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Artificial Intelligence readiness in Russian and Swiss-based mechanical and industrial engineering companies

Master's Thesis by the 2nd year student
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ЗАЯВЛЕНИЕ О САМОСТОЯТЕЛЬНОМ ХАРАКТЕРЕ ВЫПОЛНЕНИЯ

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OF THE MASTER THESIS

I, Fetisov Daniil Alekseevich, second year master student, program "Management", state that my master thesis on the topic "Artificial Intelligence Readiness in Russian and Swiss Based Mechanical and Industrial Engineering Companies", which is presented to the Master Office to be submitted to the Official Defense Committee for the public defense, does not contain any elements of plagiarism.

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АННОТАЦИЯ

Автор	Фетисов Даниил Алексеевич
Название ВКР	Готовность внедрения искусственного интеллекта в российских и швейцарских промышленно-производственных компаниях
Направление подготовки	38.04.02 «Менеджмент»
Год	2017
Научный руководитель	Самсонова Татьяна Александровна
Описание цели, задач и основных результатов	Целью данного исследования является изучение факторов, влияющих на готовность к имплементации Искусственного Интеллекта в промышленно-производственных компаниях в регионе, лидирующем в инновациях (Швейцария), и в отстающем в инновациях регионе (Россия). Для того чтобы достигнуть этой цели, была проведена консультация с экспертом промышленно-производственной отрасли, была применена Модель Принятия Технологий, дополненная внешними переменными, был составлен и проведен опрос (102 респондента), а также был осуществлен статистический анализ. Результаты исследования показывают, что осуществимость имплементации Искусственного Интеллекта намного важнее для компаний, чем потенциальная выгода. Следственно есть перспектива разъяснить компаниям потенциальную выгоду от имплементации Искусственного Интеллекта, таким образом, способствуя его внедрению во всей отрасли.
Ключевые слова	Искусственный Интеллект, принятие технологий, Модель Принятия Технологий, Швейцария, Россия

ABSTRACT

Master Student's Name	Daniil Fetisov
Master Thesis Title	Artificial Intelligence Readiness in Russian and Swiss Based Mechanical and Industrial Engineering Companies
Main field of study	38.04.02 «Management»
Year	2017
Academic Advisor's Name	Tatjana A. Samsonowa
Description of the goal, tasks and main results	The purpose of this study is to analyze the factors influencing readiness levels towards Artificial Intelligence solutions implementation by mechanical and industrial engineering companies in a region leading in innovation (Switzerland) and in a region lagging behind (Russia). In order to achieve this goal, the research consults an industry expert, uses Technology Acceptance Model enriched with external variables, designs and conducts a related survey (102 valid responses) and carries out statistical analysis. The results of the study show that feasibility is much more important for companies than potential benefits of implementation. Therefore, there is an opportunity to educate companies about the benefits of Artificial Intelligence, thus driving its implementation in the industry.
Keywords	Artificial Intelligence, technology adoption, Technology Acceptance Model, Switzerland, Russia

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INTRODUCTION

Artificial Intelligence (also known as Machine Intelligence; later referred to as AI) is the science and engineering of making machines do tasks which require intelligence when done by human beings (McCarthy, 2007). Thus the concept of AI opposes NI (Natural Intelligence). A particular use (and the most common one) of AI is through intelligent computer programs.

The increasingly rapid growth of available data incentivized most companies across various industries to use more structured approach in collecting, processing and storing it. The companies which intend to be the leaders in the market and reap the benefits first, have to use a wide range of data analytics tools powered by elements of AI - this is the minimum requirement for them to stay competitive in the VUCA[1] world (Davenport, 2013). Leading mechanical and industrial engineering companies are no exception: they are now on the threshold of massive integration of AI solutions (Faggella, 2017), potentially propelling the overall development of AI and encouraging companies from other industries to follow their lead.

In order to understand the current situation of AI implementation in industrial engineering companies better, this research compares state of affairs for two countries - Switzerland (one of the leaders of AI use in corporate sector) and Russia (the country lagging behind, especially for industrial engineering companies). This allows getting a more comprehensive picture for the analysis.

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[1] VUCA - VUCA world (volatile, uncertain, complex, and ambiguous – concept which was created by U.S. Army War College referring to the new reality after the Cold War)

The research goal of this study is to analyze the adoption of AI solutions by mechanical and industrial engineering companies in a region leading in innovation (Switzerland) and a region lagging behind (Russia).

For the research goal to be accomplished, it is necessary to fulfill the following sub-*goals:*

1. Understand the current developments in AI;
2. Design a survey determining status quo of AI solutions in mechanical and industrial engineering companies;
3. Conduct the survey among middle-level and senior-level employees of mechanical and industrial engineering companies;
4. Test AI solutions adoption using Technology Acceptance Model (TAM);
5. Enrich traditional TAM with external variables based on theoretical review and sense-check with an industry expert (in this context - Organizational Resistance to Change, Perceived Risks and Supplier Support);
6. Compare results of AI acceptance in Russia and Switzerland;
7. Give recommendations and make theoretical and practical contributions

Thus it is possible to formulate the *research questions* as follows:

1. How do the external variables (Organizational Resistance to Change, Perceived Risks and Supplier Support) influence the adoption of AI solutions by mechanical and industrial engineering companies in TAM framework?
2. What are the main differences in AI adoption between the leaders and the laggards – that is to say Swiss and Russian companies?
3. What are the potential drivers and barriers in AI adoption by mechanical and industrial engineering companies?

The research explores the following systematic processes for gathering better understanding of the topic:

- Literature review – analysis of existing researches on the topic;
- Theoretical modeling – interview with an industry expert, development of extended Technology Acceptance Model;

- Survey design – determination of the variables, formulation of questions;
- Statistical analysis – data collection, data analysis and graphic representation.

This research is structured in the following manner: introduction, three chapters, conclusion, list of references and five appendices.

Introduction points out the relevance of this study; research goal, sub-goals, research questions as well as overview of the structure are presented.

The first chapter studies previous researches on the topic of Artificial Intelligence and its applications in business, gives an overview of mechanical and industrial engineering industry, compares AI acceptance in Russian and Swiss companies and examines Technology Acceptance Model (enriched with external variables). Hypotheses for this research are also developed in this chapter.

In the second chapter research design and research model are developed, related survey is created and empirical research is conducted.

In the third chapter the research findings, theoretical and managerial implications, potential drivers and barriers as well as limitations are outlined. Also the comparison between Russian and Swiss companies is drawn.

Conclusion summarizes the results, recommendations and potential for future research.

CHAPTER 1. THEORETICAL BACKGROUND

1.1 Artificial Intelligence (AI): brief overview

First of all let us take a look at the definition of AI given by Oxford English Dictionary: “It is the theory and development of computer systems able to perform tasks normally requiring human intelligence”; thus AI is based on the principles of human cognition. The researchers mostly distinguish the following five elements of human intelligence used in AI building principles: learning, reasoning, problem-solving, perception, and language-understanding (Copeland, 2012).

There are many types of *learning*, but the most common ones used in intelligent programs are rote[2] *learning* and *generalization*. The former is basically a simple memorization of individual things – e.g. mate-in-x moves in chess or Sudoku engines: they simply try out all the possible moves until the successful outcome. The latter is based on the principle of learning the situations so that machine performs better in similar situations they have not previously come across – e.g. if a machine encounters a word with suffix ‘-ment’

[2] Rote learning - learning by memorization without proper understanding or reflection; mechanical learning (Oxford English Dictionary)

and is told that it is a noun once, it can predict that words with similar suffixes are nouns as well.

Reasoning means drawing appropriate conclusions based on presented data. There are two types of conclusions: inductive and deductive. In deductive conclusions, if premises are true, then the conclusion is true (e.g. 'Company X can either take a loan or offer its equity; company X didn't take a loan, thus it offered its equity'). In inductive conclusions premises support the conclusion, but do not necessarily guarantee it is true ('All clients of bank X receive 5% cash back; Ivan received 5% cash back, thus he is a client of bank X' – not necessarily true). There has been a significant breakthrough in teaching machines to draw inferences; however reasoning includes drawing conclusions which are relevant to the task, and data scientists are now struggling to make AI differentiate relevant conclusions from irrelevant (the so-called noise).

In terms of *problem-solving* methods it is possible to outline two types: special-purpose and general-purpose. Similar to learning principles, special-purpose method is designed to work out a specific problem, whereas general-purpose method deals with a wide range of various problems. An example of a general-purpose method in AI is means-end analysis – a program selects from the possible means (actions), executes them, and repeats if necessary until the current state is transformed into a pre-defined goal state (e.g. a robot is programmed to pick up boxes until there is nothing left).

In terms of *perception*, the environment is examined by various sensors, then information is processed and analyzed and appropriate response is made. Currently artificial perception is well-developed – cleaning robots are roaming offices, collaborative robots allow employees to work together at factories and autonomous cars can drive at moderate speed almost without any accidents. This element is predicted to grow fastest in the near future – at a CAGR[3] of 7.67% during 2017-2021 (Zervos, Ghaffarzadeh and Harrop, 2017).

It is rather easy to formulate certain phrases/sentences using a *language* (including artificial languages) and its syntax. However it is much harder to understand them. Modern AI is still not completely capable of creating comprehensive system of language

[3] CAGR - is a business and investing specific term for the geometric progression ratio that provides a constant rate of return over the time period

understanding. Some scientists believe that this step might be the most important one in creating next generation AI (Copeland, 2012).

1.2 AI development and its applications in business

Some researchers believe that the AI expansion started out with the invention of computer in the early 1940s (Panczyk and Rudzinski, 2002). The majority however think that actual development of AI began a dozen years later at the AI conference in Dartmouth College in 1956 – the so-called Dartmouth summer research project on AI. During this workshop approximately 20 scientists and mathematicians brainstormed and argued about the possibilities of machines "behaving intelligently" (Veale, 2001).

1.2.1 Expert systems

The first commercial application of AI was made in the late 1970s with the introduction of expert systems – computer software that attempts to mimic the reasoning of a human specialist (Jackson, 1998); expert systems became one of the first (if not the first) genuinely successful applications of AI (Russell and Norvig, 2010). Expert systems were introduced to solve complex problems based on drawing meaningful inferences (rule-based system). One of the biggest advantages of expert systems is that they demonstrate the logic behind every inference – why a particular decision was made, why certain options were eliminated etc.

There were several successful expert systems at the early stage – one of the first was XCON (or Expert CONfigurer, later on called R1). It was developed to validate technical correctness of customers' orders and guide the assembly of such orders for Digital Equipment Corporation (DEC). The program was a definite success: XCON achieved from 95 to 98% accuracy while validating and sorting orders and drastically increased the speed of assembly. The overall net return for DEC thanks to XCON implementation was estimated to be more than $40 million per year (Blecker and Friedrich, 2005). Another example of a successful expert system was Mycin – a program which identified diseases based on patients' symptoms and other factors. The expert system also recommended treatment and dosage of medicine – according to the data of patients: weight, allergies etc. A special commission at Stanford Medical School concluded that Mycin suggested appropriate treatment in 65% of the cases –

a better result than that of human experts (average score – 52.5%), who made decisions based on the same factors as Mycin (Yu, 1979).

In the 1980s expert systems were spreading even more rapidly. Among the leaders at the high-end expert systems market were such companies as Xerox and Texas Instruments. However after such hype of the 80s, expert systems ceased to be a separate AI concept in the 1990s. Instead, such systems were integrated with other solutions (such as PC) in accordance to the businesses' needs and the new VUCA world (volatile, uncertain, complex, and ambiguous – concept which was created by U.S. Army War College referring to the new reality after the Cold War).

The further progress of AI continued in late 1990s – this was primarily due to the surge in computing power and meticulous work of computer engineers (Mead and Kurtzweil, 2006). Such events as Deep Blue beating chess champion Garry Kasparov in 1997, Stanford robot autonomously driving in regular traffic for 131 miles in 2005 and IBM Watson winning in "Jeopardy!" game in 2011, show the skyrocketing potential of AI capabilities.

