Journal of Infrastructure, Policy and Development 2024, 8(6), 3442.
https://doi.org/10.24294/jipd.v8i6.3442

Review

Unlocking the potential: UTAUT2 framework for embracing self-driving tractors in modern agriculture

Piroska Vargáné Dudás[1], Lóránt Dénes Dávid[2,3,4,*]

[1] Doctoral School of Economic and Regional Sciences, Hungarian University of Agricultural and Life Sciences, 2100 Gödöllő, Hungary
[2] Department of Tourism and Hospitality, Faculty of Economics and Business, John von Neumann University, HU-6000 Kecskemét, Hungary
[3] Department of Sustainable Tourism, Institute of Rural Development and Sustainable Economy, Hungarian University of Agriculture and Life Sciences (MATE), HU-2100 Gödöllő, Hungary
[4] Savaria Department of Business Economics, Savaria University Centre, Faculty of Social Sciences, Eötvös Loránd University, HU-9700 Szombathely, Hungary
*** Corresponding author:** Lóránt Dénes Dávid, david.lorant.denes@uni-mate.hu

CITATION

Vargáné Dudás P, Dávid LD. (2024). Unlocking the potential: UTAUT2 framework for embracing self-driving tractors in modern agriculture. Journal of Infrastructure, Policy and Development. 8(6): 3442. https://doi.org/10.24294/jipd.v8i6.3442

ARTICLE INFO

Received: 25 November 2023
Accepted: 2 January 2024
Available online: 5 June 2024

Abstract: This article explores the application of the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework in the context of integrating self-driving tractors into agricultural practices. With a focus on understanding the factors influencing the acceptance and adoption of this transformative technology, we delve into the implications for farmers, industry stakeholders, and the future of sustainable agriculture and rural tourism.

Keywords: Industry 4.0; UTAUT2; self-driving tractors; autonomous tractors; agriculture tractors; technology acceptance; adoption

1. Introduction

This chapter give a brief overview of the current state of agriculture and the role of technology. Followed by an introduction to self-driving tractors and their potential impact on efficiency, productivity, and sustainability. Finally, it is lit the significance of addressing the human factor in the adoption of new agricultural technologies.

"Ideally, technology is a wonderful expression of the power of human cooperation in harnessing resources and knowledge across continents and generations: It is far more than the sum of its parts. It is how we use technology that counts." (Bell, 2021).

Nowadays, after a long period of planning and development, we have reached the stage where we are within sight of self-driving vehicles. These types of vehicles, if they appear on a mass scale, will change not only the way people live their daily lives, but also the structure of cities and many aspects of transport. One of the unhidden goals of using technology adoption models is to increase the adoption success of new technologies, but in my experience most of the papers focus on existing technologies. I therefore find it interesting to look at a new technology that will inexorably become part of humanity in the near future, and this is none other than the self-driving vehicle. A number of technology adoption models have been developed by researchers to find out what factors influence the adoption of a new technology. One stream of research focuses on individuals' acceptance of technology, using intention or use as a dependent variable (Thompson et al., 2008). The uptake of self-driving vehicles in agriculture is rapidly expanding and these technologies under development are already about data collection/data processing and data-driven implementation. Automating part or all of the agricultural process.

There is still a great deal of uncertainty in our country about the future of self-driving vehicles in agriculture. User acceptance is one of the key human factors that will realise the benefits of automated tractors. Acceptance is a necessary condition for the contribution of self-driving vehicles, such as the reduction of emissions and the improvement of the economic situation. Self-driving vehicles offer many benefits to the user, thereby influencing their daily routine, which is why it is essential to examine people's views on the development of this technology. In recent years, a number of studies have not only sought to gain acceptance for the new technology, but also to find out what factors influence users' willingness to use self-driving tractors. The proliferation of self-driving vehicles is penetrating all areas where the use of different vehicles is unavoidable, and this is no different in agriculture, where there have been great benefits in recent years due to the development of technologies (Schukat and Heise, 2001). To signal the digital transformation of production environments, the "Industry 4.0", which is the result of automation and the analysis of data collected directly from the fields by various sensors (Szőke and Kovács, 2021). If we approach the usefulness of digital technologies in agriculture from this perspective, we can say that they are inevitable in the planning of farmers' strategies and daily activities.

2. Review of literature

This chapter gives a review of studies related to technology adoption in agriculture and the challenges faced by farmers. Then examines the existing literature on UTAUT2 (Unified theory of acceptance and use of technology) and its applications in various domains and identifies gaps in current research and the need for applying UTAUT2 in the context of self-driving tractors.

I will conduct a literature review with the aim of examining the research to date on self-driving tractors and to examine the methods currently used and the conclusions that can be drawn from them. I also aim to further explore the acceptance of self-driving vehicles, looking for relevant constructs that may influence user acceptance of self-driving vehicles, which have not been addressed in previous research.

2.1. Industry 4.0 and agriculture

2.1.1. Industry 4.0 definition

> "Industry 4.0 describes the organization of production processes in which devices communicate autonomously with each other along the value chain: The future is a 'smart' economy in which computer-controlled systems monitor physical processes, create a virtual copy of physical reality and make decentralized decisions based on self-organizing mechanisms." (Kuhn, 1984).

The concept of Industry 4.0 was first conceived in Germany, where the groundwork for digitalization was laid at the Hannover Fair in 2011 (Kagermann et al., 2011b; Kagermann and Helbring, 2013a). **Figure 1**, in the years since, technological developments have brought about a level of change that those born in the 2000s could not imagine before the advent of electronic connectivity and digitalization, and the difficulties it would have faced. Beyond ICT (Information and Communication Technology) innovations, Industry 4.0 now marks a new way of looking at the future, whereby we are talking about the digitalization of the economy as a whole, involving the whole of society (Gál et al., 2013).

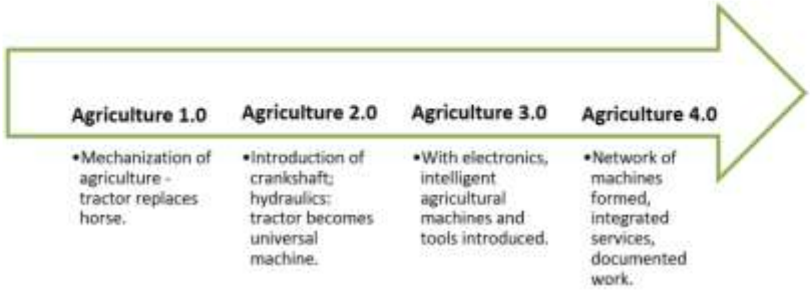

Figure 1. The agricultural mechanization revolution (based on Popp, 2018), Own compilation.

I try to introduce the concept of Industry 4.0 according to the following definitions and approaches.

In 2016, the NTP (Nemzeti Technológiai Platform, National Technology Platform) published the following statement:

> "Industry 4.0 refers to the fourth industrial revolution, which will bring a new level of organization and control to the entire value chain of products throughout their life cycle, based on cyber-physical systems, i.e. the integration of real and virtual reality, which has never existed before. This cycle follows the increasingly individualized customer needs and covers all stages of the process, from the conceptual design of the product, through ordering, product development, manufacturing, delivery to the end user and finally recycling, including product-related services. All this is based on the real-time availability of all relevant information, which implies the interconnectedness of the objects in the value chain and the ability to determine the optimal value stream from this data at any given point in time. Connecting people, objects and systems creates dynamic, real-time optimized, self-organizing, value-added networks that go beyond the corporate framework and can be optimized according to different criteria (cost, availability and resource utilization)"(NTP, 2017) (NTP, 2017).

It is based on the definition in the German Industry 4.0. results report of April 2015 (Bitkom et al., 2015) and is a literal translation of the definition already extended in the VDMA (VDMA, 2015) paper with the addition of the need for cyber-physical systems. The substance of the other approaches is similar, the only difference is the area of focus of the authors.

