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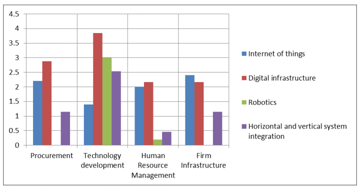

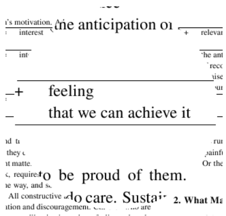

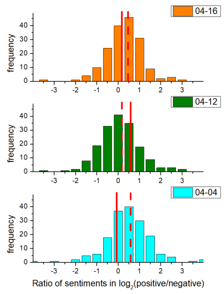

The impact of *Industry 4.0* on the value chain: the case of Lithuanian traditional industries

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Abstract. *Industry 4.0* brings changes within only a few decades after the third industrial revolution to all the spheres of industrial, business and social life. The article aims to identify the technological characteristics of *Industry 4.0* using literature review method and to evaluate the impact of each of them on the value chain using expert evaluation method. Overview of *Industry 4.0* concepts used in the literature identified the characteristics of *Industry 4.0*. Experts indicated two groups of importance of the described characteristics of the *Industry 4.0* to the value chain and scored the characteristics to the each of the part of the value chain. Internet of things, digital infrastructure, vertical/ horizontal integration and robotics are very important nowadays in the development of industries. The rest characteristics such as 3D printing, artificial intelligence, etc are indicated as having less importance at present. The transfer of findings in the process of implementation of *Industry 4.0* technological pillars across different industries as well as other actors – public, SMEs - different types of enterprises and sectors are to be researched further on.

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Short title: Industry 4.0 on value chain.

Introduction

Industry 4.0 brings numerous changes in industrial and social life within only a few decades after the third industrial revolution. *Industry 4.0* focuses on technological issues and cyber-physics interactions in the value chain and challenges all the areas: inequality, security, consumer and social behaviour, new ways of organising work and social life, ageing society and education.

Experts from traditional industry in Lithuania participated in the research. As a result, two groups of characteristics were identified with a high and low score of significance. Technological characteristics such as Internet of things, robotics, vertical and horizontal integration and digital infrastructure are indicated having a high significance in the traditional industries in Lithuania. High impact on inbound and outbound logistics, services, manufacturing and sales in the value chain has been indicated. Even with a lack of systematic scientific research a big interest from different actors (industries, government, funding agencies, SMEs) of *Industry 4.0* has been noticed.

The article aims to identify the technological characteristics of *Industry 4.0* and to evaluate the impact of each of them into the value chain using expert evaluation method.

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1. Development of *Industry 4.0*

The term *Industry 4.0* was introduced by the German Ministry of Education and Research as a guide to promote German high technology industry and its development strategy in 2011, and the Hanover Fair in 2012 followed by formation of a working group chaired by Siegfried Dais (Robert Bosch GmbH) and Henning Kagermann [1] as Scheer [2] reported. Nowadays different terms with a similar meaning have been used by different countries.

The term *Industry 4.0* indicates the "*fourth* time when technological developments bring revolutionary changes in industry and it has big impact not only on manufacturing but also on the way of operating and living" [3]. The first industrial revolution refers to the period after the introduction of steam and water-powered production methods. Some publications indicate that the first industrial revolution in reality started when the first mechanical loom was invented in 1784. "The start of the second industrial revolution is indicated with the introduction of electricity and the assembly lines which allowed mass production between late 19th and early 20th century" [4]. The discussions show that it is complicated to have a clear and definite identification about the starting of such processes and technological changes and the impact

Table 1. Comparative analysis of the concepts related to *Industry 4.0*.

Aspect	Scientific literature	Grey literature	Funding policy papers
Internet of things; M2M	Schwab [5] Bauer [12] Dujin [13] Marika [14] Liao [15] Zhou [3]	Germany Trade & Invest, Scheer [2] Capgemini Consulting, Bechtold [16] McKinsey&Company [17] Rüßmann [18]	Smit [19]
Digital infrastructure; cybersecurity	Marika [14] Liao [15] Zhou [3]	McKinsey&Company [17] Rüßmann [18]	Smit [19]
Vertical and horizontal integration	Dujin [13] Liao [15]	Rüßmann [18]	Smit [19]
Artificial intelligence	Schwab [5] Liao [15]	Germany Trade & Invest, Scheer [2]	Smit [19]
Robotics	Schwab [5] Dujin [13] Liao [15]	Germany Trade & Invest, Scheer [2] Capgemini Consulting, Bechtold [16] McKinsey&Company [17] Rüßmann [18]	Smit [19]
Autonomous vehicles	Schwab [5]		
3D printing	Schwab [5] Dujin [13] Liao [15]	Capgemini Consulting, Bechtold [16] McKinsey&Company [17] Rüßmann [18]	Smit [19]
Nanotechnology; biotechnology; material science	Schwab [5]		
Energy storage	Schwab [5]	McKinsey&Company [17]	
Quantum computing	Schwab [5] Liao [15]	Germany Trade & Invest, Scheer [2]	
Virtual/augmented reality	Liao [15]	Germany Trade & Invest, Scheer [2] McKinsey&Company [17] Rüßmann [18]	Smit [19]
Cloud technology/ computing; Big data and analytics	Liao [15] Zhou [3]	McKinsey&Company [17] Rüßmann [18]	Smit [19]

they bring to the society.

On the contrary to the first two revolutions it took only a few decades - starting from the 70's - for the rapid adoption of electronics and IT to enable automation of production in factories and a few more decades later - in 2012 - the Industry introduces again a concept that foresees revolutionary changes.

The phenomenon of *Industry 4.0* has been mostly explored in German scientific researches (Schwab [5], Brettel [6], Sendler [7], Kagermann [1], Burmeister [8] etc) though in recent times more scientists are involved into the research. Some of them explore *Industry 4.0* as a concept [5] and some of them relate to specific areas as the term *Industry 4.0* is associated with the terms of "Internet of Things", "Big Data", "Advanced Manufacturing", "Smart Manufacturing" "3D printing", "additive manufacturing", and related issues [3, 8, 9, 10, 11]. Table 1 represents comparative analysis of *Industry 4.0* concepts.

K.Schwab in his book "The Fourth Industrial revolution" [5] considers the challenges of *Industry 4.0* "staggering confluence of emerging technology breakthroughs, covering wide-ranging fields such as artificial intelligence (AI), robotics, the Internet of things (IoT), autonomous vehicles, 3D printing, nanotechnology, biotechnology, materials science, energy storage and quantum computing". Above mentioned innovations are just starting, "but they are already reaching an inflection point in their development as they build on and amplify each other in a fusion of technologies across the physical, digital and biological worlds" [5].

2. Research in *Industry 4.0*

The ongoing discussions among researchers on the necessary balance of theory-based research and application-oriented research show the scientific interest to the issue from all different sectors. On one hand, Sanders et al. [20] wrote: "Some researches in *Industry 4.0* were purely theory-oriented, not readily adaptable to an application. Application-oriented research need to be developed pertaining to the criteria of implementing lean manufacturing. Future research needs to be focussed on creating a conceptual framework and cyber physical working system, integrating these parameters in a fully functional production environment" [20]. On the other hand, numerous publications mostly found in the Research Papers of world-wide consulting companies such as Boston Consulting Group [18], McKinsey&Company [17] show the bottom-up need for further research on *Industry 4.0*.

Ref. [2] initiated by Germany Trade & Invest defines areas to research funding indicating the expectations for the future development of *Industry 4.0*. The authors define "software systems and knowledge processing" and divide research into the three specific categories naming "software-intensive embedded systems with links to electronics, communication technology and microsystems technology, simulated reality for grid applications and infrastructure, software development for high-performance computing, human/machine interaction with language and media technologies, bio-analogous information processing, service robotics and usability".