1.2.2 Artificial Neural Networks

With the development of AI another concept started to spread and applied across various industries – Artificial Neural Networks (ANN). ANN is a computing system which consists of layers of hidden nodes and layers of output nodes, which react to the external inputs (Wang, 2003). Nodes are similar to neurons in brains – they are interconnected with each other. Please refer to exhibit 1 for visual representation of an ANN.

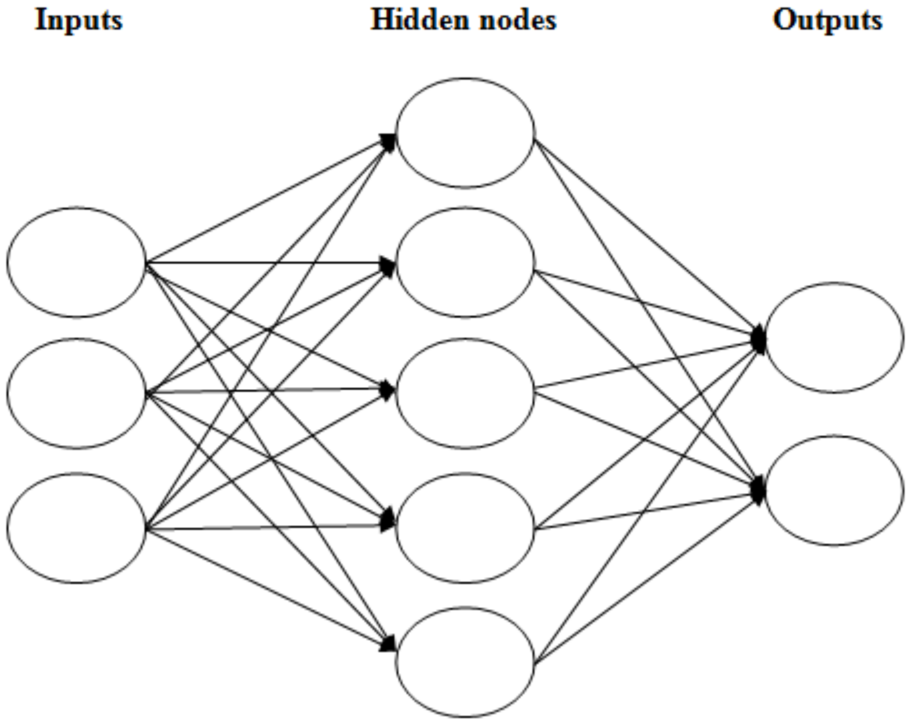

Exhibit 1. ANN example

The applications of ANN are enormous and cover most of the AI use cases – from predictive analytics and decision-making tools to pattern recognition and data mining.

ANNs are not programmed to execute the same operations; instead they learn to recognize specific patterns. Researchers point out 3 main types of such learning: supervised, unsupervised and reinforcement learning (Suzuki, 2011).

The key distinctive feature of supervised learning is that it has pre-planned target output. ANN learns by setting values of its parameters for any valid input values after having seen output values; the training data is made up of pairs of input and desired output values (Suzuki, 2011). The process of supervised learning usually includes several stages. First of all it is necessary to recognize specific type of training data. Then one has to gather training data which meets the criteria for solving a certain problem. After that it is necessary to translate training data into an appropriate code which is comprehensible for ANN. Then ANN conducts the training by itself. Lastly, the performance of ANN is assessed after the learning with the test data set – it has not been given to ANN for learning but has similar structure as the learned data. One of the most common uses of supervised learning of ANN is pattern recognition.

Unlike supervised learning, unsupervised learning does not have any target outputs. The specific feature of this type of learning is that ANN receives only examples which are not tagged. ANN determines the data structure and looks for certain patterns by itself. Unsupervised learning is mostly used for tackling various estimation problems such as clustering, filtering, forecasting and estimation of statistical distributions; the model which resorts to unsupervised learning the most is self-organizing map (Kohonen, 1989).

Lastly, in case of reinforcement learning, examples are normally not given to ANN; rather they are created via ANN's interactions with the environment. ANN collaborates with the environment so that it finds optimal actions to receive long-term reward (the ability to learn from their environment is generally considered one of the greatest benefits of ANNs). Reinforcement learning is often integrated into ANN's general learning algorithm. It is most frequently applied to deal with sequential decision-making problems, such as game engines (checkers, chess, go), telecom and others.

Thus ANN has many benefits that make it indispensable in terms of commercial use – it is very good at problem-solving (e.g. pattern recognition), decision-making as well as forecasting (these areas are especially important for the industry studied in this paper – mechanical and industrial engineering companies).

1.2.3 Deep learning

Deep learning is rather similar to ANN in terms of pattern recognition techniques. It is based on feature learning, which allows a system "to automatically discover the representations needed for feature detection or classification from raw data" (Bengio, Courville and Vincent, 2013).

Deep learning applies backpropagation method in order to establish structure in datasets. Deep learning techniques largely contributed to the significant development in such areas as visual recognition, speech recognition, video processing, object detection and many others (LeCun, Bengio and Hinton, 2015).

The main difference between Artificial Neural Networks and Deep Learning (even though these models are much interconnected most of the time) is the amount and structure of data it is applied to. Deep Learning platforms have more hidden nodes (layers) than ANNs and normally deal with significantly bigger datasets.

1.2.4 Robotic Process Automation

Broadly speaking Robotic Process Automation (RPA) is a type of software which allows imitating human behavior while executing tasks within a certain process. It can carry out repetitive tasks much faster and with higher precision than human employees, moreover RPA does not get tired of executing similar tasks over and over again. RPA systems benefit both executives and employees: routine tasks can be done faster and more accurately, while employees can do other tasks more focused on creative side, emotional intelligence and customer interaction (Willcocks, 2016).

RPA, unlike most of other AI solutions, is designed to carry out simple tasks, e.g. entering purchase invoices in a company's Enterprise Resource Planning system. Most of the time RPA systems have to be provided with specific instructions; they rarely allow any variability in decision-making process.

1.2.5 Virtual Agents

Virtual Agents (sometimes referred to as Intelligent Agents or Autonomous Intelligent Agents) receive information about the environment using sensors (or similar tools) and then execute the responsive action in order to achieve a goal. Virtual Agents vary in types; according to Russell and Norvig (Russell and Norvig, 2010), there are 5 main types of Virtual Agents:

1. Simple reflex agents;
2. Model-based reflex agents;
3. Goal-based agents;
4. Utility-based agents
5. Learning agents

The first group initiates a response based solely on the current state of environment completely ignoring historical data. Its decision-making follows the so-called *condition-action rule* (if there is certain condition then agent executes a reciprocal action).

Model-based reflex agents can operate within partially observable environments. By collecting data from the environment, the model gets the general understanding of how the environment works.

Goal-based agents are more developed than their model-based counterpart in the way that they additionally use the information about specific goals of the model. Thus goal-based agents may choose a path among multiple options so that the chosen path achieves the final goal. Goal-based agents are flexible since it is possible to modify the knowledge base which supports the model's decision-making.

If goal-based agents operate within a binary framework (goal is achieved or not achieved), utility-based agents select an action which maximizes the desired utility (utility-based agents choose the path which satisfies the goal to the biggest extent to put it simple – i.e. what is the best outcome among all the probabilities).

Learning agents, unlike the former 4 types, initially operate in an unknown environment thus becoming more competent. Learning agents have 2 core elements – the learning element and the performance element. The former is responsible for making improvements in the model and the latter deals with choosing appropriate responsive actions with the environment. Given the complexity of this type of agent, it is by far the most sophisticated.

The most common use case for virtual agents is automated online assistant (chatbot) and similar customer service and marketing tools.

1.2.6 Natural Language Processing

Natural Language Processing (NLP) has relatively narrower focus than other AI solutions – it deals with creating software capable of processing a natural language. Even though the focus is narrow, the task itself is one of the most complicated and complex ones. Some relatively successful NLP products already exist in the market as of 2017 (e.g. IBM's Watson, Amazon's Alexa, Apple's Siri, Google Translate and others), however the full integration of natural language and machine perception has not yet been achieved, and there is still huge commercial potential behind this AI solution.

1.2.7 Hybrid systems

The last AI method analyzed in this research is hybrid systems. Those are "systems that use more than one problem-solving technique to solve a problem" (Gray and Kilgour, 1997). This paper analyzes 2 types of hybrid systems since they have the widest range of use in business – namely those methods are Fuzzy Expert Systems and Data Mining.

First of all here is a brief explanation what fuzzy logic is. Unlike classical Boolean logic with only 2 possible values (True or False), Fuzzy logic operates with a range of values. Each of these values reflects various degrees of truth on a scale between completely false and completely true (Meana et al., 2016). This approach creates resemblance with human reasoning where there are few absolute values and many grey areas.

Fuzzy expert systems are expert systems which operate based on fuzzy logic principles. Fuzzy logic finds the most common use in such systems (Kantrowitz et al., 2001). These systems are quite efficient in business since they allow more precision in decision-making process. The main use cases of such systems in business are in planning, designing and as a decision support tool.

Data mining (also known as Knowledge discovery databases or Information discovery) uses AI to find useful insights in huge amounts of data. The software allows discovering relationships and associations which are not so easy to find by a human being, the main constraint being the amount of time necessary to complete the task (Port, 2001).

Normally the Data mining process works like this: first data is loaded into Data mining database, then Data mining techniques are applied, after that the software finds correlations, trends and unusual patterns, and lastly the software interprets the results (normally via visualization tools such as Wave, Tableau and others) (Brown, 2012).

Data mining process uses a number of different techniques for data analysis in order to gather useful information. Here are the main methods for data mining (Gheorghe and Petre, 2014):

- Clustering – the tool discovers a finite number of categories to describe the data;

- Classification – data items are divided into one of several predefined categories;
- Regression – a function mapping data items to a real-valued prediction variable is created;
- Association rule learning – a model describing significant dependencies between variables is created;
- Deviation detection – a model discovering the most significant changes compared to previously measured data or benchmark is created.

Both Fuzzy expert systems and Data mining tools can be very effective in commercial use since they allow to make more precise decisions based on human-like logic, and deal with huge amounts of information, analyze it very quickly and give meaningful insights.

1.2.8 Conclusion

With the exponential growth of data, both internal and external, the companies are currently facing big challenges with data analysis (which information is actually relevant?) and decision making (what should I do based on the information provided?). The AI solutions mentioned above are designed to tackle this problem, most of the times even more effectively than human employees can.

While most companies today are interested in implementing the AI opportunities, they only see such solutions as supportive tools for their management. Some researchers however have a different standpoint here. For example, Marketing Director of Yandex Andrei Sebrant in his recent interview to Malina.am shared the following view: humans are objectively worse at analyzing information, detecting patterns, making predictions and recommendations, people should consider allowing machines not only giving insights to people, but also making decisions themselves (in his example Sebrant mentioned ANNs, but meant machine intelligence in general).

1.3 Mechanical and industrial engineering companies' overview

As it follows from the name, mechanical and industrial engineering is made up of 2 elements: mechanical engineering and industrial engineering. The former profession consists of specialists who work on design, development and production of various mechanical systems; this field is rather broad and most of the times it also includes industrial engineering according to the researchers (Katz and Talmi, 2017). However industrial engineering has its own differences. It stands in between engineering and business (much closer to engineering though). Industrial engineers have to take daily operational business decisions regarding many aspects: quality control on site, ensuring maximum efficiency of manufacturing processes, optimization of productivity of workers and even performing cost analyses. The combination of these 2 professions led to creation of mechanical and industrial engineering companies.

A good example of such foundation is ABB – a Swiss-Swedish multinational corporation mainly operating in power, industrial automation and robotics. This conglomerate was created in 1988 after the merger of 2 companies: Swedish ASEA and Swiss Brown, Boveri & Cie (BBC). The history of these 2 companies goes back to the end of the 19^{th} century – they were both founded by electrical engineers. ASEA started manufacturing and selling light bulbs and generators, while BBC produced motors, steam turbines and transformers. This collaboration of engineers turned out to be quite fruitful – ABB today is one of the biggest players in the industry with operations all over the world, in approximately 100 countries (ABB official website, 2017); it currently holds 314^{th} position of 500 biggest companies worldwide by revenue (Fortune 500, 2017).

