# AI IN BUSINESS

**Proceedings of the scientific workshop on business implications of artificial intelligence**

**June 7, 2022**
**Tallinn University of Technology**

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Proceedings of the scientific workshop on business implications of artificial intelligence, June 7, 2022

Department of Business Administration, School of Business and Governance, Tallinn University of Technology (Taltech), Tallinn, ESTONIA

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### Edited by Tarmo Koppel

This volume presents the proceedings of the papers of the Scientific Workshop on AI IN BUSINESS, held in Tallinn, Estonia, on June 7, 2022. The purpose of this event is to encourage research of AI systems for business use, especially considering SMEs. This workshop aims to discuss the recent innovations, trends, practices of artificial intelligence technologies in business settings. The workshop provides a forum for researchers, practitioners, educators and graduate students to exchange their experiences and research results, to transfer knowledge to young researchers and to generate new ideas. This workshop is an annual event, see the next call at https://taltech.ee/en/conference/ai-business-workshop

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MESSAGE FROM THE ORGANIZERS

# AI transformation is platform driven

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Key words: artificial intelligence, AI change, digital transformation, business

## INTRODUCTION

Artificial intelligence (AI) is becoming a big disruptor to the global economy and also the biggest innovation driver after the industrial revolution. It will greatly disrupt the way businesses conduct their operations and how people work. AI, as a disruptive technology can remarkably increase companies' overall innovation capacity. Increased innovation level allows gaining a better level of services and products – both quantitatively and qualitatively. Artificial Intelligence has the potential to significantly increase company's innovation capacity by automating mundane and repetitive tasks, cutting costs, and improving efficiency (Girasa, 2020; King et al., 2017). AI-powered machine learning algorithms can be applied to areas such as data analysis and forecasting, allowing companies to make more informed decisions that can improve their competitive advantage. AI can also be used to create and test more innovative product ideas, by analyzing customer feedback and trends in the market. Additionally, AI can be used to develop new, more efficient processes, helping companies to increase their production capacity while reducing costs. By adopting and leveraging AI platforms and tools, companies can free up their resources and to focus on more strategic enterprises, and ultimately drive growth and stay ahead of the competition.

Businesses look to the AI to improve their operations and make these more efficient. Improving business through AI – is the goal driving every business AI project. Business AI is mainly aimed at improving efficiency and thus making a qualitative and/or quantitative jump to the next level. The role of the applied science at the same time is to determine the effectiveness of the AI in business context.

### Data centric businesses

Within the past two decades, data-centric approach has emerged, competing with process-centric business models (Deutsch et al., 2009). Data centric businesses have their focus on data, where core operations involve the collection, storing, managing, and analyzing the data. This data can come from a variety of sources, including customer and employee records, financial transactions, market research etc. By leveraging the contemporary AI-based data analytics technologies, such as machine learning, businesses are able to gain valuable insights into business environment, customer behaviour, market trends, and competitors' activity. This data can then be used to inform strategic decisions, such as marketing campaigns, product design, and employee training. Data centric businesses are rapidly becoming the norm in many industries, allowing companies to gain a competitive edge by efficiently leveraging data-driven insights (Steinau et al., 2019; Tabesh et al., 2019).

Collecting data is important, but more importantly, businesses need to make sure that the collected data is also properly analyzed. Analysis serves mainly the purposes for insights and better decision-making. Data can only be impactful, when the processes connected to data are streamlined and harnessed for maximum effectiveness.

The more data businesses collect, the more potent analytics are possible, leading to better decisions retrospectively, but also enabling predictions. Companies that fully utilize their data assets can base their production and services on actual customer feedback or other types of market data. These companies will be extremely flexible in adapting to changing market conditions and gain agility in their response to the customer needs.

## ADOPTING AI TOOLS AND PLATFORMS

### AI transformation

A wide range of AI solutions is available for business purposes, but most companies neither have the experience nor know-how to manage the AI-transformation. AI, like any change management needs a systematic approach. Most companies don't know how to differentiate between various AI solutions and have difficulties in choosing a right one for their operations. Furthermore, companies planning AI transformation, also need to know how to measure the effectiveness of such systems.

Over the next years the business environment will see continuous change. Younger companies have better chances to change faster as they have not yet heavily invested and accustomed to yesterday's technology. But digital change affects all companies – no business will be able to succeed without the AI, with exception to some niche enterprises whose main aim is to uphold some tradition.

Companies adopt AI in different ways. Small companies may be focusing on using AI from the perspective of research and development, whereas large companies are looking at the wider spectrum of business processes, mostly associated with marketing, sales, and manufacturing (Kulkov, 2021).

The AI transformation is platform driven (Yablonsky, 2020). It is impossible for any single company to solve all issues and grasp the majority of the market. Those companies that adopt to the ongoing change will succeed in the new AI era. Companies' managements face crucial decisions when selecting these transformative technologies. AI, like information technologies are fast paced, ever improving technologies. Some applications change faster than the time needed to train the personnel to use these – making these already obsolete when deployed.

**Use case driven transformation**

AI-transformation is a use case driven shift, part of a greater digital change. It is essential that organizations understand the fundamentals of AI and train their personnel according to their AI applications and business processes. Understanding of AI needs to be complemented with how it will benefit the business in general and the corresponding job of any employee. When properly deployed, business AI is a valuable asset opening new avenues for busienss, or gaining better competitiveness for the existing ones.

Business AI allows high level of customization (Diaferia et al., 2022). Use cases can get down, even to individual persons, including customer and worker level. Platforms and tools needed for the AI shift are already available. The main limitations lay within the company and the business domain itself – to which extent can the business ecosystem facilitate these new systems. AI transformation is driven by successful use cases, which demonstrate the real-world applications of AI technologies to solve a variety of business problems. Applications such as natural language processing, customer segmentation, production optimization, and other, through their successful use cases, are validating the value of AI. Companies are developing their competitive advantage by adopting AI innovations to optimize existing processes, improve automation, information management and transformation (Wamba-Taguimdje et al., 2020).

With each successful use case, businesses are increasingly encouraged to invest into AI initiatives. New AI projects give birth to new use cases, hence in turn creating more efficient processes. Besides big tech, many smaller software developers, including start-ups, develop new AI solutions. This makes the AI tools and platforms better accessible to small and medium sized companies. Affordable AI tools can now be embedded into everyday business operations with little cost. The potential for AI transformed business is increasingly growing.

**AI tools and platforms linked to every aspect of business**

Intrinsic parts that make up any business are 1) users, 2) operations and 3) systems. The effectiveness of said operations is measured by effectiveness measures. Though, using effectiveness metrics to run companies can be compared to driving a vehicle by looking at the rear-view mirror. Data-centric management can significantly shorten the time taken from feedback to a decision. Predictive analytics is a category in management, where AI tools enable predicting the outcomes of business operations, hence making early interventions possible.

Business users are traditionally considered owners, managers and workers. Also, other stakeholders are often considered as part of business users. Besides owners, managers and workers, other stakeholders may be: the general public, neighbourhood communities, local administrative bodies and any other entity or group of individuals affected by the business operations.

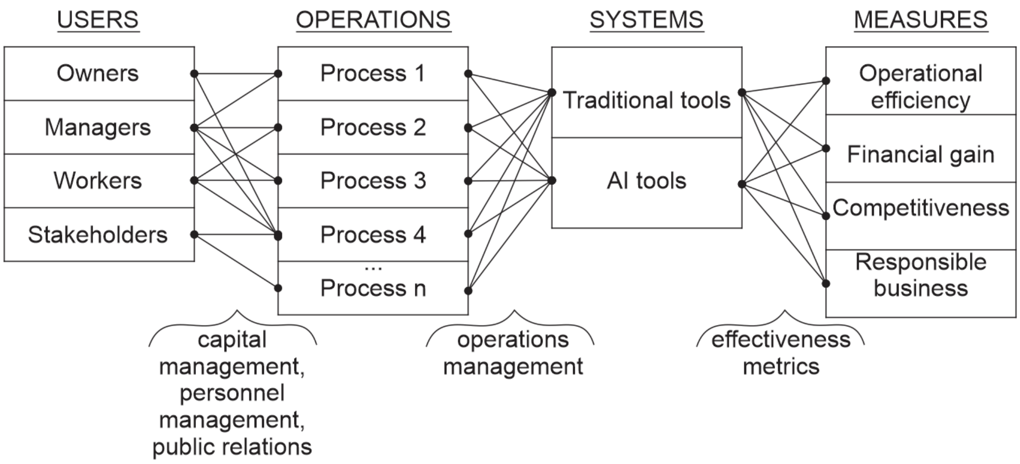


Figure 1. Business users, operations, systems and measures are all directly or indirectly affected by the AI tools

Figure 1 depicts how business users are engaged with business operations. The users are entangled with the business systems, which enable the operations. Users, operations, systems and measures are interconnected, hence affected directly or indirectly by the introduction of AI tools/platforms. These tools determine the operational efficiency, financial gain, competitiveness and responsible business indices. New AI tools are measured for effectiveness against traditional tools. Gold standard of effectiveness metrics are randomized control trials (RCT), but also A/B testing offers sufficient level of confidence, when validating new AI tools.

While each business process needs a specific tool or multitude of tools to conduct the operations, these tools can either be traditional tools (non-AI tools) or AI-based tools. Fully AI-enabled companies deploy AI-tools in all of their operations. This characterizes highly technological companies that have heavily invested into the AI-tools, aiming at high operational efficiency. On the other side of the spectrum, companies that are only relying on traditional tools may still have satisfactory operational efficiency, determined by the sector of economy and innovation potential within that sector. Also, some business domains may yet to have their AI breakthrough that would significantly impact their efficiency and make the investment worthwhile.

Companies that are quick to embrace AI transformation will collect the rewards in the form of increased productivity, cost savings, and improved customer experience. The key steps to successful AI implementation are,

1) understanding of company's needs and capacity for innovation,
2) selecting proper AI tools and platforms to enhance the business operations,
3) training the personnel to fully utilize the AI tools and platforms,
4) implementing continuous feedback measures, to monitor the effectiveness of said tools and platforms and
5) constant improvement, when the effectiveness of AI platforms/tools diminishes.

Following the effectiveness measures, companies need to remodify/retrain these or implement new tools. AI transformation is a continuous process and need to be coupled into changes in the business environment, the marketplace and within the company. AI tools and platforms need to adapt to changes to serve their initial purpose and to be useful for conducting the business. This calls for a management mindset, where continuous change and innovation are at the centre stage of operations.

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# Artificial Intelligence in Businesses: Importance and Context

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Key words: artificial intelligence, AI, enterprises, business intelligence, innovation.

## INTRODUCTION

Open-data, big-data, and other novel data science approaches are currently seen as transforming the landscape for socio-economic policy and research (Einav and Levin, 2014; Varian, 2014), as well as for business management and decision-making. The typically high level of granularity, entropy, and multidimensionality of this kind of "non-traditional sources of social and economic data" (Blazquez and Domenech, 2018) offers many high promises.

Artificial intelligence (AI) especially has the potential to significantly improve business management in a variety of ways (e.g., Enholm et al., 2022; Han et al., 2021; Loureiro et al., 2021). One of the main benefits of AI is its ability to analyse large amounts of data and identify patterns and trends that may not be immediately apparent to humans. This can help businesses make more informed decisions based on data-driven insights. AI can also be used to automate routine tasks and processes, freeing up time for employees to focus on more complex and value-added tasks. This can improve efficiency and reduce costs for businesses. In addition, AI-powered chatbots and virtual assistants can help businesses handle customer inquiries and complaints more efficiently, improving the customer experience. AI can also be used to make predictions about future business trends and customer behaviour, allowing businesses to better anticipate and prepare for potential challenges and opportunities. Also, AI can be used to optimize and streamline supply chain processes, including inventory management and transportation logistics. This can help businesses improve their overall supply chain efficiency.

Yet, commonly identified challenges are also at play, and include the often poor accessibility of such data, the lack of technical competencies required to handle this kind of data, and the difficulty of integration of such data with theoretical frameworks originally developed for traditional kinds of small qualitative or sampled quantitative data (e.g., (Kalvet et al., 2020).

The current contribution summarises the importance of topic on the European Union (EU) as well as on the Estonian level.

## PRIORITY ON THE EU LEVEL

The EU has identified AI as a key technology for the 21st century and has made significant investments in AI research and development. The EU has established a number of initiatives to promote the development and adoption of AI, including the European Research Council, the Horizon 2020 (and following) research and innovation program(s), and the Digital Single Market.

Recognizing the importance of AI, the EU has developed the European Artificial Intelligence Strategy (2018), a set of initiatives and actions designed to promote the development and responsible use of AI in Europe (European Commission, 2018). One key aspect of the strategy is the investment of €1.5 billion in AI research and innovation through the Horizon 2020 program. This funding will support the development of new AI technologies and applications, as well as the testing and deployment of AI solutions in a variety of sectors. The EU is also working to support the development of AI skills in Europe, including through the establishment of AI training programs and the creation of new AI research and education centres. The EU is working to facilitate the deployment and uptake of AI solutions in a variety of sectors, including through the establishment of AI testing and experimentation facilities and the development of AI-specific procurement guidelines.

Overall, the European AI Strategy is a comprehensive set of initiatives designed to support the development and responsible use of AI in Europe, and establish the EU as a global leader in this important technology.

According to the "Europe Fit for the Digital Age" (2019-2024), a strategy developed by the EU to ensure that the EU is well positioned to take advantage of the opportunities and challenges presented by the digital revolution, major boost is expected regarding the use of AI-related solutions: 75% of EU companies are expected to use Cloud/AI/Big Data and more than 90% of SMEs reach at least a basic level of digital intensity (European Commission, 2022b).

AI has also potential impact on the environmental sustainability of the EU. The EU Green Deal aims to transform Europe into the world's first climate neutral continent. To achieve this, it requires a new economic model and a reduction of at least 55% in net greenhouse gas emissions from all sectors of the EU economy by 2030, compared to 1990 levels. (European Commission, 2022c, 2021a)

AI and other technologies can greatly improve our understanding of and ability to address environmental issues by enabling the rapid analysis of large amounts of data. By combining Earth observation data with AI, we can more effectively and efficiently monitor environmental impacts and trends, gain new insights into the causes of these impacts, and improve our ability to make predictions. This information can be used in environmental planning, decision-making, and policy implementation, and can also help individuals and businesses adopt more sustainable behaviours. Additionally, AI-powered technologies can help optimize the safe operation of infrastructure by providing predictive maintenance and automated steering. AI has also the potential to support the green transformation in a variety of sectors. For example, AI can be used to monitor and optimize energy consumption, enabling the integration of renewable energy into electricity grids and supporting the priorities of the Green Deal in the building sector. In agriculture, AI can help improve the efficient use of water, pesticides, and fertilizers, reducing environmental impacts. In the transportation sector, AI can be used to improve transport system and infrastructure planning, increase engine efficiency, optimize electric vehicle charging, coordinate different transport modes, and manage railway systems. AI can also be applied to support the circular economy by improving eco-design and assisting in the inspection, sorting, separation, and disassembly of materials. These use cases show how AI can help us adapt to climate change, combat pollution, and preserve biodiversity. (e.g., Gailhofer et al., 2021)

What is specific about the development of AI in the EU is that interventions aim to support the development of AI technologies and applications that are aligned with EU values and principles, such as respect for human dignity, privacy, and non-discrimination. So, the EU has also established a number of regulatory frameworks to address the ethical and societal implications of AI, including the General Data Protection Regulation (GDPR) and the EU AI Ethics Guidelines. These frameworks aim to ensure that AI is developed and used in a responsible and transparent manner, while also protecting the rights and interests of individuals.

As the use of AI-enabled services is considered as a key component for future European economic and societal development, the European Co-ordinated Plan on Artificial Intelligence (European Commission, 2021b) defines a set of clear objectives for regional and national policies and activities to foster AI uptake among the EU Member States. These longer-term European policy objectives are well-aligned with the OECD estimates on the impact of AI as an essential tool for work, innovation productivity, and skills for the economies of its member countries.

## PRIORITY ON THE ESTONIAN LEVEL

Estonia is generally characterised as a country with successful digital transition (Kalvet, 2012; Kattel and Mergel, 2019; Kattel and Raudla, 2022). Indeed, according to the regular topical reports, such as European Commission's Digital Economy and Society Index (DESI), Estonian achievements are considerable, especially on digital public services (Figure 1). For example, Estonia was the first country in the world to enable remote online voting in nationwide elections in 2005 and the share of e-voters has been on a rise ever since, although considerable discrepancies exist between the take-up and perceived success of e-voting vis-à-vis other e-democracy instruments (Toots et al., 2016).

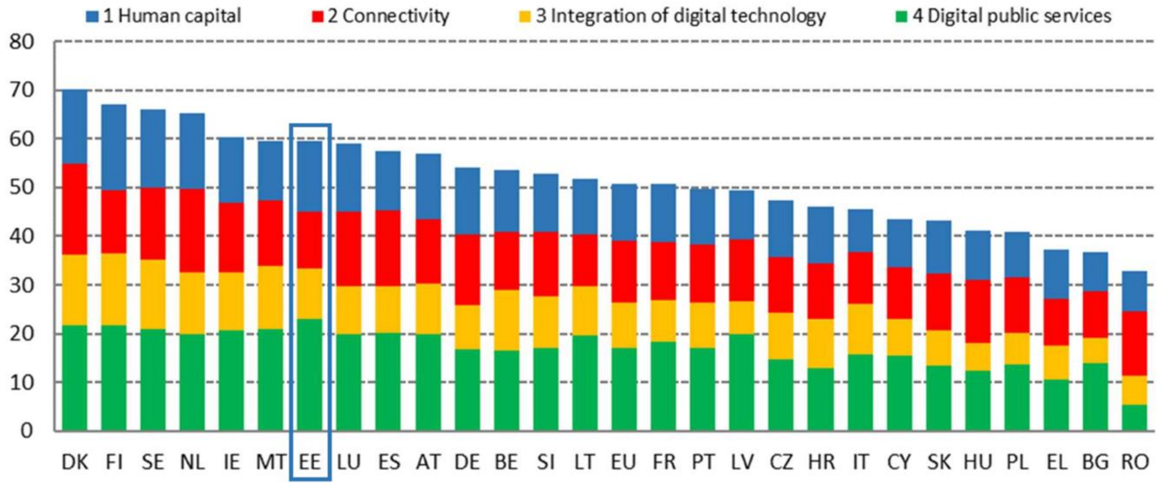


Figure 1. Digital Economy and Society Index (DESI) 2022 ranking (European Commission, 2022a)

While Estonia stands also out on the application of AI in the public sector, Estonia ranks 15th among EU countries on the integration of digital technology by businesses. There are significant differences between traditional Estonian companies that do not benefit from digital solutions and newer, highly digitalised companies (European Commission, 2022a). Only 3% use AI solutions (vs 8% in the EU) (Figure 2).

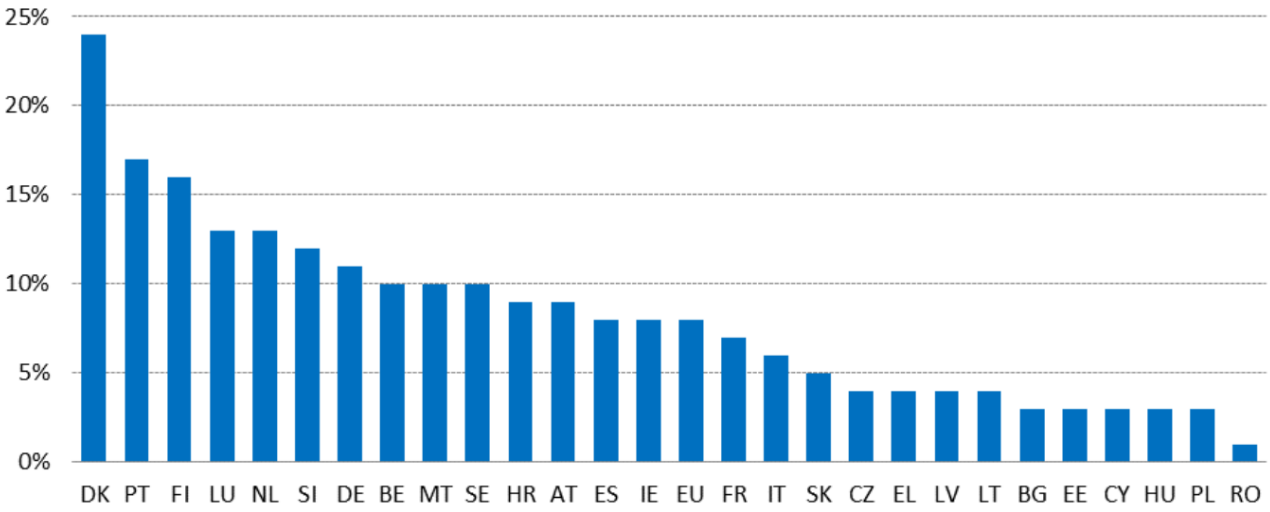

Figure 2. Enterprises using an AI technology (% of enterprises) (European Commission, 2022a)

To improve the situation, significant efforts are being made by all stakeholders. One key step takes is the development of a clear strategy for using AI. This involves identifying the specific business challenges and opportunities that AI can address, and developing a roadmap for implementing and scaling AI projects. Businesses are also encouraged and supported to invest in the necessary infrastructure and resources, such as data storage, processing power, and skilled personnel. This involves making investments in hardware and software, as well as training and development programs to ensure that employees have the skills and knowledge needed to work with AI technologies. AI has prominent position in the Estonian Research and Development, Innovation and Entrepreneurship (RDIE) Development Plan 2021-2035 (Estonian Ministry of Education and Research, 2022) and in the Estonia 2035 Strategy (Estonian Government, 2022). The National Artificial Intelligence Strategy (2022-2023) (Estonian Ministry of Economic Affairs and Communications, 2021) aims to promote the uptake of AI in both the private and public sector, increase the relevant skills and R&D base, and develop the legal environment necessary to promote the use of AI.

The latter is important to achieve that AI developed and used in a responsible and transparent manner. This may involve establishing clear policies and procedures for managing AI projects, as well as establishing ethical guidelines and oversight mechanisms to ensure that AI is used in a way that is consistent with the values and principles of the business.

Also, significant efforts are being made to foster a culture of innovation and collaboration that encourages employees to think creatively and work together to solve problems. This involves establishing cross-functional teams or working with external partners to explore new AI technologies and applications.

Concrete examples include the establishment of AI & Robotics Estonia (AIRE) technology hub dedicated to making Estonian manufacturing more competitive by helping businesses to introduce artificial intelligence and robotics solutions. AIRE is established and operated by key stakeholders in Estonia, and co-funded by the EU (AIRE, 2022). The Department of Business Administration is also running an "Industrial Strategy and Competitiveness Studies at TalTech" (TalTech Industrial, 2020-2023) action that brings together frontier research in data science, global value chains and business strategy. It is implemented in partnership with TalTech, Bocconi University in Italy, Aalto University in Finland and Nesta in the UK (TalTech, University of Bocconi, NESTA, 2022).

## CONCLUSIONS

Overall, AI has the potential to greatly improve business management by providing insights, automating certain tasks and processes, and optimizing supply chain management. However, it is important to consider the ethical and social implications of using AI in business, and to ensure that it is implemented in a responsible and transparent manner.

Overall, the EU is actively working to foster the development and responsible use of AI as a key technology for the 21st century. Estonia is also making progress, although significant challenges remain. The activities of AIBUS network and the conference (AIBUS, 2022) are important to increase awareness and improve networking.

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# Common use cases of AI-based self-learning manufacturing

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Key words: artificial intelligence, manufacturing, autonomous, self-learning

## INTRODUCTION

Artificial intelligence (AI) based self-learning manufacturing is a concept encompassing 1) artificial intelligence self-learning algorithmic strategies, 2) digital twins, 3) big data and sensor networks, and 4) robotic process automation into a finely tuned, highly efficient manufacturing system. Such a system can be compared to a philharmonic orchestra where numerous instruments are played in synchrony to each other, producing an optimized and unified output.

Self-learning systems are computer algorithms that are capable of learning from large databases and past experiences. Self-learning systems are also capable of performing tasks without direct programming, whereas mapping of all possible scenarios is not needed. By self-learning, these systems are intended to improve over time through their own experience and new data obtained by included sensor networks. Self-learning systems can even reach out to the external environment or the manufacturing ecosystem, extending beyond the production assembly.

AI-based self-learning is an emerging subdivision of artificial intelligence (AI) and of Industry 4.0. By learning from the past, the goal is to continually better the performance. This is done without relying on specific programming, which in case of traditional systems takes planning and time, as is done by human input and manual labour. Self-learning algorithms recognize patterns and can even make decisions on their own. This makes self-learning systems very capable of autonomously responding to changes in their operating environment and addressing different challenges on the shop floor.

By leveraging large volumes of data from sensor networks and elsewhere, the machine learning algorithms can effortlessly, in an unseeable manner run self-learning systems. These systems adapt to new, unforeseen situations and come up with solutions in real-time. In manufacturing, the self-learning technology can alter the way humans relate to machines. The autonomous manufacturing system is able to learn from its mistakes and improve the effectiveness of its own operations over longer time.

Today, AI-based self-learning has revolutionized the way manufacturing ecosystems work. By utilizing AI, manufacturers automate processes and make near real-time decisions based on the most recent data, even such as collected a few seconds ago. In today’s highly automated manufacturing ecosystems, AI-based decision-making is more efficient and precise than manual process management. AI-based self-learning makes it possible to optimize the entire production pipeline, by continuously monitoring and analyzing the data, while making even smallest adjustments, where and when necessary. AI systems can detect potential manufacturing problems and handle these before these manifest into production errors. Avoiding production errors is the goal of any manufacturing company, as these can become very costly and diminish the competitiveness of the enterprise. Additionally, AI-based analytics can help manufacturing companies to identify routes for improving production efficiency, optimizing material handling, while reducing waste. Manufacturing systems will increase production output and accuracy, while the entire manufacturing ecosystems becomes more profitable and sustainable. Hence, AI-based self-learning systems also contribute into the organization’s sustainable development goals.

Manufacturing systems of the future are autonomous, down to a complex level, comprehending what is unforeseen or unknown, unlike traditional systems which work by predefined instructions (Patel et al. 2018; Tavallaey&Ganz 2019). Autonomic function is achieved through a multitude of algorithms and theoretical models, which suited for autonomous manufacturing have already shown good performance (Fang et al. 2019; Wan et al. 2018). Many of the shop floor challenges can be adressed with knowledge-infused learning (Gaur, et al. 2016). Manufacturing process can be entirely decomposed into features of interests (FoIs), based on a stream of “manufacturing scenes”, that classifies events by their corresponding spatial and temporal attributes (Wickramarachchi et al. 2020, Crevier&Lepage, 1997, Vicol 2017). Streamed linked data provides storage and processing of continuous streams reflecting various states of the factory floor (Le-Phuoc et al. 2011, Kolozali et al. 2014). The afore mentioned enables updating the framework, both the physical and virtual components and to remove faulty/irrelevant segments (Tao et al. 2018).

Figure 1 depicts the components of AI-based self-learning manufacturing system. The company’s environment is divided into external and internal operating environments. The external environment is characterized by: 1) business environment, such as market conditions, labour availability etc; 2) logistic chain, of which the manufacturing company is likely deeply dependent on; 3) post-manufacturing processes such as sales, customer relations and public engagement and 4) sustainability criteria, as prescribed by the government, the industry, the customer base or the general public.