The impact of the "hybrid", i.e. the influence of real and virtual world manufacturing processes, is the most important aspect of German Trade and Invest's (GTAI, 2018) definition of Industry 4.0, which focuses on the shift from centralized to decentralized manufacturing. It radically changes the traditional mindset in production value chains, business models and industry as a whole.

The Boston Consulting Group defines Industry 4.0 (BCG, 2019) as a transformation process triggered by nine major technological innovations (simulation, autonomous robots, virtual reality big data, horizontal and vertical integration, industrial IoT (Internet of Things), cybersecurity, cloud services, additive manufacturing), in which the ability of machines and equipment to self-configure and adapt to change, data collection and analysis, and the ability to adapt to change are essential. This is expected to lead to significant positive changes in the competitiveness of enterprises (Blanchet, 2018).

Looking at the definition of Industry 4.0, we can say that at its core are the cyber-physical systems, the merging of virtual and physical reality, the flow of information that allows machines to operate efficiently without human intervention, and its unquestionable impact on the economy. And those who cannot or will not keep pace in this rapidly evolving world are likely to be left behind and at a disadvantage vis-à-vis other market player. Industry 4.0 is currently the basis of many economic development strategies(Blanchet, 2018).

2.1.2. Artificial intelligence

I find interesting the idea that artificial intelligence (AI) will not necessarily "come" in the form of a computer, but that human thinking itself will transform and change. Such theories could be strengthened by research into nanotechnology and biotechnology. A paradigm shift is in fact when we go beyond our own previous boundaries in a given field, even in a scientific field.

The importance of paradigm is that when people or groups encounter a major problem to be solved, even a global one, they may only be able to solve it by making a major change. Paradigm shifts can also occur in the social and economic sciences. And the spread of artificial intelligence could also lead to a paradigm shift in agriculture.

One of the strengths of artificial intelligence is that it can perform a task more efficiently than a human, and one area of systems that raises very sensitive issues is the software for self-driving tractors. In this case, we are talking about a dangerous system where the possibility of software errors is not allowed, because it could lead to an accident.

Artificial intelligence is present in many areas of the economy, which has brought and will bring many transformations in the coming period. These technologies can be grouped into five categories: Deep learning, Robotisation, Dematerialisation, Gig economy and Autonomous driving as **Figure 2** shows.

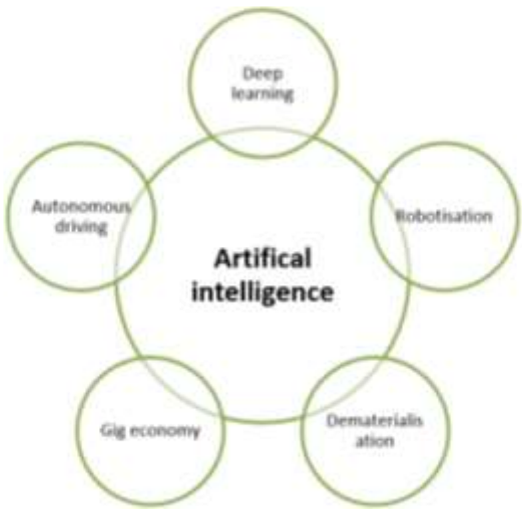

Figure 2. The five technologies of the artificial intelligence, Own compilation.

AI is already with us in our everyday lives, even if we are not aware of it ourselves.

In the centres where traffic congestion management and car and navigation systems are used to calculate the shortest, fastest or even most economical route based on constantly updated data, but AI is also part of our social lives. We make daily decisions in the online space, whether it be learning or providing a service, based on our previous habits (Quentin et al, 2018).

From both an economic and a social perspective, many agricultural jobs are being transformed or, in the worst case, eliminated as technology advances. Artificial intelligence will perform tasks that were previously done by humans more cheaply, but this will not only affect the workers, but also the functioning of agriculture as a whole. This kind of development could also lead to decline if the upward trend starts to stagnate and level off. This happens when there is a decline in customer interest, whether it is due to a lack of money, a demand for a different type of product or even a decline in the number of births, and these trends are an obstacle to the sustainability of farms. These aspects need to be taken into account when developing artificial intelligence to bring humans to the fore (Obermayer et al., 2021). In addition, the MIT study (Koleva, 2019) supports the idea that people and automation working together can be more effective than groups of only people or only automated jobs, and therefore, instead of exclusivity, it has demonstrated that people and robots working together can be more effective than groups of only people or only robots, and therefore, instead of exclusivity, the Internet of Things is the Internet of Things. In the light of the above, it can be concluded that artificial intelligence is profitable if it is seen and treated as a tool for human life and security. The effect of over-development can be to replace workers and the tool that leads to the goal of eliminating (making unemployed) people, a phenomenon that is unfortunate and one must think ahead with this in mind.

The OECD has developed guidelines on artificial intelligence, which serve as a kind of guideline for what should be observed when using these systems. The first of these is to bring about sustainable development and growth for humanity. Human rights, laws and safety measures are essential conditions for the development of AI systems, such as the possibility for human intervention in the operation of AI systems for the sake of justice, as humans need to understand the consequences of AI in order to cope with them, and to consider and manage the safe operation and potential risks for a just society. Communication about AI systems must be transparent and responsible, as people need to understand the consequences of AI systems in order to cope with them. Furthermore, AI systems need to ensure stable, safe and secure operation, and potential risks need to be assessed and managed (OECD, 2019).

Last but not least, those who develop or operate AI should be held accountable for using it as intended (Tilesch and Hatamleh, 2021). It is along these principles that people should start incorporating AI systems in order to ensure that the implementation is successful and that the joint work of AI hosts is fruitful.

2.1.3. Industry 4.0 in agriculture

One of the futuristic constructs of Industry 4.0 is the self-driving vehicle (autonomous vehicle, driverless vehicle, self-driving vehicle, robotic vehicle). Software installed in vehicles allows full automation, with an artificial intelligence system running inside them that can maintain control in any conditions (weather or traffic), i.e. they can drive without human intervention. Self-driving tractors do not follow a fixed trajectory and the ultimate goal is to become fully automated, so in addition to digitalization (such as cameras, ultrasonic sensors, built-in radar, laser-based remote sensing and electronic control units), the artificial intelligence of self-driving vehicles and its operation is a major focus and role (Andorkó, 2016). However, self-driving tractors are not yet capable of driving autonomously on public roads to reach the land to be cultivated.

The uptake of autonomous vehicles will change the value chain of the automotive and related industries, as well as transport as a whole. Two things are worth noting about self-driving vehicles, one is that they will change the way we drive and the future of humanity in a big way. The other important point is that the development of the technology is not as small as many people think, and current figures show that testing is already underway on 76 city roads (with a driver in the car, subject to official approval, in case of intervention), and once this is complete and any faults have been corrected, the technology can go live, meaning that tractors can even drive themselves from the yard to the fields. There is safety, social, ethical, legal and economic risks associated with autonomous vehicles, and answers to these questions are being sought. The easiest way to define self-driving vehicles is to describe the levels of automation, thus contributing to an easier definition.

The classification of categories varies depending on the country and organization, so I will present the SAE (Society of Automotive Engineers) (SAE, 2018), **Figure 3** also summarizes this.

- Level 0. Complete lack of automation (control is solely up to the human manager).
- Level 1. Some support for driving (driver assistance systems inform the driver with external information and can make some corrections in acceleration/deceleration or steering, but all dynamic tasks are performed by a human driver).
- Level 2. Semi-automated vehicle (support systems can take over both gear shifting and steering operations, assuming human performance intervenes).
- Level 3. A conditionally automated vehicle (the vehicle's AI system performs a dynamic driving task, both laterally and longitudinally, but assumes human control and can take back control if necessary).
- Level 4. High level of automation (depending on the driving mode, the system performs all dynamic driving tasks, assuming that the driver intervenes immediately on signal).
- Level 5. Full automation (the system is able to perform all the dynamic tasks that a human is capable of during the entire driving session).