The extended attention found in Strategy and Funding Priorities papers [2, 19] allows to emphasise the importance and lack of research of *Industry 4.0* and its implications.

Different sources provide the different technological changes that *Industry 4.0* brings; though most of them agree upon changes in technological environment and business paradigms and changing Supply chain. Dujin et al. [13] write about "the fully connected way of making things" describing as data is gathered from suppliers, customers and the company itself and evaluated before being linked up with the real production. "The latter is increasingly using new technologies such as sensors, 3D printing and next-generation robots. The result: production processes are fine-tuned, adjusted or set up differently in real time" settles [13].

During numerous interviews and speeches in World Economic Forum and similar occasions, Schwab [5] envisions the changes and impact on the individual in a global level: in ways of leadership and governance system involving:

i) multi-stakeholders (5 ways leaders can fix the world);
ii) economy (especially for growth, employment and the nature of work);
iii) business (consumer expectations, data-enhanced products, collaborative innovation and new operating models);
iv) global and national level (governments, countries and cities, and international security);
v) society (increasing inequality and community issues);
vi) the individual (identity and ethics, human connection and managing public and private information.

Vanysek [4] writes about changing business paradigms as "the changes to the value chain require companies to embrace new business models", safety and security, legal issues and IP; standardization.

The Fourth Industrial Revolution brings shifts not only in production, consumption, transportation and delivery systems all across of the industries vertically and horizontally

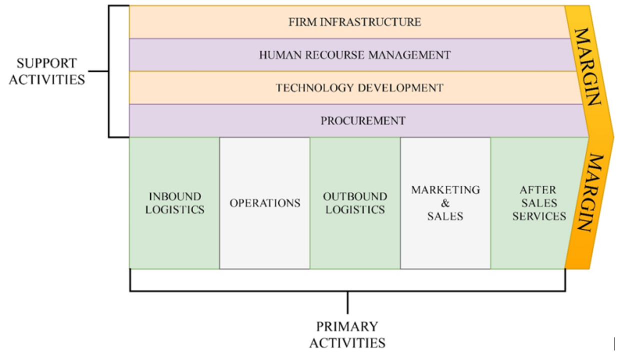

Fig. 1. The Diagram of Value Chain. Modification of Porter model. Adapted according to Ref. [10].

but also it *is marked by the emergence of new business models, the disruption of incumbents and the reshaping of the traditional way* [5].

Scientists agree that the new ways of using technologies change in behaviours, consumption, decision making, communication. Entertainment and other societal areas will emerge according to Schwab: "The changes are historic in terms of their size, speed and scope" [5].

Dujin A. [13] argues that "the roles of designers, physical product suppliers and the interfaces with the customer (contractor) will change" the way to communicate and it is "the first step is the fragmentation of the value chain". Dujin tells that "countless small entrants have lower barriers to entry". This indicates that new ways of organising participation in a value chain will be modelled. Internet, 3D printing, participation in a vertical integration chain, cloud technologies are expected to play a big role.

3. Value Chain related to *Industry 4.0* technological changes

Porter [10] discusses the impact of smart and connected products has on transformation of companies and competition and capture of the value.

Several models of Value Chain are known, including M.Porter's model, described in Refs. [9, 21] and modified due to exploring purposes [1, 19]. Fig. 1 represents the diagram of Value Chain as modification of Porter model where primary activities as well as support activities take place. Dujin [13] suggests that "after fragmentation of the value chain" new ways to participate in the value chain will appear and new models will be developed.

4. The situation in Lithuania: case of traditional industries

Traditional industries and their progress in introduction of *Industry 4.0* are especially important for investigating the topic in Lithuania as industry represents approximately 35% of annual GDP in Lithuania. Almost half of it is created by manufacturing industries. In 2017, platform *Industry 4.0* has been

Table 2. Kendall's Concordance Coeficients of Experts' Assessments

N	Value chain	Kendall W	$\tilde{\chi}^2$	p
1.	Procurement	0.9791	68.5385	< 0.0001
2.	Technology development	0.9801	68.6085	< 0.0001
3.	Human Resource Management	0.9633	67.4342	< 0.0001
4.	Firm Infrastructure	0.9878	69.1473	< 0.0001
5.	Inbound logistics	0.9701	67.9061	< 0.0001
6.	Manufacturing	0.9810	68.6734	< 0.0001
7.	Outbound logistics	0.9586	67.1026	< 0.0001
8.	Marketing&Sales	0.9682	67.7741	< 0.0001
9.	Services	0.9850	68.9497	< 0.0001

established in Lithuania under the initiative of the Lithuanian Confederation of Industrialists with participation of government, industrial institutions and industries and science. As mentioned above, in the survey more approximately 52% of Lithuanian companies declare that *Industry 4.0* is relevant and important to them [22].

4.1. Porter model for research

The research aims to evaluate the impact of technological characteristics related to *Industry 4.0* for the value chain in business in Lithuania. The expert evaluation using semi-structured interview was selected as a research method.

Five experts were selected according to their experience and competences in manufacturing industry and representation of a specific sector:
1) at least 10 years of working experience in their specific industry;
2) experience related to *Industry 4.0* issues;
3) previous or present leadership positions of a membership based industrial associations.

The concordance of the experts' evaluation was analyzed by means of the Kendall's concordance coefficient W routine, described by Kendall [23] and Podvezko [24]. Concordance coeficient W (presented in range $[0 \leq W \leq 1]$) allows estimating the agreement among assessments of experts. Minimum and maximum values can be defined as follows:
i) when experts are unanimous in their assessment and this occurs when all experts are in full agreement, then $W \rightarrow 1$;
ii) when experts' assessments vary, then $W \rightarrow 0$.
The Kendall's coefficient W was calculated according to the formula:

$$W = \frac{12 \cdot S}{r^2 m \cdot (m^2 - 1) - r \sum_{j=1}^{r} T_j)} \quad (1)$$

when r represents number of experts, and m - number of objects to evaluate by mentioned experts. S represents a sum-of-squares statistic over the row sums of ranks m_i, where e_i represents sum of ranks, and $\overline{e}$ – average of sums of ranks:

$$S = \sum_{i=1}^{m} (e_i - \overline{e}) \quad (2)$$

T represents an indicator of tied ranks of j expert:

$$T_j = \sum_{k=1}^{H_j} (t_k^3 - t_k) \quad (3)$$

H_j represents number of ranks of the same value of the j expert, and t_k represents the number of equal tied ranks in each (k) group of ties. Chi-squared distribution could be calculated using following expression:

$$\tilde{\chi}^2 = Wr(m-1) = \frac{12 \cdot S}{r \cdot m \cdot (m+1) - \frac{1}{m-1} \sum_{j=1}^{r} T_j} \quad (4)$$

By solving the practical concordance calculation task, W coefficients were calculated for each ranked object. Table 2 represents Kendall's Concordance Coeficients W of Experts' Assessments. All the W coefficients are presented in interval [0.958÷0.980] confirming the concordance of experts' evaluations. Therefore, we can rely on the evaluation of the experts.

The model of value chain proposed by M. Porter [10] was chosen for the research. In this context, two different terms - concepts and characteristics - will be used in the same manner.

The following characteristics of *Industry 4.0* were indicated to evaluate: Internet of things, digital infrastructure, robotics, horizontal and vertical system integration, 3D printing / additive manufacturing, artificial intelligence, autonomous vehicles, nanotechnology, biotechnology, energy storage, quantum computing, big data, virtual/augmented reality, cloud technologies.

The research was organised into two steps: expert evaluation of the characteristics and interview. The experts were asked to evaluate the significance of each technological characteristics (from the first column) in each of the part of the value chain in the industry in Lithuania in 2017. The experts were asked to:

i) indicate the significance of each technological characteristics giving 0-1 to each of them and in this way rating the characteristics in the sequence of importance;
ii) evaluate the importance of each of technological factor/segment to each part of the value chain giving 0-1.

