Lacity, Becoming Strategic with Robotic Process Automation, 2020).

Finally, the third sub-area that obtained a high factor loadings value was the T5 sub-area, covering the features of the RPA tools – especially with respect to the non-functional characteristics (such as safety, operational stability, ease of use). In the source literature, you can find in-depth analyses of key functionalities of tools for the robotization of processes – they take the perspective of both the construction of the robots themselves, as well as of their subsequent exploitation (Willcocks & Lacity, Automation: Robots and the Future of Work, 2016). This aspect of the analysis is also reflected in practice.

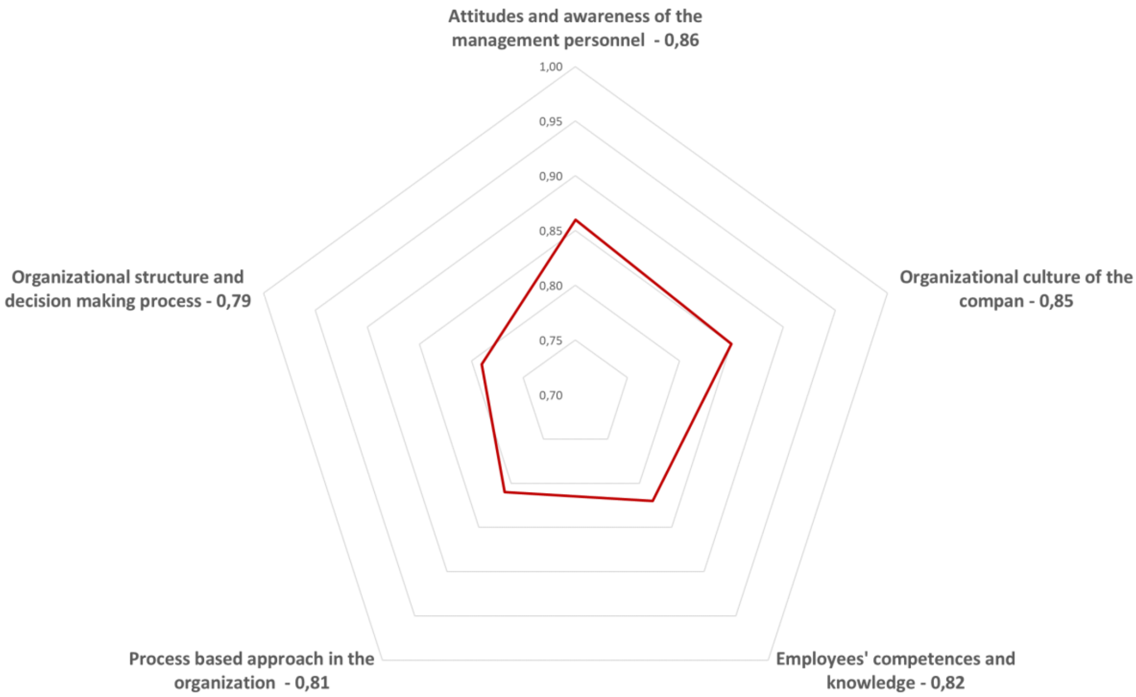

Figure 11. Decomposition a construct defined as "Organization".
Source: own research

With respect to the construct related to the Organization (figure 11), the O1 sub-area, covering the attitudes and awareness of the management personnel, obtained the highest value of factor loadings. At the moment, the source literature related to the cultural and managerial aspects of the implementation of the RPA is still underdeveloped (Willcocks, Hindle, & Lacity, Becoming Strategic with Robotic Process Automation, 2020). This may be due to the fact that RPA is perceived mainly through the prism of technology, and not of business change. In the author's view, this approach to RPA is too limited (Sobczak, 2021).

Robotic process automation is one of the digital transformation tools. At the same time, this transformation cannot be successful without the actual involvement of the decision makers (it is much more important than the involvement of other employees). Thus, this result is reflected in practice. The Organization related construct's second sub-area that obtained a high value of factor loadings was the O2 sub-area, covering the issues dealing with the organizational culture of enterprises. Without an organizational culture that is focused on openness and sharing of knowledge it will be extremely difficult to increase the level of the RPA tools' assimilation. It is worth noting that the O1 and O2 sub-areas are closely interrelated – in many cases it is up to the management personnel to decide what kind of organizational culture will be formed at the enterprise. Finally, the third sub-area that obtained a high value of factor loadings was the O3 sub-area, covering the competences and knowledge of employees. The issue of developing competences among employees in relation to the digitization of business processes (including their automatization) is relatively widely discussed in the source literature (Stjepić, Ivančić, & Vugec, 2020). In particular, this applies to issues referred to as upskilling and re-skilling. It is worth noting, however, that the development of digital and process competences among the employees of the business departments of enterprises, and at the same time the development of business competences among the employees of the IT departments undoubtedly contribute to increasing the assimilation of the robotic process automation.

With respect to the construct related to the Environment (figure 12), the E2 sub-area, covering the volatility of the environment, obtained the highest value of factor loadings.

Undoubtedly, the phenomenon of an increasing speed and frequency of changes, related to the technological, economic or legal aspects, taking place in the company's environment, which has been observed over the last few years, is a catalyst enhancing the assimilation of the robotic process automation. According to the source literature (Anagnoste, Robotic Automation Process – The operating system for the digital enterprise, 2018), it takes more time to introduce changes in classically developed IT systems than in the case of RPA. It proves the strength of the latter approach.

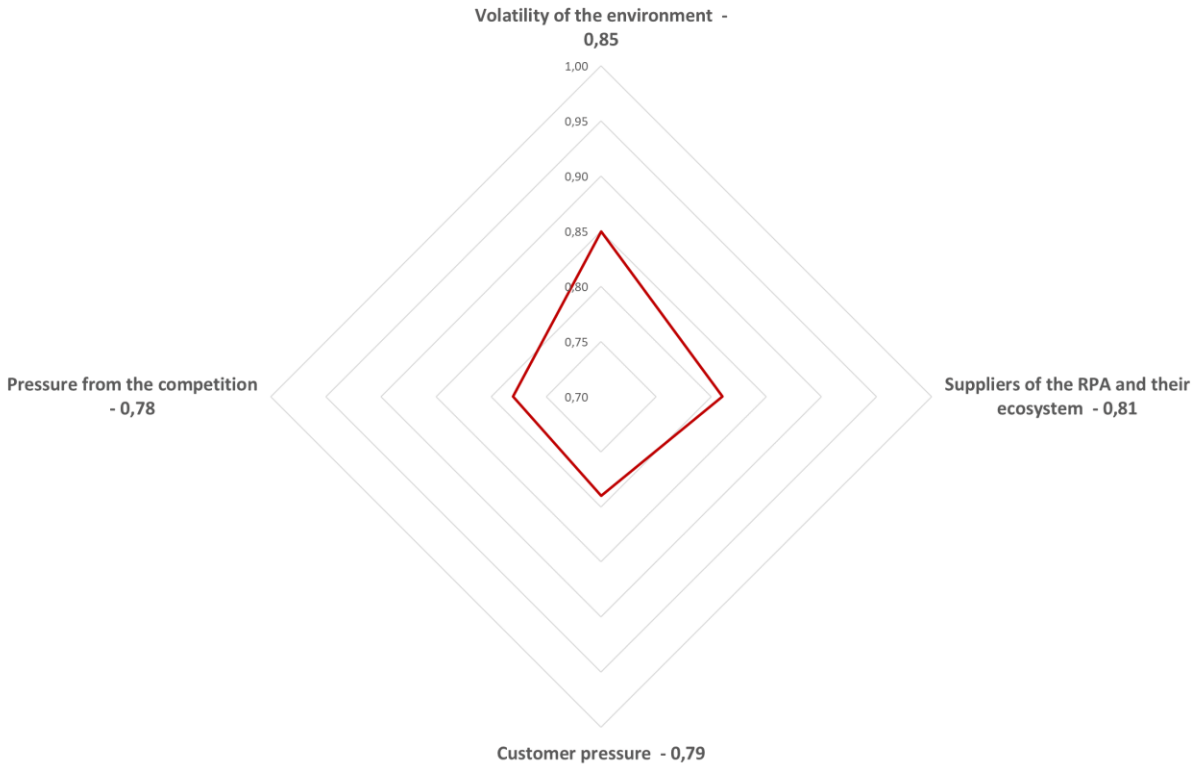

Figure 12. Decomposition a construct defined as "Environment".
Source: own research