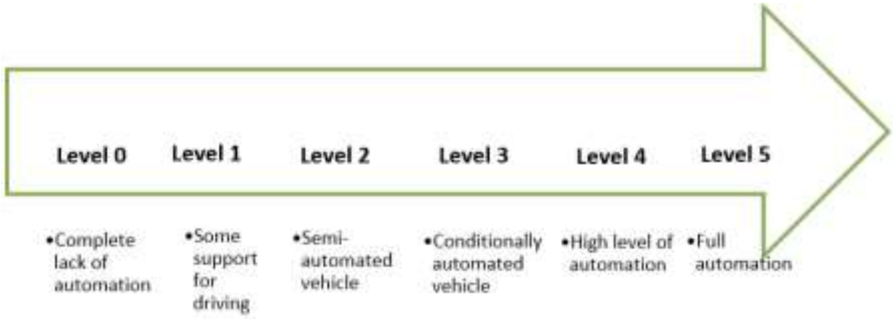

Figure 3. Industry 4.0 in agriculture (based on SAE, 2018), Own compilation.

Despite the significant benefits that can be predicted at this stage, the societal perception of self-driving cars is not uniform. In recent years, there have been several large-scale international studies, most of which have been conducted in the US, that have identified trends in public perception of self-driving vehicles. Since 2013, we have witnessed a major leap forward, with the implementation of autonomous braking, acceleration, lane-keeping at speed and braking in traffic in a test car in 2013. Then, a year later, Mercedes cars were able to drive with full autonomy up to 31 km/h. By 2015, the technology was at a stage where the test car could steer autonomously, drive in lanes at variable speeds, use the throttle and gearbox autonomously and even park without a driver. Moreover, by 2020, several car brands were expected to have their own fully autonomous driverless cars (Rowe, 2015). Many studies on the economic impact of self-driving cars mostly project private and societal benefits. In addition to transport quality and safety, the social benefits are also influenced by the policy decisions required for the uptake of self-driving cars.

In March 2018, tragic events occurred during a street experiment with self-driving cars, both in terms of safety and in terms of responsibility and social perception. In the space of a week, two self-driving cars (albeit with different technological bases) were involved in fatal accidents, to which society reacted with great indignation. This kind of reaction was very important for self-driving cars, as it showed that society is aware of the importance and impact of the technology (Kohli, 2020). After this, even some of the people who showed the most enthusiasm for self-driving cars were hesitant about whether they would actually use them in some form. For those who are open to and positive about new technologies, autonomous vehicles have other factors to consider when it comes to using such a vehicle. In these cases, concerns and a lack of confidence due to a lack of knowledge about self-driving cars are already surfacing (Abraham et al., 2018).

2.1.4. The threats of Industry 4.0 in agriculture

In Industry 4.0, we can recognize the potential of replacing simple, easily automated human activities with automated decisions by machines. The human resources freed up can be used for more complex, intuitive and creative tasks that require more thinking. This implies that less skilled or even unskilled labour may be freed up and oversupplied, and that meeting the increased demand may lead to labour shortages (Nábelek et al., 2016a; Nábelek, 2017b). New technologies are significantly changing the nature of work in all industries and occupations, including agriculture. Some approaches argue that Industry 4.0 will contribute to job retention and rapid employment growth, especially in sectors and services related to new technologies (Szalavetz 2016b). In contrast, WEF (World Economic Forum) (Schwab, 2016b) research among companies suggests that significantly more people will lose their jobs than will be created, as rapid technological development has a destructive effect on employment in some respects (Schwab, 2016b).

Industry 4.0 will redefine the skills required to fill a job, as different skills will be needed, with human-machine interaction playing an important role, but it is important to consider that automation should be complementary and not replace humans entirely.

2.2. Literature on UTAUT2 and the need for applying it in the context of self-driving tractors

This chapter details explanation of the UTAUT2 model and its key constructs. Then it highlights the adaptation of the UTAUT2 model to the specific context of self-driving tractors. Finally, it discusses on how factors like Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions apply to farmers' acceptance of autonomous tractor technology.

Nyírő (2011) provides a summary overview of the many criticisms of TAM(Nyírő, 2011). Bagozzi (2007), who participated in the development of the TAM model, criticizes UTAUT and its extensions. According to him, the UTAUT, although well-intentioned and thoroughly developed, takes into account too many variables. Bagozzi encourages us to put together the "many shards of knowledge" when making decisions today. According to his proposal, a model has an inner core during decisions: Desire for goal → desire for intention → desire for action → intention to act, which is determined by the variables and processes of human decision-making. Decision mechanisms contain an internal regulation that moderates the effects of desires on intention. It also introduces important contextual elements for understanding decision-making: the decision mechanism takes into account the multiple causes and effects of decisions and self-regulation. It includes causal factors that have a lot to do with TAM and its extensions, but also takes into account newer ones supported by emotional, social/group/cultural and intention-driven behavioral research (Berecz, 2018) (Berecz, 2018). So, during the last ten years, both TAM and UTAUT received an updated version. TAM 3, for example, due to the increasing simplification of the user interfaces of technological devices, emphasizes the factors affecting the perceived ease of use compared to the previous versions (Venkatesh and Bala, 2008). On the other hand, compared to the previous versions, UTAUT 2 analyzes, for example, voluntary use, which is a significant factor in the case of technologies intended for the mass market and for everyday use (Venkatesh, et al., 2012). Thanks to this new approach, the voluntary element of the UTAUT model has disappeared, as the authors assume that in the case of everyday technologies, people do not choose them out of compulsion, but rather voluntarily. Thanks to this, three new elements were introduced: Hedonic motivation, price value and habit (Venkatesh et al., 2012). In general, it can be said that the models examining the acceptance of technology have undergone continuous development in order to meet the market characteristics of new technologies and the social phenomena induced by the technology. From the point of view of my research, the UTAUT2 models, which take into account the adoption of technologies already used in everyday life, can be really relevant, taking into account the UTAUT model, which examines the social effects. However, not forgetting the factors influencing the TAM model (perceived usefulness, perceived ease of use and intention to use).

Venkatesh et al. (2012) developed a unified model known as the Unified Theory of Technology Acceptance and Use (UTAUT) to explain technology acceptance and use. The model includes four basic determinants (e.g., expected performance, expected social influence and its promotion) of intention and use, and four moderators (e.g., age, gender, experience, and voluntariness of use) for key regulation relationships. The theory was formulated by reviewing and integrating eight influential theories and models (Venkatesh et al., 2012) Since its inception, UTAUT has been widely used to elucidate the acceptance of technology by individuals. UTAUT2 is an improved version of the original UTAUT developed by Venkatesh et al. (2012). This model complements the original UTAUT to better understand how it influences people's acceptance and use of technology. The UTAUT2 includes four main constructs: Performance expectation, intensive expectation, social influence and external environmental factors, motivational process, position and behavioral intention were also included in the design. UTAUT2 examines people's motivations, why and how they adopt new technology, and how this affects their behavior. This is based on the previous UTAUT, which already summarizes key factors in and related to technology adoption(Venkatesh, Viswanath., & Thong., 2012). **Figure 4** compares the two models.

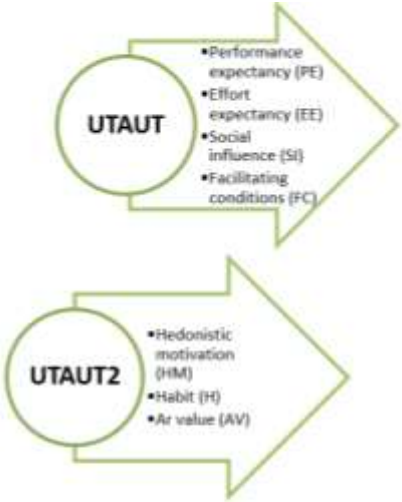

Figure 4. UTAUT and UTAUT2 (based on Venkatesh, 2003), Own compilation.