Since the 1970s the industry has become a leader in development and application of high technology, integrating the first AI solutions among other things. In spite of the fact that mechanical and industrial engineering industry is traditionally considered as the one producing machinery and hardware, it has moved significantly towards the service industry – the companies install equipment, train personnel, conduct maintenance and repair works. Such services have 2 main benefits: they significantly increase revenues and also reduce exposure to low-cost competition (Vieweg, 2012).

According to some researchers there are 4 major factors influencing industries to adopt AI solutions: substantial budget, large amount of organized data and the ability to acquire AI experts, data scientists and additional talent (Faggella, 2017). The first factor describes a company's ability to invest in a technology which may not necessarily lead to fast ROI. In terms of big amount of structured data, companies which possess such information can get much greater value out of it – more insights, more patterns, better possible forecast for the future. Lastly, in order to implement a new AI tool it is necessary to attract experts in this field. The main attraction here is generally considered to be money, but it also includes brand appeal of the company.

Keeping in mind those 3 factors, it is possible to assume that mechanical and industrial engineering companies are on the verge of mass implementation of AI solutions. Such companies have sufficient budgets to invest in such solutions, at least the leaders (total revenue of the companies in this industry in Fortune 500 list (15 overall) was approximately $650 billion in 2016). Such companies also have huge amounts of data; however data management processes in such companies are often in poor state, especially if they do not have standardized processes across the markets (interview with ABB Group Vice-President of Sales & Marketing, 2017). As mentioned before, mechanical and industrial engineering companies have significant budgets, so it is not a problem for them to attract AI experts and other talent with high salaries; also the brand image of most of such companies is positive (e.g. renewable energy companies such as GE and Siemens), which also plays a big role in talent acquisition. Overall, theoretically such companies should be about to implement more and more AI solutions in the near future.

Currently the level of adoption of AI in the industry varies significantly. Some industry leaders have been trying to integrate AI solutions for decades – e.g. Siemens have been conducting in-depth research in this area for more than 30 years and have implemented several of them – e.g. artificial neural networks in steel mills (Siemens official website, 2017), while others are still looking up to the industry leaders and assessing AI potential. This research intends to understand the overall readiness of mechanical and industrial engineering companies to implement AI solutions and their possible implications from middle management and senior management perspective.

1.4 Russian and Swiss companies' comparison

This research intends not only to look at readiness for AI adoption in mechanical and industrial engineering companies, but also to further narrow down the scope and compare such companies in 2 countries - Russia and Switzerland. The reason for this exact comparison lies in the level of development in AI. Russian companies are lagging behind their counterparts, and Swiss companies are considered the leading force in innovation and as a consequence AI implementation. Therefore in order to stay competitive and lead the change, Russian companies have to constantly monitor and follow some of the best practices of the leaders. Thus this research will analyze and compare Russian and Swiss mechanical and industrial engineering companies, outline the most important findings and suggest recommendations.

So why exactly does this research draw comparisons with Swiss companies? Why not other countries leading in AI implementation and the level of innovation in general? The traditional metric for a country's innovativeness level is the number of research papers published in this country (Cheng and Krumwiede, 2017). However, the sheer number of papers does not necessarily give the full picture for understanding the situation - a huge proportion of papers may not have sufficient citations, thus questioning the quality of such papers.

There is another approach when comparing research papers - the so-called Field-Weighted Citation Impact (FWCI). This metric shows the relation between the number of citations of researchers' publications and the average number of citations received by all other similar publications (Aldieri, Kostemir and Vinci, 2017). This metric is important to show the real value of research papers. For example, China was the leading country in the number of AI publications from 2011 to 2015, having published approximately 40% more papers than the second country in this list - the USA. However, in terms of FWCI China was only 34th, significantly lagging behind the leaders.

FWCI looks up similar publications in Scopus database; the publications are determined based on 3 characteristics: the same year of publication, type of research and studied discipline. For example, FWCI of 1.00 means that a certain publication has been cited exactly the same number of times as an average number of similar publications in the world. Thus after comparing countries' research papers on AI using FWCI metric, we discover that Switzerland holds the first position with FWCI of 2.71 (Source: Elsevier/Scopus database).

Another factor making Switzerland the most suitable country for comparison in AI readiness levels with Russia is the level of innovation of the countries. In order to determine this parameter, the best approach is to use Global Innovation Index (GII), which was developed by Professor Soumitra Dutta of INSEAD in 2007. Under GII the term ‘innovation’ is considered as “the implementation of new or significantly improved products (goods or services), a new process, a new marketing method, or a new organizational method in business practices, workplace organization, or external relations”, borrowing the definition from Oslo Manual developed by OECD (Organization for Economic Co-operation and Development) (OECD and Eurostat, 2005). In terms of the framework itself, GII is based on the innovation efficiency ratio, which in turn is calculated with innovation input and innovation output indices (the former relies on such parameters as institutions, human capital and research, infrastructure, market and business sophistication, while the latter is based on knowledge and technology outputs and creative outputs; each of these parameters also has several sub-parameters) (Global Innovation Index report, 2017). All things considered, according to GII report in 2017, Switzerland is in the first place (it actually holds its first position for the 7th consecutive year), while Russia is only 45th.

Thus in order to have a comprehensive understanding of AI readiness of companies and look at the best practices of leaders and pain-points of laggards, the best option in the framework of this research is to compare Russian companies with the Swiss ones.

1.5 Adoption of AI by companies: Technology Acceptance Model

After the development of AI and other adjacent technological advancements, many researchers started to investigate practical use and adoption of AI by companies in particular. Since users’ adoption is crucial for emerging technologies, technology acceptance became one of the most important fields for researchers. They started looking for the factors which would influence the adoption of such technologies and eventually came up with several models which satisfied their criteria. One of the very first models was Theory of Reasoned Action (TRA) developed by Icek Ajzen and Martin Fishbein in 1980. This theory tries to predict people’s actions based on 2 factors – pre-existing attitudes and behavioral intentions. Another model which aims to analyze factors influencing intentions and behavior of people is Theory of Planned Behavior (TPB) also developed by Icek Ajzen. TPB is widely recognized in social psychology as very efficient; it tries to explain consumer behavior in different situations, conditions and domains (Klöckner and Verplanken, 2012). The main idea of this theory is that intentions of consumers are built on three blocks – their attitude, subjective norm (perceived social pressure to engage or not to engage in a behavior) and perceived behavioral control (people's perceptions of their ability to perform a given behavior) (Ajzen, 1985).

TPB was later transformed and became the underlying foundation of another model more applicable to business – Technology Acceptance Model (TAM) developed by Davis in 1986. This model (along with several modifications – e.g. extended TAM, also known as TAM2) is still widely used for understanding how individuals along with organizations might adopt a new technology and which factors influence their decision (Lin, Shih and Sher, 2007). Its main purpose is to foresee the factors which motivate users to accept, use and stay loyal to a certain technology, such as various AI tools for companies in this case (Chiou and Shen, 2012).

According to TAM (see Exhibit 2), the actual use of a certain technology is directly influenced by its users' motivation (Behavioral Intention to Use - BI). While the previous statement might seem rather obvious, others are not necessarily so straightforward. BI depends on perceived Attitude Towards Using (AT), which in turn is affected by 2 factors: Perceived Usefulness of technology (PU) and its Perceived Ease of Use (PEOU). The former factor (PU) is described by Davis as "the degree to which a person believes that using a particular system innovativeness which makes the technology better than its predecessor in the minds of users". Also PU has a direct impact on BI. The latter factor (PEOU) reflects the level of complexity, which is evaluated based on how difficult a new technology is for understanding for its users. Finally TAM includes External Variables, which affect both PU and PEOU. They heavily depend on the technology which is being evaluated as well as other practicalities, such as industry, users themselves etc.

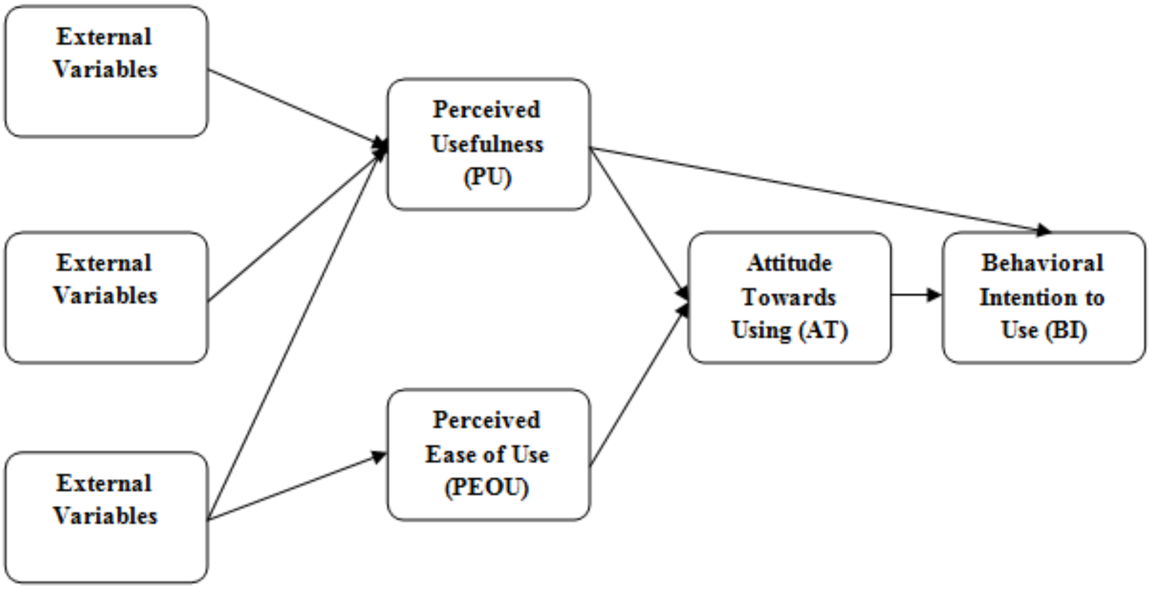

Exhibit 2. Technology Acceptance Model (source – Davis, 1989)

According to the updated version of TAM, the researchers (Davis and Venkatesh) became skeptical about the importance of Attitude Towards Using in influencing Behavioral Intention to Use, so the former parameter was removed from extended TAM. They thought that AT did not completely mediate relationship between PU and PEOU with BI (Venkatesh and Davis, 2000). Therefore, PU and PEOU become two of the most important factors influencing the intention to use a technology, AI solutions in case of this research. If we drill down even further, some researchers give a definite statement that PU plays a major role in recurrent use of a technology, whereas PEOU may not have substantial and long-lasting direct effect (Premkumar and Bhattacherjee, 2008); thus it is possible to conjecture that PU will also be the most important parameter in this research.

In order to measure PU and PEOU, the researchers (Ajzen, Fishbein and Davis) applied the following method - there were 5 bipolar adjectives with a seven-point scale (from the highest to the lowest degree). According to a number of researchers, this method proved to be reliable, provided high-quality results which were easy to measure, was easy to conduct and did not take long time to carry out (Zaichkowsky, 1985). That is why this model was selected among other technology adoption models. Given the advantages of TAM, a similar approach will be conducted in the empirical part of this research.

1.6 Adoption of AI by companies: external variables in TAM

After careful analysis of existing publications on AI adoption in Scopus, EBSCO and Google Scholar databases (the following keywords were used, either in combination with one another or alone: “Artificial Intelligence”, “AI”, “Expert System”, “Decision Support System”, “Decision Making System”, “Artificial Neural Network”, ”ANN“, “Deep Learning“, “Data Mining”, “Process Automation“, “Virtual Agent”, “Natural Language Processing”, “Technology Adoption”, “Technology Acceptance Model”, “TAM”), it turned out that most researchers focused on applications of AI solutions; publications on their adoption or integration were scarce. Most papers analyzing AI focused on Artificial Neural Networks applications, usually focused on a specific industry - most notably physics and engineering, e.g. Paguio and Dadios (2012) or Sumathi and Bansilal (2016). Overall business context was rather underrepresented - most publications on AI solutions were concerned with specific applications of AI in such industries as medicine, chemistry and engineering. Therefore the topic of adoption of AI solutions by companies was not covered sufficiently.