The manufacturing company's operating environment can be characterized largely by three categories: 1) operating systems framework, 2) the performance of said system and 3) the operational goals achieved by deployed system.

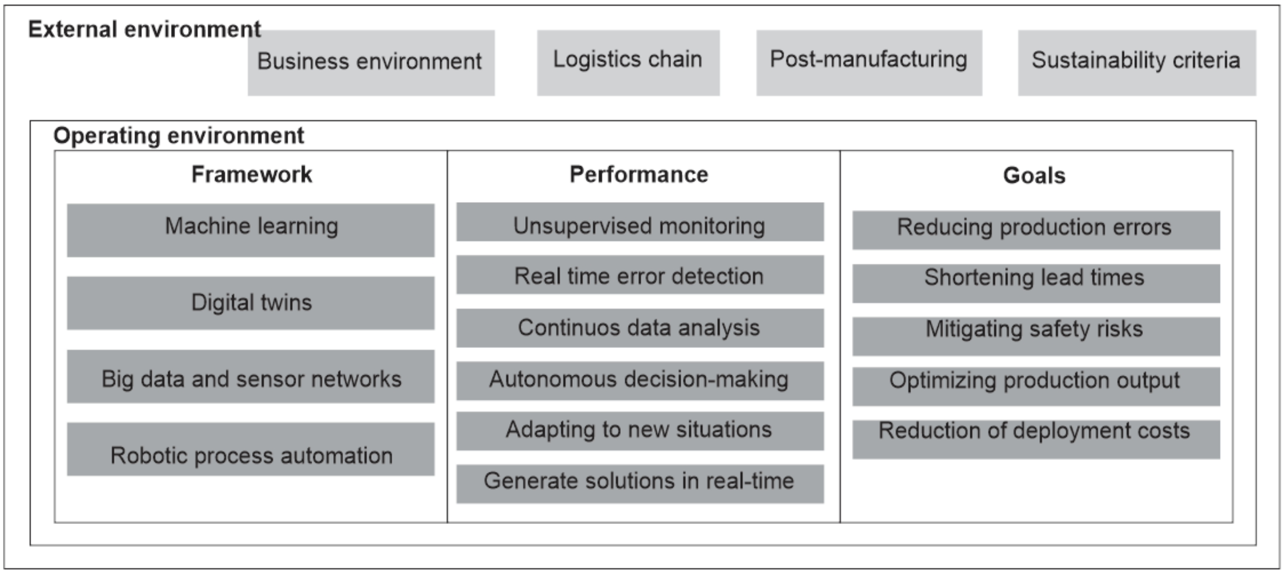


Figure 1. The components of AI-based self-learning manufacturing system

**Benefits of self-learning manufacturing systems**

Self-learning in manufacturing is becoming increasingly important in today's ever-evolving and highly competitive global market. Asian production is still cheap and capable of handling large volumes. European and American manufacturing companies are looking for new ways to stay competitive. Self-learning technology is one way to utilize both the regional and organizational innovation capacity and boost competitiveness. By doing so, self-learning platforms transform manufacturing processes to more efficient and cost-effective. Self-learning machines can optimize the production output based on real-time sensor feedback, but also account on other data. Removing the time delays and omitting the pre-training phase, will reduce the manufacturing assembly's deployment costs. Hence, by using self-learning systems, manufacturing businesses can reduce the amount of time and resources needed to train computers and enable them to carry out complex tasks without human intervention. Additionally, self-learning systems can help the management to streamline the data and henceforth improve decision-making processes. By making relevant data available, when and where its most needed, improves overall manufacturing efficiency, and reduces costs.

## SELF-LEARNING MANUFACTURING USE CASES

Manufacturing is one of the best-known use cases of self-learning systems. But AI-based self-learning techniques are applied in a variety of other fields, including medical diagnosis, autonomous vehicles and other areas. In manufacturing, there are a variety of AI algorithms offering different approaches to design and run self-learning systems. In practice, self-learning systems are most often based on,

- artificial neural networks,
- deep learning,
- evolutionary algorithms, and
- reinforcement learning.

Neural networks, deep learning and reinforcement learning are key enabling technologies, having centre role in discovering hidden patterns by analyzing data and deriving insights for smart decision-making and predictive analytics. Other concepts, such as semantic web, knowledge infused learning (Kursuncu et al. 2019), service-oriented architecture are also becoming standard for interoperability within industrial machines. Semantic web technologies are becoming increasingly important, like Reference Architectural Model Industries 4.0 (RAMI 4.0) standard for Industry 4.0 (Grangel-Gonmzales et al. 2016).

The main function of manufacturing self-learning systems is to detect anomalies in the production process. Additionally, self-learning systems can extend to the pre-production operations, such as logistics and material handling. This allows companies to take corrective action, when and where such action has the greatest benefit for the entire manufacturing pipeline. Self-learning models can also be used to improve product quality, by detecting defects early on. By taking advantage of self-learning technologies, companies can create a better and more efficient manufacturing environment, while also increasing the management processes.

The most frequent use cases of AI-based self-learning manufacturing are in **quality inspection, machinery calibration, predictive maintenance, and production monitoring.**

**Quality inspection**

Self-learning capable manufacturing edge devices can autonomously maintain quality control. In traditional production management, defects in production are common and abundant. Training a model to detect every defect is time consuming and sometimes even impossible. Some defect cases cannot be included in the training stage as new types of defects appear over time as the machinery suffers more from wear and tear. In traditional manufacturing operations, when an automated quality inspection encounters any new type of defect, they would not be able to detect it. These defects are unseen and pretrained inspection stations would not be able to detect it. Such miscalculations could lead to increased faulty product rate or breakdown of the assembly altogether.

**Machinery calibration**

Calibration errors are also widespread. Often, this error is corrected by overcompensating in direction of the error. In production, however this might not be a feasible and sustainable approach. Some manufacturing equipment, specifically robotic arms, are prone to positional errors due to robot maintenance or because of other reasons. On the other hand, self-learning devices are capable of detecting positional error and correct it by themselves. Hence self-learning systems prevent failures or robotic machinery collisions. This procedure cannot be trained beforehand as these errors differ dependent on the nature of movement and robotic arm paths.

**Predictive Maintenance**

Robotic health monitoring is crucial in many manufacturing applications. These applications include high precision processes, like welding, component assembly, material removal, drilling, riveting and other. Even great workload robots will show fatigue over time. The fatigue can reveal itself in diverse ways and often only shows up with experimentation and specialized testing. Experimentation can be time-consuming and also costly, considering large scale operations and how the production processes are tightly interconnected. A self-learning predictive maintenance system is capable of edge computing and can detect faltering equipment. AI edge device can identify both previously determined or undetermined fatigue symptoms. Fault detection runs simultaneously with the production process, hence reducing machinery down times. As undetermined symptoms can be detected by this approach, it doesn't require dedicating valuable resources for training such a system, before the actual production can commence.

The best example of such an autonomous manufacturing system is which prevents the breakdown of the entire factory. The system can even suggest replacement of a faulty sensor when discovering a new sensor with a similar functionality (Thuluva et al. 2017).

**Production monitoring**

There is a slow shift in manufacturing industry from the automated static process management to the dynamic and adaptable process management. The need to adaptively change the robot's action order has drawn attention as incidents can happen and do happen (Le-Phuoc, 2011). Monitoring of such processes must also be capable of recognizing the change in production sequences and assemblies. Traditional machine learning techniques require separate training sequence for each machine line assembly. Arranging separate training sequences in manufacturing is likely very costly. On the other hand, self-learning manufacturing devices are able to detect even the slightest changes in equipment performance. Changes in production parameters might be subtle and undetectable by manual or traditional automated monitoring. When detected by a self-learning system, autonomous decision-making may be applied to adjust operations.

Introducing autonomous manufacturing systems onto the shop floor, such as self-learning machine learning systems is not always possible. For example, the semantic web brings challenges on small and resource-constrained assemblies. Installing semantic web technologies onto resource constraint IoT devices has its challenges (Su et al. 2015). Traditional manufacturing management systems, such as those based on rule-based automation, might still be irreplaceable in certain manufacturing scenarios.

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# Industrial revolution 4.0 and development of industry 5.0: A theoretical perspective of interaction between human and machine learning environment

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**Abstract**

Aim: To examine the prospects of machine learning systems and its user ability in transformation of current industrial revolution 4.0. The subjective analysis of human interaction with machine and transfer of knowledge is the core objective of the content. The emphasis is on their capability to learn, understand, evolve and generate themselves in a self-mechanised automatization system.

Theoretical & methodological approach: For the purpose of research comprehensive literature and theoretical resources has been thoroughly analysed. The sources are selected on behalf of professional reports, scientific journals consist of empirical and conceptual research showcasing the origin of industrial revolution. Secondary research analysis comprises of terms “Industrial revolution 4.0 and 5.0”. The literature envisage methods of observation, cause and effect relationship, conceptual modelling and systematic description of contents.

Implications & limitations: The research encompasses industrial revolution and the future possibilities of on-going human interaction with machines taking 4.0 forwards to 5.0 sophistication. Preliminary advancements suggested mechanical engineering has the possible solution to human limitations. With the invention of artificial intelligence systems and augmented reality on the brink of shaping the future has opened many dimensions.

Originality & value: Various software and hardware systems can break through the divisions between the humans knowledge transfer and machine learning. In addition the benefits of technological advancement and integration of organisational systems will surpass all human and machine expectations. Alongside there are many future challenges and problems associated with cyber security and bridging the gap between inventions and its mainstream applications.

Research type: Literature review / Conceptual paper

Key words: Industrial revolution, Machine learning, Human interaction, Knowledge transfer, AI, AR

## INTRODUCTION

The ability of human beings to interact with machines and understand the potential of their efficacy will determine the outcome of continuous industrial evolution. At the moment it seems practically unimaginable that human beings will be replaced by future generations of advanced robotic engineering. The key factor is knowledge that can be transferred to the machines, so they can automatised themselves for making critical decisions (Franko *et al.,* 2020). Looking back in the past technological advancement has started taking its effect. Many inventions has created the technological process for mechanical production. The concept of smart factories, automated production lines, integrated assembly units have become a reality. By the end of 1980’s third of industrial revolution has set platforms for digitization (Petrillo *et al*. 2018). As far as human and machine interactions are concerned digital coding, digital information, communication exchange, application of internet and computer peripherals, automatizations and robotizations have revolutionised industry 4.0. Moving further on many new breakthroughs physical and digital systems will be replaced by cyber-physical systems (CPS) in the next couple of decades (Schwab, 2016).

## THEORETICAL PERSPECTIVE

The overall scenario in coming years seems more realistic than science fiction. The shift from 4.0 to 5.0 is quite precedented. Organisations have already started themselves to gear up with latest technological advancements (Upadhyay, 2019). The dependability on machines is ever increasing, so as the systems needs to be redefined. Many operational and functional stigma has been undergoing through transformation. The demand for high-quality, customised product and service delivery at the short span of time, cost factors and environment protection is very much the case. Sustaining innovation, integration of IOT, commercialization and challenges of streamlining the supply chain mechanism is very much on cards. The partnership between man and machine a d introduction of nano technologies pretty much sums up the next generation industrial revolution 6.0 (Prisecaru, 2016; Rymarczyk, 2012).

CONCEPTUAL PERSPECTIVE

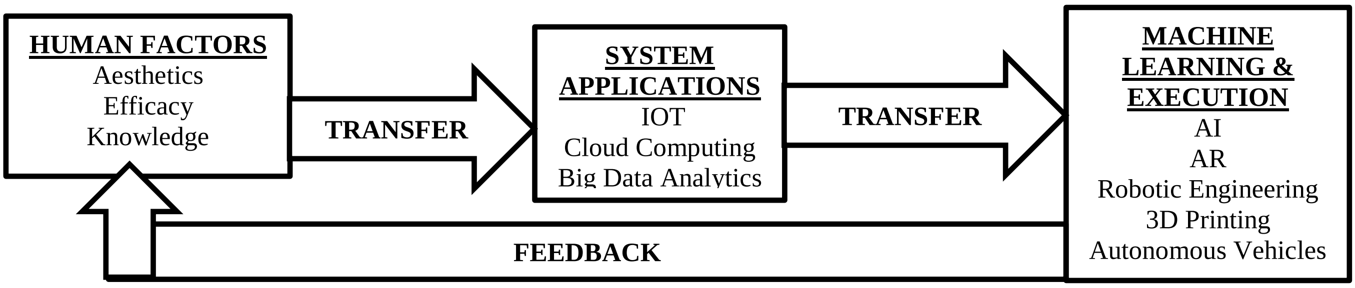


Figure 1. Human interactions and machine learning, (Author's own creativity)

**Human factors**

Human beings are on the top of the food chain and considered as the most intellectual breeds. They are known for their expressive nature, feelings, behaviour and individuality. They are most capable and advanced race which dominates the entire living organisms. They have extensive nervous system and complex functionality of brain able to produce desired effects. They generate extraordinary sense of understanding and store information in the form of learning, education and knowledge.

**Aesthetics**

Human aesthetics comprises of qualities, patterns and emptions. By and large these factors are more adjacent to human nature and selection. Aesthetics plays a major role in critical decision making (Liu, 2003). In industrial product design, designers use design aesthetics and relying more on "educated guess, talents or gut feelings in design decision making. Similarly product aesthetics are examined to develop purchasing decisions comprises of human buying behaviour and consumer market product category segmentation (Sewall, 1978; Holbrook & Huber 1979). Aesthetics are remotely related to human-machine-environment systems, human factors and ergonomics in enhancing safety, comfort and productivity during mechanical operations

**Efficacy**

Human efficacy or self-efficacy is directly influenced by the ability to produce desired effect. (Bandura, 1982) Explained the relation between individual's expectations of personal mastery and success. The outcome of expectations and the belief that behaviour can change the result by successful execution will have positive influence on the performance. (Bandura 1977) Defined the expectations is the most powerful determinant and positively correlated to self-efficacy.

**Knowledge**

In the context of learning and acquiring vital information that can be processed, transformed and transferred commonly referred as accumulation of knowledge (Tang, 2011). Knowledge is an extremely important factor that connects human interaction with machines. It has been a paramount discussion, how interpretation and communication takes place between human and machines, from sender to receiver have significant implications on functionality and operationality is concerned (Tsai, 2002).
(Fig:1.) The creation of support systems to facilitate knowledge transfer from human attributes to system applications is vital for the success of machine learning and execution, including aesthetics and efficacies.

**System applications**

System applications act as feeder for machine learning. Various sources such as internet of things (IOT), cloud computing, big data analytics helps machine to transform and develop indigenous capabilities. System applications provide information and instructions to machine. After accessing these instructions machine learns how to perform task that enables them to operate autonomously.

**IOT (Internet of things)**

Commonly known as network of things associated with process, people, products and integration of systems linked with the series of communication for review and constant feedbacks. It is a wide network of support systems, that process, collects and transmit online information (Deshmukh & More, 2016). The proposed idea is to develop big net of management that automatised and controls productions and distribution. It consist of web-net connectivity between factory, logistics, warehouse and customer support services. (Gubbi, *et al.*, 201).

**Cloud Computing**

A revolutionary idea where information can be stored and access from devices connected to internet. It offers unlimited user ability and accessibility from different places and not restricted to certain user platforms (Naha *et al.*, 2018). Key terms are servers, networks, operating systems, software and hardware applications, data storage, downloading and uploading.

**Big data analytics**

The data which can be widely used for specific purposes and have value attached to it, comes in large size requires proper screening, selecting, sorting, analysing and transferring (Osman, 2019). The big data associated with multiple large volumes generated and produced while common usage and operations, complex and variable in nature, comes in different formats text based, images, audio – video etc. Big data analytics are applied in medicine & medical health care, R&D, education & learning, business & production management, finance & risk assessments etc. (Pauleen & Wang, 2016)

**Machine learning**

Machine itself cannot learn on it own, it depending on instructions and knowledge feeded to its system. Machine then convert the information and use its central processing unit to follow the requirement of the job that is programmed to be done. AI, robotic engineering, autonomous vehicles, 3D printing and augmented reality are some of the prime examples how machine can transfer learning and knowledge into action (Rymarczyk, 2020).

**Artificial intelligence**

As the name suggest its about taking intelligent decisions, the ability of machine to assess the environment situations and devise customised solutions for more accurate results. The mechanism is designed to analyse learning and interpretation of knowledge based on instructions. Recognition of voice, alphabets & characters, image & texts translation are some of the unique qualities (Brock, 2018). AI can be applied in monitoring, reporting, solving technical problems, substituting human roles in customer services, developing campaigns and assessment of risk factors. It has radically changed the business functions & operations, innovation, enhancing more capabilities and increased value creation (Warwick, 2012).

**Augmented reality**

Commonly known as virtual reality has changed the way the things can be perceived, observed or view. It has created an ability to visualise the complex dimensions which are hidden from human eyes and experience. It is computer aided technology producing effect with the help of overlapping images and compilation of 3D or 2D. It enhances human experience by simplification of visualisation. It allows virtual access to invisible internal structure of subject, provides better orientation in locating object and in creating interactive training modules (Jung & Dieck, 2017). The augmented reality can be accessed through devices like smartphones, tablets, PC's, glasses, contact lenses also virtual retina displays. It is applicable to industrial design, construction, engineering, medicine, education and most commonly used in gamification (Rymarczyk, 2020).

**Robotic engineering**

Robotic engineering have revolutionised the concept of smart factories, often known as CPS (Cyber physical systems) are aided with computer technologies depending on the transfer of learning, knowledge and instruction loaded in the form of algorithms able of performing human physical operations (WEF, 2017). These machines are an acute example of artificial intelligence ability to work based on programmed information fed in their systems. They are quite capable of replacing humans when environment is not so conducive for them (Freeman, 2018).

**3D printing**

It is an instrument of printing the products with the application of many layers, materials such as thermoplastics, ceramics, metal powders, glass etc. Desired design can be acquired, complex products shape and size can be digitally printed. Advantages are usage of single material, ensuring strength and durability, accuracy of dimensions with wide variety of printing options. 3D technologies are used in production of machine parts, implants, clothing, footwear, weapons etc. opportunities are endless. It is cost effective, ease of use and customised products tailor made for consumers (Ramya & Vanapallis, 2016).

**Autonomous Vehicles**

They are the fleet of carriers and deliverers of produce within a specified area. They are responsible for mobility and transportation of heavy and light equipment's in production facilities fully operational and unattended by humans (Bagloee *et al.,* 2016). They have been used as intercity public transport, categorically comes under drones, air taxis, shuttle and tubes. Quite a few advantages of their operation are reduction in human errors and costs, efficient usage of fuel and electricity.

## DISCUSSION

It is hard to predict the future of industries. The revolution 4.0 has many pros and cons. The industries will constantly evolve and become self-sufficient. The concept of smart factory which was impossible couple of decades back is very well on its course to become reality (Sniderman *et al.*, 2016). The generation has already started working on intelligent factory systems and synchronisation of supply chain. The production plants of future will become automated and have the potency to correct errors and if possible works on no errors execution. By far it is very much possible to increase and regulate performance, adapt to new working conditions, saves time and reduce expenditure (Rymarczyk, 2020). Future development of 5.0 requires optimisation and integration of human physical athletics and digitalisation. The concentration will be on minimalization of material, energy and human time consumption. Corrective measures and assessment of activities created by systems and humans, flexibility in adopting autonomous process will be a priority. Streamlining supply chain and managing integration process of ordering, storing and distribution will be a vital cog in successfully automated transformation (Gregor, *et al*. 2009)

By adopting machine learning capabilities and measures it will help in ensuring better organisation & management, planning, monitoring & controlling, elimination of bottlenecks, more transparency and ready to use information for quick decision making (Mahesh, 2018). The more accurate measurements will ensure overall connectivity between devices, effective use of production space and time, transportation and logistics strengthening, improving design and remote operations covering maximum territory with an option of implementing predictive strategic control. Steady increase in the production of intelligent goods and services bound with higher quality, durability, superior functional ability by adapting these advanced technologies it will certainly enhances human user experience (Bkassiny, Li and Jayaweera, 2012).

Future advance intelligent systems will procure latest R&D opportunity, accelerating innovative systems application on industrial digital platforms, keeping a threshold of change in market demands and staying upbeat with customised consumer solutions and their grievances to rearrange replacements and making subtle changes to entire production cycle for better competitiveness. Not to forget the impact on environment and ecological balance and waste management will be handled more efficiently. The purpose is to secure better ways of satisfying human needs, wellbeing and improving the quality of life (Rymarczyk, 2020).

Every progress and development comes with some cost attached to it. There will be repercussions of industrial revolution 4.0 moving towards 5.0 (Stock and Seliger, 2016). Future job requirements will not be the same. It requires constant upgrading, raising bars of education and training, specified qualifications are more in demand. The gap between low and highly skilled labour will multiply, there will be urgent need of change in course curriculum, schools, colleges and university have to rethink and create more job opportunities for the future predicted and unprecedented trends (Rymarczyk, 2020).

Downsizing will be the biggest problem ever faced by humans, created by automation, AI and robotic engineering in assembly lines and in construction followed by jobs in commerce, administration, healthcare, call centres will soon be replaced by machines. Most of these jobs will undergo transformation or requires adaptation to work with machines standing next to them. Technical jobs, IT specialists, programmers, game developers, software and hardware engineers, planners and analysts, physicist and mathematicians, robot and machine operators will be more in demand and requires more flexible and adaptive approach to gear themselves for 5.0 (Manda and Dhaou, 2019; WEF, 2016). Alongside traditional management methods, it will create complex scenario. Low level of understanding, unreadiness for future challenges, in quest for technological substitution related to machines and software applications, slow pace of development, lack of clarity in legislation, standards, norms & certification, cyber attacks & espionage might hinder the progress (Schwab, 2016b).

In the name of marketing and advertising IOT's, constant internet connectivity privacy violations will become very common. Machine will store more than human can imagine about themselves, their aesthetics, behaviour, preferences, choices, online transaction & bank details, location will be utilised to offer them personified products and services (Yamamoto *et al.*, 2016; Rajabi and Hakim, 2015). Globally economies will be segregated and divided, it is assumed those who can afford industrial revolution 5.0 will become more advanced and rich as compared to those who are still using traditional methods of production. Brain drain, insourcing, talent loss will further deteriorate poor economies, destabilization and internal tensions will result in mass migration (Rymarczyk, 2020). Intellectuals, philanthropist, investors a total of less than five present of total population will control maximum wealth and surplus continuous to grow and become more stronger. They will have the power to change the future course of action and chances are Government might become powerless and lose control. Cyber and hybrid wars seems to be a reality motivated by financial gains, international conflicts, terrorism, sabotage cybernetic operations, production of new arms and ammunitions, use of AI, robots and biological wars might become very common (Thomas and Buchanan, 2015).

## CONCLUSIONS

Using technology can be a boon can be a disadvantage. Human race need to decide at what cost industrial revolution 6.0 can be achieved. As far as human and machine interactions are concerned lots of questions needed to be answered. There will be challenges and plenty of opportunities related to machine learning and knowledge transfer. Human factors in sync with system applications and machine learning is still in very much contention and evolving ever since industrial revolution 4.0 (Rymarczyk, 2020). The scepticism of using excessive machinery and redundancies of current working population is very much achilleas heal. Future predictions and how is it going to change the human existence on planet earth is still undecided. Forecasting and observations in the field of science can be debated. Whether we start changing the methods of production now or shall we waite for complete transformation to occur, there will be dilemma for small business to make this decision and shift requires heavy capital investments. Will this be the case with 4.0 moving towards 5.0. Economist and scholars 10 and 20 years down the line still cannot predict accurately

(Wilkesmann and Wilkesmann, 2018). Catastrophic events, bleak scenarios, smart machines & factories replacing humans seems inevitable. Taking in account of past 20 years the way production has been managed and moving forward to 5.0 will change dimensions. 4.0 based on previous scientific achievements surpass all its technical capabilities to 5.0 (Seo-Zindy, 2018). Impact on social, morale, cultural, political and ethical, values, belief will remain uncertain. Generations across 4.0 to 5.0 heading towards 6.0 in sight radical & demographical challenges and changes, environmental conservation & degradation, geopolitical scenario, cultural and behavioural acceptance, preparation for incoming threats, being vigilant will decide the future.

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# The implication of Artificial Intelligence based systems and human interactions in the workplace

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Key words: Artificial intelligence, 4.0 revolution, algorithms, algorithmic management, worker's performance

## INTRODUCTION

Industrialization has created an urgent and growing need for labor market, to keep worker's health and safety environment. The prominent goal of fourth industrial revolution is to allow manufacturers to meet this rapidly changing demand more effectively and comprehensively utilizing adaptive and responsible machinery. (Adel Badria Bryan Boudreau-Trudelc, 2018) In many industrial regions, workplace development has changed it course and switched to sustainability focused, where attention has been paid to enhance safety and health-oriented culture in the workplace. Constant developments in organization design, technological job displacement and changes in the workplace are influencing the whole work environment. Emerging technologies will create new jobs and these new industries may present in the pace between jobs being lost and certain times to acquire new, required skills. As a good example can be assumed "gig" economy, where individuals are self-employed through online platforms and provide various services. (ara L. Tamers PhD, 2020) The use of advanced technologies in the workplace may lead to more blurred boundaries between work and private activities. (Gabriele Giorgi, 2022) The adoption of artificial intelligence techniques at work will absorb, menial, routine and dangerous tasks and workers who remain employed will have preference to highly paid and appreciated jobs. However, as the adoption of artificial intelligence tools are able to automate some tedious tasks, it will also increase the possibility of management of extensively monitoring worker's activities. (Stefano, 2018). The paper aims to investigate the interaction between artificial intelligence and human interaction in the workplace, its positive sides, and drawbacks.

## METHODOLOGY

The paper was based on systematic literature review. During the first stage the research question was formulated, then research plan was developed, including the research questions and keywords. We specified the following inclusion criteria: all years, articles/reviews, English language and full text in the Web of Science, Scopus databases and Google Scholar. In parallel, we produced an excel data sheet consisting of criteria relevant for establishing the current body of knowledge. Excel data contains date of publication of journals, articles, research, discussion papers and reports. Also, research method, theoretical aim, and the main findings. The oldest article was published in 2010 and the most recent in 2022, January. Stages are shown on the figure.