Characteristics	significance	Procurement	Tech development	HR Management	Firm Infrastructure	Inbound logistics	Manufacturing	Outbound logistics	Marketing & sales	Services
Internet of things	20	2.2	1.4	2	2.4	2.4	1.4	2.2	3.6	2.4
Digital infrastructure	24	2.88	3.84	2.16	2.16	2.88	1.44	2.64	4.08	1.92
Robotics	20	0	3	0.2	0	1.6	6.6	1.8	0.8	6
Horizontal and vertical system integration	23	1.15	2.53	0.46	1.15	1.84	6.9	2.07	2.3	4.6
3D printing and prototyping/ Additive manufacturing	1	0.01	0.45	0	0.01	0.05	0.25	0.05	0.06	0.12
Artificial intelligence	1	0	0.66	0.01	0.15	0	0.02	0	0.1	0.06
Autonomous vehicles	1	0	0.25	0	0	0.2	0.1	0.25	0.05	0.15
Nanotechnology	2	0	0.9	0	0	0.14	0.4	0.16	0	0.4
Biotechnology	3	0.15	0.75	0	0	0	1.05	0	0.3	0.75
Energy storage	1	0.02	0.15	0	0	0.08	0.4	0.07	0.03	0.25
Quantum computing	1	0	0.9	0	0	0.01	0.01	0.01	0.05	0.02
Big data	1	0.15	0.15	0.1	0.18	0.1	0.05	0.1	0.13	0.04
Virtual/augmented reality	1	0.1	0.3	0.15	0.1	0.05	0	0.05	0.2	0.05
Cloud	1	0.15	0.25	0.03	0.05	0.05	0.07	0.06	0.25	0.09
TOTAL	100	6.81	15.53	5.11	6.2	9.4	18.69	9.46	11.95	16.85

Fig. 2. The impact of the characteristics of *Industry 4.0* to the value chain
(by authors according to the experts' evaluation results, 2017)

Experts also were asked to explain results and share their vision about the development of characteristics of *Industry 4.0* in Lithuania.

Fig. 2 represents the comparison of the characteristics of *Industry 4.0* to the value chain. The indicator arrow shows the comparison of the individual characteristics to the value chain. Each characteristics is indicated in the scale between the highest significance (marked by a green arrow up) and the lowest significance (marked by a red arrow down). Orange arrows indicate the intermediate scores in between.

By analysing Fig. 2 in the framework of indicator's dynamics, it is possible to conclude that technology development is seen having the biggest influence by the characteristics of *Industry 4.0*. Eight characteristics put of 14 are indicated as very important (marked by a green arrow). Also manufacturing and marketing & sales are having influence (4 and 3 characteristics are indicated as very important marked by green arrows), services, inbound and outbound logistics are indicated once as very important (marked by green arrows).

Fig. 2 represents the impact of *Industry 4.0* to value chain according to the experts' evaluation results. The scores at line "Total" represent the importance of all the characteristics to the specific part of the value chain.

The results of evaluation made by experts show that impact of each characteristics is distributed not equally. Technology development, manufacturing, marketing & sales and services are having most influence by *Industry 4.0* characteristics. Impact on logistics (both inbound and outbound) is also important. Very low impact is seen in human resource management. Procurement and firm infrastructure also gets low evaluation of impact of the characteristics.

Experts giving scores divided characteristics into two groups: high significance and low significance. High significant characteristics are: Internet of things, Digital infrastructure, robotics, horizontal and vertical integration. Low significant characteristics are: 3D printing/ additive manufacturing, artificial intelligence, autonomous vehicles, nanotechnology, biotechnology, energy storage, quantum computing, big data, virtual/augmented reality, cloud technologies.

Fig. 3 shows how experts evaluated the interrelatedness between technological characteristics and the value chain. I was calculated by multiplying average score A given by experts by a weight ratio W (in %):

$$I = A * \frac{W}{100\%} \quad (5)$$

Score value is placed in interval [0÷7].

Due to experts evaluation, vertical and horizontal integration and robotics have a big impact on manufacturing (6.9 and 6.6 respectively) and services (6.0 and 4.6 respectively) in the value chain. Digital infrastructure (score varies from 1.44 to 4.08) and internet of things (score varies from 1.4 to 3.6) are having a significant impact on all the parts of the value chain. Digital infrastructure has the highest impact on marketing & sales (4.08) as well as Internet of things (3.6).

Fig. 4 represents the impact of Industry 4.0 characteristics that have a high importance: internet of things, digital infrastructure, robotics and horizontal/vertical system integration, to the support activities of the value chain: procurement, technology development, human resource management and firm infrastructure as described according to the experts' evaluation results.

By exploring the second group of characteristics, the impact is obvious in following fields: biotechnology is important in manufacturing (1.05) and services (0.75), quantum computing and nanotechnology is seen important to technology development (0.9 each). Impact on the rest of character-

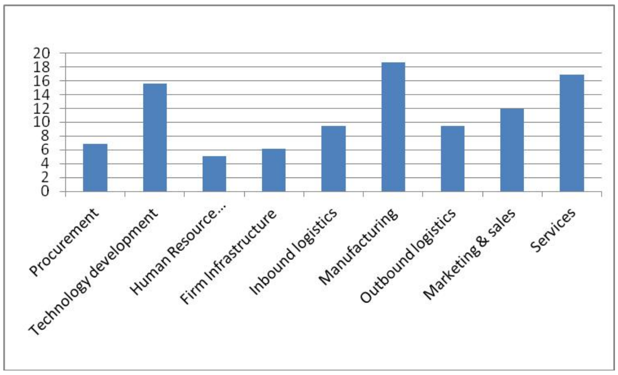

Fig. 3. Impact of *Industry 4.0* characteristics to the value chain: high significance
(according to the experts' evaluation results, 2017).

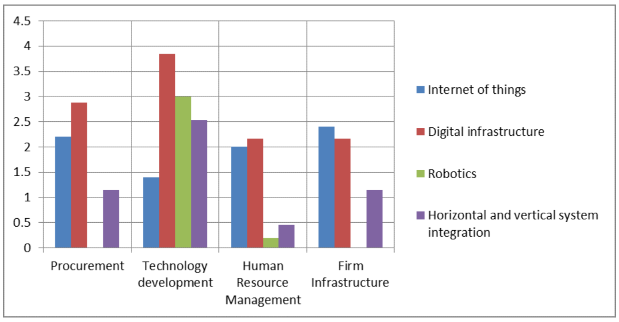

Fig. 4. Impact of Industry 4.0 characteristics of high importance to the support activities of the value chain, 2017
(by authors according to the experts' evaluation results).

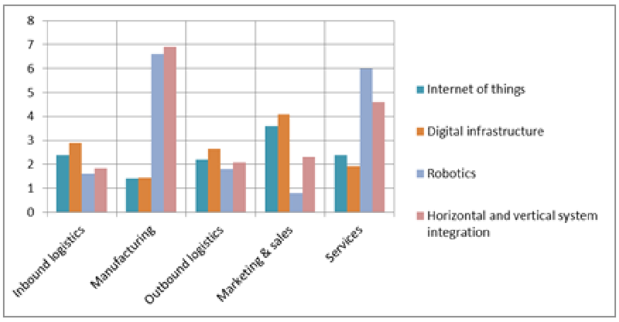

Fig. 5. Impact of Industry 4.0 characteristics of high importance to the primary activities of the value chain, 2017
(by authors according to the experts' evaluation results).

istics is not seen as having significant impact now, the scores are lower than 0.5.