UTAUT2 is used to investigate the effects of performance and expected duration of effort, social influence, facilitating conditions and hedonic motivation on behavioural intention to use conditionally automated cars (Venkatesh et al., 2012).

The question arises, for example, to what extent the questionnaire survey shows real information and data. In the UTAUT2 model, hedonic motivation, refers to the respondent's emotional state, which is not always accurately defined by the subjects at the current moment, not even when asked about their future emotional state about seeing a self-driving tractor driving and doing a job. Nordhof and colleagues conducted a survey of 9118 drivers in 8 European countries using the UTAUT2 model to explain public acceptance of self-driving vehicles. Their study revealed that hedonic motivation was the strongest of the UTAUT2 variables. Respondents who found it enjoyable and convenient were more likely to use autonomous vehicles. The method for measuring hedonic motivation, however, is still the traditional online survey.

UTAUT2 is widely used in information and communication technology research to help understand user behaviour. However, several studies have complemented the UTAUT2 model to explore the general distrust towards self-driving vehicles, i.e. they have investigated the issue of trust and legal regulation (Dwivedi et al., 2017). This kind of distrust is quite natural, as it is a new technology that people have not experienced before, however, it can be a drawback for the market introduction of self-driving vehicles (Niculescu et al., 2017).

Most research on the adoption of self-driving vehicles is based on information obtained by respondents through the media or through friends and colleagues. Rather than on direct experience of using self-driving vehicles (Nordhoff et al., 2020). Tennant et al. (2019) argue that public unease will decrease as people become more aware of the potential of self-driving vehicles. Dixon et al. (2020) suggest that simply experiencing self-driving vehicles will not be effective in creating automated vehicle acceptance. Nordhoff et al. (2021) in their analysis, found that users' expectations about how difficult it will be to use self-driving vehicles can be explained by their expectations about the performance of agricultural machinery.

The relationships between social influence and favourable conditions, and between social influence and expected performance, were moderated by technological competence. Users with low technological literacy were less likely to believe that they had the resources to use self-driving vehicles or that automated vehicles were useful than individuals with high technological literacy.

Nastjuk et al. (2020) investigated the potential benefits of self-driving vehicles for the elderly and disabled. Access to mobility can ensure safe transport for the population and increase access to education and employment opportunities. According to Golbabaei et al. (2020), the intention to adopt self-driving vehicles varies significantly between social and demographic groups. In other words, early adopters are likely to be male, young, highly educated and live close to urban areas.

3. Methodology

This chapter discusses on the research design, sample selection, and data collection methods. It explains how UTAUT2 constructs were measured and analyzed. Is taken into consideration of potential biases and limitations in the methodology, too.

First, I execute a systematic overview, starting with data collection using the Prism model. Based on a review of the scientific literature, it is considered one of the most powerful methods for data collection (Kabil et al., 2022). My secondary research aims were to synthesize and critically evaluate previous research according to a predefined set of criteria. I defined the research process in four steps.

Step 1st is the conceptualization which involves the criteria and design of the research. In order to identify the literature relevant to the study, I defined the following criteria:Step 1st is the conceptualization which involves the criteria and design of the research. In order to identify the literature relevant to the study, I defined the following criteria:

- Research focus: Examining journal articles that investigate the acceptability of self-driving vehicles (e.g. performance and expected duration of effort, social influence, facilitating conditions and hedonic motivation).
- Timeliness: In the interests of current research, the analysis is limited to journals published after 2019.
- Reliability: The selection of sources focuses exclusively on peer-reviewed English language journals. Google Scholar, Science Direct, Scopus and Web of

Scince are the selected databases that allow an efficient professional search of the databases (Vértesy, 2023).

Due to the complexity of the topic to be explored, I used the following search terms: 'Unified Theory of Acceptance and Use of Technology' self-driving cars, self-driving tractor, agriculture, artificial intelligence future mobility, autonomous car. The search process requires clear questions to identify relevant records. I matched these queries to the search field "Title summary and keywords" so that the collected articles are directly related to my topic. Then came the refinement and organization phase.

The use of technology adoption models is one of the hidden goals of increasing the adoption success of new technologies, but in my experience most of the papers focus on existing technologies. One stream of research focuses on individuals' technology acceptance, with intention or use as a dependent variable (Thompson et al., 2008).

The UTAUT2 is used to investigate the effects of performance and effort expectancy, social influence, facilitating conditions and hedonic motivation on the behavioural intention to use conditionally automated cars (Venkatesh et al., 2012). I use the UTAUT2 model to understand user behaviour and make comparisons, exploring the general distrust towards self-driving vehicles, i.e., I also investigate the issue of trust and legal regulation.

In the North East region of Hungary, I interviewed 6 farmers to investigate the different adoption factors influencing the uptake of the technology. I used a qualitative method for data collection and analysis, interviews have several advantages as answering open-ended questions requires more effort from the respondents. The most important predictor of respondents' acceptance of self-driving tractor users was expected performance, meaning that people will be more inclined to use automated tractors if they expect high performance from them. Users who have high expectations of technological performance are more likely to use self-driving tractors.

Social influence was also an important factor influencing people's behavioural intentions. People who were positively influenced to use automated vehicles by those around them were more likely to use them.

The analysis also showed that expected performance mediates the relationship between expected effort and behavioural intention. This implies that people will be more inclined to use automated machines if they expect high performance, which reduces their effort during use.

The analysis also showed that the level of technological proficiency also influences people's behavioural intentions. People who are highly technologically literate are more likely to believe that they have the resources to use automated tractors and that they can be useful to them.

4. Results

This chapter gives presentation and interpretation of findings regarding farmers' perceptions of self-driving tractors using the UTAUT2 model. It analyses the factors that positively or negatively influence technology acceptance. Then insights into the readiness of the agricultural community to adopt autonomous technology.

This chapter summarizes the results of secondary research on self-driving tractors and their application in international and Hungarian contexts.

4.1. Self-driving tractor

Self-driving tractors are revolutionizing agricultural production and farming around the world. Sensors and software on the tractor, with the help of satellites, allow them to work autonomously in the fields, freeing farmers to use their time and resources elsewhere. The benefits of self-driving tractors include time and fuel savings, improved crop yields, resource utilization and higher productivity. A big advantage of self-driving tractors is that farmers no longer have to spend all day on the back of the tractor. Tractors are pre-set to the field, start the self-driving mode and then do the work themselves. Farmers only need to go back to the tractor when it has done the work and requires further intervention by the machine. At YouTube is available a video about Kubota X Tractor—An autonomous tractor that will do the farming for you.

Since the advent of self-driving tractors, innovations in agriculture have enabled small and large-scale farmers to increase productivity. Self-driving tractors allow farmers to perform more precise operations in agricultural production, such as spreading small seeds evenly, applying fertilizers or sprays precisely and evenly. But self-driving tractors are not yet perfect. Sensors and software can sometimes make errors that affect the accuracy of operations. Legal and ethical issues related to autonomous vehicles are unclear, such as who is liable if a self-driving tractor causes an accident. Users and manufacturers need to understand and address these challenges in order for self-driving tractors to become widespread and help farmers increase production efficiency.

Research and development on self-driving tractors are ongoing. Technological innovations in the agricultural industry are improving, so we will soon see more self-driving tractors. The use of self-driving tractors not only reduces labour requirements, but also allows for more uniform and smooth operations (Abidine et al., 2022). The tractors work precisely, so that crops grow evenly and water and fertilizer are distributed evenly (Lagnelöv et al., 2021). Another advantage of self-driving tractors is that they also improve productivity. The tractors are able to work at higher speeds than conventional tractors and can work all night if necessary, covering a larger area in a shorter time (GÉPmax, 2021).

Overall, self-driving tractors represent innovative technologies that offer significant benefits to the agricultural industry.