One particular publication was related to the adoption of an AI solution in corporate sector and was elaborated quite well - the research paper by G.Rigopoulos, J.Psarras and D.Askounis (2008). The work was exploring users’ (responsible employees of a bank) attitude towards adoption of Decision Support Systems (DSS) in their daily work. The research used a revised Technology Acceptance Model for measuring adoption attitudes, focusing on PU and PEOU. However this research method showed rather limited results and did not fully explore the underlying factors influencing DSS adoption due to the lack of additional external variables as proposed by Davis (1989). Despite this limitation, the research provides a solid foundation for our research. TAM proved to be an efficient model in the context of this publication; all 6 of the initial hypotheses were supported. This research also intends to use TAM and complement it with additional external variables for better understanding of AI adoption readiness.

In terms of selection of exact external variables for TAM, researchers agree that there is no universal rule of thumb when making this decision (Legris, Ingham and Collerette, 2003). In order to determine the external variables, a number of technology adoption and user acceptance publications (mostly evaluating acceptance of an IS technology) using TAM or similar models were analyzed. The researchers considered these variables to indirectly influence the final technology acceptance decision. After the analysis a list of variables potentially suitable in context of this research was made (see Table 1).

Table 1. Research of publications on external variables used in TAMs and similar models

Authors	**Technology analyzed**	**Model**	**External variables**	**Data collection method**
Brock, Khan (2017)	Big Data	TAM	Organizational learning capabilities	Survey with 359 respondents
Cho, Sagynov (2015)	E-shopping	Attitude model (7-point Likert scale)	User acceptance, risk perception, trust	Survey with 216 respondents
Chong, Ooi, Lin, Tan (2010)	Online banking	TAM	Government support, trust	Survey with 103 respondents
Chyou, Kang, Cheng (2012)	QR code	TAM	Social influence, awareness knowledge, facilitating conditions	Survey with 287 respondents
Juan, Lai, Shih (2016)	Building Information Modeling	Customized model (partly includes TAM)	Organizational resistance to change	Survey with 300 respondents
Lin, Persada, Nadlifatin (2014)	E-Learning System	TAM	Interactivity perception	Survey with 302 respondents
Lurudusamy, Thurasamy (2016)	Broadband Internet	UTAUT (Unified Theory of Technology Acceptance and Use of Technology)	Risk perception, perceived innovativeness, social influence, performance expectancy, effort expectancy	Survey with 450 respondents

Mingxing, Jing, Yafang (2014)	Mobile Payment Systems	TAM	Trust perception, risk perception	Survey with 196 respondents
Ortega Egea, González (2010)	Electronic Records System	TAM	Institutional trust, risk perception	Survey with 254 respondents
Pai, Huang (2010)	Business Information Systems	TAM	Information quality	Survey with 294 respondents
Pantano, Rese, Baier (2017)	Augmented Reality	TAM	Quality of information	Survey with 318 respondents
Robinson, Marshall, Stamps (2005)	Technology for salespeople	TAM	Support services and trainings	Survey with 218 respondents
Shih, Chiu, Chang, Yen (2008)	RFID	TP/NP technology adoption model	Organizational resistance to change, operation efficiency	Survey with 134 respondents
Wu, Wang (2004)	Mobile Commerce	TAM	Cost compatibility, risk perception	Survey with 310 respondents

Table 1 (cont.). Research of publications on external variables used in TAMs and similar models

After making a list of existing external variables in TAM framework which are potentially applicable to this research as well, it was necessary to determine which variables are of interest in context of the research - i.e. for determining AI solutions acceptance factors in mechanical and industrial engineering companies.

In order to do so the researcher contacted Group Vice-President of Sales of Marketing & Sales in ABB and conducted an interview regarding this matter (August, 2017). Even before Mr. Vice-President was presented with the list of potential external variables, he pointed out that the support of AI solution supplier impacts PEOU and PU; he gave an example of recent AI data analytics tool in ABB - extensive online and later on-site trainings were necessary for the employees to feel confident at using the tool and getting the most out of it. Also Mr. Vice-President recommended choosing risk perception and organizational resistance to change as external variables since from his perspective they had the biggest potential to influence the acceptance of AI solutions.

Thus taking into consideration previous research studies reinforced with the interview with ABB Vice-President, also keeping in mind the industry and geographical context of research, it is possible to formulate the following research questions:

1. How do the external variables (Perceived Risks, Organizational Resistance to Change, Supplier Support) influence the adoption of AI solutions by mechanical and industrial engineering companies in TAM framework?
2. What are the main differences in AI adoption between the leaders and the laggards – that is to say Swiss and Russian companies?
3. What are the potential drivers and barriers in AI adoption by mechanical and industrial engineering companies?

1.7 Hypotheses development

As it has been mentioned before, in the framework of TAM Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) play the most important role in influencing Attitude Towards Using a certain technology (Davis, 1989). Moreover, PEOU was meant to affect PU of a technology. Also Davis conjectured that Attitude Towards Using (AT) directly influenced Behavioral Intention to Use (BI). These relations of parameters have already been supported and proved significant by a number of previous publications (e.g. King and He, 2006).

Keeping in mind theoretical background of TAM mentioned above, this research conjectures that original TAM complemented with additional external variables suited to this specific case is capable of predicting employees' attitudes towards using AI solutions by the company. Considering these variables used in the original model by Davis (1989), and additional external variables, it is possible to make the following hypotheses based on the model:

Hypothesis 1: Perceived Usefulness (PU) has direct positive influence on Attitude Towards Using (AT);

Hypothesis 2: Perceived Ease of Use (PEOU) has direct positive influence on Attitude Towards Using;

Hypothesis 3: Perceived Ease of Use has direct positive influence on Perceived Usefulness;

Hypothesis 4: Perceived Usefulness has direct positive influence on Behavioral Intention to Use (BI)

Hypothesis 5: Attitude Towards Using has direct positive influence on Behavioral Intention to Use

Even though the hypotheses of the classical TAM were successfully tested on a number of technologies (e.g. Brock and Khan, 2017), these technologies were mostly IS technologies and not AI. Although some works covered an AI solution acceptance in corporate sector (e.g. Rigopoulos, Psarras and Askounis, 2008), such publications were limited to a single solution only (Rigopoulos focused the research on AI powered Decision Support System only) and did not explore the whole spectrum of AI. Therefore, this research will bring additional value to this field of study.

In terms of external variables for TAM in the framework of this research, 3 parameters were selected as mentioned before: Perceived Risks, Organizational Resistance to Change and Supplier Support. In order to better incorporate these variables in our model, a number of publications using these parameters were analyzed.

The existing researches using Perceived Risks as an external variable appeared in publications in 2 variations: either as a parameter indirectly influencing BI (Cho, 2004) through PU, or as having direct influence (Mingxing, Jing and Yafang, 2014). However most researchers tend to use the former approach, so we will follow it as well.

Hypothesis 6: Perceived Risks have direct negative influence on Perceived Usefulness

No matter how beneficial a new technology may be for a company, it will inevitably face a certain degree of resistance (Lippert and Davis, 2006). There is clear logic behind this idea - new technology will require the change of set methods in a company, thus making employees dive into different environment, or at least slightly increase their level of stress.

That is why Organizational Resistance to Change may play a significant role in a technology adoption and appeared in several publications (e.g. Carr et al., 2010).

Hypothesis 7: Organizational Resistance to Change has direct negative influence on Perceived Usefulness

Lastly, Supplier Support was used in several researches regarding technology acceptance as an external variable in TAM (Robinson, Marshall and Stamps, 2005); also this variable was proposed to be included in the model of this research by ABB Vice-President as mentioned above. A number of studies showed that Supplier Support can have a significant impact on mitigating employees' resistance to a new technology as well as increasing the utilization of such technology (Parthasarathy and Hampton, 1993). Thus, we expect this variable to affect both PU and PEOU.

Hypothesis 8.1: Supplier Support has direct positive influence on Perceived Usefulness

Hypothesis 8.2: Supplier Support has direct positive influence on Perceived Ease of Use

1.8 Research model: extended TAM

Upon reviewing theoretical background to the research and consulting an industry expert (ABB Group Vice-President), 8 hypotheses were put together. Thus an extended TAM was developed (see Exhibit 3), which expects to measure the parameters influencing Behavioral Intention to Use AI solutions by middle and senior management employees in mechanical and industrial engineering companies.

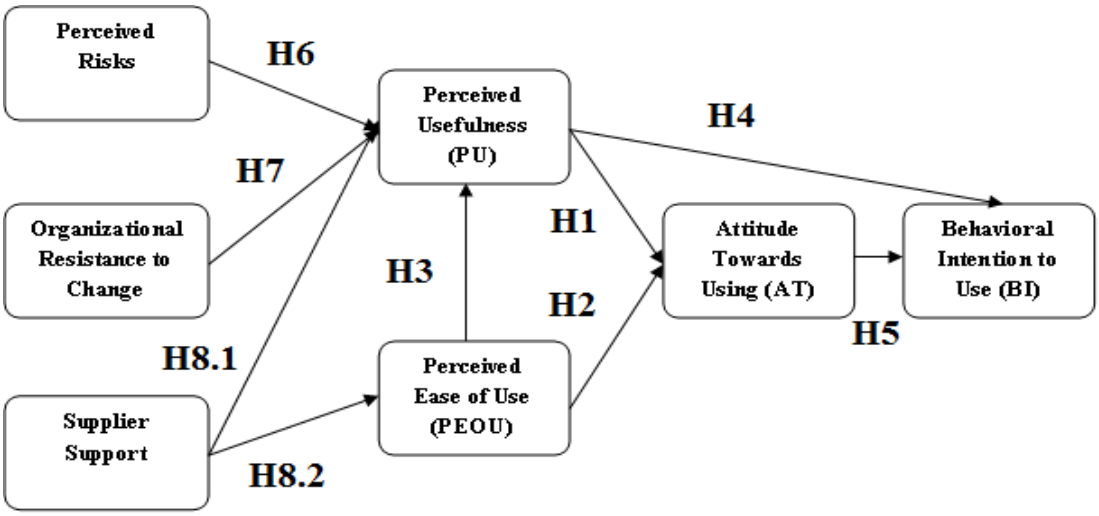

Exhibit 3. Extended Technology Acceptance Model with hypotheses

This model contains 4 basic variables (PU, PEOU, AT and BI) as well as 3 additional ones; it is meant to measure the presented variables' influence on AI solutions acceptance in mechanical and industrial engineering companies.

CHAPTER 2. RESEARCH METHOD

2.1 Research design

This research encompasses several methods of gathering data. First, an extensive literature analysis was carried out. Then after getting initial understanding of the researched topic, an in-depth interview with Group Vice-President of a major mechanical and industrial engineering company (ABB) was conducted; its primary focus was on aligning the method of gathering data and establishing the most suitable external variables, as well as discussing the general readiness levels and use cases of AI implementation in the industry. Lastly, based on the review of similar researches and the conducted interview, TAM was taken as the main research tool for this study. It consists of 7 variables; each of these includes 2 or 3 statements. The statements were compiled based on the relevant publications and expert interview and adopted to the context of this research. Each statement is based on a seven-point Likert scale (from 1 (strongly disagree) to 7 (completely agree)). Overall, there are 19 statements related to variables of TAM (part 3 of the survey) and 7 questions aimed at better understanding the respondents themselves - name of the company, country of the company's operations for a respondent, position and department the respondent works in, questions measuring current/potential AI usage in the company and hierarchical levels of AI usage.

It is worth mentioning that it is the whole company that adopts AI solutions, not the individual employees. But the only way of measuring the acceptance for the company is through its employees. Due to this fact, the respondents of the survey were asked to use a mechanical and industrial engineering company as a frame of reference while taking the survey - as a result we received individual answers taken through the prism of the whole company.

The survey starts with several introductory questions, after that a brief description of AI is given in order to refresh respondents' memory of the concept or to educate them. Lastly, 19 TAM statements go after this information block.

The survey is offered to the respondents either in English or in Russian based on the respondent's country of work (during the testing phases of the survey it was discovered that employees from Russian-based companies had significant difficulties with understanding of the questions of the survey, thus it was translated into Russian).