Fig. 5 represents the impact of *Industry 4.0* characteristics of a high importance (internet of things, digital infrastructure, robotics and horizontal/vertical system integration) to the primary activities of the value chain (inbound logistics, manufacturing, outbound logistics, marketing & sales, services) as described according to the experts' evaluation results. Robotics and horizontal/vertical integration are seen having very high importance on manufacturing and services. The same characteristics have very low importance on marketing and sales and moderate importance on inbound and outbound logistics. Internet of things have high importance on marketing and sales, inbound and outbound logistics and low importance on manufacturing. Digital infrastructure is important in all the primary activities of the value chain.

The additional comments of the experts are described below.

One expert indicated that traditional industry uses the experts "segments of *Industry 4.0* according to the personal understanding and do not do research or make evaluation for long term investment". The expert said that the challenge comes in a several ways: "no education of computer science is introduced in the Lithuanian higher education system, lack of investment and lack of governmental policy and support to introduce *Industry 4.0* in Lithuanian industry".

One expert indicated that the impact and importance of technological characteristics is to be evaluated in a time frame "as it is difficult to see *Industry 4.0* as a stable situation and clearer - in a trend of change process". The experts also indicated that only "some characteristics have a clear role in the industry in Lithuania already". One expert said that "considering a long-term impact of other characteristics might increase and the weight of each factor will change ".

Through other experts expressed their hesitation to indicate concrete changes in a longer term "as *Industry 4.0* elements in some industrial sectors are very fragmented yet", all experts agree that "*Industry 4.0* is here and changes are inevitable". The experts raise the impact for the small and medium enterprises emphasising their possibilities in the Supply chain "if they are able to adapt to changes". Experts also indicated that "the most structured information is in the Research Papers of consulting companies such as Boston Consulting Group, McKinsey, etc" which is not considered as a "real scientific literature which is still fragmented and not enough to make conclusions" [17].

4.2. Limitations

The research is not without limitations. There was not a finalised list of technological characteristics found in the scientific literature and, therefore, the list consists of frequently used characteristics found in scientific and grey literature. Knowledge in industry in Lithuania about the opportunities *Industry 4.0* gives is agreed to be fragmented and based more on a personal interest than on overall know-how existing in the country and industry. Experts in this research are from traditional industries in Lithuania. Choosing experts from different sectors (e.g. public, research, etc) and industries (e.g. laser, service, etc) and sizes of enterprises (e.g. big companies and SMEs) will bring a wider prospective of the situation in Lithuania.

4.3. Future research

Research of scientific literature is to be explored and analysed to have a strong basis for the future exploration of the issue. The issues related to new business models, the new ways to organise a supply chain and connection with societal challenges are the topics of scientific interest though at a very early stage. The shift of technological changes from manufacturing to service industry as well as competences necessary in the context of *Industry 4.0* are important topics to explore. Practical application of the scientific research findings, new opportunities and models for different types and sizes of enterprises (e.g. SMEs) in the supply chain of industries within the technological developments of *Industry 4.0*, meeting societal challenges and other issues must be explored in later researches.

Conclusions and recommendations

Most of scientific literature explores *Industry 4.0* focus on a certain technological factor or a specific industrial sector, some literature explores challenges that *Industry 4.0* is expected to bring to the society, new business paradigms and security.

Most of future funding policy papers (egg. European Commission, German Trade and Invest, Recommendations for Implementing the Strategic Initiative of *Industry 4.0*,) indicate not only technological development in the context of *Industry 4.0* but also its impact on new business models (changes in value chain, consumer behaviour, etc), societal issues (ageing, employment, work structure and organisation, etc), culture development (ownership vs access), and legal issues (Intellectual property, data protection, etc).

There are four characteristics that experts call as the most significant to the development of *Industry 4.0* in Lithuania: internet of things, digital infrastructure, robotics, horizontal and vertical integration. The mentioned above characteristics related to *Industry 4.0* are far more developed and understood in Lithuanian industry than others and, therefore, it might be explored separately from those that are less developed.

Four parts of the value chain are most influenced by *Industry 4.0*: manufacturing, technology development, marketing and sales, after-sales services. Understanding the opportunities that *Industry 4.0* and technological changes bring to industries, and long term are less understood by industries in Lithuania.

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Pre-Schoolers' Readiness for School: Research of Motivation

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Abstract. The paper mainly deals with pre-schoolers' readiness for school, while presenting the research on motivation that was conducted in March of 2017. Survey on children's motivation for school was organized in Vilnius kindergarten "Lazdynėlis" using rather simplified and adapted questionnaire for children (aged 6-7) about both inner and outer factors of motivation. Analysing children's motivation at that age is quite important for both parents, educators and children themselves as this period is a time for great changes in a child's life. It is rather challenging and new social circumstances (including new educational environment, teachers, classmates and new requirements) most often demand inner strengths and proper social support for children. Therefore, the authors of this paper would briefly discuss the main aspects of children motivation for school and present a picture of pre-schoolers' readiness for new changes in their daily routine and the factors that motivate them to cope with the challenges.

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Short title: Children Motivation for School.

Introduction

Motivation is a readiness to learn [1]. Throughout the life individuals learn incredibly complex skills without consciously trying at all. As British developmental scientist John L. Locke [2] notes, infants and children do not set out to learn any of the vast repertoire of skills that they gain in the first years as cited in Ref. [1]. Instead, they study the faces, voices and actions of others out of a deep biological need for emotional interaction with those who love and care for them. They simply find themselves in a social and cultural context that values certain skills and use them constantly.

Within the human evolution, certain proclivities on the part of the infant and child have emerged. In the same way, social and cultural mannerisms have arisen around children and in support of their learning [1, 3]. When it comes to understanding where motivation comes from, we should consider both the things that children actively try to master and the things that they just pick up along the way. As W. L. Ostroff [1] states, children's learning is dynamic and results from the interaction between inborn capacity and experience. Desire to learn is present even before the birth. As their world is suddenly filled with the new things to see, hear, smell, taste and touch, foetuses and new babies develop reflexive behaviours to organize that information and to make meaning from it [1, 4, 5]. Reflexes have evolved to help the young ones to adapt to its environment. Sometimes reflexes develop into more complex modes of behaviour and set up learning. They are important clues to the development of motivation [1].

Having all this in mind, it became rather interesting and important to measure pre-schoolers'readiness for a school. Thus, a small-scale research was conducted among the group of 22 children (aged 6-7) in order to understand and describe those children's motivation for learning and taking the part in various activities.

Main objectives could be formulated as follows.
1. To analyze whether or not children are ready for learning activities.
2. To set children's readiness for life changes.
For research, method of quantitative questionnaire on motivation along with the descriptive data analysis was used.

1. Understanding Motivation and Challenges to Overcome

Many scholars would explore motivation through emotional-cognitive perspective. According to K. Barish [5], the problem of *lack of motivation* is the problem of demoralization, whether overt or disguised. Solution to this issue lays on first principle(s): children, when they are not angry or discouraged, want to do well [5]. They want to feel good about themselves and about others. They want to earn adults'praise

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Table 1. Children's motivation. Adapted according to Ref. [5].

Motivation	=	interest	+	a sense of one's competence	+	relevance	+	ideals
Motivation	=	interest	+	confidence (the anticipation of success)	+	anticipation of recognition (praise or appreciation) for our effort		
Motivation	=	having a goal	+	feeling that we can achieve it				

and approval, and they want adults to be proud of them. Children say that they do not care, but they do care. Sustained effort is a different matter. Our ability to work hard, to sustain effort at any task, requires a feeling of accomplishment or progress along the way, and some confidence in our eventual success [5, 4]. All constructive activity involves moments of anxiety, frustration and discouragement. Children who are "not motivated" too readily give in to these feelings; they do not bounce back [5].