The Environment related construct's second sub-area that obtained a high value of factor loadings was the E4 sub-area, covering the issues dealing with the suppliers of the robotic process automation technologies and their ecosystem. The literature pays relatively little attention to the role of technology providers and the support ecosystems which they build. However, these issues are raised in numerous reports of analytical companies – such as Gartner or Forrester. The currently available RPA tools, despite the actions taken by their suppliers, are not the easiest to use. That is why the network of technological partners providing training, certifications and consultants plays such an important role. It is also very important to build an active community of the RPA tool users, which also contributes to enhancing the reputation of the vendor. Finally, the third sub-area that obtained a high value of factor loadings was the E3 sub-area, covering customer expectations. The research results obtained allow for reaching a conclusion that customers who are continuously looking for new, innovative products/services and who expect very high quality of the products/services provided, contribute to the increased assimilation of the robotic process automation.

The research also demonstrates that at those organizations that are characterized by a high level of assimilation of the robotic process automation, business processes are implemented in a different way than they have been implemented thus far. Undoubtedly, this translates into their efficiency, but at the same time it allows for a significant improvement of the already offered products/services or the introduction of new products/services. Ultimately, this may lead to a change of at least one component of the company's business model (for example, the implementation of the key activities, the cost/revenue structure, customer contact methods, etc.). On the one hand, this research demonstrates the flexibility and applicability of the TOE model. On the other hand, the results obtained are a very good starting point for the formulation of the practical recommendations (presented further on in the article). According to the author, this is an additional value of this study. As noted by L. Takayama (Takayama, 2009), a harmonious combination of the development of a scientific approach with practice represents a real challenge in many cases. Practice poses questions to the theory, but theory also demands from practice the implementation thereof – in this case the practical recommendations formulated by the author represent such an implementation.

Limitations Related to the Research Conducted

The author is aware of the limitations of the research procedure completed. Some of these limitations stem from the complexity and multi-faceted nature of the assimilation of the robotic process automation by enterprises. Other limitations, resulting from the research procedure adopted, include:

- restricting the scope of research solely to enterprises operating only in Poland; this limitation resulted from the implementation options available; the author is aware of the fact that research carried out in other countries may produce different results, therefore it would be extremely valuable to conduct the research discussed in the article not only in relation to the enterprises from Poland, but more broadly in the European countries;
- limited size of the research sample and the method applied to select the sample: the results obtained cannot be considered as representative and cannot be generalized – they present the situation only in the analyzed group of enterprises;
- subjectivism of the assessments made by the respondents filling in the questionnaire; in order to minimize this limitation the decision was made to introduce, wherever possible, a precise description of the answers that could be given;
- risk of non-reflective filling of the questionnaires by the respondents; in order to minimize this limitation each completed questionnaire was subjected to a detailed analysis, and in case of any doubts, a clarification procedure was undertaken by e-mail or in an interview with the respondent;
- potential difficulties in understanding the questions contained in the questionnaire; in order to minimize this limitation pilot surveys were carried out and the questionnaire was equipped with a dictionary of key terms;
- possibility of omitting important aspects of assimilating the robotic process automation as a result of using closed-ended questions containing a finite number of potential answers; the author is aware of this limitation, but such an approach ensured the comparability of the results obtained; at the same time the selection of the survey questions was preceded by the author's literature research on both the robotic process automation as well as the assimilation of innovations.
- possibility of a company from outside the group of industries included in the research filling in the questionnaire or the possibility of more than one questionnaire being sent from the given company; in order to minimize this limitation the right to verify (vet) the enterprise from which the questionnaire was obtained, based on the data from

external websites (in particular, the data provided in the online version of the National Court Register), was reserved;
- possibility of the questionnaire having been filled by the wrong person (and thus an incompetent one); in order to minimize this limitation the requirement to provide a business e-mail address of the person completing the survey was introduced and the right to verify (vet) the details of that person using the data from external websites (in this case it was the LinkedIn service) was reserved; if it was not possible, the author asked the respondent by e-mail to confirm that he/she was the right person at the enterprise to complete the questionnaire; only those questionnaires were included in the research pool where such a confirmation had been obtained from the respondent.

Despite the above-mentioned limitations, the research procedure completed allowed for the accomplishment of the adopted goal of the research.

IMPLICATIONS OF THE RESEARCH

The implications of the research conducted by the author are presented below, broken down into the research implications (important from the perspective of scientists) and the practical implications (important from the perspective of the managers responsible for implementing the robotic process automation at their enterprises).

Research Implications

The research presented in this article is an extension of the works carried out with respect to two topics: robotic process automation and assimilation of digital innovations. Both the former topic as well as the latter area are currently explored by a number of researchers, which was emphasized in the first part of this article. At the same time, it is worth pointing out that while a lot of research has been done on the assimilation of traditional IT solutions (e.g. CRM systems, Big data, e-commerce, EDI), there have been no studies addressing the issue of the assimilation of the robotic process automation (according to the author's best knowledge, this is the first research on this topic in Europe). It is all the more important that, as the first part of the article demonstrates, software robots and the process of the development thereof differ significantly from the traditional approach to the implementation of the IT systems. The results of the research completed enhance the knowledge of factors influencing the assimilation of the robotic process automation. At the same time, they also confirm that the TOE model can be used for research on the assimilation of innovative, non-traditional IT technologies.

The results obtained constitute the basis for further research on the assimilation of the robotic process automation by enterprises – which is also due to the fact that an ever growing group of enterprises is beginning to introduce software robots on a mass scale (i.e. they have 100 or more of such robots). Therefore, a number of issues and research questions arise – how employees will be functioning in such a working environment, but also how managers managing hybrid teams (i.e. those in which instead of, for example, 30-40 employees, there will be 10 employees and 40 software robots) will be acting.

Practical Implications

Recent years have been a period of a very rapid spread of the robotic process automation at enterprises. The observations of the developments taking place on the IT market indicate that the Robotic Process Automation (RPA) tools are currently the fastest growing group of digital transformation tools. This is indirectly confirmed by one of the largest IPOs (Initial Public Offering) on the NYSE (The New York Stock Exchange) in 2021. UiPath, the leader in the RPA tools, was established as a startup in 2005 in Bucharest. According to the valuation following its IPO on the NYSE, the company is currently (2022) worth more than USD 10 billion (as recently as in 2017 it was valued at USD 1 billion). Those enterprises that neglect the implementation of solutions in the field of the robotic process automation today may expect a significant deterioration of their market position in the coming years (Gölpek, 2015)

The research completed, the results of which are presented in this article, can be the basis for the formulation of a number of practical recommendations for organizations implementing or wishing to implement the robotic process automation. These recommendations, in accordance with the research model proposed by the author, can be divided into three categories – i.e. technology, organization and environment related. Selected recommendations are presented below, broken down into the above-mentioned categories.