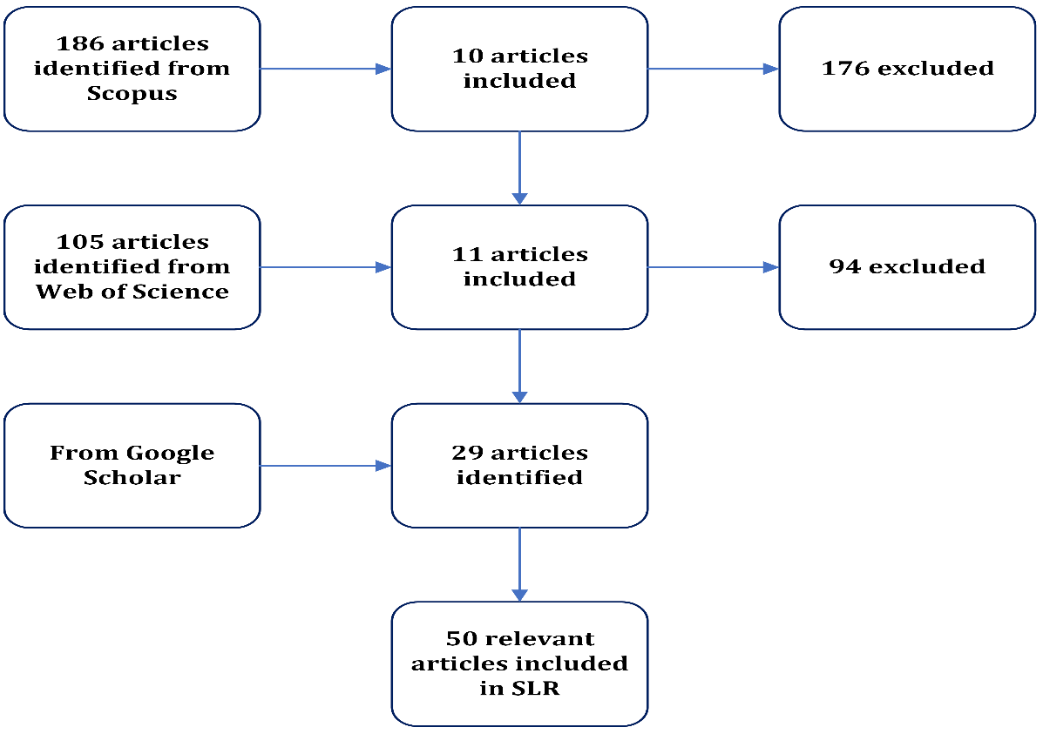


Figure 1. Research procedure

**Searches with keywords**
**Scopus-**„artificial intelligence" OR "algorithmic" OR "digital" AND "worker well-being" OR "well-being at work" OR „workers' health" OR „workers safety"
**Web of Science**-Artificial Intelligence and workers health and safety, Algorithmic management, and worker's health, AI based systems, wearable technologies, worker monitoring
**Google scholar**-AI and work management, Artificial intelligence, Algorithmic management

## DISCUSSION/CONCLUSION

Notwithstanding the fact the adoption AI devices in the workplace has various implications, the fact remains that it raises new emerging jobs, along with diminishing previous job positions. One of the obvious examples may admitted gig economy, online platform work, where workers have the possibility to choose the shift or jobs they take and, in some cases, where and when to work. (Kathleen Griesbach, 2019) At the same time Artificial intelligence based management can be more time consuming, flexible, and comprehensive in some ways, however it still needs to be well-established and accepted by the employees. Because in some cases AI based solutions gradually decrease the interpersonal and empathic aspects of management. (James Duggan, 2019) Hybrid intelligence (AI and Human intelligence collaboration) can combine best of both worlds. BPM requires to consider HI and boundaries, between work done by people and work done by software robots. (Aalst, 2021)Technology is not inherently good or bad, but neither is it neutral "So, the regulation and public policy has its pivotal role in order to solve the issue of inequalities. With strong worker's rights protections, advanced technologies can be put in the main role as creating vibrant and strong, thriving economy, with safe workplace, race, and gender equity. (Annette Bernhardt, 2021)

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# Digital Twin: Cherries and Yield Management using AI and UAV

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Key words: artificial intelligence, digital twin, orchard management, precision agriculture, smart farming, UAV

## INTRODUCTION

Smart farming leverages modern information and communication technology to advance high yield, cost-effective and sustainable agriculture through collection of data on environmental parameters, smart processing of the data and other activities that support data-driven decision making. Such smart farming services can be achieved via application of unmanned aerial vehicles (UAV) for data collection activities and artificial intelligence (AI) for data processing.

A digital twin is a virtual representation of a physical object or process capable of collecting information from the real environment to represent, validate and simulate the physical twin's present and future behaviour (Botín-Sanabria et al., 2022). It is a key technology of modern data-driven decision-making for complex system management based on industry robotization.

Our project lzp-2021/1-0134 is directed to develop a digital twin for orchard management, which is based on application of UAV and AI. At this moment, we are developing a user-centred design which is oriented to satisfy horticulture specialists' needs for an autonomous monitoring system and to help them in decision-making.

Aim of study: to design an enterprise model of orchard management, which supports the digital twin concept and provides autonomous garden monitoring.

This study is scoped with subjects: cherries and yield management based on orchard monitoring using UAV.

## METHOD

We applied an enterprise modelling method called ARTSS (Stirna et al., 2020) to achieve the aim of study. Enterprise modelling methodologies are sets of defined rules, notations, assumptions and perspectives on describing business or information system (IS) models. Typically models are created to describe business goals, business processes, concepts or actors as parts of IS. ARTSS is a branch of Capability Driven Development (CDD) (Grabis et al., 2018). It is a context and capability based methodology, which represents capabilities of business or IS to overcome business problems. Enterprise modelling is based on brainstorming and domain expert involvement.

The stages of plant phenology used in the model development were described according to BBCH scale (Bleiholder et al., 2018; Meier, 1997) . The flowering intensity was estimated in the scale from 0 (no flowers) to 9 (all fruiting branches are abundantly flowering).

## RESULTS AND DISCUSSION

The developed capability model of the digital twin is presented in Fig. 1. Meanwhile, Table 1 provides a list of adjustments to support data driven decision-making of digital twin users.

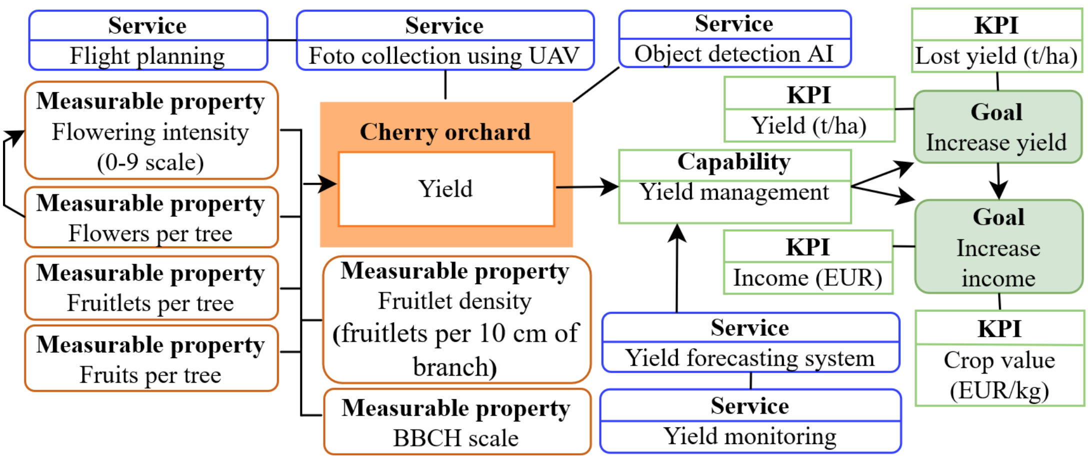


Figure 1. Capability model of yield management using UAV and AI.

Table 1. Adjustments for cherry orchard management

| Measurable properties | Capability | Adjustment | Impact on KPI* |
|---|---|---|---|
| Flowering intensity > 5 | Yield management | Protect flowers from spring frosts (when forecasted) by active protection measures (heating, watering, spraying, covering etc.). | Decreases lost yield & increases yield. |
| Fruitlet density ≥ 6 fruitlets per 10 cm of branch & BBCH = 72 (sepals beginning to fall) | Yield management | Provide the nutrients and water for the trees near the optimum level by additional irrigation and leaf fertilizing until the harvest. | Decrease of lost yield (dropped fruits) & increase of high-quality yield. Increases crop value. |
| BBCH = 75 (fruit about half of final size) | Yield management | Assess the expected yield, plan harvest organisation & fruit sale. | Decreases lost yield (over ripened, rotted fruit) & increases income. |
| BBCH = 81 (beginning of fruit colouring) | Yield management | Protect yield from bird (covers, bird repellent devices) | Decreases lost yield (bird damaged fruit) & increases income. |
| BBCH = 87 (fruit fully coloured) | Yield management | Test the fruit taste and firmness, and start to harvest. | Decreases lost yield (over ripened, rotted fruit) & increases income. |
| Flowers/ fruitlets/ fruits per tree | Yield management | Prognosing harvest organisation, fruit sale and orchard management for next season. | More stable and predictable productivity, increased crop value and income. |

* - key performance indicators

The developed capability model presents the orchard digital shadow, which provides a functionality to monitor orchards remotely using UAV, where yield estimation is achieved using AI. Speaking about modern solutions of AI, measurable properties like flowers, fruitlets and fruits can be detected using convolution neural networks (CNNs) with architecture like YoLoV5 or YoLoX.

The vertical development of the designed system can be trustworthy AI, which is the future challenge considering industrial evolution from Industry 4.0 to 5.0. However, this direction mainly depends on the scientific revolutions in the field of AI.

The horizontal development is more perspective as a trade-off between awaiting research and existing solutions. Autonomous harvesting and spraying by using UAV can be mentioned as trending development vectors.

## CONCLUSIONS

We designed the digital twin for cherry orchard management using an enterprise modelling method called ARTSS and presented six adjustments for data driven decision-making. In the future, we plan to extend the capability model with scab detection and other fruits like apples and pears.

**Acknowledgments**

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# Artificial Intelligence and Automation in Occupational Risk Analysis at the Modern Manufacturing Operations: Literature Review

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Key words: artificial intelligence, automation, health, manufacturing, risks, safety

## INTRODUCTION

Digital technologies play an important role in our daily lives as well as in our workplaces. Implementation of new systems and technologies, such as artificial intelligence (AI) or improved robotics, can change a number of aspects of human work planning and execution (European Agency for Safety and Health at Work, 2022). There is growing evidence of the use of artificial intelligence in the workplace in all sectors to simplify and / or automate tasks, but there is still limited understanding of the role of AI in occupational health and safety (OHS) system (Pishgar et al., 2021).

In order to be able to assess the new risks in the work environment in the manufacturing sector, it is necessary to understand the importance of new technologies, how it can change work environment and how affect employees at the work. Considering the development of process automation and the impact of Covid-19 on changes in work organization, the main challenges are connected with new forms of employee management through AI-based systems, work on an online platform, new systems for monitoring employee safety and health, improved robotics and AI-based systems for the automation of tasks and their interaction with the physical and mental health of workers, the assessment of new risks to the working environment, and possible problems related to changes in the qualifications of workers (European Agency for Safety and Health at Work, 2022; Goos & Manning, 2007; Goos et al., 2009).

The aim of the study is to analyze and point out main conclusions from the current scientific literature on artificial intelligence and automation in occupational risk analysis at the modern manufacturing operations.

## METHOD

An analysis of the literature was performed. Scientific articles by various authors as well as EU OHSA reports were analyzed. Such keywords were chosen for the initial analysis of the scientific literature: artificial intelligence, automation, manufacturing, occupational health and safety and altogether 19 articles from 45 were selected for the study.

## RESULTS AND DISCUSSION

The field of artificial intelligence (AI) is expanding rapidly and its use can be seen regularly in a number of well-known and important industries, such as healthcare, manufacturing and education. Although there is growing evidence of the use of AI in the workplace in all sectors to simplify and / or automate tasks, there is still a limited society understanding of the role of AI in occupational health and safety (OHS) system and risk analysis and prevention (Pishgar et al., 2021). The implementation of new systems and technologies that include artificial intelligence (AI) or advanced robotics has the potential to change a number of aspects of the way how human works. Workplace automation and employee interaction with these systems need to be further explored to address new risks and highlight health and safety impacts (OHS) and interaction of new risks in the work environment (The European Agency for Safety and Health at Work 2022). The development of artificial intelligence and automation is focused on the performance of specific tasks rather than changes in the entire work process (Parker & Grote, 2020). In the context of automation processes, workplaces are viewed from two perspectives, i.e., physical tasks and cognitive tasks, in which the risks associated with AI appear. Physical task analysis involves automation of equipment, robotics, sensors, actuators, use of materials, workload reduction (e.g. lifting weights), reduction of hazards in specific work areas now performed by the equipment, but this does not mean that the work process will not require employee presence (IFR, 2018; Goos & Manning, 2007; Goos et al., 2009). Traditionally this is understood that automation and robotics are types of work where the environment is hazardous or heavy loads must be lifted and are designed for speed and accuracy. These systems are mainly found in fully automated production. Systems with lower payloads as well as new generations of sensors and actuators have allowed the emergence of innovative types of robots (European Agency for Safety and Health at Work, 2022; Bauer et al., 2016). In addition, industries uses AI to solve a variety of other problems, such as decision-making (Akbar et al., 2016), environmental monitoring (Delabrida et al., 2015; Ding et al., 2011), lower operating costs (Shukla & Karki, 2016) and increasing productivity (Belforte et al., 2006). The second aspect is cognitive tasks, which are understood as exposure to the work process with information technology (e.g. 5G networks capable of providing incredible processing power), digitalization of equipment, use of software, learning, etc. aspects focus on different automation software. But the manufacturing sector is more focused on the physical approach – automation and robotics (Hämäläinen et al., 2018; European Agency for Safety and Health at Work, 2022). There are significant difficulties in production, as most day-to-day tasks are performed by automated systems, while assigning complex and changing tasks to employees, resulting in the increased cognitive workload, which can affect both human and production performance (Bannert, 2002; Lindblom & Thorvald, 2014; John, 2019). The integration of AI-based systems and advanced robotics can provide significant positive opportunities for workplace progress and productivity growth, as well as OHS. However, important OHS issues can also occur. Stress, discrimination in human resource decision-making and work intensification, as well as job insecurity and possible job losses, are some of the risks that employees may face (European Agency for Safety and Health at Work, 2022). The integration of new technologies and equipment in the workplace can increase these stressors and has already been shown that it especially poses psychosocial risks (Moore, 2018). These risks increase when artificial intelligence complements existing technological tools or is reintroduced in workplace management and design. Nowadays OHS recommends the use of a new system called Risk Evolution, Detection, Evaluation, and Control of Accidents (REDECA), which highlights the role of AI in assessing new risks by anticipating and controlling exposure risks in the worker's environment (Pishgar et al., 2021). Artificial intelligence (AI) is a broad and diverse field of research that has infiltrated all aspects of our lives and has become crucial over the years (Perrault et al., 2019). In general, artificial intelligence is the ability of a computer to process information and produce results that imitate how a person learns, makes decisions, and solves problems (Howard, 2019).

## CONCLUSIONS

AI-based systems and advanced robotics are not entirely new, but the increase in computing power in recent years has led to a huge increase in the availability and performance of AI-based applications. The development of technology has a significant impact on OHS, as the work environment is changing and so are the risks at work. Employees are mostly subject to cognitive strain, as they need to be able to work with new equipment that is equipped with a variety of programs that employees often do not fully understand. This results in mental overload and a higher risk of accidents. It should also be mentioned that not all production facilities automate the entire work operations, but the automation takes place at one of the stages of production, which does not completely eliminate physical activity of a human. A new REDECA system is available to identify the risks associated with AI, which highlights the role of AI in anticipating and controlling worker exposure risks.

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## Digital Business Foresight: Keyword-Based Analysis and CorEx Topic Modeling

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**Abstract**
While previous research develops big data tools to identify weak signals of technological and business changes, we lack an understanding of how to link weak signals with new business concepts and use them to evaluate performance of startups in an automated way. To address this research gap, we analyze the business description of digital companies extracted from the CrunchBase metadata and use a keyword-based text mining approach to collect business-related weak and strong signals for the period 2010-2016. We, then, employ term frequency-inverse document frequency (TF-IDF) to measure the importance and relevance of weak/strong signal keywords for subsequent business development and utilize Correlation Explanation (CorEx) topic modelling to link weak/strong signals with business concepts of startup companies founded from 2017 until 2020 time period. The ANOVA statistical method is also employed to study the relationship between weak/strong signals and the performance of new businesses. The results show no significant difference between startup companies operating in weak and strong signal related business areas in terms of acquiring venture capital funding and estimated revenue range. Moreover, we examine industry and technology profiles of startup companies by using word co-occurrence analysis and study in which sub-sectors they bring digital technologies across selected European regions. Finally, we discuss the implications of the study for strategic planning and investment policy at the firm and regional levels.

Keywords: Digital technologies, business foresight, weak signals, startup, innovation, regional specialization, entrepreneurship, text mining, CorEx topic modelling, co-word analysis.

# Greencarrier Freight Services Estonia OÜ Finnish department price inquiry tool

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Key words: pricing, chatbot, Greencarrier, transport, transport prices, Estonia, Finland.

## INTRODUCTION

This paper has been prepared by Fred Baranov, Artur Toikka, Jüri Asper, students of management and marketing at Tallinn University of Technology. The work focuses on submitting and responding to price inquiries for Greencarrier. We will try to improve this process so that it requires fewer movements from the logisticians and uses less time for employees at Greencarrier office. There is intense competition in the transport sector due to the considerable number of transport providers on the market. Due to the presence of many transport providers, prices on the market are very even, which creates favorable conditions for customers when it comes to argumentating over price.

In order to achieve a time win in the process of asking for price inquiries, it would be useful to use the help of digital solutions, which would save both the customer and Greencarrier's customer service representatives' time. By reducing the burden on Greencarrier employees, transport managers would be able to deal more with cargo planning rather than the additional activities that come with them. The pace of work depends on the transport distance and the volume of the established interstate freight connection. The work is based on speeding up the price enquiry process of the Finnish department, as one of the co-authors works in the Finnish department of Greencarrier, historically Estonia has the busiest and most extensive trade connection with Finland. The distances between the two countries are small and ferry connections and competition in this direction of transport are tight.

Greencarrier Freight Services Estonia OÜ is a significant and well-known service provider in the Estonian transport sector. The main transport routes are Finland, Scandinavia, the Baltics, Germany, the Netherlands, Belgium, Italy. As of May 2022, the company employs 41 people, 10 of whom are related to the Finnish department. The company has at its disposal more than 150 semi-trailers, two tailgate trucks and about 100 semi-trailer trucks in the form of a service outsourced by subcontractors. Greencarrier is part of the Italian – American joint venture Jas Worldwide, whose main activity is the provision of maritime transport.

This topic is up to date because it is a real concern, to which a solution is being made in the form of a chatbot or virtual agent with a digital solution. Based on Greencarrier's data, the monthly turnover of Finland and the Baltics is approximately 700,000 euros and they have about 2,000 transport orders every month. This represents about a third of the company's total turnover. As a result of the creation of the solution, it is assumed that the waiting time for customers upon receiving a response to the price request will decrease, and in the case of the employees of the company, it will not have to be dealt with so much in the preparation of price inquiries.

## DESCRIPTION

In this section, we describe the current price enquiry process in the company. The process begins with the customer having a transport need and going through several activities until the customer's transport needs are satisfied. Now, the customer must select the transport providers that suit them and send them e-mails. Each company's logistician or customer service representative must open the e-mail and respond to them with a price and usually tell customer if they have possibility to offer such transport. The customer's first email does not always have all the necessary data to create a quote. In the absence of the necessary data, an employee of the transport company sends an e-mail to the customer to ask for the missing data. The customer responds again with the missing data, to which the employee of the transport company searches for the price, prepares a price offer and waits for the customer's answer as to whether the price is suitable for him or not. An offer with an unsuitable price is rejected by the customer and there is no transportation with this particular company. Otherwise, the customer will confirm the quote, the customer service representative will check the final data and enter the order into the company's system Cargowize and to the planning list, which is located in Excel. After that, the logistician begins the search for a transport solution, after finding a solution, the customer is informed of the truck numbers and the transport of goods takes place at a given time. After the work has been carried out, transport documents will arrive from the carrier, which will be added to the order in Cargowize. At the last stage, the billing agent sends the customer an invoice together with the transport documents confirming that the goods were transported and that the goods have not been damaged (Fig. 1).

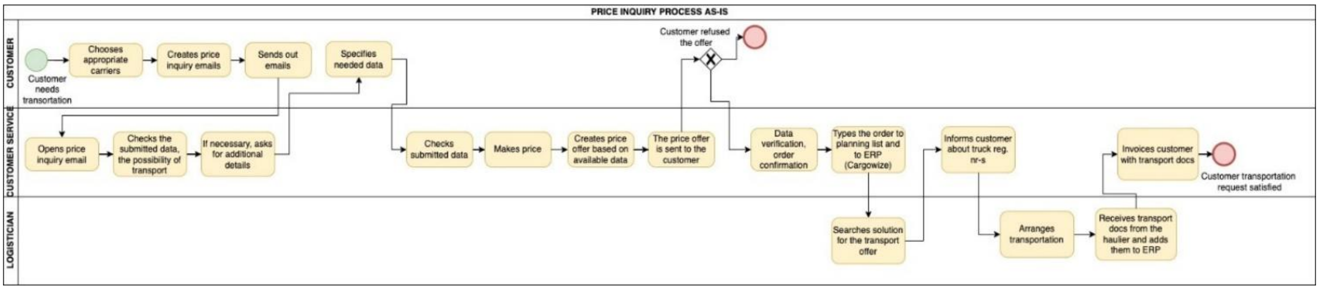


Figure 1. AS-IS price inquiry process

As a result of improving the process of answering price inquiries, the process should be faster for both the customer and the Greencarrier employee. In addition to the time gain, there is less risk that a person will be sent out to the customer due to an error, not an adequate price. Due to the too low price, the transport company may lose money after carrying out the transport, due to the excessively expensive price, the customer may not be able to place an order, because the transport price on the market is lower.

Inevitably, customer service providers must use several price lists in the transport company because there are several directions of transport and it is difficult to foresee the wishes of customers. Manufacturing companies have several partners abroad who supply components to them or production companies export finished products to their customers.

The process of submitting improved price inquiries developed by the authors should be faster in time, because the client can ask questions to the chatbot at a time of their own choosing, and he will also receive a specific answer. The improved process begins with the client using the Greencarrier chatbot and entering the data requested by chatbot into it. The virtual agent constantly responds to the submitted data, and upon receiving sufficient data, forwards the client a response with the price. It is then up to the customer to decide whether or not to accept the offer. In the case of a negative answer, the process ends. Otherwise, Greencarrier's customer service will check the data of the transport order, enters the order to Cargowize and to the planning list. At the same time, the logistician begins searching for transport options for the goods, when finding a possibility, the customer is informed about the truck numbers and transport is carried out at a time convenient for the customer. After the transport has been carried out, the transport documents are added to the specific shipment in Cargowize and the billing agent submits the invoice to the customer together with the transport documents (Fig. 2).

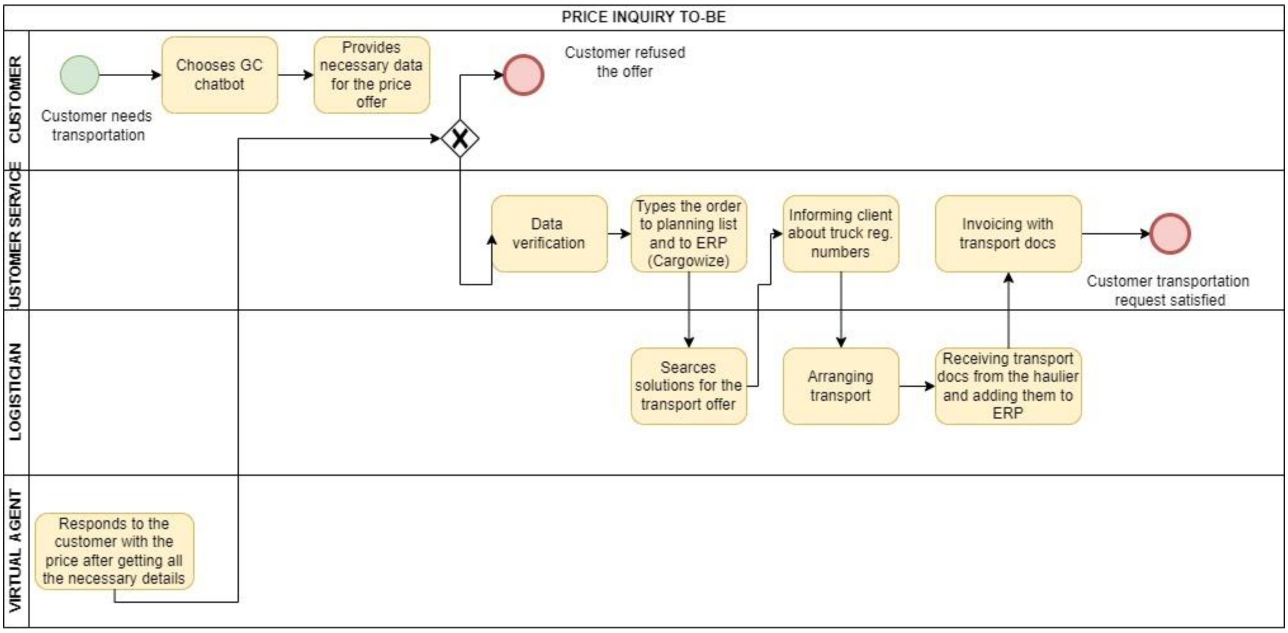


Figure 2. TO-BE price inquiry process

## METHOD

We intend to validate the solution using a questionnaire that is filled in by both Greencarrier company employees and customers, in total we expect to receive 30 responses, half of them should be from employees and other half from customers. The authors compiled a questionnaire on the Google Forms platform, it was sent out via emails. In order for the questionnaires to be more personal, authors prepared separate questionnaires according to the respondents.

Employees responded to the employee questionnaire, customers in turn responded to a questionnaire given to customers. There were 12 questions in the questionnaire aimed at employees and 14 questions in the customer questionnaire. The first part of the questionnaire asked ordinary questions related to the workplace and the number of placing or receiving orders. The second part of the questionnaire asked for an assessment of chatbot's work, where the respondent had to assess specific conditions in the 5-point system.