As K. Barish argues, children often hide their anxiety and discouragement behind defiant and rebellious attitudes: *"What is the point of studying history or math anyway, I'm never going to use it"*. Good educators – teachers who encourage and inspire children, and then demonstrate the relevance of learning – may really help. But a demoralized child is unlikely to find any relevance in what we want to teach him [5]. A child will then be criticized, repeatedly, for his lack of effort, and he will become more rebellious. And he/she will look elsewhere for a feeling of acceptance and a feeling of pride.

Therefore K. Barish (2012) would raise such questions as: *How often do we understand the problem of our children's motivation in this way? How often do we see a child's lack of effort not as a problem of demoralization but as a "behaviour" problem? How often do we blame the influence of peers, or television and other media distractions? How often do we become frustrated and angry, and then, in our frustration, tell him/her that he/she just has to work harder?* Children are not lazy. They may be frustrated and discouraged, anxious or angry; they may have become disillusioned or defiant, self-critical or pessimistic, and they may lack confidence in their ability [5]. But this is not laziness, as K. Barish continues. The misconception that kids are lazy is one of the most common, and most destructive, misunderstandings of children [5, 4, 3]. When adults understand child's lack of motivation as a problem of demoralization, they are supposed to be able to look into the real causes of child‘s lack of enthusiasm and effort, and then they will be more likely to find helpful solutions.

Undiagnosed (or under-appreciated) attention and learning disorders are the most common source of discouragement and lack of sustained effort ("motivation") in children – stresses K. Barish [5]. For these children, doing schoolwork or homework is like running with a sprained ankle, which is possible, although painful, and they will look for ways to avoid or postpone it. Or they may run ten steps and then find a reason to stop.

2. What Makes Children Get Motivated?

In most of the scholar works and practical toolkits it is stated that motivation begins with one‘s interest. Interest leads to exploration and learning, and to the development of different activities [5, 1]. All these activities (or so called projects) then become ambitions and worth targeting. Like all of us, children want to do what they are "good at". They want to shine and feel proud. Moreover, they want adults to be proud of them. A child's motivation is also sustained by ideals. Children want to become like (liked or alike), to learn from (what or whom), and to earn the respect of the people they admire [5, 4, 3]. Too often, adults (parents, educators) would overlook this fundamental aspect of children's motivation and emotional development. It is easy to forget that children look to adults and look up to us – and that we remain for our children, throughout life, sources of affirmation and emotional support [5].

Rewards and punishments have some short-term effect on children's effort [5, 3]. In this sense we are all motivated, to some extent, to earn rewards and avoid punishment. But rewards and punishments cannot create interests or goals. It can be helpful to think of children's motivation in the form of equations [5] as presented in Table 1.

3. Results of Motivation Research in kindergarten "Lazdynėlis"

As it was mentioned, the research on pre-schoolers' readiness for school and their motivation was conducted in March of 2017 in Vilnius kindergarten "Lazdynėlis". There were 22 children (aged 6-7) – 8 girls and 14 boys – who participated in this survey. First of all it was set that motivation could be divided in two spheres – internal and external, while internal motivation is mainly seen through the ability to continue working or doing some tasks without additional social support for quite a long period of time, also to cope with challenges and not to give up in problematic situations. On the other hand, external motivation relies on external conditions that support learning activities.

The quantitative type questionnaire was based on early education programme and the competences foreseen in it (social, health care, cognitive, communicational, and artistic) – willingness to participate (not participate) in kindergarten's/school activities and relations with group mates.

Analyzing data of social competence, it was revealed that all participants have friends in kindergarten, are willing to play with others (though 4 children pointed out that they prefer to play alone), share toys and other playing materials with others, and help other group mates. The above mentioned shows that children at that age have rather strong social competences and are willing to participate in different educational activities along with others.

Research data about health care competence shows that all participants would prefer to play with Lego, dolls, cars, soldier-toys, basketball, pick-a-boo etc. This fact indicates children's eagerness for a rather active style of play. Almost everyone in this survey pointed out that they care about their health; only one child would show indifference. Discussing about cognitive competence, research data allows us to explore the reasons on why children want to go to the kindergarten – "Interesting games; I have many friends over there; I've learned unknown things here; I have learned about universe and also about letters <…>". Everyone in this research says that they like going to the kindergarten as they learn new things there.

Communicational competence is also rather well developed at that age as almost all the participants pointed out that they like to read stories and fairy-tales. Only 2 children said that they are not much keen on it. 18 children have indicated and named their favourite book. 10 participants would even memorize and may repeat by heart short stories, while for a few it remains still a hard task as it is quite difficult to memorize. Also all children know the ABC, 14 of them even know how to read, while 8 children are still in the process of learning.

Artistic competence also shows children's abilities to differentiate seasons of the year and name the exact month at the given moment.

Analyzing data on children's willingness to go to school, it became rather clear that 19 participants are waiting for this event in the upcoming months, while 3 kids were not that keen on this new adventure in their lives. Majority of the participants learned about school from their parents (11) or siblings (9).

The question about what image of school children have, could be illustrated with following answers: "Teacher teaches children; We have to study there; We have to listen to a teacher; We need to count, read, and listen, learn English, and do homework; We have to sit and teacher is writing on the board; There are breaks and we have to be on time – not to be late; There is no bed time at noon at school". All these answers clearly show quite good understanding of what school is and what is to be to expect there.

Conclusions

Motivation in this work was presented mainly through the emotional-cognitive perspective. As scholars would stress, the problem of "lack of motivation" is the problem of demoralization, whether overt or disguised. Children, when they are not angry or discouraged, want to do well.

Emotional-cognitive basis of motivation was revealed in the research with children and it was set that both boys and girls are motivated for school equally, as internal reasons of being motivated would be mainly – children are happy in the kindergarten, experience much of success, and the activities are interesting for them; external ones – friends, games and toys.

School image and motivation for this would also depend on internal reasons – children will learn new things (reading, counting, painting etc.), will get to know new friends; external reasons for going to school – will have many new friends, siblings are already attending school, will have to study hard and complete the assignments.

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Comparison of Sentiments Data Extraction and Prediction

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Abstract. Exponentially increasing amount of information, variety of data forms, growing number of big data analysis ant prediction tools give the new opportunities for business but create needs for right decisions of selection. This study aims to make three-dimensional analysis of data extraction methods, forecasting methods and sentiment indexes. Historical numerical data and textual data from forex news expressed throw the two sentiment indexes are forecasting by econometric methods, Python text analysis and unique computational intelligence tool. Prediction of ensemble of *Evolino* recurrent neural networks (EERNN) is a distribution of expected values reflecting the probabilities of different states of market sentiments. The results are intended to individual investors needs and give them opportunity of choice, which depends on what data is available, the accuracy of the prediction, how much time can be taken to make the prediction and that the forecaster has enough skills to use the appropriate IT tools.

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Short title: Sentiments data.

Introduction

Effectively investing in real market which often does not comply with the effective market hypothesis requires the selection of reliable forecasting tools. Well-known econometric forecasting methods are common and frequently used to predict economic processes. There is a huge amount of text information in social media; social networks create opportunities for investors to quantify opinions and use data to make predictions. The forecasting algorithms based on artificial intelligence can be successfully integrated into business intelligence systems. The comparison of different forecasting tools enables investors to choose the best method to evaluate market irrationality and use the corresponding prediction method. Sentiments of individual investors are used as a contrarian indicator for exchange rates or finance index action. Predictions of the sentiments provide additional information for investors and can lead to better decisions in the financial markets.