Technological recommendations

- It is important to choose an adequate – in terms of the costs – model of licensing the robotic process automation tools
- It is important to prepare an adequate IT infrastructure, which will be the basis for the functioning of the software robots
- It is important that the robotic process automation tools operate in a stable manner
- It is important to ensure that the robotic process automation tools provide the adequate scope and level of security mechanisms
- It is important to ensure that the robotic process automation tools are compatible with the company's other IT solutions

Organizational recommendations

- It is important to ensure an adequate level of the management personnel support during the implementation of the robotic process automation
- It is important to build a high level of awareness among members of the company's management board on the role of IT – including the robotic process automation
- It is important to develop adequately high business, IT and process competences among the company's employees.
- It is important to implement a process-based approach at the company – as a basis (foundation) for its operations.

Recommendations related to the environment:

- It is important to implement the robotic process automation for those of the company’s customer segments that are characterized by pro-innovative or pro-quality expectations.
- It is important to provide access to the community of the users of the RPA tools applied by the company.
- It is important to provide access to the ecosystem of partners, training and certifications established by the RPA/RDA tool supplier.

According to the author, the above-mentioned recommendations can be considered to represent the key success factors in the assimilation of the robotic process automation by enterprises.

SUMMARY AND THE DIRECTIONS OF FURTHER RESEARCH

In response to the trend of the robotic process automation becoming more and more widespread as well as its increasing importance, an interdisciplinary area of research dealing with the advanced robotization technologies from the perspective of their impact on the economic and organizational aspects of the functioning of enterprises, which is referred to as Robonomics (Ivanov, 2017), is beginning to take shape. The observation of the RPA tools market, the implementations completed in this area and the research conducted allow us to formulate a conclusion that it may be of major importance in the future – both in terms of research as well as applications. This article is part of this research area.

The author intends to continue research in the field of the robotic process automation, focusing primarily on the development of a research model and practical recommendations regarding the assimilation of the robotic process automation by enterprises, including the use of big data mechanisms, machine learning and NLP (Natural Language Processing) methods as a part of the robotization (robotic automation) processes; as in the study (Lacity & Willcocks, Robotic Process and Cognitive Automation: The Next Phase, 2018), p. 26) it was indicated that the future of the RPA tools was the Cognitive Automation, i.e. one in which automation is implemented using software capable of operating effectively in unforeseen and uncertain situations. As a result of having been equipped with cognitive skills the software robots will be able to use the information they have in a way similar to human reasoning – in particular, they will be able to autonomously evaluate and interpret knowledge. This will be possible thanks to the use of artificial intelligence mechanisms (in particular, machine learning) and ensuring access to sufficiently large data sets (necessary for machine learning processes). It is to be expected that this will require a combination of a specific set of technologies, organizational measures as well as competences. At the same time, this type of robotization will allow companies to achieve benefits from the implementation of RPA that go beyond the financial aspects – in particular, leading to a rise in the quality of the company's products/services or an increase in the innovations offered by the company's products/services.

At the same time, the author is planning to extend the completed quantitative research on the assimilation of the robotic process automation by conducting the qualitative research in the future. As the target group the author is planning to select entities that achieve the above-average results in the implementation of the robotic process automation in Poland. For this purpose the author will be getting in touch with the companies that received awards or honorable mentions in the competition, conducted in 2022, for the most effective implementations in the field of hyper-automation (including the robotic process automation), the effectiveness of which is measured by comparing the business goals set before the implementation with the results obtained after it has been completed.

ENDNOTES

1. In the English language literature on the subject – in the context of the issues discussed in the article – the term "technology adoption" is used very often. However, the research presented in the article has been carried out in Poland, where there is no good, direct translation of this phrase. Some Polish researchers use the linguistic “carbon copy”, i.e. the term "technology adoption", but the author consulted it with the Polish Language Council and this was deemed as the wrong approach (in Poland the term adoption refers to a form of adopting a stranger to the family, developing a relationship similar to kinship). Therefore, the author ultimately decided to use the phrase "technology assimilation" and applied this phrase in this article. The decision had been preceded by the consultations with both the Polish linguists as well as the specialists in the field of automation/robotization/ innovative digital solutions.

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SMART LIVING TECHNOLOGIES IN THE CONTEXT OF IMPROVING THE QUALITY OF LIFE FOR OLDER PEOPLE: THE CASE OF THE HUMANOID RUDY ROBOT

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Abstract: *Smart living is an essential dimension of an ageing society because one of its measures includes living conditions (health, safety, housing). Many technological solutions are designed to satisfy the needs of older people living in cities. Humanoid robots are one of the technologies that can significantly improve the quality of life in older adults. The Rudy Robot is an example of a robot adapted to the needs of older people. The conducted research aimed to gain knowledge about the potential future use of the humanoid Rudy Robot by older adults in the context of smart living. The study mainly aimed to identify the robot's most important functionalities that could improve older adults' quality of life based on a literature review. In addition, the Rudy Robot was rated according to the most important criteria for evaluating the robot. The paper also examined whether age, sex, education and place of residence affect the assessment of the Rudy Robot technology. It should be noted that this technology is not available in Poland but has become known due to television, the Internet, etc. Respondents received a description of this technology, examples of use, and links to literature and films together with the questionnaire; thus, they knew what the Rudy Robot was and its characteristics, possibilities and potential.*

Keywords: *smart living technologies, ageing society, older people, robot, technology assessment*

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INTRODUCTION

The ubiquitous advancement of technology worldwide is accompanied by the dynamic development of cities. Increasingly progressive technological development and its greater awareness provide people with many opportunities for a safer, healthier and, generally, better life (Bibri & Krogstie, 2017; Nazarko, 2017). Winkowska, Szpilko & Pejic (2019) indicated that the growing migration of people from the countryside to cities is the reason for the perpetual development of the latter. Such development necessitates taking an interest in the smart city concept. It is a relatively new idea that focuses on implementing new technologies in urban space and an intelligent and sustainable way of managing a city to improve functioning and inhabitants' quality of life (Baraniewicz-Kotasińska, 2017). Taking a holistic approach, Szpilko (2020) argued that people and their needs were the most critical elements in the concept of smart cities, whereas technology had a supporting role. A smart city aims to achieve a high quality of life for its inhabitants and sustainable economic growth using social capital, communication and information technologies, human resources, and also the concept of smart management with community participation (Caragliu, Bo, Del, Nijkamp, 2009). At their heart, smart solutions for cities should be designed based on such factors as residents' preferences (regardless of their age), social interactions and cooperation (Szpilko, 2020). Six main smart city areas were distinguished in a report published by the Vienna University of Technology (2007). They are listed in the table below, together with the characterising factors (Table 1).

Table 1. Smart City Areas with Characteristic Factors.