A virtual Agent was created using Dialogflow platform. Chatbot asks the user questions to find out the details of his transport needs. The prerequisite for chatbot to start working is that the user initially writes a greeting, after which the chatbot begins to ask the user the questions that are necessary to submit a price request. After getting all the needed parameters (from city, to city, date of shipment) Dialogflow connects to the API endpoint made using SheetDB which creates API endpoint of Google Sheets. This API endpoint returns the table int the form of array written in json format. Fulfilment in Dialogflow enables inline code editing where is possible to create functions which will be executed when particular intent is triggered. By the time user reaches intent, which triggers function which sends GET request to the API endpoint to get the price table (Fig. 4), user has already provided necessary data for price calculation. User entered data is stored in the Dialogflow Context as a parameter which can be called from code. After getting the array of the sheet, function has mapping and sorting functionality to get the right value from the cities distance table (Fig. 3). When right value is retrieved virtual agent sends message to client with details of the order and the price for shipment and asks if user wants to place an order.

| From | To | Dist |
|---|---|---|
| Tallinn | Tartu | 180 |
| Tallinn | Narva | 170 |
| Tartu | Tallinn | 180 |
| Tartu | Narva | 200 |
| Narva | Tallinn | 170 |
| Narva | Tartu | 200 |

Figure 3. Distances from each city

```
function givePrice(agent) {

  const fromC = agent.parameters.fromCity;
  const toC = agent.parameters.toCity;
  const ldm = agent.parameters.ldm;

 return getSpreadsheetData().then(res => {
    res.data.map(d => {
      if (d.From === fromC && d.To === toC)
      agent.add(`${ldm} ldm cargo freight price from ${fromC} to ${toC}
      would be ${parseInt(d.Dist)*parseFloat(ldm)/5} euros. Do you want to place an order?`);
    });
  });
}
```

Figure 4. Parsing price table

If user respond is positive so he wants to place an order, then virtual agent asks when does client want to send the shipment and adds an order. Order is added also by the Fulfilment function which takes all the user entered parameters which were sent through the intents contexts to the final intent. Parameters are retrieved from virtual agent context and sent to the API endpoint in the form of POST request (Fig. 5).

```
function addOrder(agent){

  const orderNr = Math.floor(Math.random() * 1234);
  const ldm = agent.parameters.ldm;
  const from = agent.parameters.fromCity;
  const to = agent.parameters.toCity;
  const date = agent.parameters.date;
  const name = agent.parameters.name;

      return new Promise((resolve, reject) => {

        if (orderNr) {
        axios.post('https://sheetdb.io/api/v1/lhiwapor90knk', {
          "data": {
            "ordernr": orderNr,
            "ldm": ldm,
            "from": from,
            "to": to,
            "date": date,
            "created": new Date(),
            "name": name
          }
        });

         agent.add(`Your order nr ${orderNr} has beeen placed!`);
      } else {
        agent.add("Something went wrong, try again!");
      }

      resolve();
    });
  }
```

Figure 5. Data sending to API endpoint function

As a result of this function the data is written to another table, where are the added orders (Fig. 6).

| ordernr | ldm | from | to | date | created | name |
|---|---|---|---|---|---|---|
| 932 | 16 | Tallinn | Tartu | 2022-06-02T12:00:00+03:00 | 2022-06-02T20:09:52.366Z | Artur |
| 1188 | 13 | Narva | Tallinn | 2022-06-04T12:00:00+03:00 | 2022-06-02T20:14:40.390Z | Artur |
| 643 | 5 | Tartu | Tallinn | 2022-06-03T12:00:00+02:00 | 2022-06-03T08:11:26.971Z | Eneli |
| 1186 | 5 | Tallinn | Tartu | 2022-06-03T12:00:00+02:00 | 2022-06-03T08:11:57.747Z | Fred |
| 1166 | 5 | Tallinn | Tartu | 2022-06-03T12:00:00+02:00 | 2022-06-03T08:12:25.669Z | Fred |
| 478 | 7 | Tallinn | Tartu | 2022-04-06T12:00:00+02:00 | 2022-06-03T08:14:47.634Z | Eero |
| 136 | 2 | Narva | Tartu | 2022-06-04T12:00:00+02:00 | 2022-06-03T08:15:00.927Z | Birgit |
| 563 | 13 | Tallinn | Tartu | 2022-07-06T12:00:00+02:00 | 2022-06-03T08:17:38.846Z | Villem Tsupsman |
| 298 | 10 | Tartu | Narva | 2022-06-07T12:00:00+02:00 | 2022-06-03T08:47:47.882Z | Karel |
| 340 | 7 | Tallinn | Tartu | 2022-06-04T12:00:00+02:00 | 2022-06-03T08:48:45.012Z | Madis |
| 972 | 6 | Tallinn | Tartu | 2022-06-04T12:00:00+02:00 | 2022-06-03T08:56:53.208Z | Kevin |
| 408 | 1 | Tallinn | Tartu | 2022-06-06T12:00:00+02:00 | 2022-06-03T08:57:44.383Z | Eve |
| 976 | 6 | Tartu | Tallinn | 2022-06-04T12:00:00+02:00 | 2022-06-03T09:23:19.696Z | Sille |
| 1207 | 50 | Tallinn | Narva | 2022-06-06T12:00:00+02:00 | 2022-06-03T09:27:06.594Z | birgith |
| 398 | 8.2 | Narva | Tallinn | 2022-06-04T12:00:00+02:00 | 2022-06-03T09:47:48.931Z | Joonas |
| 368 | 3 | Tallinn | Tartu | 2022-06-04T12:00:00+02:00 | 2022-06-03T09:48:32.545Z | Andris |
| 738 | 1 | Tallinn | Tartu | 2022-06-02T12:00:00+02:00 | 2022-06-03T12:11:30.544Z | Martins |
| 297 | 79 | Tallinn | Tartu | 2022-06-04T12:00:00+02:00 | 2022-06-03T15:29:42.536Z | Märt |
| 35 | 4 | Tallinn | Narva | 2022-06-06T12:00:00+02:00 | 2022-06-03T16:39:29.847Z | Salah |
| 890 | 3 | Tartu | Tallinn | 2022-06-04T12:00:00+02:00 | 2022-06-03T18:26:42.540Z | Heleriin |
| 710 | 12 | Tallinn | Tartu | 2022-06-05T12:00:00+02:00 | 2022-06-04T08:58:56.879Z | Kristiin |

Figure 6. Table of placed orders

If writing to the table was successful, then virtual agent tells user that his order was added and number of the order. As this is just the concept for validating the general idea all the data is primitive, schemas simplified and calculations random, also virtual agent is only trained for the positive case scenario. Despite simplicity of the prototype the keypoints of data exchange are all implemented and work correctly.

## RESULTS AND DISCUSSION

When conducting the questionnaire, authors collected 20 replies from customers, from employees 18. This exceeded the authors' desire to receive at least 30 responses, 15 of them from at least both parties. The survey found that 11 of the employees who responded were men, 8 were women. 15 persons of the clients were men, 5 were women. The average age of the respondents was 31 for employees and 35 for clients. Greencarrier had recently seen changes in its workforce, meaning that longer-working workers have moved on to other specialties or gone to work for other companies, and younger workers have been replaced. Greencarrier employees have worked in the transport sector for an average of 6.5 years and customers have ordered transport for an average of 11 years. Employees of Greencarrier receive averagely 19 orders per day, customers of Greencarrier place 11 orders per day.

All of the employee respondents use the Cargowise program used in Greencarrier, while other tools highlighted are Excel, Google Maps, Soloplan Carlo, Outlook, Viber, WhatsApp, Navirec, NSwift. In addition to the company's main program Cargowise, the everyday tools of transport managers are various map applications, tracking systems and communication channels. It is up to each transport manager to decide how to communicate with the drivers. Texting is primarily used on the phone with SMS-s, but as mentioned earlier, Viber and WhatsApp are also used.

Customers who answered the questionnaire mainly use the Markus XSped program, seven of the 20 respondents mentioned it, Excel was also mentioned seven times, Outlook was mentioned 10 times. All respondents must be using email because the questionnaire was sent out by e-mail.

As seen from following figure, most of the customers who answered to questionnaire were logistician, three were managers and one warehouse manager, procurement manager, team leader and one shop manager (Fig. 7).

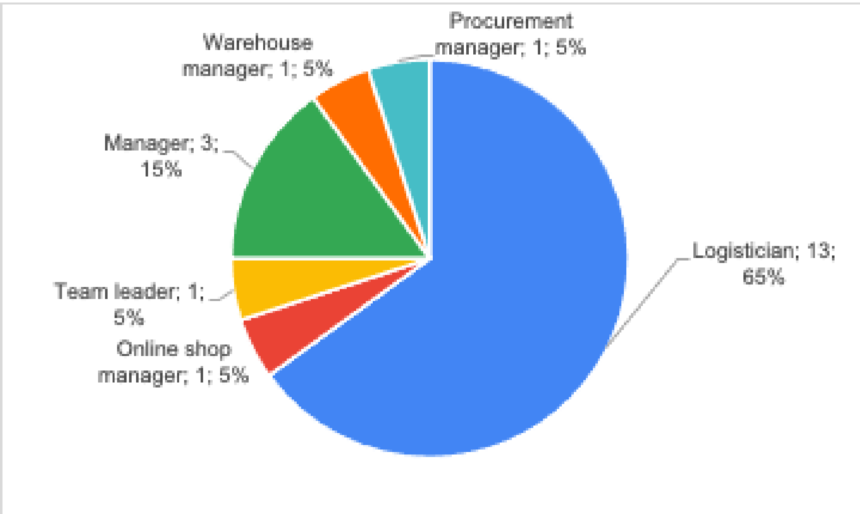


Figure 7. Specialities of customers

We had both Greencarrier employees and customers evaluate several claims on a scale of one to five where one means to "completely disagree" and five is to "completely agree". The purpose of these statements was to find out what people think of the price inquiry process right now and the virtual agent solution that potentially supports it. It can be said that customers and employees have a different opinion of the matter.

First claim to be evaluated was that the price inquiry process is a repetitive and regular activity. The results of the responses of customers and employees were quite different (Fig. 8). Customer responses were distributed more evenly and the share of people who totally or rather agreed and people who totally or rather disagreed was equal. On the other hand, most of the employees agreed with the statement when as many as 13 out of 18 employees fully agreed with the statement made.

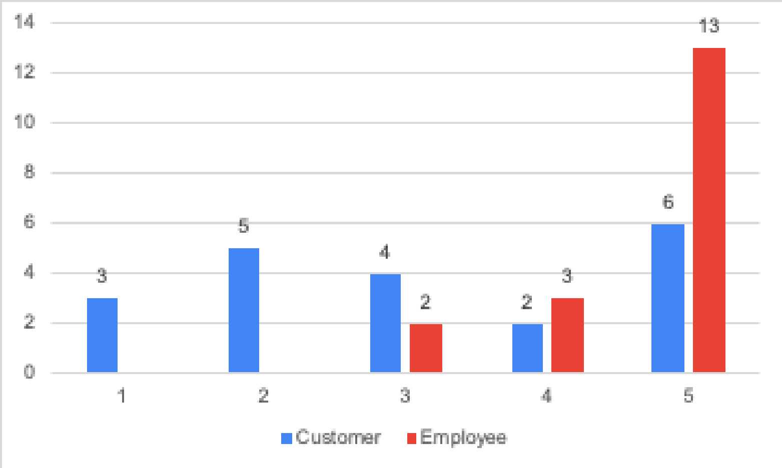


Figure 8. The price inquiry process is a repetitive and regular activity

The second claim to be assessed was that the virtual agent questions were adequate (Fig. 9). A similar pattern between customer and employee ratings emerged. Overall, the share of people who agreed with the statement of both target groups increased a little.

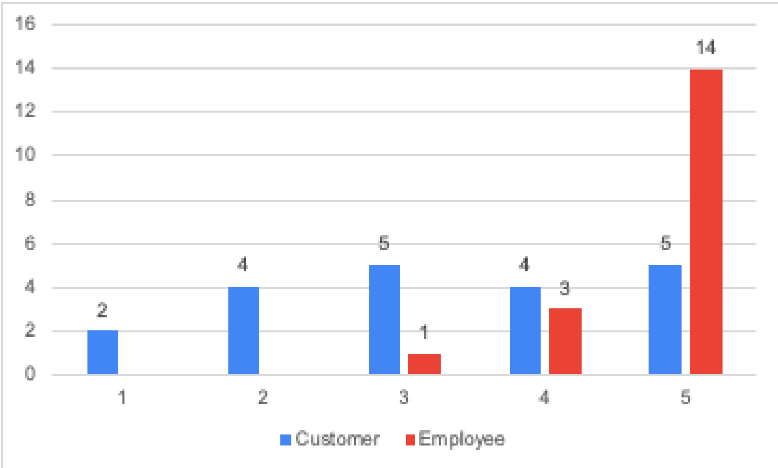


Figure 9. Virtual agent questions were adequate

The next statement that people had to assess was that "I would like to use an analogous solution when dealing with price inquiries" (Fig. 10). On the positive side, all Greencarrier employees who responded agreed with the statement made. Also, 13 customers either rather agreed or totally agreed, five customers were unsure and two customers fully disagreed with the statement made.


Figure 10. I would like to use an analogous solution when dealing with price inquiries

We presented several different statements to Greencarrier customers only to understand more accurately their opinions on the process of handling price inquiries and about the usefulness of the proposed virtual agent. We made the following statements to customers: several letters must be sent to place an order; the tool is simple and easy to understand; the solution is user-friendly; virtual agent saves time in the ordering process; the proposed solution is more effective than the current solution for handling price inquires.

## CONCLUSIONS

The main goal of this research was to find out if the proposed concept is needed by potential users who are mostly logistics sector workers and their clients. Greencarrier employees average given mark was 4,89 on scale 1-5, where 1 means strong disagreement and 5 means strong agreement, to the question if they would like to use analogic solution while dealing with price requests. It is high enough number to see the potential in this concept. Clients were not too positive about the solution and their answer to the same question was 3.7 as an average.

This can mean that clients felt that they needed to work more and employees felt that it makes their work easier. But also, the client's answers were varying, and as an average were more for the solution, not against. Authors did not recognise any obvious relationship between the gender or age of the respondents with their answers.

We can assume that something is missing for the client in this solution, or he just needs to do his job differently and it scares him. On the other side work of employees gets automated, as they do not have to manually insert orders into system coping all the necessary information from emails.

Overall it seems like this solution has potential and could be practically used in real life after some fine tuning and adding correct data, formulas and other possible or potential scenarios.

We would like to express our special thanks of gratitude to our teacher Tarmo Koppel who gave us the excellent opportunity to do this wonderful research project on the topic virtual assistants, which also helped us in doing a lot of research and we came to know about so many new possibilities in the field of natural language processing and business process automation.

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## Associated factors of the satisfaction with a virtual assistant

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Key words: virtual assistant, virtual agent, chatbot, price inquiry, process efficiency, public acceptance of AI

### INTRODUCTION

Authors developed a virtual assistant based on chatbot platform Flow XO. The function for the agent was to provide the basic solution for clients' price inquiries. The company that ordered the study, operates in the field of real estate management and also offers cleaning service to customers. Technically the developed assistant belongs to the category of rule-based ANI without the ability to learn.

The subject of the study is potential acceptance of this kind assistance from the perspective of clients and also general public. Previous research related to the field AI acceptance in the customer service perspective was found from Sanny, L., Susastra, A., Roberts, C & Yusramdaleni, R. (2020). The analyse was based on the customer satisfaction factors which influence chatbot acceptance in Indonesia. Additionally, there is related research Ates, M. (2017). A case study about the introduction of a virtual assistant into customer service (Master's thesis) which is directly related to topic of this research. Both researches are focusing of the acceptance of the virtual assistant in different costumer service environments.

At the moment all the price inquiries are processed by human resource in the company and the virtual assistant could be a solution for rising the process efficiency and level of quality by reducing the amount of operational time.

This study is the first phase in the research which should define the most crucial elements, user expectations and functionality of the virtual assistant for providing service in price inquiries process in different service groups of the company.

Results of this research can be used as a base for further studies in the virtual assistant acceptance in a environment that has generally high acceptance of ICT solutions and also in the field, that is not commonly investigated, but has a fundamental functionality in a daily business relations with customers.

Authors defined basic research question: to understand what are the most important customer parameters or assistant's characteristics that affects the acceptance of the virtual assistant.

### METHOD

The data for the study was gathered by conducting a survey with the questionnaire[4] among clients, potential customers and wider public by using systematic sampling. It contained basic information for profiling the respondents and 12 different, but related questions about the satisfactory with the virtual assistants'[5] performance. Interaction flow with the virtual assistant is shown in Figure 1. The type of service for inquiries is cleaning: deep, basic and window cleaning.

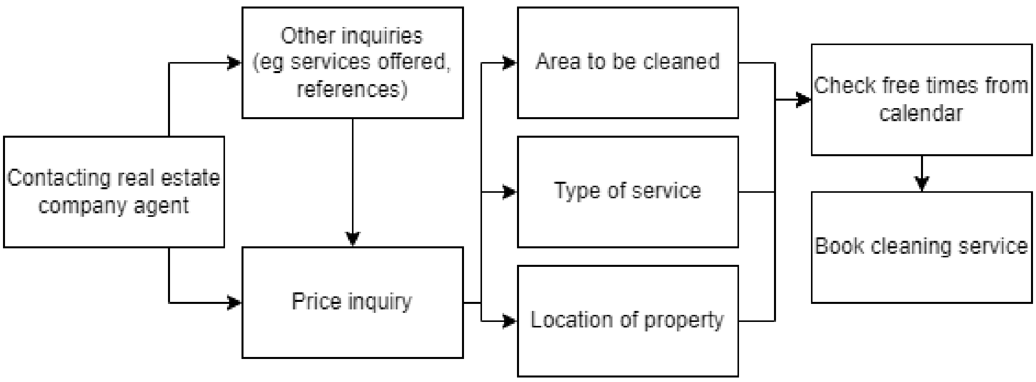


Figure 1: Interaction with the real estate management company virtual agent.

Amount of data is based on the answers from 64 respondents. Distribution of the respondents age, previous experience and role as previous customer is shown in figure 2.

The results of the survey were analysed with quantitative methods to emphasize objective measurements of the statistical data. SPSS software was used for the technical calculations. Authors prepared the dataset: respondents were divided into two groups Q1 – by median age of respondents (35 years) and Q2 – previous experience ordering cleaning services; answers were dimensioned D1 – linguistics, D2 – reliability, D3 – accuracy, D4 – competence, D5 – satisfactory.

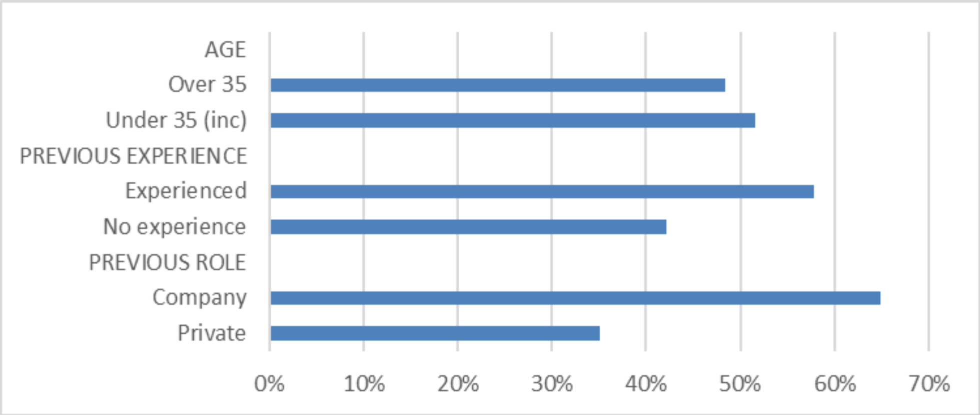

Figure 2. The distribution of respondents by age, previous experience, and previous role as customer.

Correlation (Pearson) between groups and question dimensions was calculated. Independent samples t-tests were run based on the respondents' parameters.

On top of the quantitative analyses, there was carried out a qualitative interview with two employees from the company, who are directly related to the process of price inquiries and providing the service.

## RESULTS AND DISCUSSION

Quantitative analyses found the correlation (Pearson) between all the dimensions which tackled the characteristics of the virtual agent and strong positive correlation between dimensions D3 and D4 and strong positive correlation between dimensions D3 and D5 with both significant at the 0.01 level. This finding is relevant for understanding the main aspects, which have the biggest influence on a user satisfaction. D3 – accuracy, appeared as an indicator in both connections. It carries the role as a strategic enabler for competent and satisfactory virtual assistant. It is an input for the further developments of the virtual assistant to gain general acceptance.

There was no significant correlation between the parameters of respondents (age or previous experience) and virtual assistant's performance related dimensions. This finding provides information to profile the potential user of the application and rises questions if the most common assumptions about the parameters might need to be re-evaluated.

Based on parameters of respondents there was a difference between age groups: older respondents evaluated dimension D1 (linguistic) characteristics higher than younger age group (p=.048). This finding could be related to the different cultural heritage between age groups and might not have a relevant importance to the acceptance of the virtual assistant.

Form the qualitative interviews with the company employees, there was a clear feedback to focus on technical biases and provide a more complex solution for customer-oriented service. There was a confidence of the general acceptance of this kind of virtual assistant carrying the role in the process of as a price inquiries. The threats were related to the accuracy of the input and output – is the information feed punctual enough to estimate the price for the service. The importance of D3 had the most crucial importance from the service provider's side to become trustworthy enough in the processes.

For further research, there is possibility to study the association between different parameters of the user and the characteristics of the virtual assistant to understand the limitations of the public acceptance of virtual assistants. The study provided clear input to the capabilities, which have the highest importance in the development phase of a virtual assistant.

## CONCLUSIONS

Service providers see a potential in using virtual assistants in simple processes as price offering, but there are high expectations for the technical performance and the characteristics of the AI.

There is a significant statistical relation between satisfactory and accuracy and competence of the virtual assistant. These three characteristics have the highest influence to users' satisfaction and acceptance of such virtual assistant providing them service instead interaction with people. Accuracy is not only an important factor from the customers' side, but also from the service providers' side, since it provides more capable tool that also can be considered trustworthy.

The customers' parameters as age and previous user experience do not have clear connection with the satisfaction and general acceptance. To develop this kind of service providing virtual assistant and adjusting it to potential customers' parameters, there is a need to conduct further research.

Authors are ready to share the knowledge and collected data for further research.

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## Sales Dashboard Project

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Key words: Sales process, Business development, IBM Watson, Orange, PowerBI, Process improvement

### INTRODUCTION

The aim of this research was to delve into the pragmatic view of one IT services providing start-up sales process and how to make it more coherent. Company, We were studying provides service in software engineering, testing and consultancy on that segment. Business is mainly conducted in Estonia mostly. Company affiliates in the fintech (start-ups) segment and its revenue and new projects growth has been significant over a couple of past cycles. Though fast pace in business growth is a sign of success, other and especially supportive actions must come along. Here we are reaching the core of the problem from the sales process side. Sales leads and client communication is conducted eloquently, but data fill-out into the existing system is not up-to-date and consistent. Thus, without valid data, it's difficult to run long-term goals. In order to improve the quality in the sales process and solve the current inconsistency in data fill-out we conducted a three part research. Firstly, we held interviews with company management members, employees and associated parties, secondly designed a new procedure on how to engage sales data into a prognosis scheduler and thirdly we held interviews with board members on how they felt on testing three different platforms. To conclude our primary purpose of the research with one question, it is as follows: How to help the company and its management to reach up on circumstances, where sales data will be organised diligently and quality of info will be reliable and consistent behind it?

### METHOD

Our study was performed on a problem analysis (case study) basis and realms in a qualitative method through questionnaire answering/interviews. Interviews were arranged in a group workshop and individual interview basis. All of them were conducted virtually. In origin we created a demo outlook of a potential new dashboard in three platforms for the sales process and then presented it to the company (employees, management and associated parties), in total 30 participants. At first we introduced the idea and later the potential outcome. During workshops and by individual interviews we asked 10 questions about the sales process and our solution on how it is attained by the involved persons.

Results of the answers gave us following picture as shown in table 1 and figure 1.

Table 1. Statistic average overlook of the respondents answers to questionnaire

| | Management rep. | Employee | Associated party |
|---|---|---|---|
| Data accuracy | 4,75 | 3,13 | 2,87 |
| Benefit to company | 4,0 | 3,26 | 2,45 |
| Improvements to business flow | 4,14 | 3,46 | 2,72 |
| Simplicity | 4,4 | 3,13 | 3,01 |
| Adaptability | 4,0 | 3,33 | 3,09 |
| TOTAL | 4,25 | 3,26 | 2,82 |

Based on feedback, most eager to commence the change comes from the management representatives and less eagerly from employees or associated parties. Assessments are in 1-5 ratings and results to reflect the outcome as to how painful the current situation to a certain group of members of the company is. As a background, interviews were conducted by the company management, employees and associated parties. In total 6 management representatives, 15 employees and 9 associated parties. Under management representatives we view an extended panel (actual members of board and department execs), under employees we consider actual employees from different departments and associated parties are mostly contracted specialists or specialists with certain licences who cooperate with the company in certain projects.

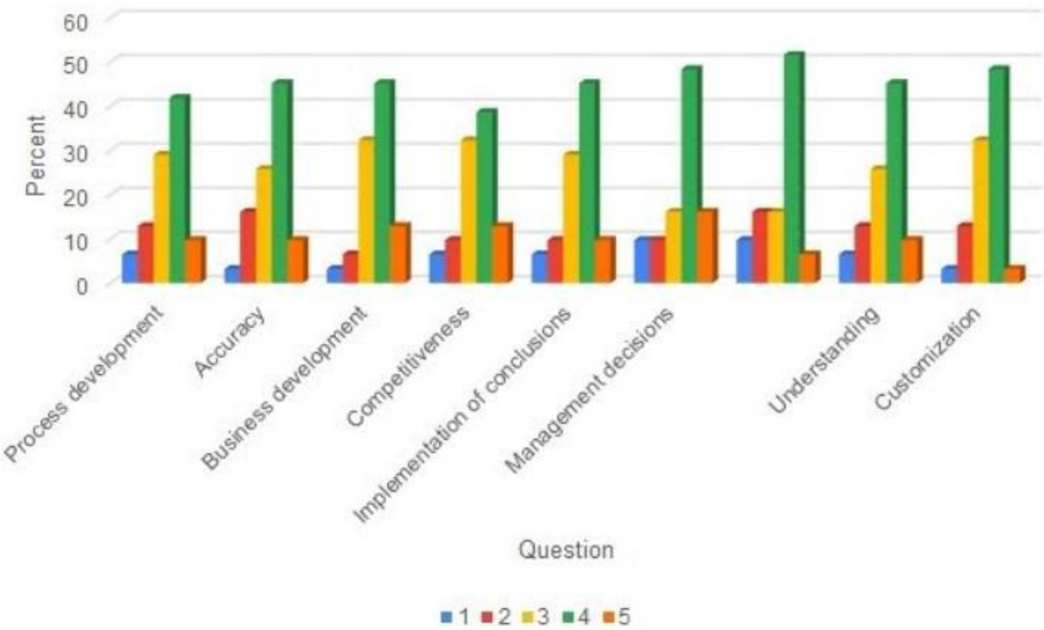


Figure 1. Survey summary – overall fixation of the responders answers

Above table 1 gave an approximation of how the answers divided between the responders as categorised by their roles. It's clear that inquisition of making changes comes from management and influences the most outsourced specialised and also somewhat employees. Current survey summary shows how the ratings culminated in thorough view. Thus, in overall new approach was assessed as a way forward.