Robotization has started with the application of the autonomous (self-sufficient) capacity of agricultural machinery. The different milestones of robotization are as **Figure 5** shows (GÉPmax, 2021):

1) Traditional farming: Machines are autonomous, human-driven, manually controlled.
2) Precision farming techniques: Machines have simple autonomous technology (e.g. automatic steering, line management, soil-dependent machine adjustment, etc.), all technologies working independently of each other.
3) Machine-to-machine coordination and optimization: Machines can communicate

with each other to take advantage of the coordination and synchronization of tasks between machines, for example, a tractor driver can control several machines.

4) Real-time machine automation: Machines can be automatically controlled based on environmental and other conditions, but the technology controls the machine, for example, choosing the right speed for the ground conditions, route planning based on central logistics instructions.
5) Supervised autonomy: The smart tractor or smart machine performs the cultivation or mission task autonomously (e.g. the combine controls the tractor pulling the trailer when transferring the crop), but the machine(s) is still at a visible distance from the person in control, who in turn is in contact with the remote logistics centre.
6) Full autonomy and robotization: In the agriculture of the future, machines will perform their tasks autonomously, under the control of a remote control centre (GÉPmax, 2021).

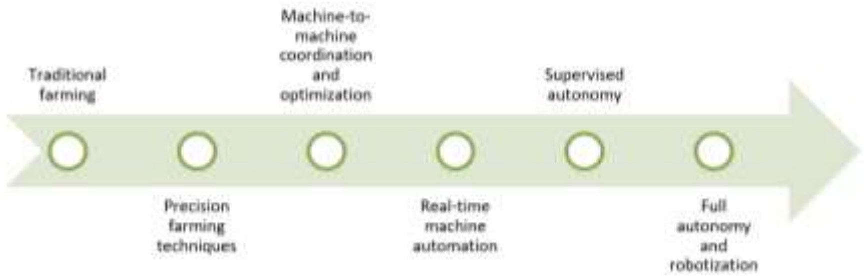

Figure 5. Milestones of robotization (based on GÉPmax, 2021), Own compilation.

4.2. International outlook

The uptake of automated agriculture is not uniform around the world, and is largely influenced by economic and human factors, as well as technological acceptance and knowledge of the information available. Presumably, younger, more capital-rich, more highly educated farmers are using the potential of the new technology (Younger, 2004).

Precision farming is a method for optimizing and increasing the efficiency of agricultural production processes by integrating data collection, digital technologies, farming machinery and tools. However, its uptake is not uniform in different regions of the world and is influenced by a number of factors (Fountas et al., 2018).

Socio-economic conditions, agro-ecological conditions, technological and organizational factors, and the quality and availability of human resources all play an important role in the spread of precision farming. In general, young farmers with larger areas, higher education levels and capital are using new technologies (Business, 2017).

Precision farming first spread to the US, Europe and Australia, and has been adopted in South American countries and some Asian countries (Fountas et al., 2018). The US currently has the largest market share, with nearly 50%, partly due to government subsidies and high labour costs (Bussiness, 2017). The US Department of Agriculture (USDA), the National Aeronautics and Space Administration (NASA) and the National Oceanic and Atmospheric Administration (NOAA) are also contributing to the spread of large-scale precision farming (Technavio, 2017).

Precision technology, which is spreading in Argentina, is used over large areas and covers 21.6% of the 33 million hectares of land under cultivation. Seed monitors, row guides and yield mapping are widely used, while automatic steering is even less widespread (INTA, 2018).

In Brazil, precision technology has mainly been used in soya and maize (82%), wheat (22%) and beans (13%). However, farmers are not fully exploiting the precision tools available and on average only use them on 65% of their land. Vehicle navigation is also available with a queue guide (42%) or automatic steering (37%) (Bernardi & Inamasau.R.Y, 2014).

4.3. Situation at home

The use of autonomous agricultural machinery is not yet common in Hungary, but in recent years the number of farmers using site-specific crop production has increased. It is mainly spreading in arable farming, where the income potential provides sufficient resources for the purchase of equipment. Precision farming promotes soil-friendly and environmentally friendly cultivation. Although it has been present in domestic agriculture for more than 15 years, it is still an unknown concept for many farmers. According to a 2015 survey, only half of arable crop farmers have heard of it, and that depends on the size of the farm. Those farmers who do use it tend to be younger, have a tertiary education and farm at least 300 hectares, which is in line with international experience (Kemény et al., 2017). Robotization, self-driving vehicles, precision farming and satellite positioning all contribute to increasing agricultural efficiency and reducing the amount of labour, which can lead to significant cost savings. Precision farming allows for more accurate determination of nutrient supply, which can reduce environmental pressures and improve energy efficiency. IoT systems and self-driving machines are becoming more widespread in agriculture, making it possible to cultivate fields without human intervention.

Drones and satellites can be used to collect data, allowing for up-to-date monitoring of processes and planning in the greatest detail (Vértesy, 2023). With the proliferation of self-driving tractors, there is of course a need for labour-intensive businesses, making the employment of properly trained skilled workers inevitable (Magda et al., 2017).

> “Once machine brains overtake humans in general intelligence, the new superintelligence that will emerge could be powerful. From then on, the fate of our species will depend on the will of machine superintelligence, just as the fate of gorillas depends more on us humans” (Bostrom, 2014).

He defines machine intelligence as superintelligence because he believes it can surpass the human brain in every respect.

Industry 4.0 will inevitably have an impact, and businesses will have to face up to the expected positive impacts and challenges. In the fourth industrial revolution, we are talking about automated systems that can communicate with each other, working with huge amounts of data to change our daily lives. We are now living in a world of digital society and digital economy, and continuous training and intensive development of employees and representatives of businesses are essential to ensure that the right professionals are available.

One of the radical innovations of Industry 4.0 is the self-driving tractor. These vehicles are fully automated and can maintain control in all conditions, meaning they can drive without human intervention. This type of innovation has two things to mention at the moment, one is that it is predicted to fundamentally change the future of humanity, and the other is that it is much further ahead than the public would think, as it is currently undergoing final phase testing in 76 areas (Kézy et al., 2018). It is also a major epochal change in scientific thinking and analysis, because it will actually require a new and more complex way of thinking and analysis in the future.

The Digitális Jóléti Program (Digital Wellbeing Programme, DJP) is a long-term programme launched by the Hungarian government to develop digital skills, support innovation and expand digital infrastructure in Hungary. In this framework, the Magyarország Digitális Agrár Stratégiája (Digital Agricultural Strategy of Hungary, DAS) has been prepared, which aims at the digitalization of agricultural production. The DAS aims to contribute to increasing the profitability of agricultural production through the collection and processing of information, automation and robotization of technological operations, while making efficient use of available environmental resources. Digital solutions in agriculture, such as precision farming, drones or robotic tools, can help to produce more efficiently, reducing costs and increasing production capacity. The DAS includes infrastructure development for the digital agricultural economy, the development of digital services, the regulation of agri-digitization, the training of digital professionals, and the development and application of technologies and solutions for the agricultural sector. The DAS aims at the digitalization of Hungarian agriculture, which can contribute to increasing the efficiency of agriculture, reducing the environmental burden and improving the quality of agricultural products.

61% of the farmers surveyed had used a precision farming tool or practice in the last marketing year. Of the tools and practices used, navigation systems were the most frequently mentioned (40%) and variable rate irrigation (2%) the least frequently mentioned (GÉPmax, 2021). The results presented above shows that some actors in the Hungarian agricultural sector are already consciously preparing for the digital transition and have started to move towards precision farming. This suggests that, in the medium term, their planned investments can be aligned with the objectives of the DAS and they can successfully apply for CAP (Common Agricultural Policy) support. However, the question arises as to whether those actors who have been delaying their preparations so far will be able to catch up in the digital switchover (GÉPmax, 2021).

Overall, therefore, a strategy is proposed that encourages social acceptance, anticipates the expected positive usability and anticipates the obstacles, as this technology is seen as an essential element of economic policy. The digitalization of the agricultural sector is a rapidly evolving field that is constantly generating new technological solutions and services that can have an impact on all aspects of farming. Changes in the sector are not only occurring at the domestic level, but also in international markets, where new innovations are emerging that may have a direct impact on farming (GÉPmax, 2021).