Investors are a group of people directly related to the market rationality and irrationality. Investors express their expectations, views and approaches of market processes using the internet, forums, surveys and realistic market actions. Different aspects of investor behaviour were investigated. Pompian [1] identifies four categories of investors: the preserver, the follower, the independent and the accumulator, - each of whom has distinct behavioural biases and risk profiles. Grinblatt et al. [2] analyse whether IQ influences trading behaviour, performance and transaction costs. Merkle and Weber [3] combine the survey data about return expectations, risk expectations and risk tolerance with investors' actual trading data and portfolio holdings. The authors found that the behaviour of investors has multiple characteristics; many different factors play significant roles in investment decisions. The search of information plays a significant role in investment decision-making. Ozsoylev et al. [4] investigated an empirical information network of investors and found out that central investors earn higher returns and trade earlier than peripheral investors with respect to information events.

Studies about why some investors are successful, and the others should choose a different career path often provide conflicting answers. Crongvist et al. [5] investigated the behaviour of investors and found that investors' styles have a biological basis and are partially ingrained from birth, and that investors' styles also depend on previous investor experience. Li et al. [6] studied the differences between institutional and individual investors and found that institutional investors are better informed, trade more selectively and react asymmetrically to up-and-down-market movements. Less informed individual investors allocate their investments evenly across stocks, and they are more influenced by market sentiment and attention-grabbing events.

Investors' opinions are important in trading activities be-

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cause they are the main factor that influences their behaviour in the financial market. Sentiments of investors are positive and negative opinions ratio. Measuring the sentiments is important for selecting an informative data set for prediction. Preis et al. [7] suggest that Google Trends data and stock market data may reflect two subsequent stages in the decision-making process of investors.

Research on investment in finance uses different sources of sentiment data. The most popular data come from social media: StockTwits [8, 9, 10] and text analysis [11, 12, 13]. Data for predictions of the stock or exchange market are also used by constructing sentiment indices based on a survey of investors, Facebook's Gross National Happiness Index [14].

Attempts to predict stock returns, volatility and trading volume are very controversial. The findings of Corredor et al. [15] show that sentiment has a significant influence on returns, varying in intensity across markets. Kim and Kim [16] discovered evidence that investor sentiment is positively affected by prior stock price performance. Chen et al. [17] discovered that a younger, speculative industry fits in a linear local sentiment-returns model but an industry with experience fits in a nonlinear and asymmetrical prediction of sentiments and returns. Liu [18] found out that the stock market is more liquid when sentiment indices rise, that is when investors are more bullish. Albu et al. [10] investigated a possible connection between the asymmetric volatility and the dynamics of two sentiment indices. Aboura [19] found that an individual investor's sentiment index is more informative when financial markets are bearish. To summarise, it could be stated that there is no evidence that analysts' opinions presented in the news media accurately predict subsequent stock returns. This contradiction of findings is based on different measures of sentiments, different selection of data and different prediction time. Sentiment indices cannot be used as leading indicators of financial market changes, but information about sentiments can be used in other ways. Linardos et al. [20] proposed an innovative system, combining information from news releases and technical indicators in order to enhance the predictability of the daily stock price trends, and experimental results confirm the aforementioned impact. Azar and Lo [21] developed a simple hypothetical trading strategy, based on the content of tweets, which outperformed several benchmarks.

Predicting the sentiment indices can help investors develop new strategies for trading. The simplest way to predict the sentiments of individual investors is to use well-known econometric methods. Sentiment analysis by text classification is used to measure investors' sentiments and can be used as an indicator of information from the media. Dougal et al. [22] measured the media's conditional effect. This increases explanatory power by one-third and identifies amplification or attenuation of prevailing sentiment as a tool used by financial journalists. Oliveira et al. [23] verify the statistical relationship between some sentiment variables and each stock return, volatility and trading volume. The authors found some evidence that the volume of *Twitter posts* is relevant for modelling the next day trading volume. Sprenger et al. [24] found the sentiment (i.e. bullishness) of tweets to be associated with abnormal stock returns and message volume to predict the next-day trading volume.

Algorithms based on artificial intelligence use data of sentiments for input like teaching data to predict the finance variables. Ho and Wang [25] developed an Artificial Neural Network (ANN) model using new sentiment analytics to predict the stock price movements. Chen et al. [26] proposed a nonlinear, autoregressive model with exogenous sentiment inputs to predict stock price movement.

Piñeiro-Chousa et al. [27] used a model based on artificial intelligence to investigate financial variables and variables related to social media activity, such as number of tweets, number of followers or the experience of the users.

The aim of this paper is to compare text classification and artificial intelligence-based forecasting tools with well-known econometric forecasting methods. By extracting the advantages and disadvantages of forecasting, evaluating the accuracy will allow investors to choose the most appropriate investor sentiment forecasting method or a combination thereof.

1. Materials and methods of sentiment forecasting

The opinion is the main characteristic of human behaviour, and sentiments are the ratio of positive and negative opinions. This research investigates the sentiments of individual investors, such as the expectations that guide their behaviour. Two different measures are used for prediction: the sentiment survey from the American Association of Individual Investors (AAII) [28] and the speculative sentiment index (SSI) [29].

The AAII Sentiment Survey asks a simple question to more than 170,000 members of the AAII: "I feel that the direction of the stock market over the next six months will be: Up-Bullish; No Change-Neutral; Down-Bearish" [30]. Useful measures for prediction are the difference between bullish and bearish sentiments and logarithmic function of the bullish and bearish ratio. Rotblut's [31] studies have shown that American individual investors' sentiments can be used as an indicator of the stock market, especially for long-term financial goals.

The SSI includes data obtained from real investors with actual positions. SSI is the ratio of long to short positions in the exchange rate or stock index. The SSI is useful for the larger imbalances. A good rule of thumb is to look for readings of greater than +2 or less than -2 in which the trend agrees with the contrarian element of the indicator. The SSI is used as a contrarian indicator to price the action of exchange rates: EUR/USD (euro and United States dollar), USD/JPY (United States dollar and Japanese yen), GBP/USD (Great Britain pond and United States dollar), AUD/USD (Australian dollar and United States dollar), XAU/USD (gold prices and United States dollar) and the stock index SPX500.

Weekly data of sentiments were used to examine three very different groups of forecasting tools: econometric methods, text classification and artificial intelligence.

Econometric methods. Econometric forecasting methods are based on a paradigm that the future is a continuation of the past. One of the main advantages of these methods is their universality. Econometric methods are used for stocking prices, exchange rates and other financial instruments. Moving averages (MA) are the most commonly used financial market forecasting tools. The Simple Moving Average (SMA), Weighted Moving Average (WMA), and Exponential Moving Average (EMA) show tendency of price fluctuation based on point prediction. Trends also predict one point in the future. Regression function is selected by the determination coefficient. Bollinger bonds determine interval for predicting the price. Econometric methods are simple to use, and they do not require special skills or information technology resources.

Sentiment analysis by text classification. Investors in financial markets pay attention to economic and political news, and they share information and insights with each other. It is difficult to cover the large output of information. The investor's job is to monitor market news and data, choose what is important at the moment and make a good trading decision. Market news and information is available through a multitude of sources. The Internet is an obvious source, and free content is available on many special market websites, servers and TV programmes. Text classification can help to classify the text according to whether it represents a positive mood, negative mood or neutral mood. Natural text processing is made by the Python algorithm with text tokenization and using WordNet [32]. WordNet is a large lexical database that is an important tool in computational linguistics and natural language treatments. Brief news items from marketpuls webportal [33] were selected as they provide a concise view of the best known, real-time information sources (CNN, Bloomberg, Reuters, MarketWatch and others). Prediction of sentiments by text classification is based on the paradigm that the future is a result of events that occurred in the past. Political and economic news report the events that influence the opinions of investors.