Old model of the sales data process was hectic. Company is using their own crm platform, but details of the sales project were inserted inconsistently and by employee alone, no centralization was at place. Now our process is more centralised as it will give a sole view of the effect of figures and helps management to understand better sales flows and make better prognosis for quarters coming ahead. We used in our research three programs: IBM Watson SPSS Modeler, Orange Data Mining and Microsoft PowerBI. Same dataset was given as input to all systems for forecasting. In comparison Orange and Watson were similar in usage, although Orange has better user interface. PowerBI is easier to use for the end user and more intuitive. Orange and Watson requires heavy training for the end users or power user(s) in the company who prepares the data and models for the usage. From the plus side Orange and Watson seemed more powerful tools with a lot more possibilities (those were not explored in this research). 3 selected programs forecasting (in EUR) by month (12 months in the future):

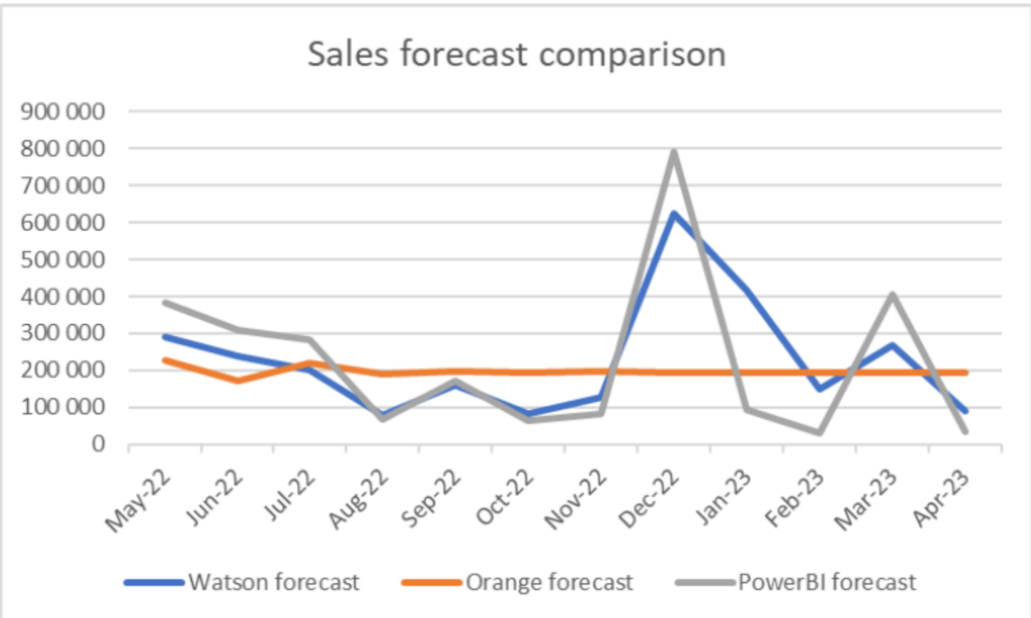


Figure 2. Company sales projections comparison between tools

*Data in table represents sales volume prognosis for the next twelve months. Each line gives a correspondance of how platforms provided data analysis and accuracy.

Watson and PowerBI forecast future sales quite similarly, but Orange forecast is totally different. Comparing all pros and cons, then PowerBI seems the best option for small companies forecasting, because of forecasting accuracy, user interface and shortest learning curve for end users.

## RESULTS AND DISCUSSION

Our aim of the whole work was to address the existing issue and propose a one probable outcome. We can't confirm that it will fix all the existing angles of the core of the problem, but it's way forward on making the overall process more salient. Our conduction of research was constructed by three steps:

- Designing of the idea: Focus was directed to understand the overall business model, its key challenges and components. Then as finding out that company is growing fast it needs to be clear on exerting quality in every step it configures as daily assignments go by. Thus, the sales process was picked out due it's centrality on business model and driver on growth.
- Constructing solution: We had a deliberation on what platform to use on carving out new potential solutions. In the end we came down to either orange, PowerBI or watson. We exerted trials with all of them and also had testing interviews with the managing members. Outcome came as divided, one platform by feedback was to simple to comply with overall needs, one was too powerful but also too expensive and one was a little bit of both (having enough capabilities) and not being too expensive either.

Each member of board gave a following feedback to the all of these platforms as follows:

Table 2. Member of board interview reflections

| Functionality | Watson SPSS Modeler | Orange | PowerBI |
|---|---|---|---|
| User Experience | 1. Complicated<br>2. Too thorough and time-consuming<br>3. Attractive/seamle ss | 1. Comfortable<br>2. Got a result I got simply<br>3. Too simple | 1. Very simple to use<br>2. Data files uploading is easy<br>3. Whole journey was the easiest out of three |
| Operability | 1. Modeling is ambiguous<br>2. In times, too extensive<br>3. Sufficient. | 1. Comfortable to use<br>2. How much can be achieved must be mapped<br>3. Wish and outcome somethings don't overlap | 1. Main prospects are covered<br>2. Sales task is covered well, about rest I don't have info<br>3. Power lies in simplicity |
| Data integration | 1. Comfortable.<br>2. Difficult to compose ad hoc tasks.<br>3. Journeys to achieve goals are too long | 1. Inscribing data isn't always easy<br>2. Everything worked logically<br>3. Data management in integration was understanding to me | 1. Logical<br>2. No unnecessary moves required<br>3. little bit too constrained |
| Analysis | 1. Data is assessed accurately.<br>2. Simple and comprehending<br>3. To me not sharp enough | 1. Analysis predicts results what's expected<br>2. It's important to follow how program interprets data<br>3. Wasn't meeting expectations | 1. Covers results well<br>2. Graph was configured as expected<br>3. Task performed well, otherwise too simple. |

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| | | | |
|---|---|---|---|
| Overall rating (1-5) | 1. I'll give 4<br>2. I'll give 3<br>3. I'll give 5 | 1. I'll give 5<br>2. I'll give 4.<br>3. I'll give 3. | 1. I'll give 4<br>2. I'll give 4<br>3. I'll give 3 |

*Respondent nr 1 represents Member of Board who is in charge of sales, respondent nr 2 represents Member of Board who is charge of engineerial development and respondent nr 3 represents Member of Board who is a Chairman.

## CONCLUSIONS

Our research helped us come to close with the set purpose, helping the company to solve the data lacking issue of scheduling sharp sales analysis and help conduct better prognosis for next quarters. Problem as a statement was easy to discover, inconvenient procedure and lack of data sufficiency. We quickly learned that customer relations are divided between employees losely and needed new categorisation. We walked through three stages of research and got a better understanding of a company, its aims and proposed a solution for the future. Our biggest learning was that the structure of the procedures were incoherent within the company and thus building a new visual prototype wasn't only an achievement we put together. We had an open dialogue with the company management and arranged two workshops and individual interviews on the way. Prototype was based on the received feedback and outcome of the questionnaire suggesting that we are on the right track of making new suggestions for companies' strand toward better sales and sharper prognosis for it. Key of the solvement is not down to new tools nor conceptualising better procedure structures. It's a big picture of seeing the implication updates can bring to the company.

# Implementing AI speech to text function in the Up Catalyst production process

Sander Trofimov

Key words: voice to text, voice recognition, smart data entry, production technology

## INTRODUCTION

This work on digital change was carried out on the example of UP Catalyst's production process. This company manufactures carbon nanomaterials from CO2 and bio-waste. The product portfolio includes carbon fibres, -nanotubes, -spheres, graphite and graphene. These materials are used in the battery, paint, coating and concrete industries. The company is in the start-up phase and is 2 years old, but is based on a 10 years of research experience. The company employs 14 people who together have more than 50 published articles. Up Catalyst is coming out of laboratory production, which means that the kg-scale reactor has been completed and the validation of the material for this reactor is in progress. The transition to a t-scale reactor is expected in 2023, and the construction of the first plant is then underway.
The process presented in this work was chosen because it is the most standardized and the author is the owner of this process.

### Process description and improvement method

Up Catalyst's production process begins with placing an order and ends with product packaging. This process consists of 7 steps, the flow chart of which is shown in Figure 1. During this process, the person performing the process has to fill in the synthesis report manually and later rewrite it into the database. The operator has to write the most information in the first stage of the process, about 78% of the total report.

In the first step, the carbon nanomaterial synthesis takes place in molten salt of 800 ° C and a electrolysis is done in it. During this time, production is on high alert and people should focus primarily on safety. As a result, a smarter method of data entry than paper and pen is seen as an option.

Ideally, the expected result is a system of voice commands that tells the operator how far away they are in their process, gives them instructions on what to do next, and asks them for information. The main idea that would be suitable is to find a way to enter data with voice commands. For this purpose, Google home and Microsoft's windows speech recognition software were introduced.

Microsoft's speech to text AI runs throughout the operating system. It allows you to enter data as well as navigate between applications. This program was tested in this paper as it is widely available program. Office 365 users also have the ability to use the even more powerful "dictate" feature of Word. However, when using it, you need to find an intermediate to help bring the doc type file data into the table. To do this, the data entry method must follow the csv file format, separating the columns with commas. Then save the doc file as a txt file and open the file in the table application.

Google's voice command software is also a widely used program, but it was difficult to solve this problem without writing any code. Different integrations would help Google home to achieve this task, such as the assistantcomputercontrol (Link) application or IFTTT. Using the csv technique, the data could also be entered into a table.

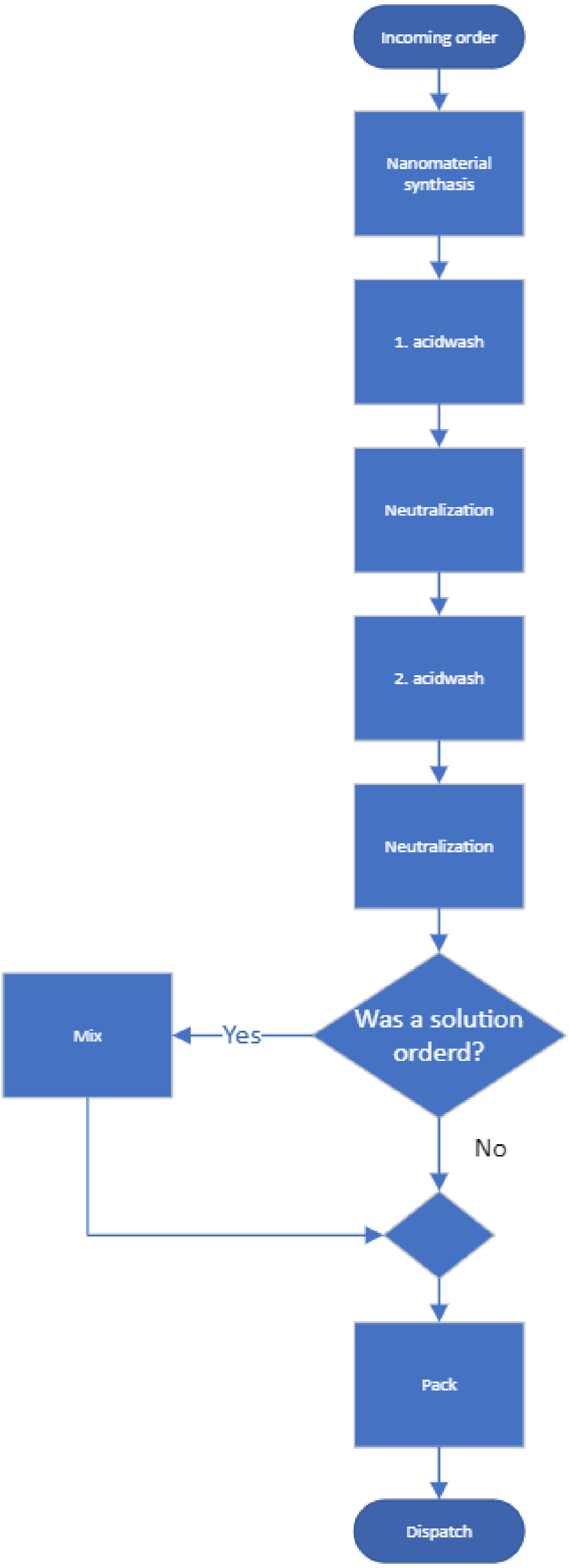


Figure 1. Production process flowchart

**Tests performed**

Microsoft's windows speech recognition software was first tested independently and then given to 5 operators (n = 5) who had to follow the process and enter data using it. The format of the required data is Table 1. During the process, everyone used the same computer and the same headset with a microphone. Data entry time and error rate were measured. Physical interactions with the computer were not allowed. These results were then compared to a conventional process where the operator enters the data on paper and then into a computer. After receiving the results, a survey was conducted on the operation of the application.

Table 1. Synthesis report form

| |
|---|
| Date of process start |
| Time of process start |
| Operator |
| Batch Number: |
| Reactor |
| Synthesized Material |
| Synthesized Material p/n |
| Furnace time start |
| Furnace kWh start |
| Furnace temp |
| $CO_2$ flow (slpm) |
| Electrolysis Time Starts |
| Electrolysis kWh start |
| Voltage (V) |
| Current (A) |
| Electrolysis Time end |
| Electrolysis kWh end |
| Voltage (V) |
| Current (A) |
| Furnace time end |
| Furnace kWh end |
| Raw quantity before grinding (g) |
| Raw quantity after grinding (g) |
| Used HCl (ml) |
| End product quantity (g) |
| End of process date |
| End of process time |

## RESULTS AND DISCUSSION

The results are shown in Table 2. In the case of the smart process, it was assumed that we could automatically convert this doc file into a table, but in reality, we did not do it. In the normal process, 1 error occurred while entering the data, where the wrong number was written to the table from the paper.

It can be seen that the smart process takes 4.5x more time than the usual way. The biggest problem with this software is that it hears the Estonian-English accent and does not always understand it. The most common mistake was the number “two”, which often read “too”. It can be said that the program did not understand the context very much. Interestingly, however, the feedback does not conclude this. There were times where the program asked you to spell words out to understand it better. These cases added a significant amount of time to the whole process. It also had difficulty understanding certain letters there. For example, vowels were the letters it had difficulty understanding. But this could be the result of the application operator as well.

The subjective method was used to evaluate the application, with people giving their feedback immediately after the experiment. Scores were given in the 5 points system. None of the participants wrote a comment, but the general feedback was rather negative. With the average score of 2,85 it is considered quite good, if we take account the oral feedback and the time it took to complete the process. The highest average score was given to the simplicity of the application (4) and the lowest for the overall satisfaction (2,26) categories.

Tabel 2. Usual vs smart process

| | Time taken to write data (sec) | Time taken to enter data (sec) | Number of errors made (pcs) |
|---|---|---|---|
| The usual process | 52,2±6,91 | 135,2±23,16 | 0,2±0,4 |
| A smart process | 861,8±129,06 | 0* | 39,6±13,63 |

Tabel 3. Averages of the application feedback

| Criterion | 1- Strongly disagree | 2 | 3 | 4 | 5 – Strongly agree |
|---|---|---|---|---|---|
| Dimension – Comfort | | 2,4±1,15 | | | |
| Voice commands are convenient for navigation | | 1,6±0,72 | | | |
| Voice commands are convenient for entering information | | 2,2±1,04 | | | |
| The microphone is comfortable to carry and use | | | 3,4±0,88 | | |
| Talking about AI seems natural | | 2,2±0,64 | | | |
| Dimension – Accuracy | | | 3,3±1,24 | | |
| The AI understands when you want to navigate | | | | 3,8±0,64 | |
| The AI understands when you want to enter data | | | | | 4,6±0,64 |
| AI understands your spoken language | | | 2,6±0,88 | | |
| AI understands numbers | | | | 4±0,8 | |
| AI understands words | | 2,4±0,72 | | | |
| AI understands punctuation | | 2,4±0,88 | | | |
| Dimension – Simplicity | | | | 4±1,05 | |
| Setting up the program is easy | | | | 4,2±0,64 | |
| The program is easy to use | | | | 3,6±1,28 | |
| AI voice command features are easy to remember | | | | 4,4±0,72 | |
| AI has a wide range of voice command features | | | | 3,8±0,64 | |
| Dimension – speed | | 2,3±1,25 | | | |
| The AI executes commands quickly | | | 3,4±0,88 | | |
| AI is a short time to think | | 2±0,8 | | | |
| AI can write long sentences | | 1,6±0,72 | | | |
| Dimension – Satisfaction | | 2,3±1,00 | | | |
| I am happy with this data entry program | | 2±0,4 | | | |
| The AI did a good job | | 2,2±0,64 | | | |
| The AI did what I expected | | | 2,6±1,28 | | |

## CONCLUSION

Microsoft's "windows speech recognition" software is not suitable for implementing the Up-Catalyst production process in this form, because it takes too long and its accuracy is not acceptable. One reason might be that while setting up the experiment where different people used a program that tries to calibrate itself to only one person's voice. This program did not add much to the vision set out in the beginning of the work. But when researching different programs, it seems that this is not impossible. The aim of digitization is to make conventional processes more efficient, provided that the existing process is efficient. We have seen that this form of data entry is not effective, which means that you have to deal with changing it first. This process will continue to be made more efficient, but initially not using AI technology.

## Designing of a retail chatbot and analysing its impact on customer experience

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Key words: chatbot, retail, business chatbot, artificial intelligence, e-commerce.

### INTRODUCTION

In recent years, as a result of technological advances as well as the global pandemic, most of the developed world's retail businesses have adapted to the need to do business with greater or lesser emphasis on their e-channels. According to Eesti Pank, Estonia's e-commerce total turnover of 2021 was €249 million, and it grew by 59% compared to 2020 (Eesti Pank, 2022).

The popularity of e-commerce as a shopping channel has created a situation where e-retailers are increasingly looking for ways to contribute to the development of their own e-commerce sites. The aim is to facilitate customer contact, reduce the administrative burden and enable the entire sales process to be carried out with a minimum of human consultants.

One of the ways to improve an e-commerce site is to introduce a retail chatbot, which can be powered by artificial intelligence. With the right implementation, retail chatbots present an opportunity for retailers to improve their customer's experience, increase sales and save them money and time.

The aim of this study was to create an efficient interaction chatbot in the e-shop of a coffee retail company to help the customer to choose a specific coffee machine and to analyse how the implementation of an AI-based chatbot impacts the customer experience in the sales process and whether it is justified to implement such a solution.

Previous similar research by Oguntosin and Olomo has been conducted within the context of developing an e-commerce chatbot using Python and React.js as programming languages, but this study focuses on creating a chatbot using simple user-friendly programme that needs no specific knowledge in programming (Oguntosin& Olomo, 2021).

### METHOD

As mentioned above, the aim of this study was to design an effective retail chatbot and analyse its impact on customer satisfaction. To achieve this, the author designed a communication chatbot, tested it within a pilot group, conducted a questionnaire survey to find out if the chatbot met customer requirements and analysed the results (Fig. 1).

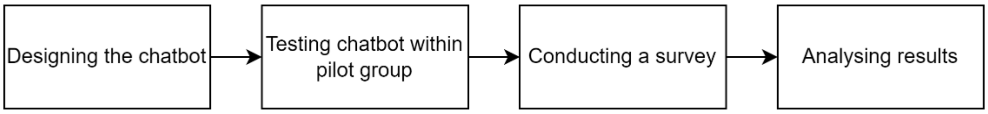


Figure 1. Process map of the study

#### Designing the chatbot

The chatbot was designed using Dialogflow Essentials platform. A total of 28 intents were created to which different number of training phrases and responses were added to provide answers about the specifications of a coffee machine model (Table 1).

#### Questionnaire

That chatbot was tested within a pilot group of 20 participants and then a questionnaire was administered to the testers. The questionnaire consisted of six questions about the respondent's characteristics and eight positive statements on which the respondent was asked to rate on a 5-point scale (1 – strongly disagree, 5 – strongly agree) (Table 2).

Table 1. List of intents.

| Intent | No of training phrases | No of responses |
|---|---|---|
| additional products | 3 | 1 |
| bean container | 3 | 1 |
| cleaning products | 5 | 1 |
| coffee drinks | 12 | 1 |
| coffee grounds container | 5 | 1 |
| coffee type | 3 | 1 |
| colors | 8 | 2 |
| contact | 7 | 1 |
| dimensions | 9 | 1 |
| fallback intent | 0 | 5 |
| filter type | 4 | 1 |
| grinder | 6 | 1 |
| how to | 4 | 1 |
| info request | 3 | 1 |
| j.o.e system | 2 | 1 |
| leaving | 6 | 1 |
| ok | 4 | 1 |
| origin | 3 | 1 |
| payment | 6 | 1 |
| point of sales | 7 | 1 |
| price | 6 | 1 |
| screen | 4 | 1 |
| size of water tank | 6 | 1 |
| warranty | 3 | 1 |
| weight | 4 | 1 |
| welcome intent | 16 | 4 |
| wifi connection | 6 | 1 |

Table 2. List of questions

| No. | Responders's characteristics | Dimension |
|---|---|---|
| 1 | Your age: | Responder |
| 2 | Your sex: | Responder |
| 3 | How often do you drink coffee? | Responder |
| 4 | What do you consider to be the most important features of a coffee machine? | Responder |
| 5 | How often do you shop online? | Responder |

| No. | Statements | Dimension |
|---|---|---|
| 1 | The chatbot is able to answer the most common customer queries regarding the coffee machine model | Design |
| 2 | The chatbot is able to provide adequate information about the product features. | Design |
| 3 | The chatbot can understand the customer's needs. | Design |
| 4 | Communication with the chatbot is fast and saves the user time | Platform |
| 5 | The chatbot is able to provide accurate answers. | Platform |

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| | | |
|---|---|---|
| 6 | Chatbot is polite in its replies. | Platform |
| 7 | By using the chatbot, it is possible to get information faster than reading it on a leaflet/website. | Preference |
| 8 | I would prefer to receive information from a chatbot than from a human consultant. | Preference |

## RESULTS AND DISCUSSION

During this study, the author tested previously created retail chatbot within a pilot group in order to draw conclusions about the justification of such a solution. Questionnaire was conducted within a group of 20 participants of which 40% were men and 60% women. The age distribution of the participants was as follows: 40% were in the 20-29 age group, 45% in the 30-39 age group, 15% in the 40-49 age group. The average age of respondents was 31. 75% of the participants admitted to drinking 2-3 cups of coffee per day. 95% of the participants admitted to shopping online.

Main result of the study is that all eight statements were given more than 2,5 points on the scale of 5 and on average all statements in total received 3,79 points out of 5, which indicates that participants had a positive opinion on the chatbot (Table 3).

The least rated statement was:” I would prefer to receive information from a chatbot rather than from a human consultant.”, which received an average of 3,15 points out of 5. That indicates that people are not against a chatbot but are not convinced in its effectiveness against human consultant.

The most rated statement was: “chatbot is polite in its replies.”, which received an average of 4,55 points out of 5. That indicates, that if responses are formulated in a polite way when creating a chatbot, then it potentially makes a polite impression on the customer.

The highest average rating was given to statements concerning the platform’s ease of use and capabilities, the lowest to statements regarding respondents’ preference with using such solutions (Table 4).

As a result of the analysis, no significant association was observed between respondents’ age and opinions nor sex and opinions (Tabel 5). Although some correlation was observed between respondents’ coffee consumption frequency and opinions, with the highest correlation of 0,7 between coffee consumption frequency and a statement reading: “communication with the chatbot is fast and saves the user time”, which means responders with higher coffee consumption habit gave a higher rating to the chatbot regarding saving users’ time.

Author of the study sees scope for further research on this topic. The main suggestion would be to conduct a survey within a larger and more diverse pilot group and to increase number of specific questions on which to ask respondents about, so that more detailed conclusions on how a chatbot impacts customer experience could be drawn. Another opportunity for further research would be to compare customer experience when using a retail chatbot versus a real human consultant.

Table 3. Statements’ scores

| No. | Statement | Average score |
|---|---|---|
| 6 | chatbot is polite in its replies. | 4,55 |
| 2 | the chatbot is able to provide adequate information about the product features. | 4,20 |
| 4 | communication with the chatbot is fast and saves the user time | 4,05 |
| 1 | the chatbot is able to answer the most common customer queries regarding the coffee machine model | 3,85 |
| 7 | by using the chatbot, it is possible to get information faster than reading it on a leaflet/website. | 3,65 |
| 5 | the chatbot is able to provide accurate answers. | 3,60 |
| 3 | the chatbot can understand the customer’s needs. | 3,25 |
| 8 | i would prefer to receive information from a chatbot than from a human consultant. | 3,15 |

Table 4.

| Dimension | Average score |
|---|---|
| Platform | 4,07 |
| Design | 3,77 |
| Preference | 3,40 |

Table 5. Pearson correlation coefficients

| Statement no. | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| Age | 0,0 | 0,2 | 0,2 | 0,1 | 0,2 | 0,2 | -0,3 | -0,2 |
| Sex | 0,2 | -0,1 | - | -0,1 | -0,1 | -0,1 | -0,4 | -0,1 |
| Coffee consumption | -0,0 | 0,4 | 0,3 | **0,7** | 0,4 | -0,2 | 0,2 | 0,4 |
| Internet purchases | 0,2 | 0,4 | 0,4 | 0,3 | 0,2 | -0,1 | 0,3 | 0,4 |

## CONCLUSIONS

This work investigated the effectiveness of implementing a chatbot as an AI solution as part of process improvement and assessed the impact of such a solution on the customer.

As a result of this research the author found that created retail chatbot is an effective tool to provide positive customer service experience and sufficient information about a specific product. Despite the indication that there are still some hesitations on whether artificial intelligence tool such as could replace human resource, the author considers that it is justified to implement such solutions.

**Acknowledgements**

The author would like to acknowledge Tarmo Koppel who has helped to achieve the goals of the research.

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## Tallinn Pharmaceutical Plant document's quality improvement by AI paraphrasing tool QuillBot

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Key words: AI, paraphrasing, content quality, pharmaceutical company.

### INTRODUCTION

This resource investigates whether it is beneficial to use AI paraphrasing tool to improve the quality of documents. The document that is being improved in this resource is Tallinn Pharmaceutical Plant's Site Master File (SMF). This file is created by the pharmaceutical manufacturer and includes specific information about the site's quality management policies and activities, as well as the production and quality control of pharmaceutical manufacturing operations performed at the named site, as well as any closely integrated operations at adjacent and nearby buildings. The author chose QuillBot to improve the quality of company's Site Master File. QuillBot's paraphrasing tool uses AI to assist people rewrite and improve any sentence, paragraph, or article.

It is critical to improve the quality of this document since future audits and parent company visits will require that we have a quality site master file that is written appropriately. Because the company does not have any native English speakers, it was decided to use AI to improve the document.

The study "Can AI be a content generator? Effects of content generators and information delivery methods on the psychology of content consumers" explores the influence of content creators (human vs. AI) and information delivery modalities (text vs. audio vs. video) on users' perceptions of content to answer this question. The findings show that content generators and methodologies play a significant impact in improving content quality, satisfaction, and readability. Users' perceptions of the quality, readability, and credibility of human-generated and AI-generated information are same, according to the findings. (Kim et al., 2020)

Previously mentioned study demonstrates that the quality of AI-generated information in various documents can still be improved, because the study only considered restricted news content. This research is being carried out to see if artificial intelligence can increase content quality. If this is conceivable, it might have a significant impact on future work projects, as AI could assist employees in producing higher-quality documents.

### METHOD

A site master file in English was created by the author. Semantic analysis was carried out by the paraphrasing tool QuillBot to improve the linguistic and general content quality.

QuillBot is comprehensive AI writing collaborator that rewrites full paragraphs and refines content. This tool is used to improve quality and increase the speed of writing. It was founded in 2017 by three computer science students with deep knowledge in natural language processing (NPL) and the solution is powered by AI paraphrasing technology. QuillBot reassembles the user's content using natural language understanding to improve the intelligibility of the intended message. Rohan Gupta, Co-founder and CEO of QuillBot has said: "Our vision for QuillBot has always been to make writing easier, so that people can spend more time focusing on what they should write instead of how they should write it".

The author's text and the text generated by AI were both documented in the same data file. Both texts were placed next to each other for comparison and made look similar so AI and human written text would not be distinguishable. The author chose 6 Tallinn Pharmaceutical Plant employees for participants, who are all experts in pharmaceutical field. The author stated to participants the purpose of this study and sent data file to them, so they could prepare for the interview. The participants were not told which content was created by human and which by AI. After participants had read the data file an interview was conducted. The interviews were done in a semi-structured format, where interviewees were asked questions about content's strength, weaknesses, quality in linguistics and opinion about which content was created by AI and which by human. After the interviews participants were asked to complete a computer-based quiz to express their general opinion on which text performed better in terms of linguistic correctness and content quality.