Smart City Area	Characteristic Factors
1. **Smart Economy** (Competitiveness)	entrepreneurship, productivity, labour market flexibility, innovative spirit, international embeddedness
2. **Smart People** (Social and Human Capital)	flexibility, creativity, participation in public life, level of qualification, social and ethnic plurality
3. **Smart Governance** (Participation)	transparent governance, public and social services, participation in decision-making.
4. **Smart Mobility** (Transport and ICT)	local accessibility, availability of ICT infrastructure, (inter)national accessibility
5. **Smart Environment** (Natural Resources)	pollution, environmental protection, attractivity of natural conditions, sustainable resource management
6. **Smart Living** (Quality of Life)	cultural facilities, health conditions, individual safety, housing quality, education facilities, social cohesion, tourist attraction

[Source: Vienna University of Technology, Smart Cities Ranking of European medium-sized cities, 2007.]

As noted by Gudowsky et al. (Gudowsky, Sotoudeha, Caparia, & Wilfing, 2017), cities in the future should be adapted to the needs of an ageing society. In 2019, the world had 703 million persons aged 65 years and more, and the number of older adults is projected to double to 1.5 billion in 2050 (United Nations, 2019; Ejdys, & Halicka, 2018). According to the OECD report on data from the Aging in Cities (OECD, 2015), 43.2% of all older adults lived in cities in the OECD region in 2015. This means that the ageing trend of the population will become more prominent. Therefore, many facilities and technologies will have to be adapted for older adults. In the context of an ageing society, it is important to take a closer look at smart living, which relates to the city's level and quality of life (Stawasz, & Sikora-Fernandez, 2015; 2016). Experts interviewed for The Smart Living Report stated that smart living aims to create a safe, effective, energy efficient, personalised and better-managed living space (for home, work, urban living, and transportation) (Infuture Hatalska, 2019).

Due to age, older adults have various health issues related to mobility, movement and general fitness, memory and others. Smart living can be helpful with technologies supporting their functioning, e.g., technologies supporting daily independent functioning at home (reminder systems, special prams/devices facilitating independent movement, intelligent home building elements). With today's high level of technological development, the so-called smart environments (present in smart living) can be very useful for older people. Such systems can include data-collecting from various sensors designed to record the person's behaviour at home or uninterruptedly monitor their health (Tannou, Lihoreau, Gagnon-Roy, Grondin, Bier, 2022). In addition to intelligent living environments, simple individual solutions, such as smart door locks or an innovative doorbell with a built-in camera (eliminating the need to get up and walk to the door), can be an excellent example of smart living technologies for older adults (Tech-Enhanced Life, 2021). As already mentioned, the health of older adults requires continuous monitoring and medications must be taken regularly. Various devices (e.g., smart pillboxes) are developed to facilitate adherence to the schedule. Such pillboxes may, for example, make a noise when it is time to take medication or even send remote alerts to family members and caregivers (The Senior List, 2022). Technologies that use the IoT (Internet of Things) concept have been emerging in increasing numbers recently and can also be used in the care of older adults. Chan et al. proposed an activity monitoring system studying older people's behaviours and alerting caregivers in case of a fall (Chan, Campo, Bourennane, Bettahar, & Charlon, 2014). The smart bracelet proposed by Angelini et al. (Angelini, Nyffeler, Caon, Jean-Mairet, Carrino, Mugellini, & Bergeron, 2013) tracks the wearer's health status and reminds them of scheduled tasks or medications.

As many older adults require assistance, their growing numbers mean an increase in the demand for caretakers (Brooke & Jackson, 2020; Cajita, Hodgson, Lam, Yoo, Han, 2018). Humanoid robots can be a useful technology substituting humans. Furthermore, as living conditions (health, safety, housing) are a measure of smart living, robots can be an excellent example of smart living technology. Nowadays, there are several different humanoid robots on the market that are designed to care for people. One example is the Pepper Robot (Softbank Robotics, 2021), which is 120 cm tall and is designed to interact with humans. It can establish contact with a human being through conversation and using a touch screen. The robot is equipped with several touch sensors, microphones and diodes. It also has perception modules necessary for recognition and interaction.

Another good example of a robot designed to care for and interact with people is Care-O-Bot 3 (Fraunhofer IPA, 2022). This humanoid robot can be used for various purposes, such as help and support in caring for older adults at home and in nursing homes, cleaning, or general help. It has an arm and a gripper for manipulating objects, a tray to carry and transfer objects, and a flexible torso allowing butler-like gestures (Joseph, Christian, Abiodun, & Oyawale, 2018).

Thirdly, a Cody Robot (Robots, 2022) is a humanoid nurse tasked with helping people with a disability. It was designed to support research into human–robot interaction. Cody is equipped with an omnidirectional mobile base and compliant arms and can lift its torso using a linear actuator.

The Rudy Robot is yet another example of a humanoid robot that can support older adults in their daily life due to its structure, functions and possibilities. The main goal of the article and the research was to obtain knowledge on the future potential use of an exemplary robot — the Rudy Robot — by older adults in the context of smart living. The Rudy Robot for the care of older adults can be an extremely useful technology that fits smart living and smart homes. The robot can make older adult's life easier and more enjoyable as it has many different uses for daily functioning. This robot provides 24/7 access to emergency services. The Rudy Robot may remind a person to take their medicine and dispense and dose them (Robotics Business Review, 2017). Additionally, Rudy Robot offers Remote Patient Monitoring (RPM), enables social interactions, can call for help, help find lost items and even move things that an older adult cannot carry (Martinez-Martin, Escalona, Cazorla, 2020; INF Robotics, 2022). It can encourage older people to engage in activities, such as games, music and dancing, to keep them physically and mentally active. Overall, the Rudy Robot can also be a good companion and friend, helping to lessen the feeling of loneliness (Martinez-Martin, Escalona, Cazorla, 2020).

Therefore, the Rudy Robot can be extremely helpful for older adults. The constant and dynamic technological development results in a greater supply of advanced robots offering even more possibilities and innovative solutions. A significant contribution can be made by the advancement of artificial intelligence used in robots designed to care for older adults. Technologies for smart living and smart homes are to facilitate daily functioning. Such technologies can offer greater comfort and increase the living standard in general, while for older adults, such solutions can significantly facilitate everyday life at home (e.g., for those living independently). Therefore, robots can be an ideal technology for smart living and smart homes. A literature review found some work describing the potential of exemplary robots in improving the quality of urban life for older people (Martinez-Martin, Pobil, 2017; Görer, Salah, Akin, 2016; Martinez-Martin, Costa, Cazorla, 2019; Wilson, Pereyda, Raghunath, de la Cruz, Goel, Nesaei, Minor, Schmitter-Edgecombe, Taylor, Cook, 2019; RAMCIP Project, 2022). The existing robotic technologies for elderly care were reviewed, analysing their benefits for older people (Martinez-Martin, Pobil, 2017), e.g., an autonomous robotic exercise teacher for older people (Görer, Salah, Akin, 2016) or a robot that suggests and monitors physical activity (Martinez-Martin, Costa, Cazorla, 2019). One article (Wilson, Pereyda, Raghunath, de la Cruz, Goel, Nesaei, Minor, Schmitter-Edgecombe, Taylor, Cook, 2019) describes the integration of robots into intelligent environments to provide more interactive support for older adults with functional limitations and the RAMCIP project aims to research and develop real solutions for assistive robotics for older people (RAMCIP Project, 2022). Also, research is also emerging on public acceptance of these technologies (Beer, Prakash, Mitzner, Roger, 2011; Cajita, Hodgson, Budhathoki, Han, 2017; Ezer, Fisk, Rogers, 2009; Langer, Ronit Feingold-Polaka, Mueller, Kellmeyer, Levy-Tzedek, 2019). E.g., a literature review (Beer, Prakash, Mitzner, Rogers) identified various features of the robot that may influence acceptance. In contrast, another article conducted a survey to explore older people's expectations of domestic robots and their relationship to robot acceptance (Ezer, Fisk, Rogers, 2009). Furthermore, guidelines for trust-building and a method for measuring trust in human-robot interactions in rehabilitation were proposed (Langer, Ronit Feingold-Polaka, Mueller, Kellmeyer, Levy-Tzedek, 2019). However, it is also necessary to investigate how these technologies are viewed by the public to determine the most important features/functions of robots (Ejdys, Halicka, 2018). It is also worth investigating whether the age, sex, education and place of residence of the respondent impact the result of the technology assessment.