Artificial intelligence based forecasting. Algorithms of artificial intelligence simulate the intelligent human activities. Forecasting or foresight is one of the most important intellectual activities. In 2005, Shmidhuber et al. [34] proposed the new class recurrent neural network algorithm *Evolino* (EVolution of recurrent systems with Optimal LINear Output). This recurrent neural network was adopted for forecasting of finance markets by the correct choice of parameters such as the number of neurons, the number of epochs, the

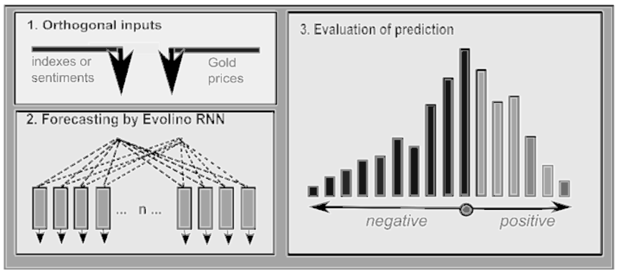

Fig. 1. Prediction model based on *Evolino* RNN (Source: created by authors).

amount of data and their relationship with the training data for predictions of financial markets [35]. Later we constructed the ensemble from 176 *Evolino* with two orthogonal inputs [36, 37] and tested it to predict exchange rates. The scheme of the prediction model is shown in Fig. 1.

Historical data of AAII and SS indexes of sentiments is using for the first input. The second input is the historical data of gold prices in American dollars (XAUUSD). Orthogonality of the inputs makes predictions more accurate and prediction times shorter [38]. Forecasting is done by 176 *Evolino*, and each of *Evolino* uses a different historical data set. The result is the distribution of the expected values of sentiments. The prediction is evaluated according to the last known value of the sentiment index and by calculating the probabilities of the expected change of sentiments. Prediction by ensemble of *Evolino* RNN (EERNN) is based on the paradigm that the future is the distribution of opportunities.

Three different groups of forecasting tools can be compared in data mining: overall classifier accuracy, forecasting errors and complexity of process. Overall classifier accuracy is expressed as ratio of true predictions of directions of sentiments change and total number of predictions.

2. Forecasting of sentiments

All selected forecasting methods were used for forecasting the AAII data and the SSI data of EUR/USD, GBP/USD, USD/CHF and USD/JPY from 11 January 2016 to 21 April 2016. Forecasting by ensemble of *Evolino* RNN was done only for AAII because the SSI data were insufficient.

Forecasting by SMA, WMA, EMA, BB and trend did not require a big set of data or special skills of a decision-maker, and the length of time taken to complete the forecasting process does not matter.

The *text classification* method to predict the sentiments of individual investors was tested by online sentiment analysis with Python NLTK text classification on positive, negative and neutral sentiments [32]. The daily financial market news flow is huge, but it is difficult to find texts that are subjective. This means that to find positive or negative sentiments in the texts of daily news is difficult because journalists are trained to write objective articles that don't have a negative or a posi-

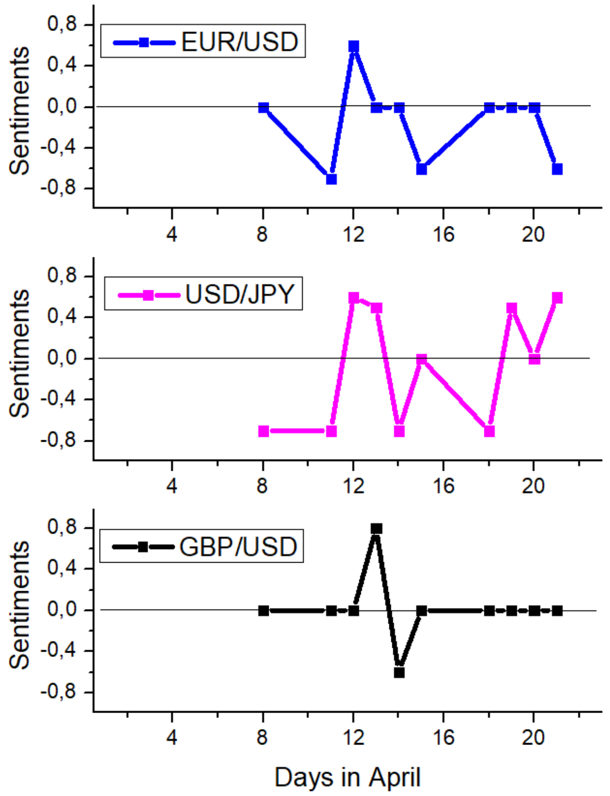

Fig. 2. Dynamics of sentiments of news is about three main exchange rates - EUR/USD, USD/JPY and GBP/USD.

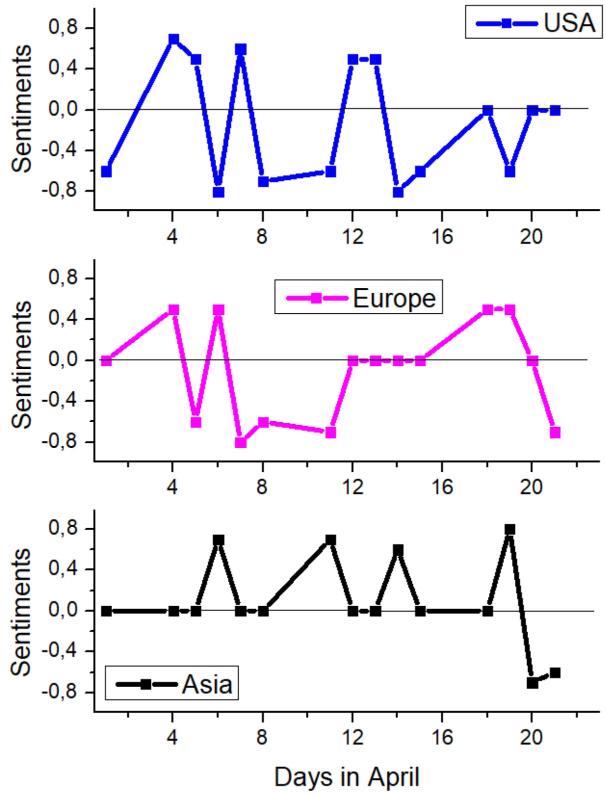

Fig. 3. Dynamics of sentiments of news shows the USA, Europe and Asia markets.

tive bias. Therefore, sentiment may be more visible on social networks and blogs, where opinions are more often and obviously expressed. On the other hand, if the text has polarity (positive or negative), it is appropriate to point out because it means that even journalists cannot convey new information without a subjective opinion which is really important.

Daily sentiments of news about the three main exchange rates - EUR/USD, USD/JPY and GBP/USD - are presented in Fig. 2. Sentiment analysis from website text-processing [32] uses a hierarchical classification of a combination of subjective classification and polarity classification. The first step is to use subjectivity classifier that determines whether the text is objective or subjective. If the text is objective, then the sentiment is given 0 value and polarity classification is not used. However, if the text is subjective, then the polarity classification is used to determine whether the text is positive or negative. Negative sentiments are evaluated on a scale of [-1÷0) and positive sentiments on a scale of (0÷1].

Neutral sentiments are indicated by a dashed line, positive sentiments are indicated above this line, and negative sentiments are indicated below this line. Another way of evaluating text sentiments is to group news according to the economic zones of the USA, Europe and Asia - see Fig. 3.

Economic indicators such as interest rates, employment, gross domestic product (GDP) and the European Central Bank and federal reserve systems affect the capital market sentiments because the variety of financial market news runs the stock indices courses. News about these events is published every day. Sentiments of US economic zone vary the most, and the Asia zone sentiments - the least. A visible trend is that news with positive sentiments changes to negative sentiments the next day and vice versa. Daily sentiments are summarised into weekly data and compared with real AAII data and SSI data of exchange rates and stock indices.

Investors have their own language, so it is appropriate to establish a text classification programme to use specifically for financial market sentiments. The idea came from the fact that the analysis of articles on the currency pair of the British pound sterling and the US dollar found that one of the most relevant topics was Brexit (British withdrawal from the European Union). The paragraph, about the British withdrawal from the European Union, also projected the country's national currency exchange rate loss. However, sentiment analysis using text classification links these paragraphs to a positive sentiment.