In the quizzes participants had to choose which text had better linguistics, was more effective, had more versatility and intelligibility. Each category had different number of questions, for example about text effectiveness it was possible to answer to 2 questions about that and choose for which text to give a point to. If the participant chose text number 2 for the answer, one point was given to text number 2 (AI text).

It was also possible to not give any points to neither of the texts and choose the choice "neither".

## RESULTS AND DISCUSSION

Figure 1 gives an overview of how participants assessed human written text and AI generated text in computer-based quizzes.

Conducted interviews and assessment quiz showed that all the participants (100%) are more satisfied with AI generated content in effectiveness, linguistics and content versatility. In content intelligibility, one participant gave 3 points (20% of all points given to intelligibility) in computer-based quiz to human written text on being more understandable. Other participants gave together 15 points (80% of all points given to intelligibility) in computer-based quiz to AI generated text being more understandable.

During the interview it was possible to see why the participant thought AI generated text was less understandable for them than human written text. Participant number 5 said that text number 2 (AI generated text) did not mention that listed risk management tools are used in the company, whereas text number 1 (human written) mentioned correctly that listed risk management tools are used. Participant also mentioned that AI written text did not specify where has asphalt been laid on the ground, whereas human written text specified that the (company) territory is asphalted. The assessment was conducted after interview so it is possible to see accurate assessment to contents.

Conducted interviews and quiz assessments showed that participants prefer AI generated text to human written text. They assessed that AI generated text is more effective, has better linguistics, versatility and intelligibility. Considering the results it is possible to use AI content improvement tool to help improve Tallinn Pharmaceutical Plant's Site Master File content quality, which gives non-native English speakers quality assistance on creating better quality English documents.

In the future researches it is possible to further study if and how AI content improvement tools can improve content's quality, intelligibility and linguistics in work instructions and validation documents.

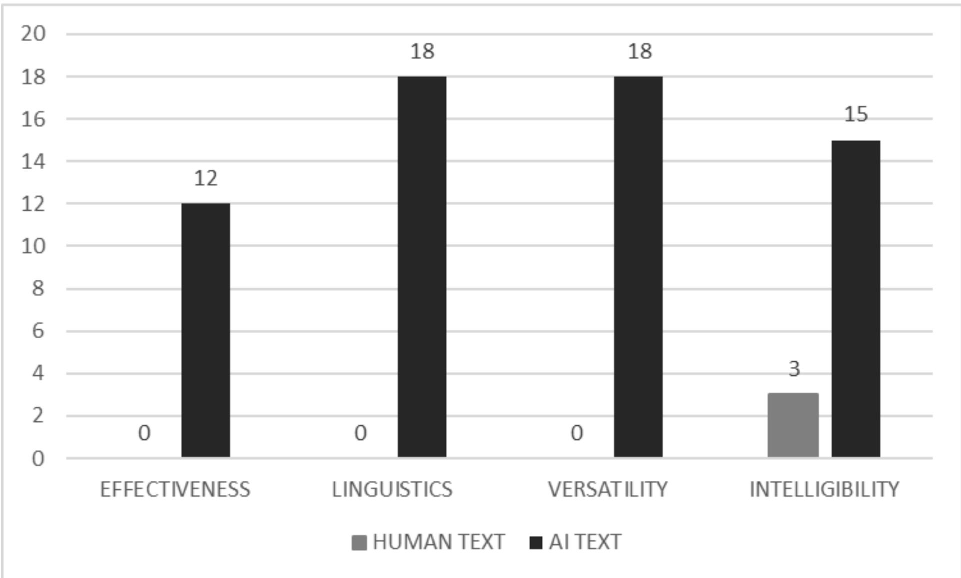


Figure 1. Participants assessment as a sum of points given to human written text and AI genereated text by QuillBot, considering content's effectiveness, linguistics, versatility and intelligibility.

## CONCLUSIONS

Participants prefer AI-generated text to human-written content, according to interviews and quizzes. They found that AI-generated text is more effective, has better linguistics, adaptability, and intelligibility than human-generated content. Conducted interviews showed that it is possible for AI content improvement tool to improve it's details when generating a content. This would make AI generated text more understandable and correct. The results of the computer-based quizzes also demonstrated that the AI content improvement tool can be improved to improve content intelligibility.

Based on the findings, an AI content enhancement tool can be used to help improve the content quality of Tallinn Pharmaceutical Plant's Site Master File, which would provide non-native English speakers with excellent support in developing better English documents.

Further research on whether and how AI content improvement technologies can improve the quality, intelligibility, and language of job instructions and validation documents is possible.

**Acknowledgments**

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# Evelekt AS turnover forecasting using the machine learning method

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Key words: machine learning, prediction, forecast, turnover.

## INTRODUCTION

Evelekt AS does not currently have a method for forecasting future sales figures and turnover. The research problem of this work was poor forecasting of sales figures, which causes great challenges in budgeting and forecasting is inaccurate. Better forecasting of sales figures and turnover would help top management to make better management decisions and investments.

The topicality of the issue is that the company wants to start building a new logistics center, but it is not clear whether the investment should be made immediately or postponed. Evelekt is largely engaged in the sale and import of furniture, and this market is currently very volatile, so management needs more accurate data for the future. The problem in forecasting sales volumes is the uncertain situation in China, long supply chains and their problems, the war in Ukraine, high inflation, which affects people's purchasing power, rising input prices and pressure on labor shortages. The research question in this work was how to improve sales forecasts through machine learning and make better management decisions.

## METHOD

The data subject of this work was the sales turnover forecasts of the company Evelekt AS. Data were collected from the company's internal programs, the website of Statistics Estonia, EuroStat and other Internet sites. The company's internal warehouse management software, internal sales software, accounting software and other software were used to collect the data. All data are historical and the work compared sales forecasts before and after the change. All data were compiled into a single Excel spreadsheet, which was later used as source material in machine learning programs.

Data were collected both structured and unstructured. Historically, key historical indicators were collected from various programs and transferred to an Excel spreadsheet. Unstructured data were collected through an in-house survey, which was answered by seven people involved in the topic. Data were collected between January 2018 and December 2021. The sample size was four years of sales.

## RESULTS AND DISCUSSION

To analyze the data, the author used two different AI solutions – Dataiku.io and Akkio.io. Two different platforms were used to better validate the results. Both software are created to help people better analyze and visualize data through a machine learning method. In my opinion, the biggest difference between those two is the input and processing of data. Akkio makes it easier to add and process data, but the data visualization side is weak. In Dataiku the processing of data into suitable data is more complicated, but the data visualization side is stronger.

Based on Dataiku.io, the author compiled a bar chart comparing the sales forecasts calculated by machine learning with the actual sales turnover. The table below also shows the parameters for this comparison. (Figure 1)

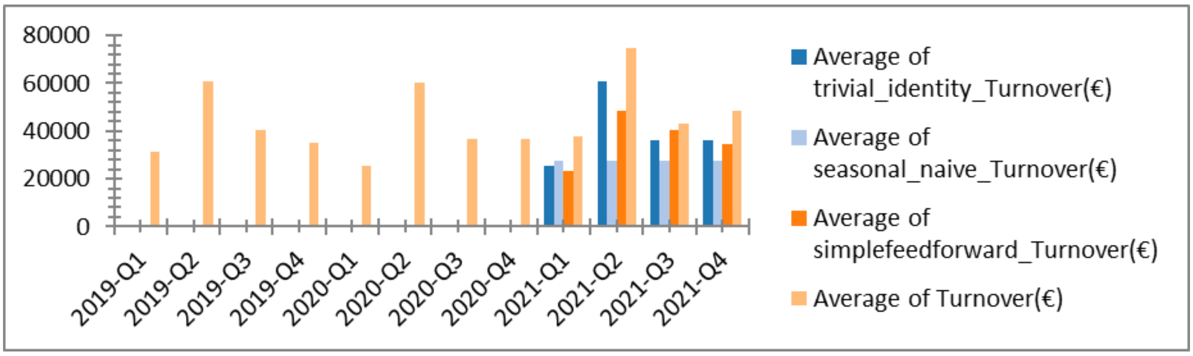


Figure 1. Sales forecasts

In order to get feedback from the company's managers, the author conducted a survey of seven executives, which consisted of 10 questions and was related to this research topic (Figure 2). The survey contained 10 questions through which the author wanted to know the following:

1) How long have you worked at Evelekt? (over 70% responders are working more than 10 years in company)

2) Previous Experiences with machine learning (over 70% responders don't have previous experiences)

3) Machine learning helps to improve company processes (57% believe that machine learning would help to improve company processes)

4) Machine learning helps to make a better decisions for top management (71% believe that machine learning would help top management to make a better decisions)

5) Machine learning helps a company increase its competitiveness (71% believe that machine learning would increase company competitiveness)

6) The results are clear and understandable (Only 43% believe that results are understandable and clear)

7) Is the prediction of training result of this model is realistic? (57% of responders are sure that predicition of this model is realistic)

8) Accuracy and quality of data used in the forecast (57% believe that used data was quality and accuracy)

9) Could this model be used to forecast turnover in the future? (Over 85% of responders are ready to use machine learning method in future)

10) Using machine learning forecasting could be Evelekt's direction in the future? (71% believe that machine learning method should be one direction where Evelekt should be going)

All questions could be answered in a 5-point system (1-strongly disagree, 5-strongly agree)

The survey revealed that five of the seven employees had no or minimal exposure to prior machine learning.

Table 1. Survey results by question

| **Question** | |
|---|---|
| How long have you worked at Evelekt? | over 10 years |
| Previous Experiences with machine learning | 2,14 |
| Machine learning helps to improve company processes | 3,86 |
| Machine learning helps to make better decisions for top management | 3,57 |
| Machine learning helps a company increase its competitiveness | 4,14 |
| The results are clear and understandable | 3,14 |
| Is the prediction of training result of this model is realistic? | 3,29 |
| Accuracy and quality of data used in the forecast | 3,29 |
| Machine learning prospect | 4,14 |

Table 2. Key indicatiors

| Model | MASE | MAPE | RMSE |
|---|---|---|---|
| FeedForward | 1,28 | 1,89 | 33565,65 |
| SeasonalNaive | 1,50 | 0,96 | 39676,86 |
| TrivialIdentity | 1,43 | 2,52 | 34929,42 |

## CONCLUSIONS

The aim of this work was to test whether machine learning can make better sales forecasts than a person. The aim was also to find out whether it is possible to introduce the machine training method in the company in the future and whether people are ready for it or the company still needs internal trainings for it. Analyzing and comparing the obtained results with the actual results, it can be stated that machine learning is not yet able to completely replace people in forecasting. There are a number of forecasting tools in place that need to be found to give you the most accurate results. AI's sales forecasts were too modest compared to actual sales. In order to make more accurate predictions through machine learning, the quality of the data must be of a very high standard. The results showed that using Dataik's solution, the forecasts were more modest than the actual turnover figures. The difference was about 20% (twenty percent). When testing the Akkio solution, the results were about 25% (twenty five percent) lower than the real numbers. I also prepared a Survey for the company's management. It was attended by 7 people and there were a total of 10 questions on this topic. The survey shows that most of management members had little or no previous experiences with machine learning methiod. The survey also shows that they believe that in the future, machine learning could be used to process data to make better management decisions. People with an IT background are more optimistic about the success of machine learning.

Evelekt AS currently sees no reason to introduce the machine learning method, as the company does not have the necessary know-how and is not sure about its effectiveness. The author of the work proposes to Evelekt to start contributing to raising the awareness of machine learning, so that in the development of technology to be ready to use greater efficiency in planning and to make better management decisions.

## Using chatbot to help people involved in traffic accidents

Thomas Tammus[1]

Key words: AI, chatbot, road accidents, government, private sector.

### INTRODUCTION

**Background**

The project studied in this work belongs to the list of Innosprint projects initiated by the Estonian government. Innosprint is a design-based approach, where in five days teams will reach from problem definition to a user-tested solution. The Innosprint team is led by the public sector owner and involves stakeholders from different roles and agencies. The team may also include representatives from the private and third sectors. The core of the team consists of people who are most involved in the project and have the background needed to develop solutions, including both service developers and service providers. (Republic of Estonia. Government Office, 2022)

The aim of this project was to understand the implementation of Bürokratt, ie the virtual assistant of the Estonian state, in the private sector. Bürokratt is a vision of the digital functioning of public services in the age of artificial intelligence. It is an opportunity for a person or user to use direct public pathways and information services with colloquial communication with the help of virtual assistants. In the future, Bürokratt will allow a person to get everything they need from one device and through a virtual assistant in one communication session. Thus, Bürokratt has created an interoperable network of public artificial intelligence attached to public information systems, which, from the user's point of view, acts as a single channel for direct access to public and information services. (Republic of Estonia. Ministry of Economic Affairs and Communications, 2022)

However, the aim of this project was to study the possibilities of using the Bürokratt in one of four areas: traffic accident, dental service, public transport and investment, from which the use of the Bürokratt as an assistant in assisting people involved in a traffic accident in cooperation with the Traffic Insurance Fund was chosen.

**Relevancy and the problem**

The goal of the state is to centralize data banks related to citizens and thereby make people's lives easier to solve their everyday problems.

Being connected with the Bürokratt, the Estonian Motor Insurance Bureau (*Eesti Liikluskindlustuse Fond* or LKF) is also able to react faster and easier to traffic accidents, and people in turn can get a quick solution to the problem. Why using a chatbot to register traffic accidents can be especially beneficial is a situation where a person does not know how to act in the event of an accident. However, due to ignorance, the police are often called first, who do not actually attend in most venues of accidents, as almost 90% of cases do not require police intervention, being ordinary blemishes or minor insurance cases without the other party. The secondary action is to write to LKF, whose answers take too long to respond (LKF goal is to respond within 24 hours), and people are left without the necessary information. Often, however, LKF information contains nothing more than a recommendation to contact your insurance provider. As a result, the question arose as to whether and how successfully this Bürokratt environment could be connected to a central speech robot to assist those involved in road accidents.

Although, there are different researches about using AI chatbot technology to help people in traffic accidents (Ouerhani, 2019) or with insurance related questions (Cardona, 2019), this topic has not been studied before in Estonia and regarding Bürokratt, so it is an initial project of this kind. As this project is still in its infancy, in its project construction and data collection phase, I will give an overview of the activities so far and the feedback on the prototype of the first chatbot in the following work. Work on setting up a Bürokratt and implementing it in the private sector is ongoing in the country.

### METHOD

The initial development phase of the project involved five one-day development sprints. Citizens involved in road accidents were first asked whether the chatbot could help them in the situation of accident and what information the chatbot should contain. Also, an LKF representative was interviewed to understand in which cases they would benefit most from the chatbot. About 90% of the respondents answered that the chatbot can help them and therefore also provided valuable feedback about information and the order of the questions the chatbot should contain. The input from the citizens showed that the chatbot should not be too complicated and should be able to guide people to the desired solution in as few steps as possible. Also for LKF, speed and simplicity are the main keywords, because in this way chatbot can help a person to reach a specific solution during a stressful situation as quickly as possible. As a result, the first chatbot was built considering the feedback.

Depending on the type of case, the first chatbot consists of seven responses and subsequent paths that are visible in Figure 1.

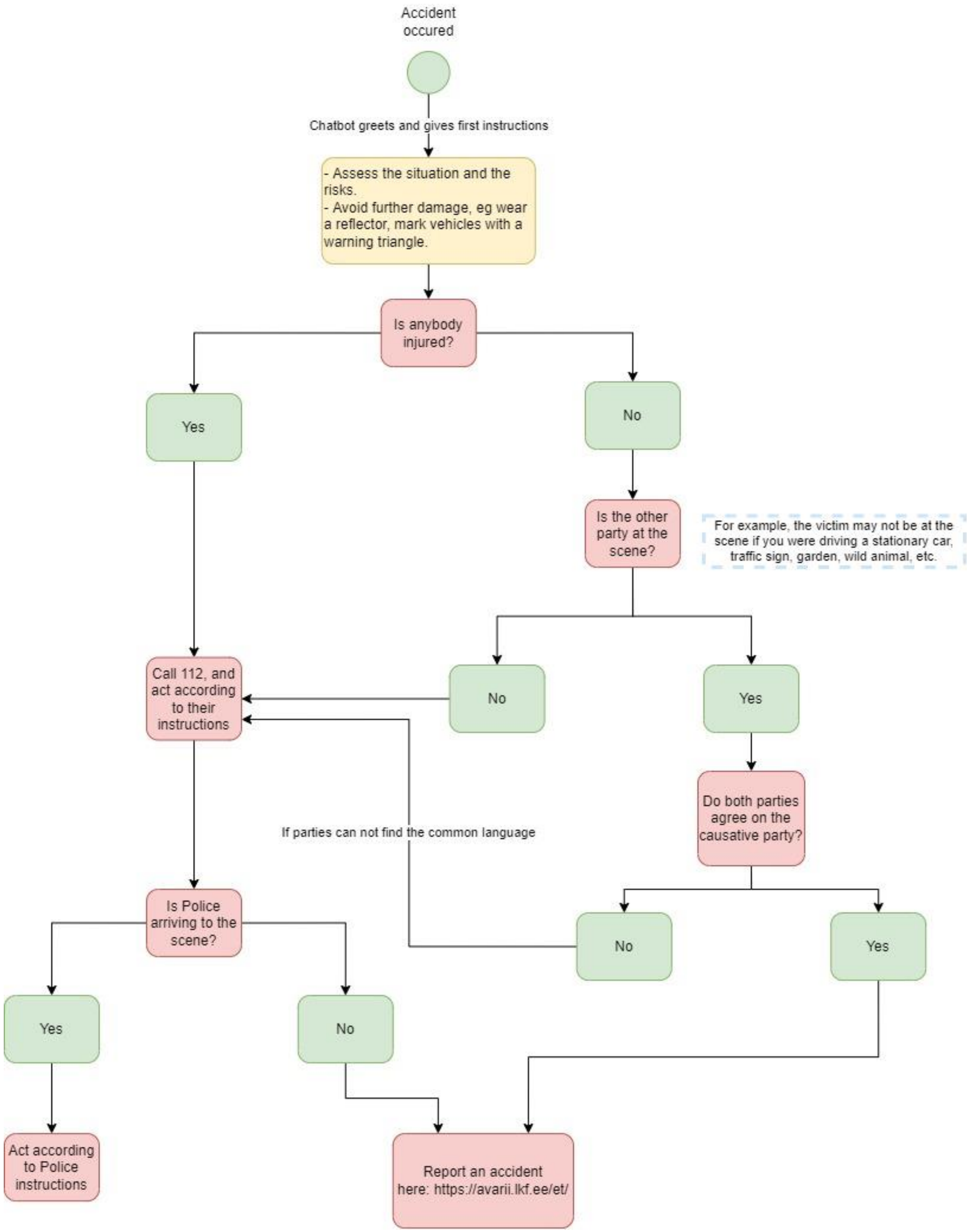


Figure 1. Process map of accident assistant chatbot. Chatbot itself can be found from here (chatbot logic from the link is a little different from the diagram due to the capabilities of the platform). (Dialogflow. LKF chatbot, 2022)

The first prototype of the chatbot was built using the Dialogflow environment, and the test was conducted with 32 participants who have participated in accidents and who completed a feedback questionnaire after using the chatbot. The feedback questionnaire assessed six criteria and included an open-ended question for comment. Each criterion was evaluated on a five-point scale, where 1 meant that the customer did not agree with the parameter and 5 that the customer was satisfied with the capabilities of the parameter experienced in the chatbot. The criteria were the speed of the chatbot, the chatbot's knowledge of the situation and understanding of the situation, and humane communication. The feedback from the test users provided an overview of the weaknesses and strengths of the first test chatbot, as well helped to create an improvement plan, which will not be presented in this work.

## RESULTS AND DISCUSSION

In the analysis of the feedback survey data, each response was analysed separately and diagrams were created for each of the criteria as well as for the main responses to the open-ended question. The test questionnaire was filled in by 32 users, not all participants answered to the open-ended question.

The results of the feedback questionnaire are shown in Figs. 2-3.

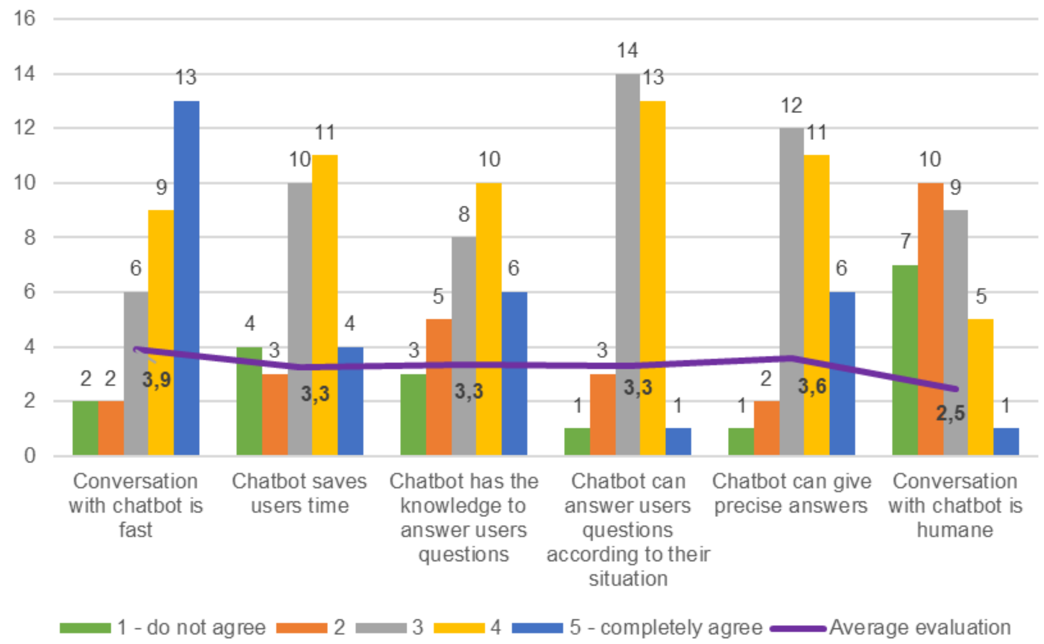


Figure 2. Evaluation of chatbot. Criteria evaluation, marks 1-5.

Feedback for the chatbot is rather positive or neutral. Users evaluate chatbot speed ("Conversation with chatbot is fast"), knowledge ("Chatbot has the knowledge to answer user's questions", "Chatbot can answer users questions according to their situation", "Chatbot can give precise answers") and principle of time-saving ("Chatbot saves users time") mostly with marks 5, 4 or 3, accordingly. Although, the majority of users are not satisfied with the chatbot answering style. Criteria, "Conversation with chatbot is humane" is mostly evaluated with marks 2 (10 users), 3 (9 users) or 1 (7 users), that indicates that users would like to have more less robotic conversation by the chatbot. Also, we get more detailed overview from the open-ended question answers in Figure 3.

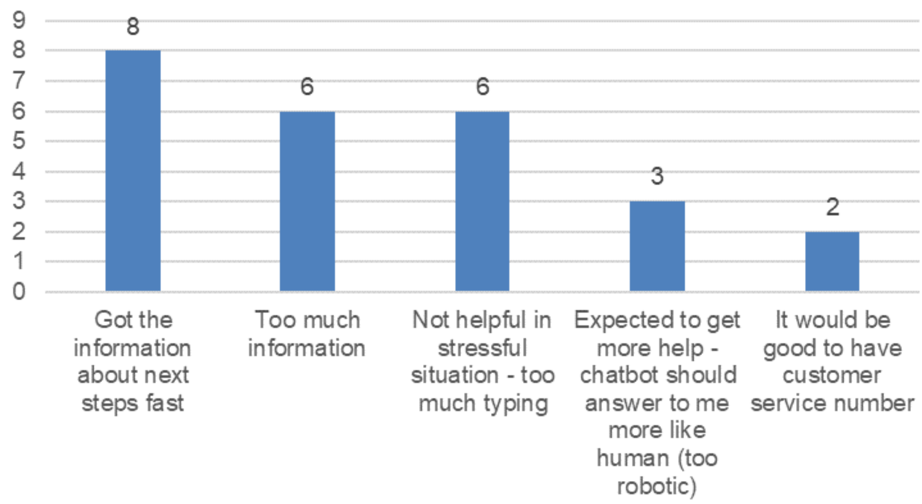


Figure 3. Evaluation of chatbot. Open-ended question answers.

On Figure 3 we see comments from the users that were distributed on 5 categories. From the answers we see that the majority of people are happy with the chatbot speed, but do not like the robotic answers, too much typing when answering and information capacity provided by the chatbot. Reason for that might be the issue that in stressful situations users might not have the time or concentration to read or write the lengthy text on their mobile screen. And as seen in Figure 3, recommendation from two users are to replace the chatbot with customer service instead. This recommendation might indicate the fact that talking to customer service agents is more humane and without unnecessary information about the certain incident that may be provided by the chatbot (Salesforce EMEA, 2022).

These results are beneficial in improving and developing the chatbot regarding user's needs, although, lot more tests, development and training is needed to build the suitable chatbot that fills the majority of the issues learnt from the first test. It is necessary to find a suitable platform for chatbot building and training before next user tests will be performed. People find it necessary that you should type as less characters as possible or only push the relevant buttons on the screen to make the process even faster. Also, the development team might need to think about developing AI call bot, that helps people who are not able to write or do not have the smart phone.

## CONCLUSIONS

What we learned from the study is that the citizens who end up in traffic accidents need help dealing with the incident from outside sources to find the correct solutions regarding their type of accident. Hypothesis regarding the research was that Bürokratt chatbot, the AI initiative by Estonian Government, can help people who had ended up in traffic accidents to find the right pathway when dealing with the incident. With the input from the citizens and LKF it was managed to test the first prototype of the chatbot. We understood that the future chatbot has to be quick in finding the right paths and the conversation has to be more humane. Otherwise, person involved in the incident does not get the help what is needed or does not find itself helped as expected.

This research has helped Estonian Government to launch the first initiatives to expand Bürokratt services to private sector. Hopefully, tests in other areas (investment, dental service etc.) will be started soon and also traffic accidents chatbot will be expanded not only to LKF, but to all of the insurance service providers in Estonia.

## ACKNOWLEDGEMENTS

I would like to acknowledge Estonian Ministry of Affairs and Communications, Innosprint team and Estonian Motor Insurance Fund for helping to reach the goals of this research and look forward to further successful cooperation. Special thanks to PhD Tarmo Koppel in supporting the students throughout the semester.

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# Implementing chatbot to assist costumer service of consumer protection and technical regulatory authority

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Key words: chatbot, public administration, natural language understanding, natural language processing

## INTRODUCTION

Consumer Protection and Technical Regulatory Authority (CPTRA) is a governmental body in Estonia. One of its responsibilities is to advise customers and resolve arguments between consumers and businesses. Since May 2022 CPTRA began to use an artificial intelligence based chatbot in order to better handle various inquiries. The AI platform used is “Bürokratt” and it is planned to be introduced to many other governmental agencies across Estonia.