The article and research aimed to understand the potential future use of a robot by older people in the context of smart living. Additionally, the article also aimed to learn the public's evaluation of this technology in the context of various criteria. To date, no such studies have been conducted. As respondents find it easier to comment on a specific technology, the Rudy Robot was chosen as an example, and the questionnaire referred to it specifically. Together with the questionnaire, the respondents received a few photos of this robot, a description of its functionality, examples of its use, links to literature, etc. Therefore, respondents knew what the Rudy Robot was and understood its capabilities. However, it should be emphasised that most robots in the context of smart living have very similar properties. Thus, the study results can be generalised to all humanoid robots.

Humanoid robots are not yet widely used at the moment. In Poland, such robots are not yet available because of the price and fear of using new technologies. However, knowledge is spread through television, the Internet, etc. (INF Robotics, 2022; Robotics Business Review, 2017). In general, people do not trust new, unfamiliar technologies. However, it is a technology that has a great potential for further development, and given the demographic situation, it could be one of the key solutions to improve the quality of life of older people in the city (Arthanat, Wilcox, Macuch, 2019; Oh, Oh, Ju, 2019; Luxton & Riek, 2019). A paper (Arthanat, Wilcox, Macuch, 2019) has already explored the ownership of smart home technology among older people, their willingness to adopt SH (Smart Home) technology, and identified customer factors associated with technology adoption. Another article developed five robot design concepts and conducted interviews to assess preferences for the developed design concepts (Oh, Oh, Ju, 2019). Some researchers overviewed the applications of smart technologies in contemporary rehabilitation practice and research and presented trends and future opportunities in smart environments and smart mobile devices used by older people (Luxton & Riek, 2019).

In their previous research, the authors of this paper identified and described nine groups of technologies that improve the quality of life of older people (Halicka & Surel, 2021) and prepared a ranking of these technologies (Halicka & Kacprzak, 2021). The authors identified the most desirable group of technologies improving the quality of life of older people (Halicka, 2019) among current and future users, described humanoid robots in detail (Ejdys, Halicka, 2018), and identified the factors and their interrelationships that determine the attitude and future use of humanoids by older people in Polish society (Ejdys, Halicka, 2018).

METHODOLOGY

This research focused on obtaining information on the future use of the selected technology — the humanoid Rudy Robot — that facilitates urban life for older adults in the context of smart living. The article's main objective was to answer the following research questions: (1) What are the most important expected robot functionalities that facilitate the quality of life of older people in the context of smart living? (2) What are the most important criteria for evaluating a robot? (3) How was the Rudy Robot rated according to different criteria? (4) Does age affect the assessment of the analysed technology? (5) Does sex affect the assessment of the Rudy Robot technology? (6) Does education affect the assessment of the analysed technology? (7) Does the place of residence affect the assessment of the Rudy Robot? The respondents have not used this technology so far. Therefore, their answers were not based on experience but the information taken from the description attached to the questionnaire, literature, films, etc. The research process consisted of four main tasks presented in Fig. 1.

Research Task 1: Identifying and classification criteria for technology evaluating
Method: literature review
Research questions 2

Research Task 2: Respondents' evaluation of five group of criteria, ordering of group of criteria, selection of two highest rated
Method: questionnaire survey
Research questions 2

Research Task 3: Evaluation of this technology in the context of the two rated criteria
Method: questionnaire survey
Research questions 1, 3

Research Task 4: Investigation whether age, gender, education, place of residence influence the evaluation of the technology
Method: statistical methods
Research questions 4, 5, 6, 7

Figure 1. Tasks in the Research Process.
[Source: elaborated by the authors.]

As Fig. 1 demonstrates, the entire research process consists of four main tasks. The first task is to identify the criteria for the evaluation of the Rudy Robot. The set of criteria is taken from the literature and is rather general. This makes it possible to evaluate and compare various technologies, not only the exemplary Rudy Robot.

Research is conducted by the authors to evaluate different technologies (e.g., wheelchairs: Wheelie7, smart bracelet) that can improve older people's quality of life in the context of smart living. In the future, the authors intend to develop a technology ranking and select the best technology that can be used by older adults and improves their quality of life. Additionally, the survey was also sent to potential manufacturers. In the next study, the authors will evaluate the technology from the perspective of a potential future manufacturer. Therefore, the set of criteria is rather general consciously. Also, respondents were asked to evaluate the criteria (the responses of users and producers may differ). The humanoid Rudy Robot has enormous potential for further development and is continuously improved, which necessitates the knowledge of criteria considered by potential technology users as the most significant for producers/technology developers to consider.

Based on the literature review (Halicka, 2020; Ejdys, 2020; Halicka, 2017), five main criteria groups for evaluating the Rudy Robot technology were selected: Competitiveness, Demand Criteria, Technical Criteria, Social and Ethical Criteria, and Ecological Criteria. Each group contains several key statements for respondents to consider. Five to seven criteria were identified in each group, making a total of 31.

Another task (Fig. 1) was to evaluate the individual five groups of criteria by the respondents, organise these groups and select the top two.

The third research step was the evaluation of the technology (the Rudy Robot) in the context of the two highest-rated criteria.

The last task was to investigate whether age, sex, education and place of residence impacted the technology (the Rudy Robot) assessment in the context of two criteria groups. It was checked how the Rudy Robot would be assessed by older adults in the context of the highest-rated groups of criteria. In the study, the research method was a diagnostic survey using the CAWI (*Computer-Assisted Web Interview*) survey technique. As the assessed technology was not widely used, the conducted research mainly concerned the robot's functionality, assessed based on information from the description attached to the questionnaire, literature, films, etc.

RESULTS

The survey was conducted in Poland at the turn of 2020 and 202, targeting people over 40. The representative research sample comprised 1152 respondents (citizens of all Polish voivodships).

The first assessed criterion was the competitiveness of the Rudy Robot. Over 22 % of respondents considered this criterion very important, and almost 13 % — important. More than 8 % assessed this criterion as very irrelevant. Detailed data on the assessment of the "Competitiveness" criterion are shown in Fig. 2.

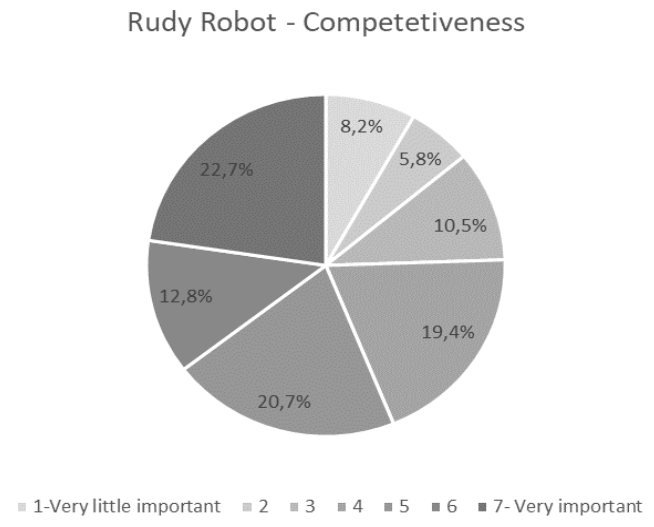

Figure 2. Assessment of the Competitiveness criterion for the Rudy Robot.
[Source: elaborated by the authors.]