And finally, I would like to quote László Mérő’s thought, which can serve as a valuable point of reference: “A very clever man is not known for making good predictions about the future, but for seeing clearly that the future is impossible to predict, and yet, knowing this, he is able to adapt to it in advance" (Mérő, 2016).

5. Conclusion

While the market demand for self-driving tractor technology is undeniably driven by the need for increased efficiency and productivity in agriculture, it is crucial to recognize that the impact extends beyond the technological landscape. To provide a more comprehensive perspective on the significance of this technology, it is recommended to expand the analysis to encompass its effects on farmers and industry stakeholders.

Mohd et al. (2022) expanding the analysis to industry stakeholders is equally critical. This includes examining the economic implications for equipment manufacturers, service providers, and those involved in the supply chain. The adoption of self-driving tractors can spur innovation in the agricultural machinery sector, creating opportunities for manufacturers to develop and refine autonomous technologies. The emergence of a new market for maintenance, software updates, and technical support services adds layers to the economic landscape of the industry. Understanding these dynamics is essential for stakeholders to make informed decisions, invest strategically, and contribute to the overall growth of the agricultural technology sector (Paunov and Satorra, 2019).

Furthermore, exploring the potential societal and policy implications of widespread self-driving tractor adoption is crucial. This involves considering aspects such as job displacement in traditional agricultural roles, the need for regulatory frameworks to govern autonomous farming practices, and the societal acceptance of this transformative technology (Sara et al., 2023). By delving into these dimensions, the analysis can offer insights into the broader implications of self-driving tractor technology on the fabric of rural communities and the agricultural sector as a whole. While addressing market demand is a pivotal aspect of introducing self-driving tractor technology, a more comprehensive understanding necessitates an expanded analysis of its impacts on individual farmers and industry stakeholders (Balvinder and és mtsai, 2023). By considering the broader socioeconomic, economic, and policy dimensions, we can ensure that the adoption of self-driving tractors is not only technologically sound but also socially and economically sustainable. This holistic perspective is crucial for navigating the evolving landscape of agriculture and maximizing the benefits of autonomous technologies for all stakeholders involved (Lowenberg-DeBoer et al., 2021). In conclusion, the application of the UTAUT2 framework in the context of self-driving tractors in agriculture provides valuable insights into the factors influencing technology adoption. The findings of this study shed light on the dynamics of farmers' acceptance of autonomous tractor technology and offer implications for the future of modern agriculture.

The results indicate that key UTAUT2 constructs, such as Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions, play crucial roles in shaping farmers' attitudes and intentions toward adopting self-driving tractors. Farmers who perceive higher performance benefits, find the technology easy to use, experience positive social influence, and have adequate support systems are more likely to embrace autonomous tractor technology (Shi and és mtsai, 2022).

Moreover, it is evident that addressing concerns related to trust, security, and awareness is essential for fostering widespread acceptance. Education and outreach programs that highlight the tangible benefits of self-driving tractors and provide support for implementation can contribute significantly to overcoming resistance and skepticism among farmers.

The integration of self-driving tractors into agriculture represents not just a technological shift but a cultural and behavioural change for farmers. Recognizing this, policymakers, industry stakeholders, and researchers must collaborate to develop comprehensive strategies that not only enhance the technological infrastructure but also facilitate a smooth transition for farmers.

As we move forward, it is imperative to continue monitoring technological advancements, engage in ongoing dialogue with the farming community, and adapt strategies to align with evolving needs and concerns. The successful integration of self-driving tractors into agriculture requires a holistic approach that considers not only the technological aspects but also the social, economic, and environmental dimensions of modern farming practices.

In essence, this study contributes to the growing body of knowledge on technology adoption in agriculture and underscores the importance of a user-centred approach in implementing transformative technologies like self-driving tractors. By understanding and addressing the factors influencing acceptance, we pave the way for a more efficient, sustainable, and technology-driven future for agriculture.

In recent years, the agricultural landscape has witnessed a transformative wave propelled by technological innovations. Among these, the emergence of self-driving tractor technology stands out as a revolutionary force poised to reshape traditional farming practices. This technology not only responds to the market's demand for efficiency and precision but also holds significant promise for advancing sustainable agriculture (Ghobadpour et al., 2022). The market demand for self-driving tractor technology is rooted in the imperative for increased productivity and streamlined operations in modern farming. As global populations burgeon, the need for enhanced agricultural efficiency becomes more pressing. Self-driving tractors promise to meet this demand by optimizing tasks such as plowing, seeding, and harvesting, allowing farmers to achieve higher yields with reduced manual labor (Ravis and Notkin, 2020).

The potential impact of self-driving tractor technology on agricultural productivity is profound. These autonomous machines are equipped with advanced sensors, artificial intelligence, and GPS technology, enabling them to operate with unparalleled accuracy. This precision in farming tasks translates to increased efficiency, minimized errors, and improved crop yields. With the ability to work continuously without fatigue, self-driving tractors can accelerate farming operations, especially during critical periods such as planting and harvesting seasons (Mohd et al., 2023).

Resource utilization is another critical aspect addressed by self-driving tractor technology. These autonomous machines can optimize the use of resources like fuel, water, and fertilizers, contributing to more sustainable farming practices. By precisely managing inputs based on real-time data and field conditions, self-driving tractors help reduce waste and minimize the environmental impact of farming activities (Karunathilake et al., 2023).

Environmental sustainability is a cornerstone of the case for adopting self-driving tractor technology. Conventional farming methods often contribute to soil degradation, excessive use of water, and overreliance on chemical inputs. The precision and efficiency of self-driving tractors enable farmers to adopt more sustainable practices, implementing conservation techniques and reducing the environmental footprint of agriculture. (Dhanaraju et al., 2022)

Furthermore, the implementation of self-driving tractors aligns with the broader goals of sustainable agriculture, promoting eco-friendly practices and minimizing negative impacts on ecosystems. By optimizing the use of resources and reducing the need for manual labor, this technology contributes to a more sustainable and resilient agricultural sector. (Nath, 2023)

In conclusion, the market demand for self-driving tractor technology is not merely a reflection of technological progress but a response to the urgent need for enhanced productivity and sustainability in agriculture. The potential impact on agricultural productivity, resource utilization, and environmental sustainability positions self-driving tractors as a cornerstone in the evolution towards more efficient, responsible, and sustainable farming practices. As these autonomous machines become increasingly prevalent, they hold the promise of not only meeting market demands but also steering agriculture towards a more sustainable and resilient future.

Acknowledgments: This paper was supported by the Hungarian University of Agriculture and Life Sciences, Doctoral School of Economic and Regional Sciences as well as the Flagship Research Groups Programme of the Hungarian University of Agriculture and Life Sciences, Hungary.

Conflict of interest: The authors declare no conflict of interest.

References

Abidine, A. Z., BC, H., SK, U., & DJ, H. (2022). Autoguidance system operated at high speed causes almost no tomato damage (Hungarian). Semantic Scholar.

Abraham., H., Reimer.B., Fitzgerald.C., et al. (2018). Consumer Interist in Automation: Change over One Year. Available online: https://www.researchgate.net/publication/322400007_Consumer_Interest_in_Automation_Change_over_One_Year), pp.50-67 (accessed on 2 June 2023).

Andorkó, I. (2016). Legal sc-fi or the potential impact of technological developments in motoring on jurisprudence (Hungarian). Available online: http://jogaszvilag.hu/rovatok/szakma/jogi-sci-fi-avagy-az-utozas-technologiaifejlodesenek-lehetseges-hatasai-a-jogtudom (accessed on 2 June 2023).