Implementing Bürokratt in CPTRA is a pilot project and the AI is still in its early stages of development. Currently the chatbot is expected to be able to answer most commonly occurring situations and redirect the customer to a live agent if needed. At the time of writing this report, the chatbot has been trained to recognize and answer 30 intents at CPTRA. However, the AI is able to learn as it is being used.

AI based chatbots have been used for public administration purposes in various instances which are well covered in previous research by Nirala, K.K., Singh, N.K. & Purani [1]. In our current research we expand upon the previous research and provide a case study. This is a first preliminary research which aims to give insight to the early capabilities of the chatbot and point out some of the challenges which might be relevant when expanding the chatbot to other institutions.

## METHOD

In this study Bürokrats ability to handle real world inquiries was observed and analysed in order to assess the benefits and drawbacks of using AI based chatbot for answering consumers questions. The chatbot saves all conversations in a log file. Since the chatbot had been operational only for a few weeks, the available data was limited. For the purpose of this study 50 conversations were reviewed, categorized and analyzed. Of the 50 logs 17 were excluded because they were either tests or incoherent messages.

Most conversations followed a similar expected pattern and were quite short. Firstly, there would be a greeting from the chatbot inviting people to write their questions. After receiving the question, would assess if it undersood the question. If the AI had enough matching data, it would offer a response based on trained intents which sometimes included a follow-up question. The relevance of the responses were assessed and successful intent recognitions were counted.

In most cases the chatbot would not understand the first question and would straight away offer to redirect the client to a live person who would resolve the issue within the chatbot conversation platform. Since the redirecting intent was a simple yes/no response and occurred in every conversation, the redirecting intent was not included in the count.

In this study data collection was halted at the point of redirection in order to distinguish chatbots role and provide privacy. The final outcomes and the length of the conversations were noted and analysed.

Furthermore, qualitative interviews were conducted with both employees who use the chatbot in their day-to-day work. They were asked to assess the current capabilities and properties of the chatbot and provide personal comments about everyday use of it. Employees were asked to assess if the chatbot made answering each inquiry easier compared to tradition means such as e-mail or over a phone call.

## RESULTS AND DISCUSSION

Of the 50 logs 33 were analyzed and assessed. The results showed that the chatbot was not able to fully resolve a single inquiry. There were 3 conversations in which the AI successfully recognized an intent other than redirection. However, all conversation leads to the chatbot offering to redirect the conversation to a live agent. Employees were able to resolve the inquiry in 18 cases. However, in 15 instances (45%) the client chose not to be directed to a live agent and left. This might imply that roughly half of the respondents were not comfortable using chatbot and would seek to resolve their questions in a traditional manner by calling or e-mailing.

Most conversations were relatively short – 20 out of 33 (61%) conversations were shorter than 7 exchanges and 30 out of 33 (91%) conversations were shorter than 10 exchanges (Figure 1).

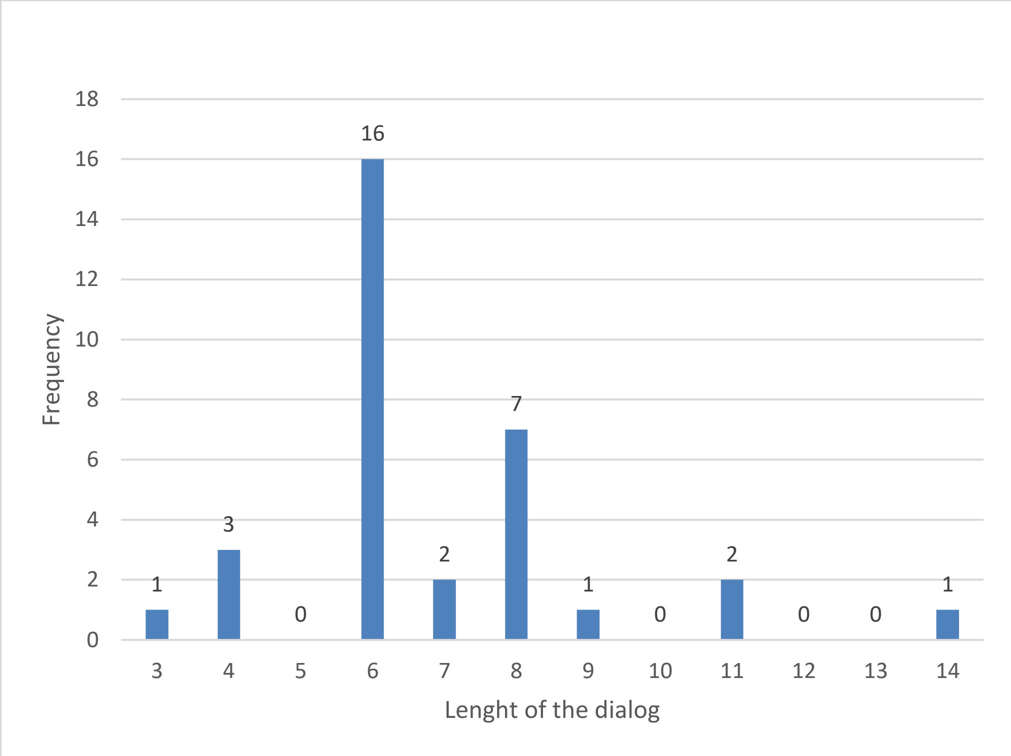


Figure1. Lenght of dialog frequency distribution

During the qualitative interview the employees stated that chatbot made answering inquiries easier and more pleasant compared to answering over the phone or via e-mail. It was stated that client's input was more expedient and clearer when using the chat window compared to cumbersome e-mail communication. In addition, the chat window allowed the employees to ask relevant questions, gave them more time to think (compared to phone convesation) about the answers and share useful links promptly.

When asked about some of the issues or drawbacks the main problems pointed out were relatively low amount of trained intents and low intent recognition. The questions encountered were more complex than expected and in some cases, there was a language barrier. In addition, there had been issues with the server stability which in some cases would cause unresponsiveness.

Regarding future perspective the respondents were optimistic in the AI's ability to learn and be developed to a more capable version. It was noted that a lot of work still needs to be done to improve upon the chatbot and there were fears that due to high amount of human interaction required the development may be too slow and user acceptance of the chatbot would be low. These findings could be significant when implementing the Bürokratt chatbot in other institutions.

## CONCLUSIONS

Since the project is in its early stages, the chatbot is not yet capable of resolving issues independently. Thirty trained intents in not enough given the complexity and variability of the inquiries. A great amount of work needs to be done to improve the AI's capabilities in intent recognition and natural language processing. Slow development may reduce user acceptance. Meanwhile, the chatbots platform is being used daily for the live conversation option which has become a valuable tool in answering inquiries. An additional benefit is the increased employee satisfaction and enthusiasm.

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## Predicting workers absenteeism in production company

Ene Saluste

Key words: production process, workers absenteeism, prediction, sick days, AI

### INTRODUCTION

This research was made based on company which is specialized in comprehensive ventilations solutions. The company operates in different countries: Estonia, Finland, Sweden, Denmark, and United Arab Emirates. The headquarter, central warehouse and production unit is in Tallinn, Estonia. The diversity of products is quite large, in 2021 the production volume was 6 million pieces and 12 600 different products. In this production unit works approximately 200 employees. All employees are divided between 40 different skill categories, each category describes the skill what kind of work section this employee can do. This production unit is using production planning system Asprova and production planning is automized. There are three main input resources for production: materials, machines, and manpower. To plan materials and machines is quite easy, but company is facing challenges with manpower. All plannable absences like vacations, training days, etc. are in the system, but sick days are unpredictable. Recent pandemic time has pointed out the need to consider possible sick days in production planning. Accurate planning is very important since Tallinn production unit serves all the company´s markets. The aim of this research was to find out is it possible to predict employees' absences in certain period by employee skill using artificial intelligence.

### METHOD

In this study the author used prediction tools Akkio and Dataiku DSS. Author´s focus was on Akkio tool. These tools were chosen because the author is complementing her knowledge in TalTech University, and these were introduced in practical lessons. Data used for this study was taken from Estonian Environmental Agency/Weather official database, Republic of Estonia Health Board official website and company´s database: sick days information for period 01.01.2020 until 30.04.2022 and employees' information. Database had 18 different parameters and 1403 rows. From company´s database was taken a) personal information: code, name, age, employee type (worker or team leader), department, occupation, skill, salary per working day, type of residence were each employee lives (apartment or private house), production volume in euros and b) sickness year, month, and days in specific month. For example, if sickness was from 29.05.2020 until 01.06.2020 in the database were three days in May 2020 and one day is June 2020. From Estonian Environmental Agency/Weather official database were taken each month´s average temperature (°C), average rainfall (millimetres) and average hours of sunshine (hours) in Estonia. From Republic of Estonia Health Board website were taken virus disease cases (piece) per month in Estonia. First parameters were chosen during small workgroup brainstorming and later when the author made a quick research in the internet to find out what parameters may have impact to employees' sicknesses salary per working day and type of residence were added.

In Akkio program training model predict was used. Predicted parameter was days and training mode fastest (10s), the author tried with the best accuracy results also high quality and higher quality training mode, but the results were lower (fastest mode accuracy ±54.37%, high quality mode accuracy ±60.05% and higher quality mode accuracy ±60.61%) and these modes weren´t tested any more.

In Dataiku DSS program at first the dataset was prepared; all empty rows were removed. In the second step was used visual recipes Split with splitting method Randomly dispatched data with ratio 80% (like in Akkio program) and random seed 42. Next step was AutoML prediction with quick prototypes prediction model with two algorithms: Random forest and Ridge regression. Using the best algorithm, the prediction was created.

### RESULTS AND DISCUSSION

The author made several predictions (Table 1) to see how different parameters influence the result. In Table 1 predictions are presented by accuracy result. The best result came where all parameters were included and then the accuracy was ±54.37%, RMSE and MAE were also the best, still the result is very low. The results of these predictions show that the more parameters, the better the result, at least with the chosen parameters.

Table1. Prediction results overview

| Prediction no | Used parameters | Accuracy[1] | RMSE[2] | MAE[3] |
|---|---|---|---|---|
| 1 | All parameters | ±54.37% | 5.3 | 3.9 |
| 2 | Without type of residence and salary per day | ±57.07% | 5.7 | 4.1 |
| 3 | Without production volume and department information | ±57.43% | 6.0 | 4.2 |
| 4 | Without virus diseases cases, production volume, salary per day and type of residence | ±58.39% | 5.9 | 4.2 |
| 5 | Without employee name | ±58.65% | 5.6 | 4.2 |
| 6 | Without production volume | ±58.97% | 5.9 | 4.3 |
| 7 | Without weather information, virus diseases cases, production volume, salary per day and type of residence | No result | No result | No result |

[1] Predictions are usually within this percentage (plus or minus) of the actual outcome. Lower is better.
[2] RMSE (Root Mean Square Error) is a standard way to measure error in a model predicting quantitative data. It estimates the standard deviation of a model prediction from a typically observed value. Lower is better.
[3] MAE (Mean Absolute Error) is a common measure of forecast error in time series analysis. It is the mean of absolute value of the difference between predictions and actuals. This helps you understand the average size of prediction errors without considering if they are above or below actuals. Lower is better.

In Dataiku DSS program the prediction was made using all the parameters. Random forest algorithm's result was 0,081 and Ridge regression algorithm´s result was 0,079. The author believes its possible to get better accuracy when more personal and health information can be used, but GDPR regulations prohibit without employee's written acceptance to collect or ask personal information. Using other modern tools like face recognition may be possible to evaluate each person's fatigue on daily bases, and this could give useful input to predict possible illness in the near future.

## CONCLUSIONS

The aim of this research was to find out is it possible to predict employees' absences in certain period by employee skill using artificial intelligence to improve production planning accuracy. All these predictions show low accuracy to predict at a sufficiently accurate level the absences. To get higher accuracy is needed more personal information about employee's health status. Then it is probably possible to predict sicknesses for a short time. For longer time production planning such method is not giving enough reliable information. This research didn´t give positive results to improve production manpower resource planning, but the author will continue testing artificial intelligence to improve sales predictions. For the company right products at the right time is one of the most important key performance indicators.

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## Artificial intelligence predictive capabilities for cinema's movie schedule

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Key words: movie schedule, program management, cinema, predictive artificial intelligence.

### INTRODUCTION

Movie industry is one of the most attractive industries, generating globally both vast amounts of revenue and equally as much media attention. Thus, the number of films produced keeps growing and the demand to fit the growing range into a quality screening program is becoming more vital than ever. Although the recent pandemic years have slowed down the influx of new releases, the industry believes that cinema theatres will return to its former revenue capacity. However, the need to minimize the costs and be ready for unpredicted environmental circumstances is more crucial than ever.

For customers it is important to see variance in the cinema's film program but for cinemas it is more important to maximise the revenue earning per each release. For cinema program managers it is a challenge to find a balanced path in the middle and to create a quality program that serves both interests. For that purpose, cinemas spend a lot of resources to analyse and create schedules, more often basing it on the subjective evaluation of selected individuals than real data. That creates more strain on payroll as well as preventing schedules being released as soon as the demand of the product arises e.g customers would like to buy tickets for new cinema week.

Previous studies on similar topic have focused on user experience and examined film recommendation using sentiment analysis and machine learning (Pavitha et al., 2022), cosine similarity and KNN algorithm (Singh et al., 2020). To date there has been no study conducted on predicting the best possible cinema's film program for next period of time according to last week's sales results.

Recommendation systems have become the most essential fount of a relevant and reliable source of information in the world of internet. Simple ones consider one or a few parameters while the more complex ones make use of more parameters to filter the results and make it more user friendly (Singh et al., 2020). This indicates that there could be a major undiscovered resource for the further cinema film program development with using the help of different platforms of AI to increase the business value.

To reduce the resources spent on movie result analysis and cinema's next week's film programming the authors of this research paper have conducted a research to evaluate if there is a way to use the help of an artificial intelligence to predict the cinema's film program while also increasing business value at the same time.

### METHOD

For analysis the authors have collected sales data from a local cinema market leader (one unit) for period of 01.05.2016-31.05.2022 as shown in Table 1. Authors combined the sales data with the available historic data of movie recommendation platform Rotten Tomatoes. For extra background and context, the authors conducted qualitative research with 6 program managers and 6 sales managers in the company to better assess the parameters that affect the results of each movie.

Table 1. Period 01.05.2016 – 31.05.2022 sales data of local cinema market leader (one unit)

| Parameter | Total data |
|---|---|
| Ticket sales (pcs) | 485 292 |
| Ticket category | 29 |
| Date | 396 |
| Admissions | 2479583 |
| Genres | 9 |
| Languages | 5 |
| Local distributor | 60 |
| Global distributor | 364 |
| Show category | 5 |
| Event | 1454 |
| Auditorium | 6 |
| Show | 485289 |
| Location | 1 |
| Show ID | 16549 |
| Day of the week | 7 |
| Director | 1215 |

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| | |
|---|---|
| Length | … |
| Weather conditions | … |
| Temperature | … |
| Min temperature | … |
| Max temperature | … |
| Wind speed | … |
| Auditorium capacity | 762 |
| Occupancy rate | 35% |

Two platforms which were used for AI's predictive analytics were Akkio and Dataiku. Both platforms used same data and parameters to predict the most accurate cinema's film program with the aim to increase business value. This data from previous sales periods was used to test two different artificial intelligence predictive analytics tools as shown in Figure 1.

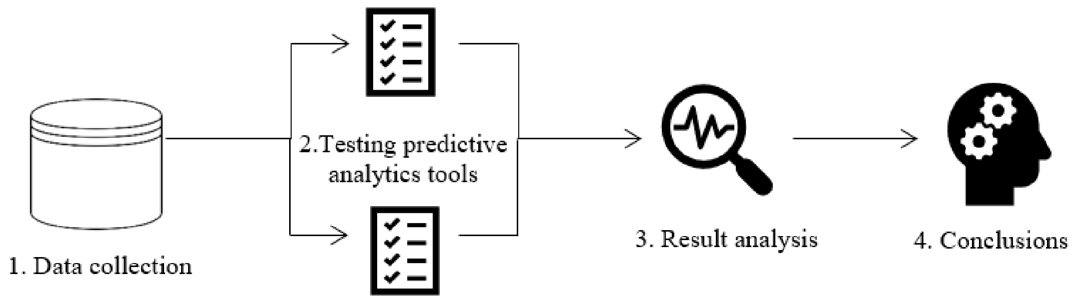


Figure 1. Build-up of the conducted research to conclusions.

## RESULTS AND DISCUSSION

The result of the qualitative research showed that the affecting parameters are more multidimentional than the authors had expected. Industry specialists referred to the aim of this research as "impossible". It was said that there is a lot of information that can not be put into data and can only be interprated by people who know the industry and the movies being released. Parameters that were suggested as essential in program creation were the following:

1) Director of the movie
2) Cast
3) Budget of the movie
4) Weather conditions
5) Day of the week
6) Holidays (inc. school breaks)
7) Media topics during the release (f.i negative press about the cast)
8) Movie length
9) Presales
10) Demography in the region
11) Capacity of the auditoriums + occupancy rate
12) Service time between screenings
13) Reference movies (similar movies or previous releases in a movie series)
14) New releases

Based on the interviews the authors expanded the available data from sales system and added available data from pre-existing databases (weather conditions, movie length, day of the week). Unfortunately other parameters weren't available for the authors in a quantitative form and therefore could not be included into the data. Thus in the opinion of authors caused a serious effect on the whole quality of the qualitative research and the validity of the results.

Testing of the data confirmed relatively inconclusive results. Akkio's prediction quality was a low 60% although taking „presales" as a leading parameter in its predictions. That parameter was also mentioned in the qualitative research results. Dataiku also presented Presales as a top field. Unfortunatey no prediction accuracy was available. Other top fields were quite unreasonable showing true lack of context in AI's work. For instance ShowID has no real affect on any of the admission results.

Table 2. Results of data analysis and predictive analytics of Akkio and Dataiku platforms

| | Akkio | Dataiku |
|---|---|---|
| Analysed data rows (n) | 485 292 | 485 292 |
| Parameters (n) | 24 | 24 |
| Type of predicted parameter | Numerical | Numerical |
| Prediction quality / Accuracy (%) | 60,11% | |
| Top fields | Presales, Date, Auditorium, temp, Event, tempmin | Presales, ShowID, windspeed, temp, tempmin, tempmax |
| $R^2$ score | NA | 0,43312 |
| MAE | NA | 2.3472 |
| RMSE | NA | 4.7336 |
| MAPE | NA | 85,7% |
| The best algorithm with the highest score | NA | Random forest |

## CONCLUSIONS

Cinema companies as well as other businesses are looking for more time and cost efficiency as well as quality in creating cinema schedule. It derives from having a growing range of releases as well as increasing costs in cinema operations. The aim of this research was to assess whether artificial intelligence could be a tool for helping cinemas to achieve those goals.

The methods of this research combined qualitative and quantitative ways of collecting and analyzing data. Qualitative data created context for quantitative data collection. Unfortunately it also presented lack of pre-existing datasets in order to better assess the AI tools. Unfortunately it also translated in inconclusive research results.

The authors of this paper still believe in making the cinema film programming more efficient and profitable with the help of predictive AI. Combining predictive AI with recommendation systems might not only make cinema film programs more accurate, but also cost-wise beneficial. The study at hand showed also as Pavitha and his team's studies concluded (Pavitha et al., 2022) that system can be very accurate, but it does have limitations. It needs extensive data in order to better understand the context. This particular research showed that even with partial data, AI could see some accurate logic.

As this study contained limited parameters, future studies should focus on more efficient and suitable platforms with wider data and parameters which include also regional and international film-review aspects, more data about the physical room that the cinema operates in, media analysis and wider range of datasets.

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# “SupAssistant” virtual assistant for customers and staff

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Key words: virtual assistant, chatbot, return material authorisation (RMA), chatbot integration with mysql and Google Sheets

## INTRODUCTION

“S” is a wholesales company selling specialised electronics to a limited number of specialised companies (Buyers). No sales to end users. The number of customers is very limited, about 100 companies in Estonia, 150 in Latvia and 150-200 in Lithuania. 99% of customers are returning customers, most with a very long history of cooperation. About 20-30% of these customers make more than 5 purchases per week, each purchase consists of a variety of different products, each might have a different warranty period and each one has its own serial number which is being scanned and saved in ERP (Enterprise resource planning software) upon sales. This means a large number of invoices with even more serial numbers.

“S” has 2 main departments: Sales and Tech.Support. “S” also arranges warranty repairs, replacements to everything they sell.

Sometimes equipment fail / break down and it is important for both the Buyer and Tech.Support to know if a specific piece of equipment is still under warranty or not. Today the only option is to ask from Sales. This always takes time and requires human interaction/communication. Phone calls and emails tend to lose information or have other issues (misheard, misspelled, wrong serial number of a product, wrong invoice number, etc.) and getting an answer might take minutes, hours or even days. In case a product is being sent to warranty procedures or repairs, a Return Merchandise Authorization (RMA) form has to be filled in with all the necessary and correct data.

The aim of this research is to find out if a chatbot solution would replace some routine communication and speed up decision making (product is still under warranty or not? warranty repairs or paid repairs?), simplify and speed up the communication between “S” and Buyers.

My research started from a simple query to find our if an invoice is paid or not and what is the due date. Later it was extended to the RMA procedure and this became the main focus of this research.

## METHOD

The subject of this research is virtual assistant (VA) called “SupAssistant”. I used Flow XO to build a chatbot which interacts with customers or personnel of the company, is able to communicate with a remote MySql database, prepare an email with the gathered data and save RMA data to Google Sheets. In addition, Live Chat can be used.

“Flow XO for Chat is our feature-rich chatbot platform that allows anyone to create code-free online chatbots (bots) quickly and easily” (https://flowxo.com/product/flow-for-chat/). All these means of communication (MySql, Live Chat, Email, Google Sheets) were used to test the possibilities of Flow XO.

I used modified data from company “S” ERP database. All data indicating to real customers was replaced, deleted or not used in its original form. Data was imported into a test-database. In case this VA goes live, data available for VA will be copied/synchronized automatically from ERP or the actual ERP database will be made accessible for VA.

In Flow XO a chatbot consists of different flows, which are triggered by triggers. Triggers can be keywords, incoming emails, direct buttons from other flows, etc. SupAssistant is made up of 4 flows (Fig. 1, Table 1).

Table 1. Flows in SupAssistant

| Flow nr | Flow name in Flow XO | Description of flow |
|---|---|---|
| 1 | Identify yourself! | Identification of the user |
| 2 | Find invoice deadline | Find invoice from invoice database and show paid / unpaid information to the user |
| 3 | New RMA | Flow to search for sales history and data based on product serial number. RMA/Warranty procedure initiation |
| 4 | send_email | Send email and save data in Google Sheets |

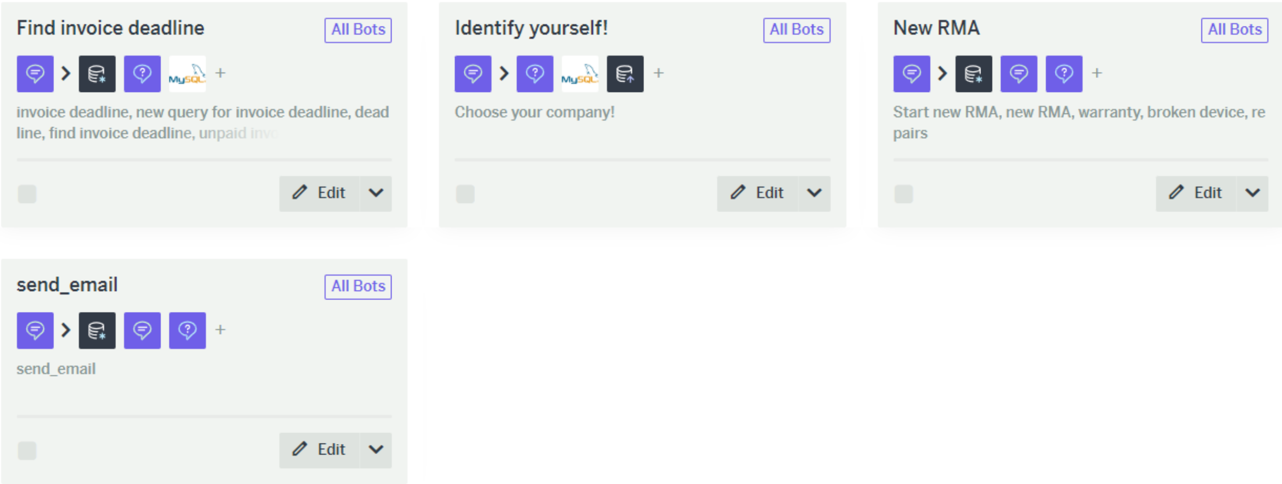

Fig.1. Flows in SupAssistant

Each flow consists of an unlimited number actions to create a fluent and human-like communication between the chatbot and the user. Flow XO offers a large number of different action types. Some of them might run on the background (queries from databases, calculations, etc.), some are visible (messages, questions, etc.)

A detailed explanation about the most important functions of SupAssistan can be found in Table 2. (Flow name can be found in Table 1).

Table 2. Important function in SupAssistant

| Flow nr | Function | Explanation |
|---|---|---|
| 1 | Identification | Virtual Assisant (VA) needs the user to be identified.<br>NB! Currently this is done by choosing 1 of 3 companies. User data is currently being queried from a MYSQL database located in a remote server.<br>In real life this will be done automatically, as this chatbot would be part of CRM&ERP where the user is identified via logon to the CRM&ERP.<br>Customer data is being extracted from the customer database and used for further actions, saved as attributes for the VA |
| 2 | Find invoice | VA checks via REGEX if entered value is correct (min 4 and max.10 numbers and no letters) and then queries the MYSQL database for the entered invoice number. NB! Currently VA looks for all invoices, but in real life it would search only for the invoices for this specific customer. |
| 3 | Query 1, "EXACT SN from database" | VA looks for the exact number from the Serial Numbers table ERP database. Result will be an invoice number. This is done by using the built-in GET_ROW function. |
| 3 | Query 2, "Partial SN from database" | VA searched for all invoice with the entered SN being part of any serial numbers in the system. This is done by a SQL query. Result will be a MYSQL response which will have to be modified/parsed. |
| 3 | Find invoice data | VA queries the MYSQL database for all invoice data based on the invoice number from Query 1 or modified Query 2 results |
| 3 | Generate answer | VA will generate an anwer based on the results:<br>1) nothing found. Show what was searched for. Request to enter new SN or quit<br>2) too much found. Show what was searched for. Request to enter new SN or quit<br>3) exact sn not found, partial found, 1 invoice found. VA will explain what was entered by the user, how VA extender the search what was found in result<br>3) exact sn found, 1 invoice found. VA will explain what was found. |

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| | | |
|---|---|---|
| 3 | Display result | VA will display the result:<br>- queried SN<br>- invoice nr.<br>- invoice date<br>- serial numbersfound (VA will show extender SN here if it was used<br>- Product name and article number in database<br>- Warranty end if existing in datebase |
| 3 | Notify about warranty | VA tells the user the product at hand is under warranty.<br>VA asks the user to make a choise:<br>1) Send a prefilled RMA application to the Tech.Support team of the Seller<br>2) Start over with a new Serial number (start flow 3)<br>3) Quit<br>4) Talk to a real person (start live chat) (Only when warranty time is not over) |
| 4 | generate email content and send email | VA generates email content to both recipients and sends the emails |
| 4 | Google Sheets | VA modifies dete formats and adds a row to Google Sheets predefined sheet |

SupAssistant was tested on a selection of customers and tech. support personnel.