Another criterion was "Demand". More than half of the survey participants indicated it was important. Only 3.7 % of the respondents assessed it as of very little importance. Detailed information on the evaluation of the "Demand" criterion is shown in Fig. 3.

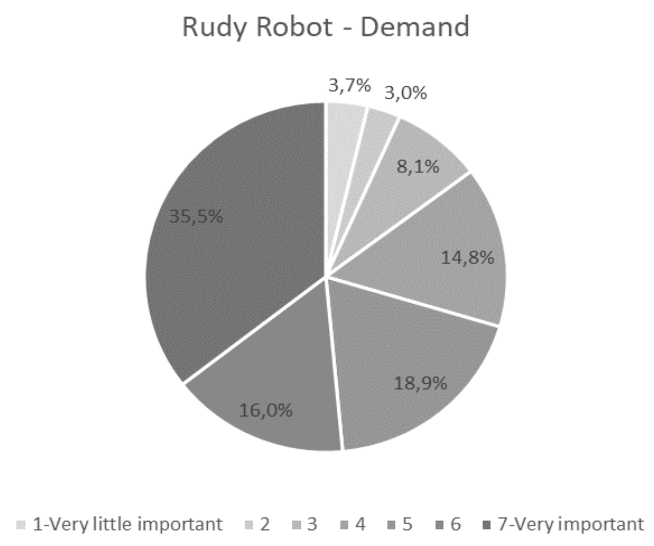

Figure 3. Assessment of the Demand criterion for Rudy Robot.
[Source: elaborated by the authors.]

The next important criterion was related to the. Almost 37 % of the respondents answered that the "Technical Criteria" of the Rudy Robot were very important, 18.1 % believed they were an important aspect, and a small proportion (4.8 %) of respondents thought this criterion was of very little or little importance. Detailed information on the technical criteria for the Rudy Robot technology is shown in Fig. 4.

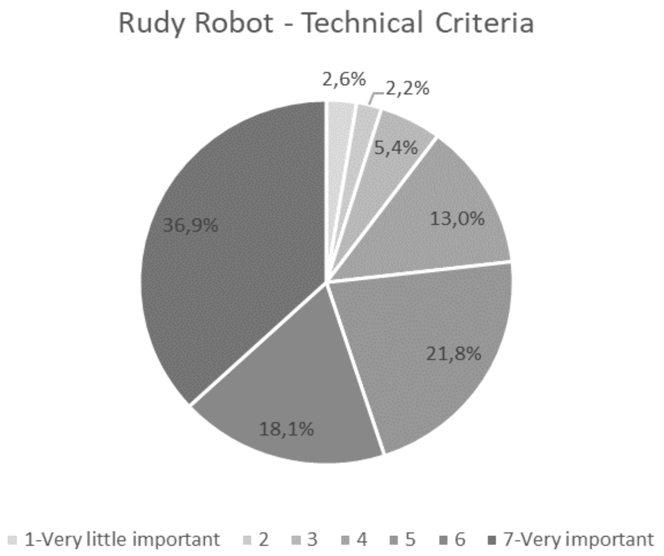

Figure 4. Assessment of the Technical Criteria for the Rudy Robot.
[Source: elaborated by the authors.]

The fourth criterion is related to social and ethical issues. A decidedly larger part of the respondents replied that social and ethical criteria were important for the technology of the Rudy Robot. About 16 % of the respondents considered this criterion to be of little importance, and 15.5 % had no opinion on this subject. Detailed information on the evaluation of this criterion can be found in Fig. 5.

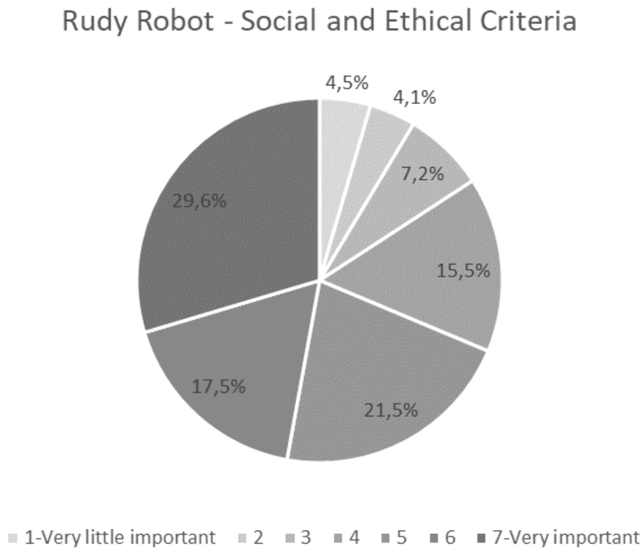

Figure 5. Assessment of the Social and Ethical Criteria for the Rudy Robot.
[Source: elaborated by the authors.]

The last criterion was related to ecological issues. More than 60 % of the respondents believed that ecological criteria were an important aspect of this technology. About 18 % decided that these issues were not important, and more than 15 % of the respondents did not have an opinion on the issue. More detailed data related to the assessment of this criterion are shown in Fig. 6.

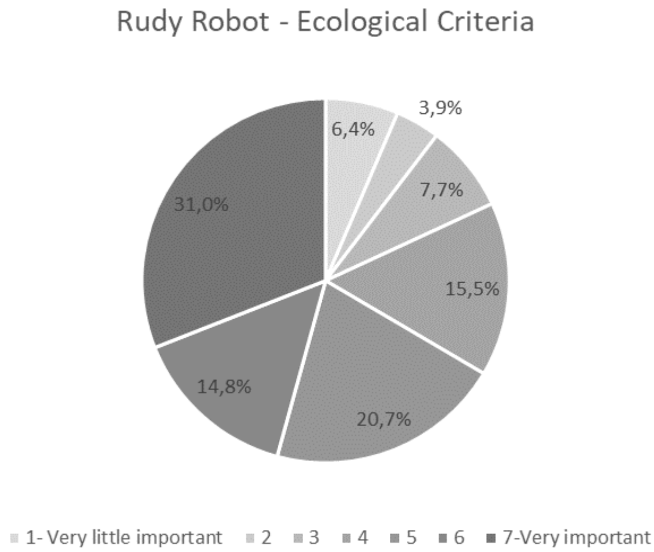

Figure 6. Assessment of the Ecological Criteria for the Rudy Robot.
[Source: elaborated by the authors.]

The following are the ratings of the five most important groups of the Rudy Robot technology criteria. Based on the above analyses and criteria evaluations, two groups of criteria with the highest scores can be distinguished: Technical Criteria (76.8 %) and Demand for Technology (70.4 %). The listed groups have been identified based on the analysis of the ratings given by the respondents. The highest rating was given to criteria which received the highest number of answers: 5 — rather important, 6 — important, 7 — very important. This indicated the high importance of a criterion.