Bagozzi, R. (2007). The Legacy of the Technology Acceptance Model and a Proposal for a Paradigm Shift. Journal of the Association for Information Systems, 8(4), 244–254. https://doi.org/10.17705/1jais.00122

Kaur, B., Mansi, Dimri, S., et al. (2023). Insights into the harvesting tools and equipment's for horticultural crops: From then to now. Journal of Agriculture and Food Research, 14, 100814. https://doi.org/10.1016/j.jafr.2023.100814

BCG. (2019). Boston Consulting Group, Survey Industry 4.0. Available online: https://www.bcgperspectives.com/content/articles/engineered_products_project_business_industry_40_future_productivity_growth_manufacturing_industries/ (accessed on 2 June 2023).

Bell, A. (2021). Quotes (Hungarian). Available online: https://www.citatum.hu/szerzo/Alice_Bell (accessed on 2 June 2023).

Berecz, A. (2018). Proposal for a classification of e-learning models (Hungarian). Journal of Applied Multimedia, XII(4), 55-75.

Bernardi, A., & Inamasau.R.Y. (2014). Adoption of precision agriculture in Brazil. Adoption factors (Portuguese). Available online: https://www.alice.cnptia.embrapa.br/alice/handle/doc/1003682 (accessed on 2 June 2023).

Bitkom V, & Zvei. (2015). Industry 4.0 implementation strategy—Industry 4.0 platform results report (German). Available online: https://www.plattform-i40.de/IP/Redaktion/DE/Downloads/Publikation/umsetzungsstrategie-2015.html (accessed on 2 June 2023).

Blanchet, M.-R. T. (2018). The Industry 4.0 Transition Ouantified-How the fourth industrial revolution is reshuffling the economic, social and industrial model, Roland Berger GmbH, Munich, Germany. Available online: https://www.rolandberger.com/en/Publications/ The-Industrie-4.0-transition-quantified.html (accessed on 2 June 2023).

Bostrom, N. (2014). Superintelligence: Paths, Dangers, Strategies. Oxford University Press.

Bussiness. (2017). Bussiness Intelligence and Strategy Research. Available online: https://bisresearch.com/industry-report/precision-irrigation-market.html (accessed on 2 June 2023).

Dhanaraju, M., Chenniappan, P., Ramalingam, K., et al. (2022). Smart Farming: Internet of Things (IoT)-Based Sustainable Agriculture. Agriculture, 12(10), 1745. https://doi.org/10.3390/agriculture12101745

Digitaleurope. (2016). Digitaleurope and the EC’s skills strategy 2016. Available online: http://www.digitaleurope.org/Bring2mind/DMX/Download.aspx?Command=Core_Download&EntryId=1089&language=en-US&PortalId=0&TabId=35 (accessed on 2 June 2023).

Dixon, G., Hart, P. S., Clarke, C., et al. (2018). What drives support for self-driving car technology in the United States? Journal of Risk Research, 23(3), 275–287. https://doi.org/10.1080/13669877.2018.1517384

Dwivedi, Y. K., Rana, N. P., Janssen, M., et al. (2017). An empirical validation of a unified model of electronic government adoption (UMEGA). Government Information Quarterly, 34(2), 211–230. https://doi.org/10.1016/j.giq.2017.03.001

Fountas, S., FK, V. E., Gaitain-Chremaschi, & C., K. (2018). Can presicion agriculture increase the profitability and sustainability of the production of potatoes and olives. Available online: https://www.mdpi.com/2071-1050/9/10/1863 (accessed on 2 June 2023).

Gál T., Nagy L., Dávid L., et al. (2013). Technology planning system as a decision support tool for dairy farms in Hungary. Acta Polytechnica Hungarica, 10(8), 231-244. Available online: http://acta.uni-obuda.hu//Gal_Nagy_David_Vasa_Balogh_46.pdf (accessed on 2 June 2023).

GÉPmax. (2021). Robotic machines and autonomous devices in agriculture (Hungarian). Robotic machines and autonomous devices in agriculture. Available online: https://gepmax.hu/lapozhato/2021-es-kiadvanyaink/ (accessed on 30 December 2023).

Ghobadpour, A., Monsalve, G., Cardenas, A., & Mousazadeh, H. (2022). Off-Road Electric Vehicles and Autonomous Robots in Agricultural Sector: Trends, Challenges, and Opportunities. Vehicles, 4(3), 843–864. https://doi.org/10.3390/vehicles4030047

Golbabaei, F., Yigitcanlar, T., Paz, A., & Bunker, J. (2020). Individual Predictors of Autonomous Vehicle Public Acceptance and Intention to Use: A Systematic Review of the Literature. Journal of Open Innovation: Technology, Market, and Complexity, 6(4), 106. https://doi.org/10.3390/joitmc6040106

GTAI. (2018). Industrie 4.0 Germany Market Report and Outlook. Available online: https://www.gtai.de/resource/blob/829986/e5c70ab44e4a3752251386bc32205cc2/FDI_Report_2018_GTAI.pdf (accessed on 2 June 2023).

INTA. (2018). Competitiveness and efficiency-Tecnologia precisa INTA reports Ano XII#135 (Spanish). Available online: https://www.argentina.gob.ar/inta (accessed on 2 June 2023).

Kagermann, H., W., W., & HelbringJ. (2013a). Securing the Future of German Manufacturing Industry: Recommendations for Implementing the Strategic Initiative Industrie 4.0. Final report of the Industrie 4.0 Forschungsunion im Stifterverband für die Deutsche Wirtschaft e.V., Berlin.

Kagermann, H., Wolf-Dieter, & Lukas. (2011b). Industry 4.0: On the way to the 4th Industrial Revolution with the Internet of Things (German). VDI Nachrichten, 13, 2.

Karunathilake, E. M. B. M., Le, A. T., Heo, S., et al. (2023). The Path to Smart Farming: Innovations and Opportunities in Precision Agriculture. Agriculture, 13(8), 1593. https://doi.org/10.3390/agriculture13081593

Kemény, G., Lámfalusi, I., & Molnár, A. (2017). Comparative study of precision arable crop production=Comporative study of precision arable crop production (Hungarian). Agrárgazdasági könyvek Agrárgazdasági Kutató Intézet, Budapest.

Lukovics, M., Udvari, B., Zuti, B., & Kézy, B. (2018). Self-driving cars and responsible innovation (Hungarian). Közgazdasági Szemle, 65(9), 949–974. https://doi.org/10.18414/ksz.2018.9.949

Kohli, P., & Chadha, A. (2019). Enabling Pedestrian Safety Using Computer Vision Techniques: A Case Study of the 2018 Uber Inc. Self-driving Car Crash. Advances in Information and Communication, 261–279. https://doi.org/10.1007/978-3-030-12388-8_19

Koleva, N. (2019). An Empirical Study on Human Resoureces' Attitude Towards Manufacturing Digitalization. In: Proceedings of the 2019 International Conference on Creative Business for Smart and Sustainable Growth (CREBUS).

Kuhn, T. (1984). The structure of scientific revolutions (Hungarian). Gondolat kiadó.

Lagnelöv, O., Larsson, G., Larsolle, A., & Hansson, P.-A. (2021). Life Cycle Assessment of Autonomous Electric Field Tractors in Swedish Agriculture. Sustainability, 13(20), 11285. https://doi.org/10.3390/su132011285

Lowenberg-DeBoer, J., Behrendt, K., Ehlers, M., et al. (2021). Lessons to be learned in adoption of autonomous equipment for field crops. Applied Economic Perspectives and Policy, 44(2), 848–864. https://doi.org/10.1002/aepp.13177

Magda, S., Marsalek, S., & Magda, R. (2017). Skills of the agricultural workforce and future needs (Hungarian). Available online: http://real-j.mtak.hu/20493/3/gazd_2019_63_3_.pdf (accessed on 2 June 2023).

Mérő, L. (2016). Human mathematics (Hungarian). Tericium Kiadó.