## RESULTS AND DISCUSSION

RMA enquiry flow became more attractive and more complicated to realize than the invoice due date enquiry. As a result, it became exact and quick enough that some people involved in the testing procedure asked when it would become live. There is no statistics about how long the RMA enquiry took traditionally, this varies from minutes to days, depending on how many people are involved. With the use of VA it takes a up to a minute to get a result and send the RMA request.

A test group of 11 people answered a simple questionary which helps to evaluate the VA.

27,3% of all people answered were women and 72,7% were men. 4 out of these 11 persons (1 woman, 3 men) are employed by the company.

Each person was asked to answer 15 questions about VA. Each answer was scored based on the total amount of points it received.

Table 3. Results of the questionary

| | | | How many times per question | | |
|---|---|---|---|---|---|
| nr | Question | Score | "5" | "4" | "3" |
| 1 | Agent has knowledge to answer customers questions | 85,45% | 5/11 | 4/11 | 2/11 |
| 2 | Agent helps me significantly in communication with the Company | 83,64% | 6/11 | 3/11 | 0/11 |
| 3 | Agent is polite with customers | 89,09% | 6/11 | 4/11 | 1/11 |
| 4 | Agent is fun and enjoyable to talk to | 69,09% | 3/11 | 2/11 | 4/11 |
| 5 | I prefer the agent giving me choices rather than me asking questions | 94,55% | 8/11 | 3/11 | 0/11 |
| 6 | agent is on time and i did not have to wait | 94,55% | 8/11 | 3/11 | 0/11 |
| 7 | communication with agent is precise | 90,91% | 7/11 | 3/11 | 1/11 |
| 8 | I got all the necessary information from the assistant | 87,27% | 6/11 | 3/11 | 2/11 |
| 9 | I got all the answers and "case closed" | 90,91% | 6/11 | 5/11 | 0/11 |
| 10 | Talking to the agent is faster than talking directly to the company | 92,73% | 8/11 | 2/11 | 1/11 |
| 11 | talking to the agent is more productive than searching the company databases for the same data | 92,73% | 8/11 | 2/11 | 1/11 |
| 12 | Using agents more effective than other means of communication | 81,82% | 4/11 | 5/11 | 1/11 |
| 13 | Virtual assistants help save time | 83,64% | 6/11 | 3/11 | 0/11 |
| 14 | I am happy with the service i was offered | 90,91% | 7/11 | 3/11 | 1/11 |
| 15 | Assistant did exactly what it should have done | 98,18% | 10/11 | 1/11 | 0/11 |

Questions nr. 4 (Agent is fun and enjoyable to talk to) and nr.12 (Using agents more effective than other means of communication) received the lowest score, meaning there is enough room to develop the communication skills of the VA. On the other hand, functionality seems to be enough as most of the questions got a score of 90% and more. I think we could also say that the subjects of this questionary are willing to talk to a chatbot and found VA more effective than talking to a real person.

100% of employees found that “Talking to the agent is faster than talking directly to the company” deserves the maximum number of points. This either points out a communication problem and something has to be changed in the internal communication within the company or VA was doing exactly what it was designed to.

Based on the results of the questionary and possibilities of the VA engine, further development plans are already under discussion for both main functionalities (Invoice inquiry and RMA request).

Some examples are brought as follows:

- Get a list of all unpaid invoices, with an option to choose some of them and automatically generate a bank link for payment.
- Generate a shipment with shipping companies: VA would use the customers location to find the closes parcel machine or ask the user which is the closest parcel machine, use XML data exchange to generate a parcel label. This service would immediately be possible with the following shipping companies in Estonia:
    * Omniva (https://www.omniva.ee/private/parcel). They use XML data exchange (https://www.omniva.ee/public/files/failid/manual_xml_dataexchange_eng.pdf)
    * Itella (https://itella.ee/ariklient/info-abi/liidestamise-opetused/automaatse-andmevahetuse-opetus/)
- Option to find out the status of a RMA request: user asks VA „what is the status of my RMA“ and, bot finds the RMA case and gives all the necessary details.
- Made inquiries about purchase orders which are not delivered yet:
    * delivery status,
    * ETA (estimated time of arrival).
- Change delivery location or method of an existing order.

All of this is currently done manually and each procedure takes minutes. With the use of VA time consumtion for each procedure for decrease by a magnitude.

## CONCLUSIONS

Virtual Assistant can successfully replace manual labour, especially when we are talking about searching for numeric facts in a closed environment (database which consists of fixed data).

It was most difficult to make data from one system be understandable for other systems. My research included data from and to 4 different systems: original data from ERP, converted information in MYSQL, information necessary for VA, information from VA to Google Sheets. I was not able to make the VA make calculations with DATA/TIME (how many months since time X, how many days until time Y, etc.) because of my lack of data format conversion skills. In addition, some letters in Estonian are also problematic to non-Estonian software solutions and would have to be replaced in case of automatic data conversion. Last but not least although Flow XO is advertised as a code-free chatbot solution coding had to be used to make the chatbot do what I wanted.

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## Chatbot as a Customer Service tool in small and seasonal home business

Anneli Karu

Key words: chatbot, ordering flowers, summer flowers, flowers, plants, customer communication, seasonal business, Dialogflow, home business, small business, garden.

### INTRODUCTION

It's a summer flower and plant garden in Estonia, small home business. That also means seasonal business which only works in spring and summer period. The business has two owners who are also key employees and do everything themselves. As it's a seasonal business, the sales period is very busy and workload often falls at the same time. Most customers come in a beautiful weather and in these days there are also much more customer questions to answer. Customers use mostly Messenger or the phone as communication channels. But especially in sunny weather, business owners need to water their plants and flowers more than usual, so there is no time to respond via Messenger at all or it is just taking too much their valuable time. At the same time, people in Messenger expect a quick response and the Messenger is a tool where people communicate more and more.

One of the options available today would be to integrate a chatbot with Messenger. This would help answer simpler customer questions quickly and submit orders as well, without using company resources. This current study focused on finding out whether and how much the chatbot can solve described problems and be useful for the customers and business ownesrs.

Google Dialogflow was chosen as the chatbot, with a total of 72 intents set there, 5-20 phrases under each intent. It is a simple application that was easy to use and easy to integrate. The free period of use allowed to get acquainted enough to make a decision on its longer use.

### METHOD

The methods that have been used are customer surveys and interviews with business owners. The customer survey consisted of a total of 15 questions with predetermined scale or dropdown choices. For business owners were 6 open questions.

The analysis is based on the answers of 23 customers and the results of two business owners' interviews.

Table 1. Customer survey input

| Question | Answer options | Comment |
|---|---|---|
| 11 questions | 1; 2; 3; 4; 5 | One choice per question, 1 is disagree and 5 is strongly agree, mandatory field. |
| How often on average do you buy flowers per year? | once a year;<br>twice a year;<br>every month during the summer;<br>every week during the summer;<br>hard to say | Dropdown list, one choice, mandatory field. |
| Where do you usually buy flowers? | from garden;<br>by phone;<br>online | Dropdown list, one choice, mandatory field. |
| Gender | woman;<br>man;<br>don't want to say | Dropdown list, one choice, mandatory field. |
| Age | Number | Free text field, mandatory. |

## RESULTS AND DISCUSSION

Testing period was 8 days. All customers who received the survey provided feedback. Customers were free to rate the chatbot for their cognitive approach. Since the customers expectations for the chatbot were not asked, it’s not possible to compare whether the ratings were slightly different due to different experiences or different expectations.

The results show that the average age of the customer is rather higher, customers mainly prefer to buy goods from the garden on the spot and make purchases mainly twice a year. Both the feedback from the customers and the interview results with the business owners clearly show that the chatbot is fast and answers simple questions clearly, saving everyone time. At the same time, personalization and ordering have been assessed as weaknesses. Although these questions still got higher scores than expected, although very many orders were not completed.

Of all the initiatives, only 7 customers achieved the expected result with an order, others either gave up completely or continued ordering by communicating with a real person or by telephone. Although the chatbot was set up better than expected in my opinion, there were a lot of problems with making an order. Messenger is often used from a smart device and is designed to communicate quickly and this is probably why there are often many typos and misspellings that are difficult to describe when training a chatbot. In addition, a lot of information was asked about the size, color and growing conditions of the flowers and plants. For example, size is constantly changing and color combinations often depend on a particular individual, so such information cannot be trained for a chatbot. However, the possibility of ordering could be maintained if there are buyers who do not ask these additional questions. The chatbot should definitely be trained more to make it more reliable, but then the question arises -whether there will be enough orders during the few summer months to develop the chatbot.

As the chatbot is in Estonian, this is probably one of the reasons why it is more difficult to use. The grammar of the Estonian language is specific and the use of language is low in the world view, which is why AI solutions cannot handle it so well yet.

For simpler questions chatbot was the perfect tool. For questions like the are you currently open, what is your exact location, how to contact you, initial information about the assortment (or even suggestions), where you can park, what payment options are available, etc. the chatbot is able to answer very well. this is the part that could definitely stay in use.

Table 2. Customer survey results

| **Question/criteria** | 1 | 2 | 3 | 4 | 5 | Average |
|---|---|---|---|---|---|---|
| Chatbot can have the knowledge to answer all your questions | | 4 | 2 | 12 | 5 | 3,8 |
| Chatbot pays individual attention | 1 | 1 | 6 | 8 | 7 | 3,8 |
| Chatbot provides the latest information | | | 4 | 10 | 9 | 4,2 |
| Chatbot is able to present products and services well enough | | | 2 | 11 | 10 | 4,3 |
| Chatbot can provide information about products and services according to your preferences | | 1 | 9 | 9 | 4 | 3,7 |
| Chatbot allows you to personalize your product or service | | 1 | 10 | 9 | 3 | 3,6 |
| Chatbot handles various problems | | | 5 | 12 | 6 | 4,0 |
| Communication with the chatbot is fast | | | | 10 | 13 | 4,6 |
| Chatbot saves you time | | | 2 | 3 | 18 | 4,7 |
| Chatbot is able to give accurate answers | | | 4 | 12 | 7 | 4,1 |
| Did chatbot make it easier to order flowers? | 1 | 7 | 7 | 7 | 1 | 3,0 |

| | Once a year | Twice a year | Every month during the summer | Every week during the summer |
|---|---|---|---|---|
| How often on average do you buy flowers per year? | 1 | 12 | 8 | 2 |

| | From garden | By phone | Online |
|---|---|---|---|
| Where do you usually buy flowers? | 14 | 3 | 6 |

| | Woman | Men |
|---|---|---|
| Gender | 20 | 3 |

| | |
|---|---|
| Average age of the customer | 47 |

Table 3. Business owners interview results

| Question | Person 1 | Person 2 |
|---|---|---|
| Did chatbot make it easier to communicate with customers? | Yes, customers received a much faster response, but lot of clarification was needed regarding the orders. | I don’t have an overview. |
| Did chatbot provide enough information to customers? | More or less | Yes, in my opinion |
| Did customers have a positive attitude towards the chatbot? | Nobody didn’t mention. | Can't say, didn't ask and nobody mentioned it. |
| How much did the chatbot confuse customers? | Ordering part was confusing because there was a lot of questions that chatbot couldn’t answer about how to grow etc | I heard complaints about orders, people still called and clarified. |
| Were the orders understandable and doable? | So-so | I don’t think so. |
| Would you like to continue using the chatbot? | Chatbot is the perfect helper for simple and specific questions. | Why not, we could keep up with the times and make some use of it. |

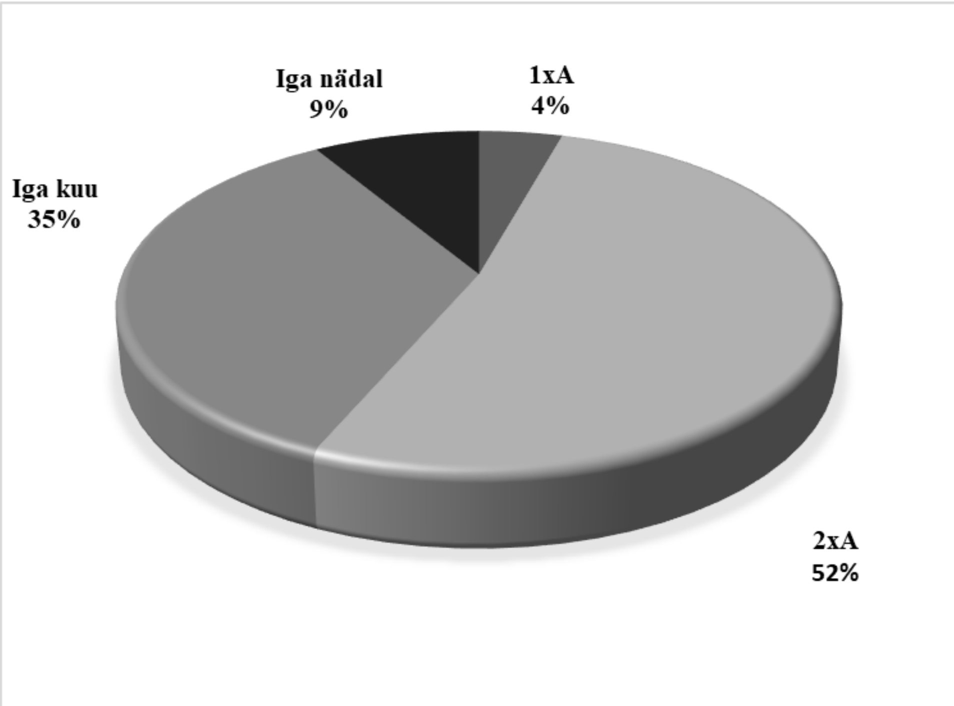


Figure 1. How often on average clients buy flowers per year.

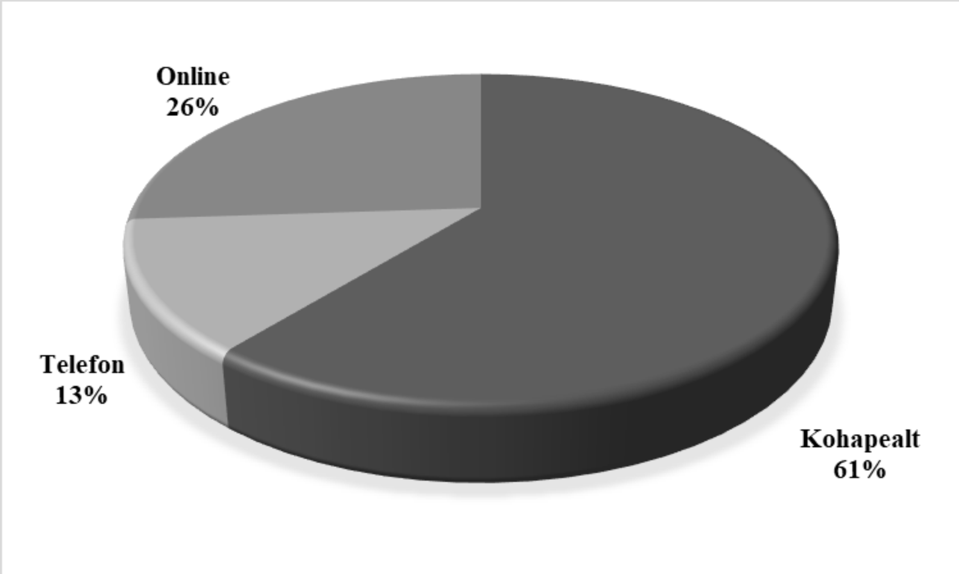

Figure 2. Where clients usually buy flowers.

## CONCLUSIONS

Chatbot is a perfect tool to reduce the workload of employees, but only if the chatbot is properly trained and the specifics of the company are suitable for using it. Teaching the Estonian chatbot is definitely more complicated as the English version. This must also be taken into account for more complex solutions.

The ordering process currently generates as much communication as without it and this part should be trained more if there is a wish to continue using it. It is currently not convinced of its feasibility and efficiency, so this part should be analyzed more before deciding.

For simpler questions chatbot is the perfect tool because customer gets a quick response, customer is happy and business does not have to spend its time answering for basic questions. In this aspect, there is plan to continue using the chatbot.

# Evaluation of virtual assistants on the Amelia platform

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Keywords: service agent, virtual assistant, chat robot, chatbot

## INTRODUCTION

Artificial intelligence is at the heart of the digital revolution in today's society. Artificial intelligence is changing the world economy, which is why there is a great demand for jobs in artificial intelligence.

The virtual assistant service is suitable for various companies. It is ideal for companies that are starting out, planning to expand or want to work more organized and efficient. Routine and time-consuming business support activities can be delegated to a virtual assistant.

I am very interested in the topic of virtual assistants and I believe that if you are thinking about starting your own business in the future, it is definitely worth hiring a virtual assistant right away. Apart of the research work, I got to know Amelia, one of the most famous virtual assistant platforms in the world, and the aim was to evaluate the virtual assistants working on this platform and get to know more about Amelia platform´s possibilities.

Amelia is a leading Enterprise Conversational AI software company with a long history of automation and chat AI innovation. As the market-leading digital employee and chat AI solution, Amelia delivers the best elements of human interaction into the user experience on a daily basis - creating deeper connections and increasing business value through conversation, expression, emotion and understanding.

## METHOD

The content of the work was to evaluate the virtual assistants working on the Amelia platform. In my couse work, five virtual assistants were evaluated by six testers. These five virtual assistants were working in various areas and the average age of testers was 34 years, the youngest was 27 and the oldest 44. 5 women and 1 man participated in the testing. Testers used online environments an average of 5 times a month.

The testers had a task to ask questions about the specifics of exact product or service. The total amount of questions was twenty two.

During the task, questions were simulated based on the specifics of this product or service. The testers rated on a scale of 1 to 5 virtual assistans in nine different categories, which were : interaction, entertainment, trend, adaptation, problem solving, accuracy, reliability, communication skills, and satisfaction from one to five scale.

## RESULTS AND DISCUSSION

The highest rating was in reliability criteria. It got the rating of 3,38 out of 5. The honesty, trustworthiness, loyalty and morality of the agent were assessed in this category. The points in the trend category were also high 3,7 point out of 5. The points in the trend category were also high. Testers believed that the service agent provides the latest information and the use of a brand agent is very trendy and it is generally recommended to use a service agent in the company.

The lowest points were in customization category. It got 2,86 out of 5. So the testers thought that the virtual assistants did not customize well to their personal preferences.

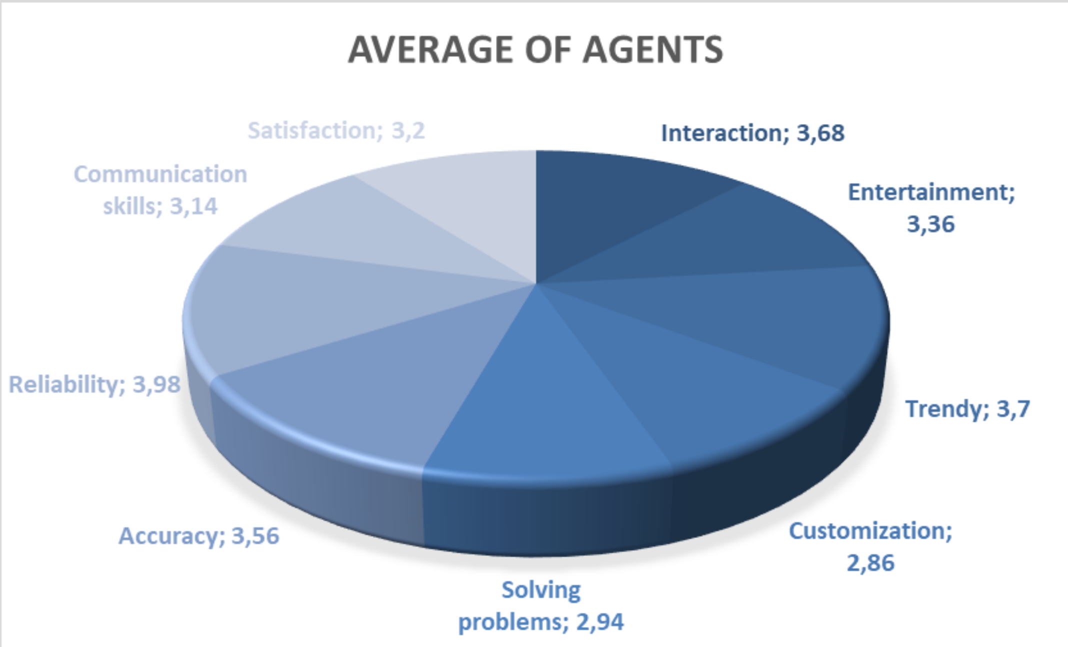

Figure 1. Average criteria for agents

A more detailed view by agent in Figure 2.

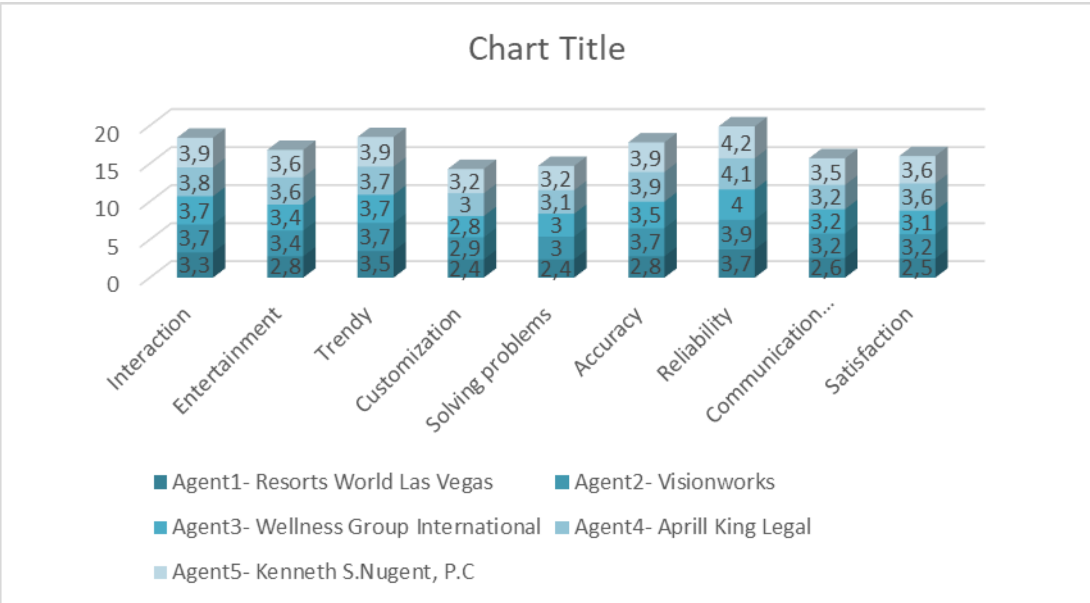

Figure 2. Agents by criteria

Of the evaluated agents, Ken Nugent, P.C. Lawyers, where Amelia served as a digital legal assistant to help relieve the administrative responsibilities of the company's receptionists, administrators and legal teams.

Ken Nugent, P.C. Lawyers wanted to find a way to handle customer service inquiries faster. The 30-year-old Georgia-based company employs more than 200 people and 47 attorneys in the southeastern United States. Fast and efficient service has always been a key element of the company.

As the digital communications landscape continues to change and more customers move toward online channels, the company's founder and namesake Ken Nugent wanted to offer a seamless digital experience. In January 2020, the company invented Amelia, a market leader in Conversational AI for telephone and web-based customer services.

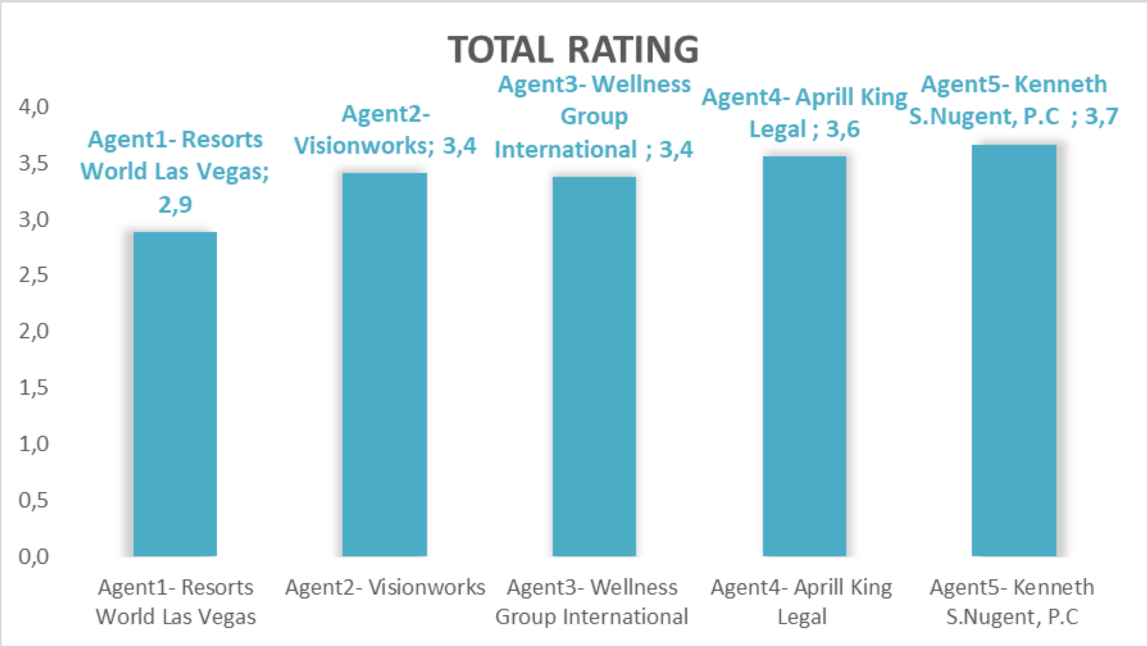

Figure 3. Agent's overall score

Agent one got the lowest rating. This virtual assistent works in tourism field. The second and third virtual assistants got the second lowest rating. Agent two works in the field of eye health and agent three works in nutrition. Agent four and agent five got the best ratings and both of these agents work in the field of law. The testers also commented that the agents in the field of law were really caring and the agents always tried to find the best solution for the problem. Testers also mentioned that the responses of agents were quick and full of details.

## CONCLUSIONS

In conclusion I got a great overview of virtual assistents, which are working on Amelia platform.The results showed that the overall average total rating of the assistents was 3,4 out of 5. This rating shows that Amelia platform is really user-friendly, it helps clients and causes users good emotions.

The best performers were assistents in the field of law. Because of this result, I would recommend hiring virtual assistents for companies in the law area to work efficiently and reduce expenses.

Throughout the work, I also got to know more about Amelia and its useful possibilities.

I definitely recommend hiring virtual assistants on the Amelia platform to delegate routine and time-consuming business support activities.

I would like to thank the testers for their help in evaluating the virtual assistants and making sure that they provide all the necessary information and are pleasant interlocutors.

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Amelia, Global Leader in Conversational AI: https://amelia.ai/

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