2.2 Sample description

The survey was presented to two categories of respondents - employees from mechanical and industrial engineering companies (middle or senior management levels) from either Swiss-based companies or Russian-based ones. This means that companies do not necessarily have headquarters in Switzerland or Russia, but have offices and ongoing operations in these countries.

The survey was sent directly to senior and middle-level managers; those employees were also asked to share the results with their colleagues. Because of the personal influence of certain senior-level executives, the survey was shared with a large number of employees. It is rather difficult to estimate the exact number of employees this survey was offered to, but it was approximately 160 people. The total number of respondents is 102 employees (54 from

Switzerland and 48 from Russia; please refer to Appendices 1 and 4 in order to examine survey sample as well as interesting insights from the responses). Therefore, the rate of response to the survey is 62,5%.

2.3 Statistical analysis

In order to perform the analysis, 2 types of statistical software tools were used - IBM SPSS Statistics and its added-on module AMOS 24.0.

First of all, in order to test the fit of the model, this research applied Confirmatory Factor Analysis. Based on it, several indices were calculated, such as ratio of Chi-Square to Degrees of Freedom (DF), Incremental Fit Index (IFI), Tucker-Lewis Index (TLI) and Comparative Fit Index (CFI). After that Convergent Validity, Composite Reliability and Discriminant Validity were calculated.

Lastly in order to test the hypotheses, this research resorts to structural equation modeling method (i.e. path analysis using latent variables – questionnaire items).

2.4 Measurement model & structural model

The statistical analysis was conducted using item-total correlation technique. This method allows determining the degree of correlation between statements used in the survey; it also allows to relate the statements with corresponding variables.

Next, Confirmatory Factor Analysis was carried out in order to test the fit measurement of the model.

The model proved to be an adequate fit. The relation of Chi-Square to Degrees of Freedom equals 2.386, the result which does not exceed the threshold accepted by most researchers (e.g. Hu and Bentler, 1999) (please refer to Table 2 in order to compare the fit indices with the respective thresholds). The levels of IFI, TLI and CFI do not exceed the maximum amount either, having 0.96, 0.938 and 0.957 respectively, showing a very good fit indeed.

In order to test Convergent Validity, AVE (Average Variance Extracted) values of latent variables was analyzed. Each of them is more than 0.5, which is the threshold, thus proving their validity. Moreover, AVE indices are all higher than squared correlations between variables. Composite Reliability is measured by more than 0.7, also exceeding the threshold. All these indices confirm the fit of the model.

Table 2. Fit indices compared to thresholds (Hu, Bentler, 1999)

Index	Recommended value	Measurement model value
Chi-Square over DF	< 3	2.386
IFI	> 0.9	0.96
TLI	> 0.9	0.938
CFI	> 0.9	0.957
RMSEA	< 0.1	0.055

CHAPTER 3. RESULTS AND DISCUSSION

3.1 Structural equation modeling results

After testing the fit, the research applied structural equation modeling for testing the hypotheses. This model allows establishing the existence of statistical significance of the influence of external variables on Perceived Usefulness and Perceived Ease of Use.

Moreover, the relationships between variables of the basic model were tested in order to validate it.

After the analyses, it was established that all 9 hypotheses are supported by the data (please refer to Table 3).

Table 3. Results of hypotheses

#	Hypothesis	Estimate	Result
1	Perceived Usefulness -> Attitude Towards Using	0.078	Supported
2	Perceived Ease of Use -> Attitude Towards Using	0.62	Supported
3	Perceived Ease of Use -> Perceived Usefulness	0.88	Supported
4	Perceived Usefulness -> Behavioral Intention to Use	0.442	Supported
5	Attitude Towards Using -> Behavioral Intention to Use	0.134	Supported
6	Perceived Risks -> Perceived Usefulness	0.377	Supported
7	Organizational Resistance to Change -> Perceived Usefulness	0.224	Supported
8.1	Supplier Support -> Perceived Usefulness	0.092	Supported
8.2	Supplier Support -> Perceived Ease of Use	0.11	Supported

The first 5 hypotheses were focused on the basic model, thus confirming its validity. The latter 4 dealt with the impact of external variables on either PU (e.g. PR, ORC and SS) or PEOU (SS).

Let us examine the former group first. Here we can see that both PU and PEOU have statistically significant impact on AT with Estimates of 0.078 and 0.62 respectively ($p < 0.05$). It is worth mentioning that PEOU has bigger impact on AT than its counterpart PU. Thus we can induce that for an average mid-level or senior-level employee of a mechanical and industrial engineering company the key factor for forming an attitude towards an AI solution is how easy it is to learn it and what efforts are necessary for its use, not the benefits it can potentially bring. Therefore, hypotheses 1 and 2 are supported by the data.

Moreover, the ease of use of a technology has a very strong effect on its perceived usefulness, which follows from SEM results (Estimate equals 0.88, $p < 0.05$). Hypothesis 3 is confirmed.

Hypotheses 4 and 5 are concerned with the impact on the intention to use (BI) AI solutions in the companies by 2 factors - PU and AT. Both of these variables proved to influence BI having Estimates of 0.442 and 0.134, thus supporting the hypotheses.

Since all of the hypotheses related to classical TAM are supported, it is possible to conclude that in the context of this research TAM is an acceptable instrument for investigating the adoption factors of AI solutions by mechanical and industrial engineering companies.

Now let us consider the second group of variables - the ones that measure the impact of external variables on PU and PEOU. First we will focus on variables which are conjectured to influence PU. Perceived Risks, Organizational Resistance to Change and Supplier Support all proved to be statistically significant antecedents of PU. Also since PR and ORC were hypothesized to have negative influence on PU, these variables were considered as reversed-scored in SPSS, meaning that their Likert scale scores were reversed for the correct analysis.

It is worth mentioning that ORC was proposed to be included in the model by ABB Group Vice-President during our interview, and the modeling proved his professional conjecture right.

Supplier Support also proved to impact PEOU. However, SS has much smaller influence on PU than other external variables, having an Estimate of 0.092 (also relatively small impact on PEOU - 0.11). In spite of this fact, hypotheses 8.1 and 8.2 proved to be statistically significant.

Taking everything into account, all of the hypotheses mentioned above (1 through 8.2) are supported by statistical analyses.

Due to the fact that all the hypotheses were supported by SEM, it is possible to answer Research Question 1 - the external variables ORC and PR have direct negative influence of PU, while SS have direct positive impact both on PU and PEOU.

3.2 Comparison of Russian and Swiss companies' survey responses

Initially this research was considering statistical analysis based on TAM for respondents of Russian and Swiss-based companies separately. However, the preliminary analyses showed that the responses for two samples are very similar, thus such comparison appeared to be pointless. Therefore, two samples were combined and analyzed together using TAM. However, the responses to the multiple choice questions in Part 1 turned out to be rather insightful (please refer to Appendix 4).

The split between the countries is rather similar - 54 respondents work in Switzerland while 48 are employed in Russia. Most of the companies are large multinational corporations headquartered outside of Russia (84%). The company which had the most respondents from was ABB (46%).

In terms of current status of AI solutions in enterprises, more than a half of Swiss respondents stated that AI solutions either have been implemented already or are being implemented at the moment. Less than 6% of the respondents stated that no AI solution currently exists in their company, while the plurality of respondents (37%) said that the idea of AI solutions integration has been proposed and now it is being evaluated. In Russia there is a very different situation: less than 8% of the companies are currently using AI solutions. Moreover, looking closely at individual responses it appears that those companies using AI are all foreign companies operating in Russia (e.g. Schneider Electric, Siemens and ABB). 37.5% of the companies are not even planning to integrate AI solutions in the near future, and the biggest group (45.8%) is now evaluating this possibility.

The most common AI solutions in Swiss companies appeared to be Data Mining Tools and Expert Systems. In Russian companies the majority of respondents stated that there were no AI solutions in their company. Not surprisingly the next most popular responses were similarly Data Mining Tools and Expert Systems (again these were foreign companies).

The most popular departments using AI solutions were Sales, Operations and Finance in Switzerland and Sales, Operations and Marketing in Russia. This may explain the reason for Virtual Agents being the third most popular AI solution in Russia - Virtual Agents are very commonly used in Marketing (Forbes, 2017).

The hierarchical use of AI solutions is rather similar across countries - senior management represents the biggest part, twice as much as middle management.

Having analyzed the data from 2 countries, now it is possible to answer Research Question 2. It is important to emphasize that even though there is a significant difference in the use of AI solutions and its potential implementation, Russian companies are rather open to AI solutions acceptance according to TAM; no inherent resistance to adoption of AI was found during data analysis. Therefore, we can conclude that Russian companies are just as ready to implement AI solutions and are motivated by similar factors as their Swiss colleagues. There may be other factors influencing AI implementation in Russian companies, thus there is an opportunity for future research.

3.3 Potential drivers and barriers

After careful analysis of the results of statistical modeling, it is possible to outline several drivers and barriers towards adoption of AI solutions by industrial engineering companies.

As it has been mentioned before, Perceived Ease of Use has much greater impact on Attitude Towards Using than Perceived Usefulness. This may be explained by the risk-averse behavior of big organizations - usually they do not want to change a standardized process unless this change does not incur significant problems with high level of certainty, is easy to implement and there is a clear benefit of the implementation; also employees, especially the middle level, may not necessarily understand clear benefits of AI solutions implementation, which can be a barrier for acceptance of AI.

As it is shown in Table 3, there is a very strong influence on PU by PEOU. This may mean that the easier the use of an AI solution is for an employee, the more benefits they find in such a solution. Therefore, it is reasonable to assume that a potential driver for AI implementation in companies can be the education of employees with regards to AI benefits. Also the support of AI solutions' suppliers to the employees using the AI has the potential to facilitate the integration and thus acceptance; therefore, it is another driver for AI implementation.

3.4 Theoretical and Managerial contribution

This research is focused on understanding the underlying factors influencing adoption of AI solutions by mechanical and industrial engineering companies. The research applies

Technology Acceptance Model in order to assess the adoption factors of AI. TAM has not been used often for AI adoption research; only a handful of related studies exist in EBSCO, SCOPUS and Google Scholar databases. Neither has TAM been widely used for measuring the acceptance of a technology by an organization and not individual consumers. The classical model is also refined with additional external variables (Perceived Risks, Organizational Resistance to Change and Supplier Support), which have been determined after analysis of related researches and the interview with an industry expert; the role of these factors gives a new perspective on the research of AI acceptance.

Moreover, few researches focused on the assessment of a technology implementation (especially powered by AI) in mechanical and industrial engineering companies, making this study useful for the companies in this industry.

Furthermore, the comparison between Russian and Swiss AI status quo (or comparison between leading and underperforming regions in terms of AI) has been investigated insufficiently.

The model proves that Organizational Resistance to Change and Perceived Risks have significant direct negative correlation with Perceived Usefulness. Thus companies may disregard substantial rewards for AI implementation, prioritizing risks over benefits. Future researches on this topic may investigate the ways of changing this point of view so that it is easier to integrate AI solutions across an organization and get the most out of this promising technology. For example, a significant step forward in AI adoption in a company could be education of employees about AI solutions' benefits and the ways of overcoming risks and barriers towards implementation.

This research is especially useful for corporate stakeholders, i.e. mechanical and industrial engineering companies. It compares Russian companies to the leaders – the Swiss ones, so that the former can analyze the data, realize that the acceptance towards AI solutions implementation is similar to their Swiss colleagues and possibly look for opportunities for its implementation.

Since there is a fast rise of AI development now, the AI solutions are going to be integrated in more and more companies, therefore organizations embracing AI in the near future will most likely benefit from the technology becoming early adopters. The use of AI solutions is not limited to specific departments or functional areas: its potential is significant and it is likely to continue to grow exponentially in the near future (Purdy, Daugherty, 2016).

3.5 Limitations

The research also has a number of limitations which may be improved in the future researches.

First of all, the survey sample is relatively limited (102 respondents), even though sufficient for this Master Thesis. In order to have more precise results for analyses, this sample should be increased by 100% (approximately 100 responses for each country).

The next limitation is the external variables. This research took 3 variables after analyzing related publications and checked them with an industry expert. However, there may be other suitable external variables explaining significant part of variability in the model. This is an opportunity for future research.