Mohd, J., Abi, H., Ibrahim, H. K., & Rajiv, S. (2023). Understanding the potential applications of Artificial Intelligence in Agriculture Sector. Advanced Agrochem, 2(1), 15–30. https://doi.org/10.1016/j.aac.2022.10.001

Mohd, J., Abid, H., Ravi, P. S., & Rajiv, S. (2022). Enhancing smart farming through the applications of Agriculture 4.0 technologies. International Journal of Intelligent Networks, 3, 150–164. https://doi.org/10.1016/j.ijin.2022.09.004

Nábelek, F. (2017b). Potential labour market effects of automation in Hungary, 2012-2016 (Hungarian). MKIK Institute of Economic and Business Research GVI.

Nábelek, F., Sturcz, A., & Tóth, I. J. (2016a). The labour market effects of automation. Estimating the exposure of municipal labour markets to automation (Hungarian). MKIK Gazdaság-és Vállalkozáskutató Intézet GVI.

Nastjuk, I., Herrenkind, B., Marrone, M., et al. (2020). What drives the acceptance of autonomous driving? An investigation of acceptance factors from an end-user's perspective. Technological Forecasting and Social Change, 161, 120319. https://doi.org/10.1016/j.techfore.2020.120319

Nath, D. (2023). Smart Farming: Automation and Robotics in Agriculture. In: Recent Trends in Agriculture. Integrated Publications.

Niculescu, A. I., Dix, A., & Yeo, K. H. (2017). Are You Ready for a Drive? Proceedings of the 2017 CHI Conference Extended Abstracts on Human Factors in Computing Systems. https://doi.org/10.1145/3027063.3053182

Nordhoff, S., Louw, T., Innamaa, S., et al. (2020). Using the UTAUT2 model to explain public acceptance of conditionally automated (L3) cars: A questionnaire study among 9,118 car drivers from eight European countries. Transportation Research Part F: Traffic Psychology and Behaviour, 74, 280–297. https://doi.org/10.1016/j.trf.2020.07.015

Nordhoff, S., Madigan, R., Van Arem, B., et al. (2020). Interrelationships among predictors of automated vehicle acceptance: a structural equation modelling approach. Theoretical Issues in Ergonomics Science, 1–26. https://doi.org/10.1080/1463922x.2020.1814446

NTP. (2017). Industry 4.0 National Technology Platform (Hungarian). Available online: https://www.i40platform.hu/sites/Industrie%204.0_Definition.pdf (accessed on 2 June 2023).

Nyírő, N. I. (2011). Adoption and diffusion of media technology innovations (Hungarian) [PhD thesis]. Corvinus University of Budapest Doctoral School of Business Administration.

Obermayer, N., Csizmadia, T. H., & Kigyós, T. A. (2021). Analysis of managerial motivations and barriers to the implementation of Industry 4.0 based on the opinions of domestic CEOs. Available online: https://www.researchgate.net/publication/349160381_Az_Ipar_40_implementacioval_kapcsolatos_vezetoi_motivaciok_es_akadalyozo_tenyezok_elemzese_hazai_vallalatvezetok_velemenye_alapjan (accessed on 2 June 2023).

OECD. (2019). AI Principles Overview. Available online: https://oecd.ai/en/ai-principles (accessed on 20 March 2024)

Paunov, C., & Satorra, S. (2019). How are digital technologies changing innovation? (2019). OECD Science, Technology and Industry Policy Papers. Available online: https://doi.org/10.1787/67bbcafe-en (accessed on 2 June 2023).

Popp, J. E. (2018). Outlook of Precision Farming in Hungary. International Journal of Engineering and Management Sciences, 3(1), 133–147. https://doi.org/10.21791/ijems.2018.1.15

Quentin, A., Carmon, Z., Wertenbroch, K., C. A., et al. (2018). Consumer Choice and Autonomy, in the Age of Artificial Intelligence and Big Data. https://link.springer.com/article/10.1007/s40547-017-0085-8

Ravis, T., & Notkin, B. (2020). Urban Bites and Agrarian Bytes: Digital Agriculture and Extended Urbanization. Berkeley Planning Journal.

Rowe, R. (2015). Self driving cars, timeline TopSpeed. Available online: http://www.topspeed.com/cars/car-news/self-driving-cars-timeline-ar169802.html (accessed on 2 June 2023).

SAE. (2018). SAE International Releases Updated Visual Chart for Its "Levels of Driving Automation" Standard for Self-Driving Vehicles. Available online: https://www.sae.org/publications/journals (accessed on 2 June 2023).

Sara, O., Pere., R., José, R., et al. (2023). Machine Learning Applications in Agriculture: Current Trends Challenges, and Future Perspectives. Agronomy, 13, 2976.

Schukat, S., & Heise, H. (2021). Towards an Understanding of the Behavioral Intentions and Actual Use of Smart Products among German Farmers. Sustainability, 13(12), 6666. https://doi.org/10.3390/su13126666

Schwab, K. (2016a). The Fourth Industrial Revolution WEF Geneva., Klaus Schwab. Világgazdasági Fórum.

Schwab, K. (2016b). The Human Capital Report 2016. Available online: https://www.weforum.org/publications/the-human-capital-report-2016 (accessed on 2 June 2023).

Shi, Y., Siddik, A. B., Masukujjaman, M., et al. (2022). The Antecedents of Willingness to Adopt and Pay for the IoT in the Agricultural Industry: An Application of the UTAUT 2 Theory. Sustainability, 14(11), 6640. https://doi.org/10.3390/su14116640

Szalavetz, A. (2016a). The economic impact of Industry 4.0 technologies: Questions from a start-up research (Hungarian). Foreign Economy, 60(7-8), 27-50.

Szalavetz, A. (2016b). Chronicle of an announced revolution in Hungary: industry 4.0 technologies and domestic manufacturing subsidiaries (Hungarian). Foreign Economy, 60(9-10), 28-48.

Szőke, V., & Kovács, L. (2021). Technologies of Agriculture 4.0. Gazdálkodás, 65(1), 64–85.

Technavio. (2017). Global precision agriculture market 2015-2019. Available online: https://www.technavio.com/report/precision-agriculture-market-industry-analysis (accessed on 2 June 2023).

Tennant, C., Stares, S., & Howard, S. (2019). Public discomfort at the prospect of autonomous vehicles: Building on previous surveys to measure attitudes in 11 countries. Transportation Research Part F: Traffic Psychology and Behaviour, 64, 98–118. https://doi.org/10.1016/j.trf.2019.04.017

Thompson, R., Compeau, D., Higgins, C., & Lupton, N. (2008). Intentions to Use Information Technologies. End User Computing Challenges and Technologies, 79–101. https://doi.org/10.4018/978-1-59904-295-4.ch006

Tilesch, & Hatamleh. (2021). Artificial Intelligence-Taking control of our destiny in the age of AI (Hungarian). Budapest: Libri.

VDMA. (2015). Industry 4.0 Readines (German). VDMA's Impulse Foundation Aachen Cologne. Available online: https://www.egsautomation.de/?gclid=Cj0KCQiA3uGqBhDdARIsAFeJ5r0VOVi1KkkL-sjVdCVqdJRw-2OQ5CJhMkiwnPsRe2L0oKs_6dYf004aAhlfEALw_wcB (accessed on 2 June 2023).

Venkatesh, Morris, Davis, & Davis. (2003). User Acceptance of Information Technology: Toward a Unified View. MIS Quarterly, 27(3), 425. https://doi.org/10.2307/30036540

Venkatesh, V., & Bala, H. (2008). Technology Acceptance Model 3 and a Research Agenda on Interventions. Decision Sciences, 39(2), 273–315. Portico. https://doi.org/10.1111/j.1540-5915.2008.00192.x

Venkatesh, Thong, & Xu. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. MIS Quarterly, 36(1), 157. https://doi.org/10.2307/41410412

Venkatesh, Viswanath., & Thong., Y. J. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. MIS Quarterly, 36(1), 157-178.

Vértesy, L. (2023). A change of mindset in crop production: Circularity and sustainability: Workshop paper Circular economy (Hungarian). MATE Press.

Younger, P. (2004). Using the internet to conduct a literature search. Nursing Standard, 19(6), 45–53. https://doi.org/10.7748/ns.19.6.45.s63