Referring to the above analyses and conclusions, the most important criteria for the Rudy Robot gerontechnology were technical, demand, and social and ethical criteria. Indeed, technical criteria are a vital element when it comes to such advanced technology as the Rudy Robot. The technology is primarily designed for older adults, so it is not complicated to use or prone to failure. The demand for this technology is also an important factor, mainly because the use of such a robot could replace humans. People unable to take care of their parents/grandparents would thus be relieved of the duty. Therefore, for further analysis, the Rudy Robot technologies were considered in the context of the two most important criteria groups: technical (T) and demand (D). Five evaluation criteria were identified in the technical group (T1–T5) and eight — in the demand group (D1–D8) (Table 2).

According to the respondents, the Rudy Robot was rated the highest in terms of T5, which means a very large potential for further improvement of this technology (the average rating of the respondents was 5.20, with a rating scale from 1 to 7) (Fig. 7).

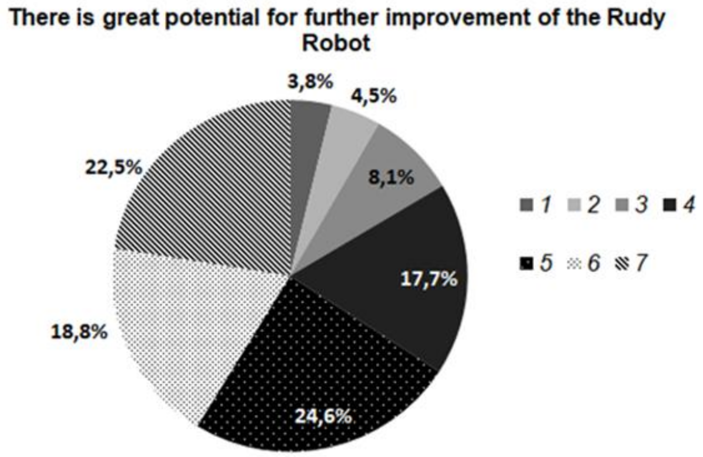

Figure 7. Evaluation of the Rudy Robot in the context of criterion T5 ("There is great potential for further improvement of the Rudy Robot").
[Source: elaborated by the authors.]

This technology was also highly rated in terms of D2 ("The use of the Rudy Robot will be a source of additional benefits for its potential users, which is unavailable in the case of using other solutions") and D3 ("The popularisation of the Rudy Robot is in line with the forecasts concerning the directions of technology development and the expectations of older adults"). Therefore, according to the respondents, the Rudy Robot will be a source of additional benefits for potential future users, unavailable in the case of using other solutions (the average rating of the respondents of 5.03, a rating scale from 1 to 7). Furthermore, the dissemination of the analysed technology is in line with the forecasts concerning the directions of technology development and the expectations of older adults (the average rating of the respondents was 5.05, with a rating scale from 1 to 7). The Rudy Robot was rated the lowest in terms of T2 and T3, indicating a high probability of serious technical problems during the development of this technology (the average grade of 3.65, with a rating scale from 1 to 7). According to the respondents, the use of the Rudy Robot depended on the use of hard-to-reach and expensive materials (the average grade of 3.80, with a rating scale from 1 to 7).

Respondents had not used the Rudy Robot technology but had ideas about humanoid robots. They also knew their expectations for an improved quality of life. Therefore, based on their expectations and knowledge taken from the Internet and films about humanoid robots, they were able to assess whether that technology would be able to meet their potential requirements and, thus, be a source of additional benefits for them. Based on this information, they could also determine the potential of the technology.

The next part of the study checked whether sex influenced the evaluation of the Rudy Robot technology. The critical level of significance was assumed at the level of $p = 0.05$. The non-parametric Mann-Whitney U test (Wilcoxon 1945; Mann, Whitney, 1947) was used to examine the influence of sex on the assessment of this technology in the context of dementia and technological criteria (Table 2).

When analysing Table 2, it can be noticed that significant differences depending on sex in the assessment of the Rudy Robot technology ($p <0.05$) occur in the case of the criteria D1, D2, D3, D6 and T3. In the case of the remaining criteria, no significant differences were found between technology and sex assessment.

Table 2. Statistics of the Mann-Whitney U test for assessment of the Rudy Robot.

Acronym and the name of the criterion	Statistics of the Mann-Whitney U test		
	U	Z	p
D1: There is a need for the Rudy Robot on the part of institutions responsible for the care of older adults (e.g., nursing homes)	149718,5	2,61717	**0,008867**
D2: The use of the Rudy Robot will be a source of additional benefits for their users, which are unavailable through other solutions;	150871,5	2,41196	**0,015868**
D3: The popularisation of the Rudy Robot is in line with the forecasts concerning the directions of technology development and the expectations of older adults.	151300,5	2,33561	**0,019512**
D4: The Rudy Robot is characterised by higher ease of use and simplicity of operation compared to the technologies used so far	158312,5	1,08762	0,276762
D5: The use of the Rudy Robot is consistent with the previous habits of older adults	156965,0	1,32745	0,184361
D6: Changes in the environment make the Rudy Robot more attractive for older adults (e.g. due to new legal regulations, consumption trends, or technological standards)	150177,5	2,53548	**0,011230**
D7: The infrastructure necessary for the efficient use of the Rudy Robot is available.	164407,0	0,00294	0,997657
D8: Potential users are ready to pay the Rudy Robot in relation to the prices of the technologies used so far	162538,0	0,33558	0,737189
T1: The Rudy Robot is implemented and successfully used by older adults.	156430,5	1,42258	0,154859
T2: Serious technical problems are likely to occur during the development of the Rudy Robot	155349,5	-1,65982	0,096951
T3: The widespread use of the Rudy Robot depends on the use of hard-to-reach materials.	150382,0	-2,54284	**0,010996**
T4: The Rudy Robot can complement the solutions currently available on the market.	155358,5	1,61337	0,106665
T5: There is great potential for further improvement of the Rudy Robot.	157286,5	1,27023	0,204004

[Source: elaborated by the authors.]

It was then checked whether age, education and place of residence impacted the assessment of the analysed technology. The ANOVA Kruskal-Walls test was used to examine the influence of age, education, and place of residence on the evaluation of the Rudy Robot technology in terms of technological and demand-related criteria (Table 3).

Table 3. Statistics of the ANOVA Kruskal-Walls test for assessment of the Rudy Robot.

Acronym	Age		Education		Residence	
	T	p	T	p	T	p
D1	1.559	0.458	8.491	0.369	2.647	0.754
D2	7.867	**0.019**	1.779	0.619	10.155	0.071
D3	5.523	0.063	2.686	0.443	6.113	0.295
D4	6.434	**0.040**	5.997	0.1127	7.100	0.213
D5	0.55	0.759	8.901	0.306	5.820	0.324
D6	8.052	**0.018**	14.590	**0.002**	3.433	0.634
D7	1.652	0.438	8.369	0.385	6.861	0.231
D8	0.497	0.780	8.641	0.345	10.989	0.052
T1	0.809	0.667	14.906	**0.002**	13.900	**0.016**
T2	2.039	0.361	4.867	0.187	3.548	0.616
T3	1.666	0.435	2.886	0.409	6.856	0.231
T4	1.212	0.546	7.247	0.644	12.027	**0.034**
T5	2.515	0.284	2.684	0.443	9.759	0.082

[Source: elaborated by the authors.]