Also the research equalized the notion of employees' responses with company's standpoint. It should be said that employees' responses may still be subjective (they may not know the precise state of affairs in their company) and not correspond to the company's vision. However, this research considers that in order to gain a company's perspective, the best way is to get each employee's perspective.

Lastly, only 2 countries are analyzed, which may limit the scalability of this research. A more extensive research may be conducted, combining several countries from each group of AI solutions implementation - leaders, average and laggards.

CONCLUSION

This research is aimed at investigating the adoption factors of AI solutions by mechanical and industrial engineering companies in an innovation leading region and a region with AI implementation level falling behind the leaders. Being able to adapt fast-developing AI solutions into a company's workflow can be the distinctive feature bringing the company to a leading position due to increased productivity, cost reduction and other factors. Even though the concept of AI is not new, only few companies truly understand and reap the benefits of this technological development, thus there is space for companies to use AI and drastically improve their competitive position.

In order to understand the factors influencing AI adoption by companies, it is necessary to analyze the factors impacting acceptance of individual employees of these companies. After investigating existing methods of technology adoption in theoretical and empirical researches Technology Acceptance Model was chosen for this research (it has been widely used for Information Technologies adoption studies, but has not been very common for investigating AI adoption). This research uses classical TAM (Davis, 1989). In addition to classical TAM, 3 additional external variables were added to it; they were selected after thorough analysis of existing literature and an interview with the industry expert (Group Vice-President of ABB).

Keeping in mind research objective and research questions, a total of 9 hypotheses are developed, where the first 5 are a part of classical TAM and the latter 4 are concerned with external variables. The method for this research is quantitative with some elements of the qualitative (i.e. interview with industry expert).

The data was gathered via surveys sent directly to the employees of mechanical and industrial engineering companies in Switzerland and Russia. The surveys consisted of 2 main parts - questions targeted at understanding status quo of AI solutions in companies and questions related to the acceptance of AI solutions by employees. Questions in the second part were developed based on previous researches using TAM and adapted to the context of this research. Each tested variable included at least 2 questions (since during the statistical analysis some questions could prove to be exceedingly correlated and thus had to be excluded - this indeed happened in this research as well). The questions from the second part were measured using a seven-point Likert scale.

The data from the surveys was analyzed in IBM SPSS Statistics first and then in AMOS 24.0. After the cleansing of data, exploratory factor analysis was conducted (EFA), after that confirmatory factor analysis (CFA) and lastly the structural equation modeling method. These types of analyses are commonly used when applying TAM, especially the former two (EFA and CFA).

The results of statistical analyses reflected that the research model met the fit requirements (reliability, convergent validity as well as discriminant validity) and proved to be relevant in the framework of this research.

Moreover, 9 out of 9 hypotheses developed for the research proved to be supported. The former 5 hypotheses of the classical TAM were supported, thus proving the model to be appropriate. The latter 4 hypotheses were supported as well, meaning that the chosen external variables indeed influence perceived usefulness or perceived ease of use.

After the analyses mentioned above, the survey responses of employees from Switzerland and Russia were compared. Since the results of TAM questions were very similar, the research focused on the questions from the first part of the survey - i.e. status quo of AI solutions. Here big discrepancies were detected. Much more AI solutions were implemented in Switzerland than in Russia. However, the levels of acceptance towards AI did not vary significantly across the countries, thus it potentially can mean that there are favorable conditions for AI implementation in Russian companies; though thorough analyses need to be conducted in order to confirm this hypothesis, thus there is an opportunity for future research.

Bigger impact on AI acceptance by Perceived Ease of Use rather than Perceived Usefulness may be an evidence of risk-averse behavior of industrial engineering companies, which are hesitant to change a standardized process unless this change is easy to implement and it has a straightforward benefits. This poses a barrier towards AI implementation, but there is a solution to that – educating employees of all levels about the benefits of AI. Also the suppliers of AI solution should help the employees in using such solutions, thus driving the acceptance of AI even faster.

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APPENDICES

Appendix 1
Survey sample. Part 1

Question	**Response options**
Basic information	[Includes country of work of the respondent, company, job title, department]
How would you evaluate your company's readiness for Artificial Intelligence (AI) use?	· No AI solutions exist or are under consideration · An AI solution has been proposed and it is being evaluated · Based on the evaluation, an AI solution has been accepted and is being implemented · An AI solution exists and is being used · AI failure (an AI solution has gone into decline and has been phased out)

Provided there is one, what type(s) of AI solution(s) is there in your company?	· Expert System/Fuzzy Expert System · Decision Making tool · Artificial Neural Network · Deep Learning Platform · Data Mining tool · Robotic Process Automation · Virtual Agents (e.g. chatbots) · Natural Language Processing tool · Other Machine Learning Platform (please specify) · Other (please specify)
In which functional areas are the AI solutions used in your company?	· Finance · Planning · Marketing · Sales · HR · Operations · Entire company · Other (please specify)
At which hierarchical employee levels are the AI solutions used in your company?	· Managing Director · Senior Management · Middle Management · Line Management · Other (please specify)

Survey sample. Part 2

Tested variable	Questions
Perceived Usefulness	1) Using AI solutions can improve performance of the workflow in my company 2) Using AI solutions can increase productivity of the workflow in my company 3) AI solutions can help to accomplish tasks faster

Perceived Ease of Use	4) I expect that setting up AI solutions will not cause major problems 5) I expect that learning to use AI solutions will not be difficult 6) I expect that AI solutions will be easy to use
Attitudes Towards Using	7) The use of AI solutions will benefit my company 8) Using AI solutions is a good idea 9) My company is constantly tracking available AI solutions
Intention to Use	10) I am willing to test AI solutions' capabilities on my projects 11) I would recommend other companies to start using AI solutions
Perceived Risks	12) There is a high probability of losses for our company if an AI solution is implemented 13) There is a high chance of potential failure to using AI solutions
Supplier Support	14) It would be important for our AI solution supplier to provide extensive on-site training for its users 15) It would be important for our AI solution supplier to provide online training for its users 16) It would be important for our AI solution supplier to provide training manuals and reference materials for users
Organizational Resistance to Change	17) My Company would be among the last to try a new technology even if it appeared promising 18) My Company is reluctant to adopt a new technology 19) My Company finds reasons not to implement a new technology

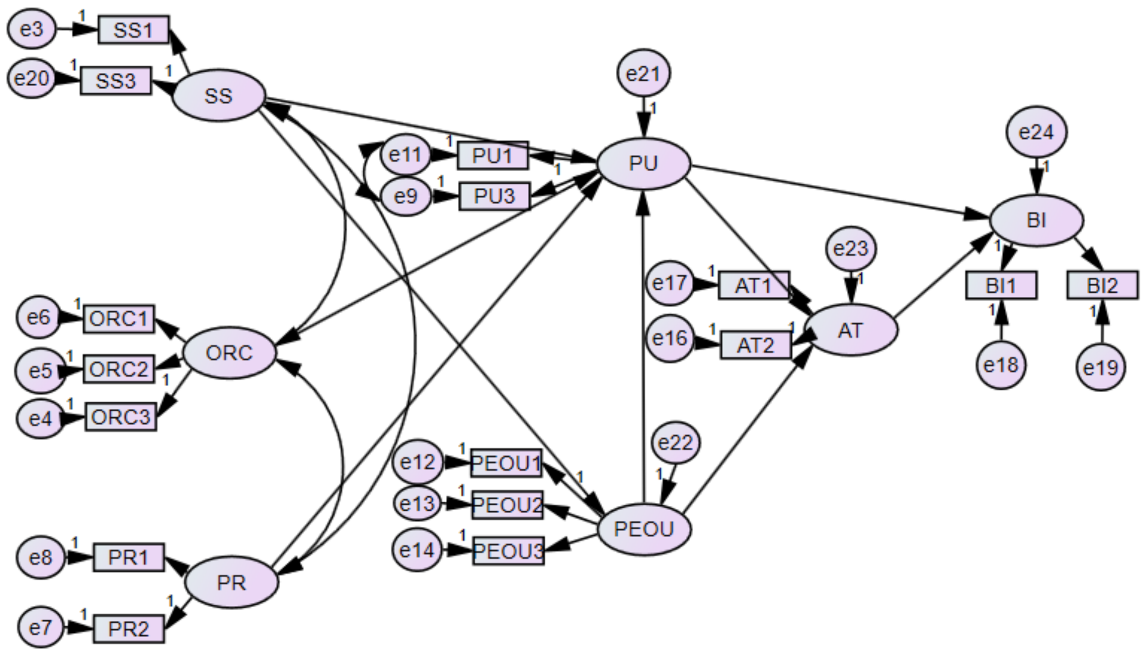
Appendix 2
Descriptive statistics

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
PU1	102	3	7	5,75	,805
PU2	102	4	7	5,98	,808
PU3	102	4	7	6,32	,706
PEOU1	102	1	6	3,75	1,094
PEOU2	102	2	7	4,84	,962
PEOU3	102	2	7	4,80	1,108
AT1	102	3	7	5,81	,805
AT2	102	3	7	6,02	,796
AT3	102	2	7	4,74	1,043
BI1	102	3	7	5,44	,991
BI2	102	2	7	5,24	,946
PR1	102	2	7	4,97	1,038
PR2	102	2	7	5,23	,943
SS1	102	2	7	4,65	1,474
SS2	102	1	7	3,93	1,713
SS3	102	1	7	4,25	1,709
ORC1	102	3	7	5,73	,858
ORC2	102	3	7	5,55	1,021
ORC3	102	3	7	5,74	,943
Valid N (listwise)	102				

Appendix 3

Statistical model



Model specifications

Computation of degrees of freedom (Default model)

Number of distinct sample moments:	136
Number of distinct parameters to be estimated:	45
Degrees of freedom (136 - 45):	91

Model result

Result (Default model)

Minimum was achieved
Chi-square = 217,121
Degrees of freedom = 91
Probability level = ,000

Regression weights

			Estimate	S.E.	C.R.	P	Label
PEOU	<---	SS	,072	,062	1,169	,242	
PU	<---	PEOU	,391	,065	6,015	***	
PU	<---	PR	,192	,137	1,403	,161	
PU	<---	ORC	,116	,127	,910	,363	
PU	<---	SS	,027	,028	,930	,352	
AT	<---	PU	,118	,256	,459	,646	
AT	<---	PEOU	,418	,134	3,127	,002	
BI	<---	PU	,920	,316	2,908	,004	
BI	<---	AT	,184	,220	,839	,402	
SS1	<---	SS	1,217	,287	4,246	***	
ORC3	<---	ORC	1,000				
ORC2	<---	ORC	1,176	,139	8,483	***	
ORC1	<---	ORC	,848	,115	7,368	***	
PR2	<---	PR	1,000				
PR1	<---	PR	,982	,154	6,384	***	
PU3	<---	PU	1,000				
PU1	<---	PU	1,109	,219	5,065	***	
PEOU1	<---	PEOU	1,000				
PEOU2	<---	PEOU	,956	,104	9,181	***	
PEOU3	<---	PEOU	1,090	,120	9,075	***	
AT2	<---	AT	1,000				
AT1	<---	AT	1,092	,197	5,552	***	
SS3	<---	SS	1,000				
BI1	<---	BI	1,000				
BI2	<---	BI	,798	,181	4,423	***	

Standardized regression weights

			Estimate
PEOU	<---	SS	,110
PU	<---	PEOU	,880
PU	<---	PR	,377
PU	<---	ORC	,224
PU	<---	SS	,092
AT	<---	PU	,078
AT	<---	PEOU	,620
BI	<---	PU	,442
BI	<---	AT	,134
SS1	<---	SS	1,093
ORC3	<---	ORC	,786
ORC2	<---	ORC	,854
ORC1	<---	ORC	,733
PR2	<---	PR	,794
PR1	<---	PR	,709
PU3	<---	PU	,595
PU1	<---	PU	,576
PEOU1	<---	PEOU	,787
PEOU2	<---	PEOU	,856
PEOU3	<---	PEOU	,847
AT2	<---	AT	,736
AT1	<---	AT	,796
SS3	<---	SS	,774
BI1	<---	BI	,843
BI2	<---	BI	,695