Artificial intelligence. During the same ten weeks, the AAII sentiments were predicted by the EERNN. Predictions were made by analysing the histograms of expected values according to the value of the previous week. The data from the AAII is presented in $\log_2$positive/negative scale. 400 numbers represents the minimal length of time series. Three histograms of April 2016 are presented in Fig. 4.

The main part of this histogram is right of the last known value (black line), so the prediction means that sentiments

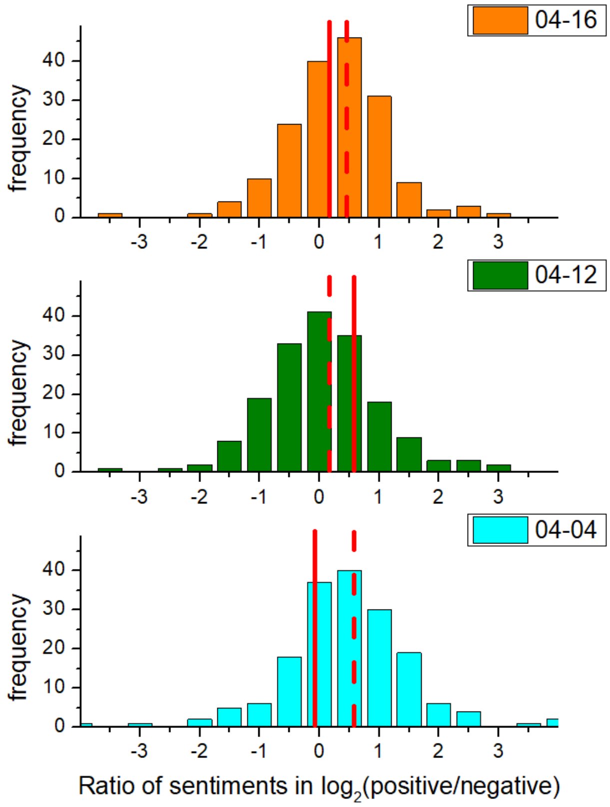

Fig. 4. Evaluation of prediction of AAII sentiments by ensemble of *Evolino* RNN 04 April 2016; 12 April 2016; 16 April 2016. Black line represents last known value, dashed line – real value.

will become more positive. The probability that the sentiments will grow is 59%; the probability that the sentiments will decrease is 41%. The dashed line represents the real value of the sentiments of that week. The EERNN correctly predicted not only a change in direction of sentiments but value of sentiments too.

For next week predictions (12-18 April 2016, see Fig. 4), the main part of the histogram and mode is left value of the previous week (black line). More negative sentiments are a clear prediction of this week. The probability of more positive sentiments is 40% and more negative is 60%. The real value (dashed line) shows that the direction of change of the sentiments was predicted correctly and the mode value has been reached.

For third week predictions (19-26 April 2016, see Fig. 4), the growth of positive sentiments occurs, and the mode of the histogram coincides with the actual value of the week. So the prediction is accurate enough. The probability of sentiment growth is 54%; the probability of a decrease in sentiment is 46%. Prediction sentiments by EERNN are informative and easy to interpret but they require information technology resources.

3. Comparison of forecasting methods

Sentiment data generated on the internet has been increasing rapidly. Data mining is a process that leads to better decision-making. Data are based on surveys of individual investors' opinions, the AAII and the decisions of individual investors, and the SSI is simple to use in numerical form. Econometric methods and algorithms of artificial intelligence require time series data. The text classification method depends on the selection of data in text form. The amount of data is not enough to get predictions using econometric methods, but the AI model uses about 60÷100 points of the data range. Every day, 2-3 pages were used to find sentiments in the finance news. It was difficult to select the information from the huge flow of news.

Sentiment analysis is based on classification of sentiments into positive, neutral and negative. Sentiments changing direction is usually more important for decision-making than prediction of the real value. The comparison of overall classifier accuracy of investigated forecasting methods is presented in Table 1.

The overall classifier accuracy of AAII data forecasting is equal to 1 only for ensemble of *Evolino* RNN, which means that all predicted directions were right. The SMA and WMA methods correctly predicted the sentiments 9 out of 10 weeks, BB correctly predicted 8 out of 10 weeks and text classification correctly predicted 7 out of 10 weeks. The forecasts using other methods were incorrect. Econometric methods predicted the SSI data with very weak accuracy; only BB and trend exceeded 50%. MAE, MAPE and RMSE measured the accuracy of predictions of the AAII and SSI data. The comparison of forecasting errors is presented in Table 2.

Table 1. The comparison of overall classifier accuracy (OCA) (originally created by authors)

	AAII OCA	AAII range	SSI OCA	SSI range	Range total
SMA	0.9	II-III	0.4		III-IV
WMA	0.9	II-III	0.4		III-IV
EMA	0.4		0.5		VII
BB	0.8	IV	0.6	I-II	II
Trend	0.5		0.6	I-II	V
Text classification	0.7	V	0.5		VI
EERNN	1	I			I

Table 2. The comparison of errors of forecasting (originally created by authors)

	MAE AAII	MAPE AAII	RMSE AAII	MAE SSI	MAPE SSI	RMSE SSI	Range total
SMA	3.80	11.90	4.53	0.49	121.23	0.59	IV
WMA	3.47	10.90	4.13	0.46	112.72	0.55	III
EMA	4.55	14.80	5.29	0.54	138.3	0.61	V-VI
BB	3.32	10.54	4.13	0.23	101.91	0.29	II
Trend	7.56	24.76	9.19	1.91	219.25	2.15	VII
Text classification	6.03	10.39	8.09	0.83	181.75	1.02	V-VI
EERNN	0.09	3.92	0.11				I

Forecasting methods according to errors of forecasting occurred in the following order: AI, BB, WMA, SMA, EMA, text classification and trend.

The complexity of forecasting using the investigated methods is different. The econometric methods are simple to use, and they are sufficient for basic computer literacy. The text classification method predicted using online sentiment analysis with Python NLTK text classification. This tool is simple to use but requires time for data selection and evaluation. The ensemble of *Evolino* RNN requires the skills of information technologies for data preparation, running and interpretation of forecasting. The forecasting time was about 4-5 hours, and the sources of IT included 8 processors.

5. Conclusions

The uncertainty of financial markets is one of the key aspects to which all participants in the financial markets must adapt. The most important factor in determining the uncertainty in the market is the limitation of rationality. Investors' rationality is affected by various psychological factors, so sentiment forecasting can provide additional information for investment decision-making.

To evaluate investors' sentiments, data were selected from individual investors' surveys: the AAII and SSI. Investors' sentiment has been predicted using three completely different types of methods: econometric, text classification and algorithms based on artificial intelligence. The innovative model based on artificial intelligence and tested early in the prediction of exchange rates was adopted to forecast the individual investors' sentiments and create new opportunities for investors.

The overall classifier accuracy of the AAII by all forecasting methods except the trend exceeds 50%. Only the ensemble of *Evolino* RNN guessed correctly the sentiments change in direction in 100% in ten weeks of testing. The SSI data was predicted with very weak overall classifier accuracy: only BB and trend exceeded 50%.

Forecasting methods according to errors of forecasting (MAE, MAPE, RMSE) occurred in the following order: AI, BB, WMA, SMA, EMA, text classification and trend.

Choosing a sentiment forecasting method depends on the availability of the data, the accuracy of the prediction, time to be taken to make the prediction and that the forecaster's skills to use the appropriate IT tools. Each of the tested prediction methods can be used to develop a trading strategy by combining them with the other trading indicators. These studies can be applied to the activities of investment funds.

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