Based on Table 3, a 95% probability exists that age does not affect the assessment of the analysed technology (p> 0.05) in the context of all technological criteria (T1–T5) and the following demand criteria D1, D3, D5, D7 and D8. Fig. 8 shows the values of the acceptance responses for selected statements (statistically significant: D2, D4, and D6) regarding the evaluation of the Rudy Robot technology in terms of demand in three age groups. The analysis of Fig. 8 showed that the lowest acceptance of D2 was found among respondents aged 40–49 (the average grade of 4.8). On the other hand, the average rating was 5.05 among respondents over 60 years of age. Thus, people over 60 estimated that the use of the Rudy Robots would be a source of additional benefits unavailable from other solutions. Statements D4 ("The Rudy Robot is characterised by higher ease of use and simplicity of operation compared to the technologies used so far") obtained an average rating of 5.0 from people over 60 years of age. In turn, statement D6 was assessed by people over 60 at about 4.7. Thus, people in this age group assessed changes in the environment that made the Rudy Robot more attractive to older adults on average at 4.7 (on a scale of 1 to 7).

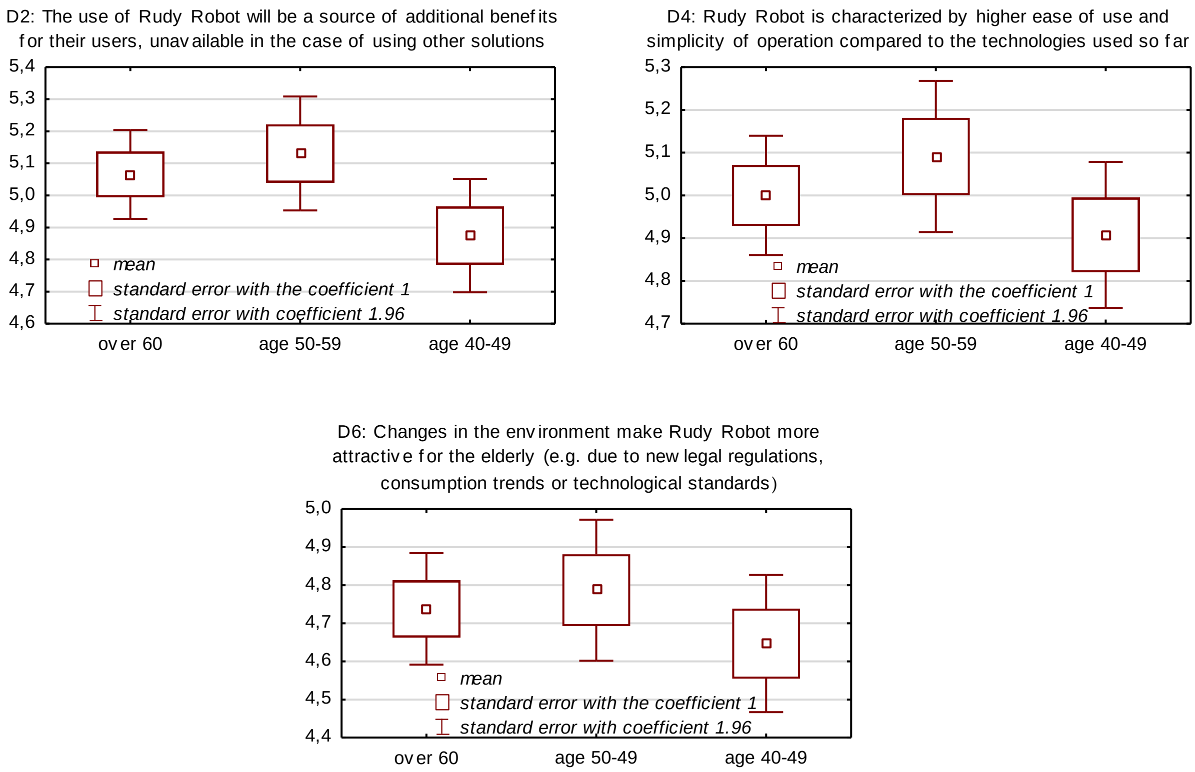

Figure 8. Technology Assessment of the Rudy Robot in terms of Demand in Three Age Groups.
[Source: elaborated by the authors.]

Based on Table 3, statistically significant differences (p <0.05) were found depending on education in the case of the Rudy Robot technology assessment only in the context of the D6 and T1 criteria. However, it should be stated with a probability of 95% that the place of residence affects the assessment of the technology in terms of the criteria T1 and T4.

DISCUSSION OF THE RESULTS

The conducted research aimed to gain knowledge about the future use of robots by older adults in the context of smart living. The main assumption of the study was to look for answers to the following questions: (1) What are the most important expected robot functionalities that facilitate the quality of life of older people in the context of smart living? (2) What are the most important criteria for evaluating a robot? (3) How was the Rudy Robot rated according to different criteria? (4) Does age affect the assessment of the analysed technology? (5) Does sex affect the assessment of the Rudy Robot technology? (6) Does education affect the assessment of the analysed technology? (7) Does the place of residence affect the assessment of the Rudy Robot? As the assessed technology is not widely used, the research is mainly concerned with the robot's functionality, which is assessed on the basis of information taken from the description attached to the questionnaire, literature, films, etc. Robots that care for older people can be a very useful and life-changing technology. Technologies for smart living and smart homes are designed to simplify lives in a simple and smart way. Older people may have age-related challenges with independent everyday functioning at home, which can be resolved using technologies. It should be noted that the use of this type of technology should be simple and intuitive, especially for older adults. The research results demonstrated that the most important functionalities of the Rudy Robot that make life easier for older adults in the context of smart living are (Joseph, Christian, Abiodun, Oyawale, 2018):

- notification of family members about threats to the health or life of the older adult,
- the Remote Patient Monitoring (RPM) capability,
- remote monitoring of the situation at home,
- prevention of falls,
- detection of falls,
- non-contact emergency response,
- entertainment (telling jokes, dancing),
- interaction.

The Rudy Robot provides key information based on trends in the health and activity of older people. This information can help optimise treatment, improve performance indicators, and save costs.

Moreover, based on the conducted analyses, the respondents indicated that demand and technical were the most important criteria in assessing the Rudy Robot technology. The robot was rated the highest in the context of the potential for further improvement of this technology (an average of 5.20 on a scale from 1 to 7). On the other hand, the Rudy Robot was rated the lowest in terms of T2, indicating a high probability of serious technical problems occurring during the development of this technology (the average grade of 3.65 on a scale from 1 to 7).

Based on the analysis, a probability of 95 % exists that the respondent's sex does not affect the assessment of the Rudy Robot technology in the context of most demand and technical criteria, such as D4, D5, D7, D8, T1, T2, T4 and T5. The same 95% probability also exists that the respondent's age does not affect the evaluation of the technology in the technical aspect. Age affects the evaluation of the Rudy Robot technology only in terms of the following demand criteria D2, D4 and D6. Furthermore, it was found that the education of the respondent did not affect the assessment of most technical criteria. Education affects the assessment of this technology only in the context of the D6 and T1 criteria. In turn, the place of residence affects the assessment of the analysed technology in terms of the criteria T1 and T4.

In their future research, the authors intend to extend the research to a larger sample and other EU countries. They also intend to consider other technology assessment criteria, such as Technology Readiness Levels (TRL) or Life Cycle Analysis (S-LCA). The authors also plan to evaluate other life-enhancing technologies for older people (Wheelie7, smart bracelets) and would like to evaluate technologies from the perspective of a potential future manufacturer and develop a ranking of life-enhancing technologies for older people.

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