Residual covariances matrix

	BI2	BI1	SS3	AT1	AT2	PEOU3	PEOU2	PEOU1	PU1	PU3	PR1	PR2	ORC1	ORC2	ORC3	SS1
BI2	,057															
BI1	,071	,089														
SS3	,075	-,090	,000													
AT1	,035	,061	,031	,014												
AT2	,060	,066	-,287	,012	,012											
PEOU3	,071	,048	-,362	-,051	,024	,000										
PEOU2	,058	,104	,017	,006	-,019	,017	,000									
PEOU1	,135	,089	-,133	,072	,075	,014	-,025	,000								
PU1	-,003	,122	,108	,107	-,042	,086	,110	,093	,103							
PU3	,120	,061	-,226	,124	,119	,195	,143	,139	,092	,083						
PR1	,058	,141	-,003	,310	,221	,529	,483	,332	,290	,099	,000					
PR2	,182	,182	,048	,279	,205	,608	,532	,532	,204	,190	,000	,000				
ORC1	,178	,260	,101	,189	,149	,429	,322	,396	,196	,103	,068	,014	,000			
ORC2	,174	,323	,079	,219	,196	,523	,354	,461	,245	,054	-,009	,018	-,029	,000		
ORC3	,071	,206	-,258	,188	,205	,481	,314	,526	,164	,058	-,016	-,055	,015	,015	,000	
SS1	,115	-,040	-,002	-,017	-,212	-,176	,143	-,052	,072	-,079	-,042	,063	,120	,045	-,143	,000

Standardized residual covariances matrix

	BI2	BI1	SS3	AT1	AT2	PEOU3	PEOU2	PEOU1	PU1	PU3	PR1	PR2	ORC1	ORC2	ORC3	SS1
BI2	,488															
BI1	,722	,719														
SS3	,484	-,564	,000													
AT1	,478	,796	,234	,157												
AT2	,820	,875	-2,163	,163	,134											
PEOU3	,679	,437	-1,936	-,527	,257	,000										
PEOU2	,637	1,097	,107	,077	-,239	,133	,000									
PEOU1	1,326	,835	-,721	,768	,822	,098	-,204	,000								
PU1	-,038	1,725	,866	1,778	-,706	,977	1,437	1,081	1,353							
PU3	2,027	,982	-2,068	2,346	2,292	2,529	2,132	1,850	1,887	1,444						
PR1	,619	1,439	-,019	3,807	2,734	4,661	4,901	2,968	3,733	1,464	,000					
PR2	2,123	2,046	,303	3,766	2,802	5,901	5,952	5,231	2,879	3,066	,000	,000				
ORC1	2,288	3,229	,698	2,808	2,232	4,582	3,960	4,282	3,065	1,848	,721	,161	,000			
ORC2	1,874	3,353	,458	2,735	2,472	4,692	3,658	4,194	3,199	,803	-,079	,168	-,284	,000		
ORC3	,828	2,318	-1,626	2,543	2,797	4,666	3,514	5,176	2,326	,945	-,155	-,559	,164	,135	,000	
SS1	,859	-,293	-,006	-,151	-1,846	-1,086	1,016	-,325	,666	-,837	-,275	,457	,967	,301	-1,045	,000

Variances

	Estimate	S.E.	C.R.	P	Label
SS	1,732	,536	3,233	,001	
ORC	,544	,122	4,444	***	
PR	,556	,133	4,166	***	
e22	,726	,159	4,560	***	
e21	-,022	,032	-,698	,485	
e23	,175	,056	3,104	,002	
e24	,447	,144	3,099	,002	
e3	-,416	,573	-,726	,468	
e4	,337	,064	5,247	***	
e5	,280	,069	4,065	***	
e6	,338	,058	5,804	***	
e7	,325	,081	3,992	***	
e8	,532	,099	5,367	***	
e9	,265	,048	5,529	***	
e11	,360	,063	5,738	***	
e12	,450	,079	5,719	***	
e13	,244	,052	4,734	***	
e14	,344	,070	4,914	***	
e16	,282	,064	4,369	***	
e17	,230	,069	3,346	***	
e20	1,159	,418	2,774	,006	
e18	,255	,132	1,932	,053	
e19	,429	,101	4,249	***	

Model Fit

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	45	217,121	91	,000	2,386
Saturated model	136	,000	0		
Independence model	16	1002,041	120	,000	8,350

RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	,197	,817	,727	,547
Saturated model	,000	1,000		
Independence model	,380	,292	,198	,258

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	,847	,779	,960	,938	,957
Saturated model	1,000		1,000		1,000
Independence model	,000	,000	,000	,000	,000

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	,758	,594	,650
Saturated model	,000	,000	,000
Independence model	1,000	,000	,000

NCP

Model	NCP	LO 90	HI 90
Default model	126,121	86,823	173,125
Saturated model	,000	,000	,000
Independence model	882,041	784,763	986,777

FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	2,150	1,249	,860	1,714
Saturated model	,000	,000	,000	,000
Independence model	9,921	8,733	7,770	9,770

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	,055	,017	,082	,378
Independence model	,220	,205	,236	,000

AIC

Model	AIC	BCC	BIC	CAIC
Default model	307,121	325,335	425,244	470,244
Saturated model	272,000	327,048	628,996	764,996
Independence model	1034,041	1040,517	1076,041	1092,041

ECVI

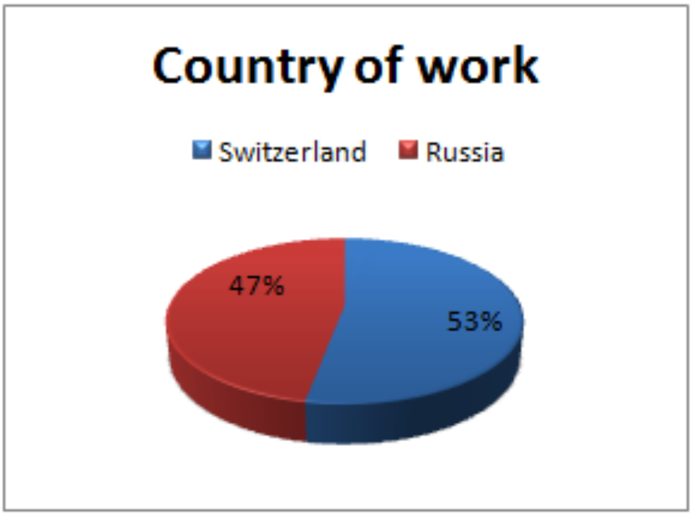
Model	ECVI	LO 90	HI 90	MECVI
Default model	3,041	2,652	3,506	3,221
Saturated model	2,693	2,693	2,693	3,238
Independence model	10,238	9,275	11,275	10,302

HOELTER

Model	HOELTER .05	HOELTER .01
Default model	54	59
Independence model	15	17

Appendix 4

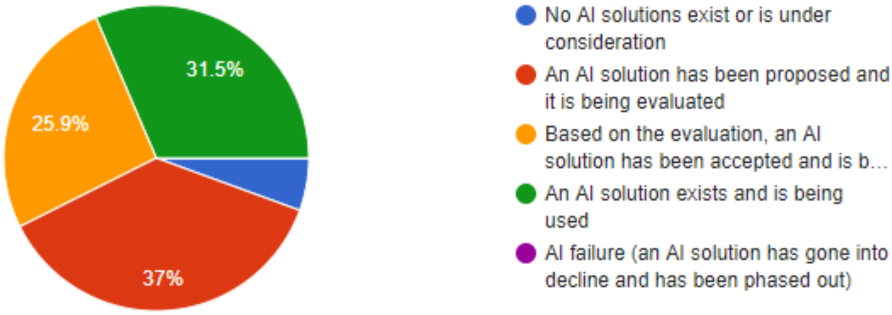
Useful country-specific insights from the survey



Switzerland

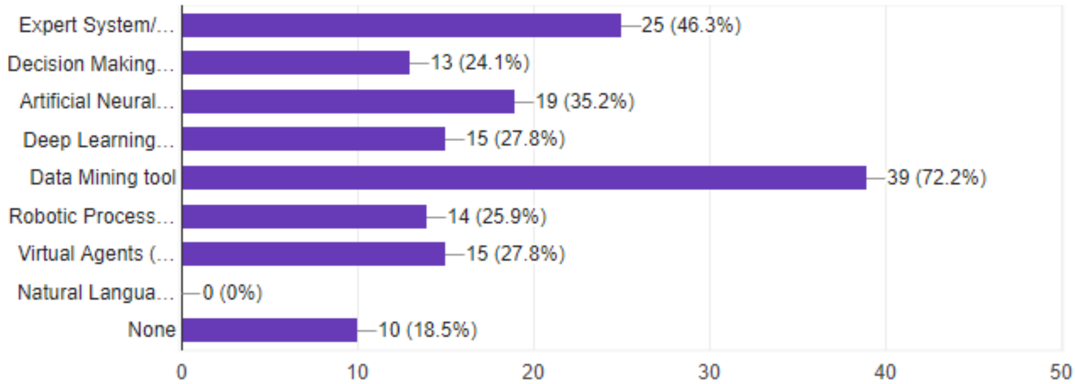
How would you evaluate your company's readiness for Artificial Intelligence (AI) use?

54 responses



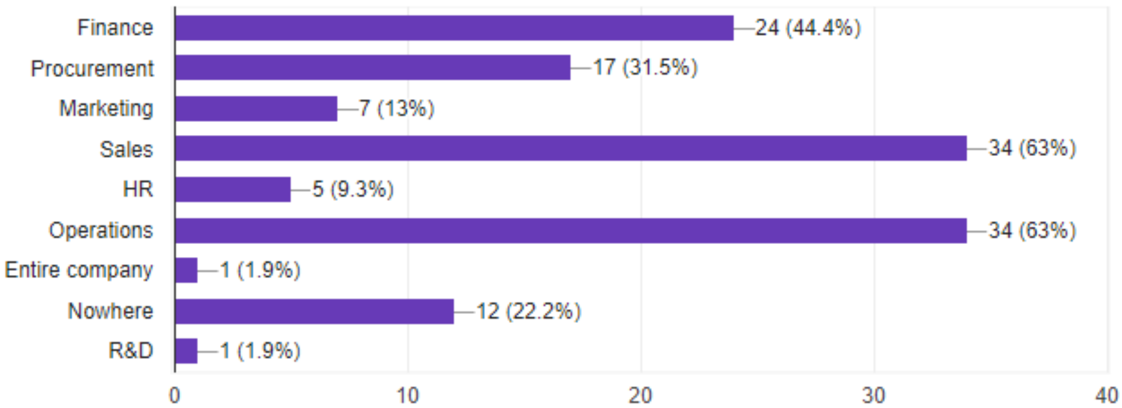
Provided there is one, what type(s) of AI solutions is there in your company?

54 responses



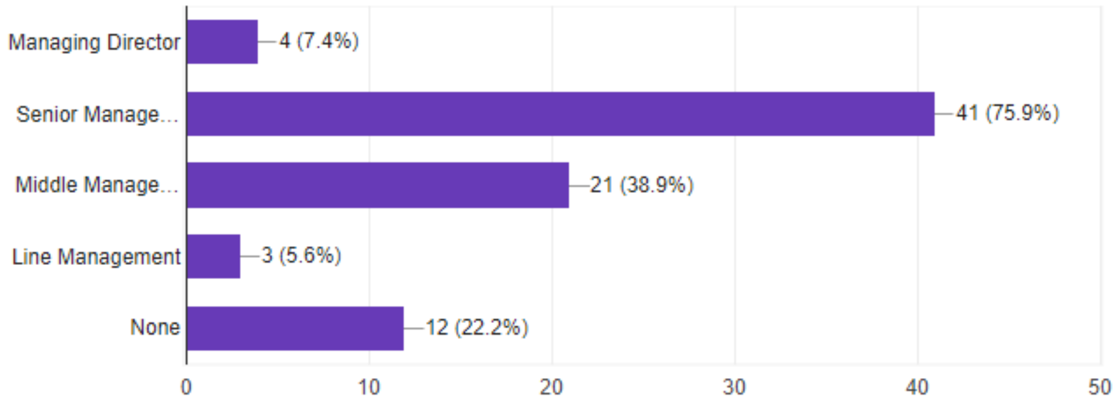
In which functional areas are the AI solutions used in your company?

54 responses



At which hierarchical employee levels are the AI solutions used in your company?

54 responses

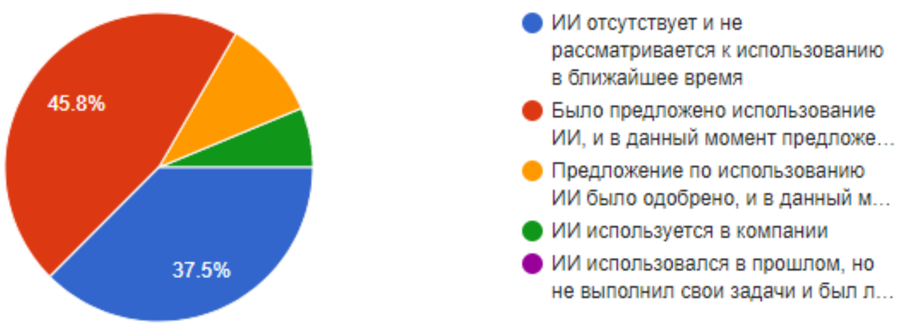


Russia

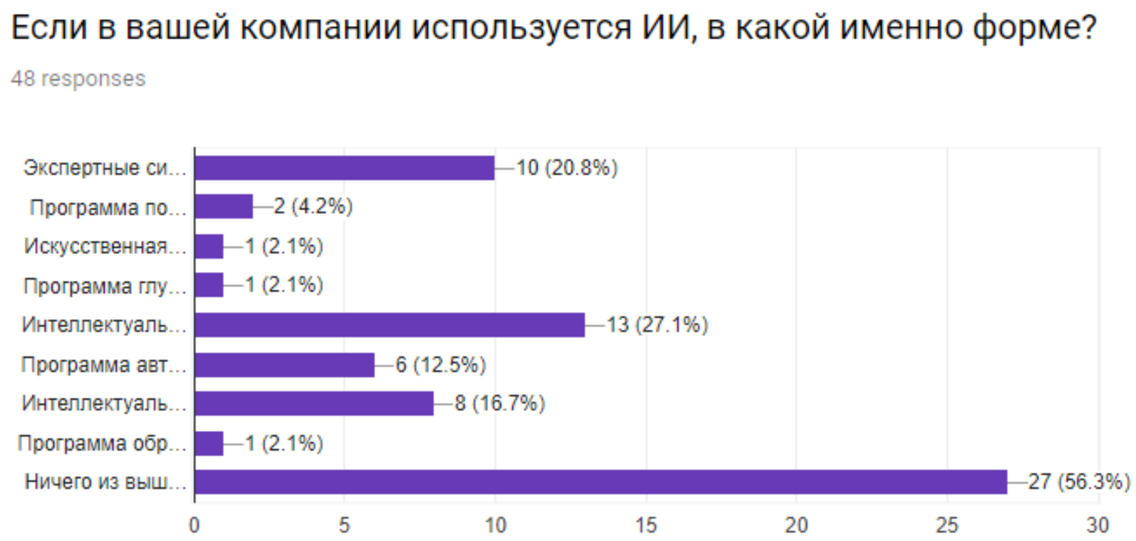
[How would you evaluate your company's readiness for Artificial Intelligence (AI) use?]

Как вы оцениваете текущее использование ИИ в вашей компании?

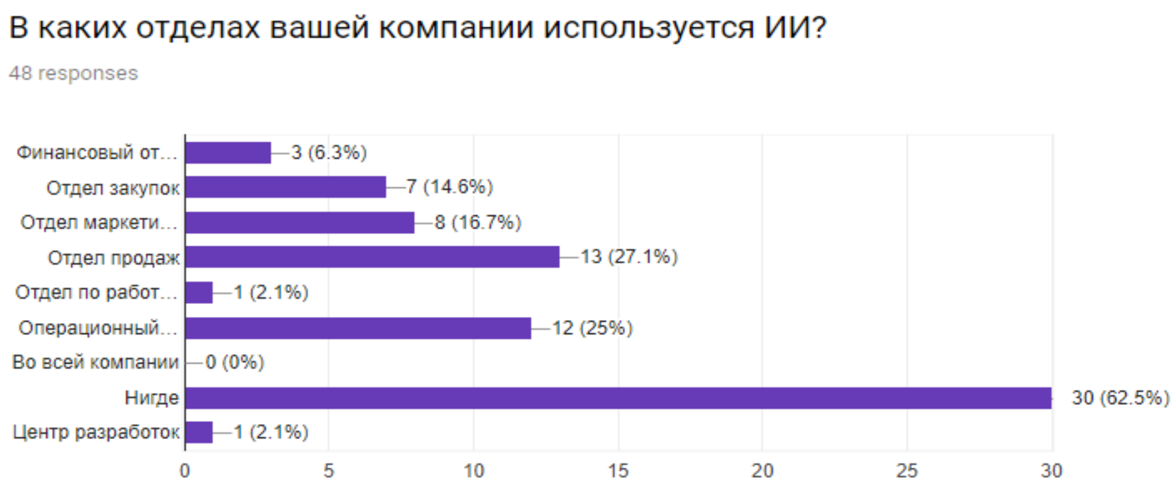
48 responses



[Provided there is one, what type(s) of AI solutions is there in your company?]



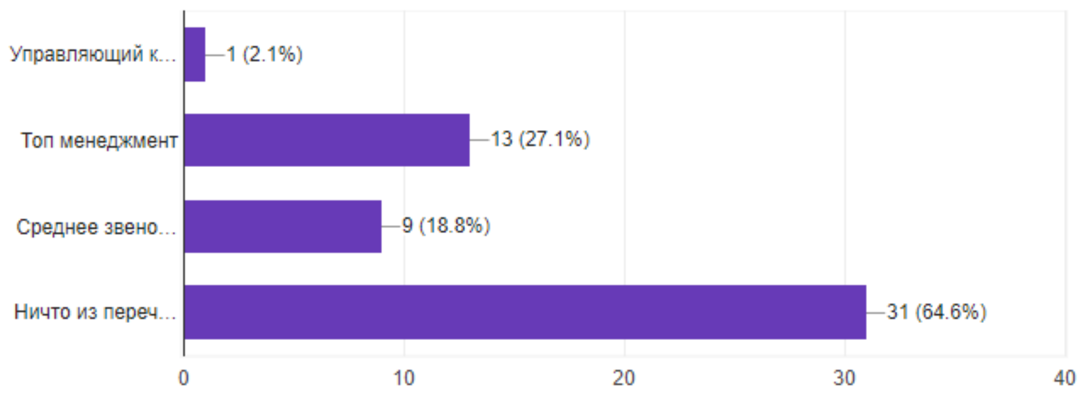
[In which functional areas are the AI solutions used in your company?]



[At which hierarchical employee levels are the AI solutions used in your company?]

На каком иерархическом уровне используется ИИ в вашей компании?

48 responses



Appendix 5

List of survey participants

Company	Country	Position/department
ABB	Switzerland	Business analyst
Abb	Switzerland	Lean Management Expert - Financial Transformation
Eaton	Switzerland	Key Account Manager
ABB	Switzerland	Senior Data Analyst
Siemens AG	Switzerland	Regional Coordinator, Communciations
GE	Switzerland	Business analyst
ABB	Switzerland	Division Controller, low voltage products
Eaton	Switzerland	Project leader, operations
GE	Switzerland	Operations & Direct Sourcing Leader
ABB	Switzerland	Global SCM Training Excellence Manager

Abb	Switzerland	Human resources manager
ABB	Switzerland	Supply Planner
Siemens	Switzerland	Communications Manager
ABB	Switzerland	IS Enterprise Architect
Abb	Switzerland	Senior Business Analyst
ABB	Switzerland	Business analyst
GE	Switzerland	Project Manager
Siemens	Switzerland	Supply Chain Manager
ABB	Switzerland	Business Specialist for Supply Chain
Abb	Switzerland	Customer Manager
ABB	Switzerland	Group Head Quality & Supply Chain at ABB
Siemens	Switzerland	Business Development Manager at Siemens Switzerland
ABB	Switzerland	Global Business Development Manager
ABB	Switzerland	Global Supply Chain Manager
Abb	Switzerland	Head of Sales, Power Grids division
GE	Switzerland	Product Manager
Abb	Switzerland	Data Scientist
ABB	Switzerland	Head of Indirect Materials and Services

ABB	Switzerlan d	Strategy Consultant
Abb	Switzerlan d	Product Manager
Siemens	Switzerlan d	Finance Transformation Manager
Abb	Switzerlan d	Division controller
ABB	Switzerlan d	Product manager
Siemens	Switzerlan d	Project manager
ABB	Switzerlan d	Business controlling
GE	Switzerlan d	Lean Finance Management
Siemens	Switzerlan d	Talent acquisition manager
GE	Switzerlan d	HR manager
Abb	Switzerlan d	Project leader
ABB	Switzerlan d	Account manager
ABB	Switzerlan d	HR consultant
GE	Switzerlan d	Account manager
ABB	Switzerlan d	IS architect
Siemens	Switzerlan d	Project manager
Abb	Switzerlan d	Senior data analysts
GE	Switzerlan d	Account manager

ABB	Switzerland	Business analyst
Siemens	Switzerland	Sales manager
Abb	Switzerland	Product Manager
Eaton	Switzerland	Account manager
ABB	Switzerland	Head of government relations
ABB	Switzerland	Product Manager
General Electric	Switzerland	Sales manager
ABB	Switzerland	Business Developer
Шнейдер Электрик	Russia	Менеджер проектов. Департамент по решениям и проектам.
SIEMENS AG	Russia	Customer Service, Automotive Service Manager
Силовые Машины	Russia	Руководитель продаж ключевым клиентам
Силовые Машины	Russia	Старший менеджер по тепломеханическому оборудованию
Силовые Машины	Russia	Начальник службы технологических систем управления
АББ	Russia	менеджер по внедрению проектов
силовые машины	Russia	проектный менеджер
Шнейдер	Russia	Менеджер по развитию бизнеса
Глобал Электро	Russia	Директор
Сименс	Russia	Менеджер отдела закупок
Турбоатом	Russia	Старший менеджер, отдел по работе с персоналом
Шнейдер Электрик	Russia	Руководитель проектов

Шнейдер Электрик	Russia	Руководитель проектов
Шнейдер Электрик	Russia	проектный менеджер
Шнейдер Электрик	Russia	Руководитель проектов
АББ	Russia	Менеджер отдела продаж
Силовые Машины	Russia	Начальник отдела автоматизации
Шнейдер Электрик	Russia	Начальник отдела управления персоналом
АББ	Russia	Старший менеджер по продажам
Шнейдер Электрик	Russia	Менеджер проектов
Шнейдер	Russia	Менеджер проекта
Шнейдер Электрик	Russia	Менеджер по развитию бизнеса
Шнейдер	Russia	Специалист отдела продаж
АББ	Russia	Руководитель проектов
АББ	Russia	Финансовый аналитик
АББ	Russia	Финансовый аналитик
Силовые Машины	Russia	Руководитель проектов
Силовые Машины	Russia	Финансовый аналитик
АББ	Russia	Проектный менеджер
Силовые Машины	Russia	Специалист по продажам
АББ	Russia	Финансовый аналитик
АББ	Russia	Менеджер по работе с персоналом
Шнейдер Электрик	Russia	Специалист по продажам
ABB	Russia	Key account manager
Шнейдер	Russia	Специалист транспортного отдела

Шнейдер Электрик	Russia	Менеджер отдела продаж
АББ	Russia	Специалист по продажам
Абб	Russia	Старший специалист по продажам
Силовые Машины	Russia	Директор по работе с корпоративными клиентами
АББ	Russia	Специалист по продажам
АББ	Russia	Руководитель проектов
Силовые Машины	Russia	Специалист по продажам
Силовые Машины	Russia	менеджер, отдел продаж
Зименс	Russia	Специалист отдела продаж
Силовые Машины	Russia	Менеджер по продажам
Шнейдер Электрик	Russia	Специалист по закупкам
Силовые Машины	Russia	Начальник производства
Силовые Машины	Russia	Специалист по продажам