

**The Use of Artificial Intelligence (AI) in the Wine Sector: Use Cases, Benefits,  
Implementation Challenges and Drivers**

**Author: Attila Loibl**

**Corvinus University of Budapest**  
**Doctoral School of Economics, Business and Informatics**

**Institute of Data Analytics and Information Systems**

**Supervisors Dr. Peter Feher and Dr. Daniel Homolya**

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**Corvinus University of Budapest**  
**Doctoral School of Economics, Business and Informatics**



**Business Informatics Doctoral Program**

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Cases, Benefits, Implementation Challenges and Drivers**

**Doctoral Dissertation**

**Author: Attila Loibl**

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*“The important thing is not to stop questioning.”*

*Albert Einstein*

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## **Abstract**

Artificial Intelligence (AI) is an innovation that has gained widespread attention in recent years, not only in popular culture but also across academic, practical, and policy domains. However, the technology has been under development for approximately eight decades at the time of this dissertation, with multiple use cases recognized earlier in different areas. The commoditization of AI, lowered barriers to entry and increased awareness about the technology's potential benefits is expected to result in its adoption in industries that were previously considered as traditional sectors with low levels of digital maturity. The wine industry is one of those segments, and with a significant weight in global agricultural production, employment and cultural heritage, identifying how AI can transform the wine value chain can provide valuable insights.

The objective of this study is therefore to understand the impact of AI on winemaking, by answering four main research questions. These are aimed at understanding the use cases, benefits, implementation challenges and adoption drivers of AI in the wine value chain. The results are achieved through applying a variation of different methods of academic inquiry, starting with the review and bibliometric analysis of relevant academic literature, continuing with the utilization of the Delphi method, where two rounds of surveys are conducted with a 19 highly relevant experts in this field. To ensure that more granular insights are captured, the results are then corroborated by in-depth interviews with 10 respondents and the systematic analysis of the outcomes of those with qualitative and quantitative techniques.

The findings of this research show that AI adoption in the wine sector is primarily shaped by economic and environmental pressures, climate-related risks, labour shortages, market competition, and growing consumer expectations for digital and personalised experiences. These external drivers contrast with internal constraints, including cultural resistance, risk aversion, limited digital skills, and concerns about preserving authenticity. The study identifies the most feasible use cases in precision vineyard management (such as disease detection, irrigation optimisation, and climate forecasting) as well as process optimisation in fermentation and quality control, and

emerging applications in consumer personalisation. AI adoption offers clear benefits related to efficiency, cost reduction, sustainability, and product consistency. However, uptake remains hindered by high investment costs, inconsistent data quality, infrastructural limitations, and underdeveloped governance and policy support. Together, these findings highlight an adoption landscape where operational potential is strong, but socio-technical and institutional barriers continue to shape implementation outcomes.

This study provides important insights into the driving forces of AI implementation in winemaking, as well as the potential benefits and challenges associated with such a significant transformation. This research is intended to contribute to the growing number of contributions on AI's implications on business model innovation. To the best knowledge of the author, no previous study was conducted that analysed the impact of AI on winemaking by applying a multifaceted mix-methods approach, with a comprehensive review of academic literature and the systematic collection of highly relevant expert opinions, which also highlights the novelty of this research.

**Key words:** artificial intelligence, AI, business model innovation, wine industry

## I. Artificial Intelligence (AI) and winemaking background

**Artificial Intelligence (AI)** is the field focused on designing systems capable of simulating or replicating intelligent behaviour, based on the understanding developed over human intelligence and thought processes. AI is exhibited by a system if it takes the steps required based on the knowledge obtained through a series of preceding steps. To define AI, one can consider two dimensions focused on **thought processes and reasoning** (first dimension) and **behaviour** (second dimension). The potential definitions of AI along these are summarized in Table 1.

Table 1. Potential definitions of AI (source: (Russell & Norvig, 2009))

<b>Thinking humanly</b> , meaning the creation of machines that mimic human cognitive processes, like learning and decision-making, by modelling these in computer programmes that produce human-like outputs.	<b>Thinking rationally</b> involves modelling intelligent thought through logical rules and inference, following the logicist tradition inspired by Aristotle's concept of systematic "right thinking".
<b>Acting humanly</b> refers to designing machines that imitate human behaviour, evaluated by tests like the Turing Test, involving language, reasoning, learning, and knowledge management.	<b>Acting rationally</b> refers to AI systems making optimal decisions to reach goals, focusing on rational behaviour for effective decision-making in uncertain environments.

### I. 1. The brief history of AI

The development of AI was a process spanning multiple decades starting in the middle of the 20<sup>th</sup> century. Whilst it is not within the scope of this thesis to present a detailed explanation of how the technology was formed, a high-level overview will be still provided in this section, to familiarize the readers with the key underlying building blocks, easing the understanding of future reading. This summary is based on Russel Norvig's book titled "Artificial Intelligence – A Modern Approach" (Russell & Norvig, 2009).

The first scientific contribution can be dated back to the 1940s (Mcculloch & Pitts, 1943). In their paper, the authors presented a model where **artificial neurons** can be activated and deactivated by an adequate number of adjacent neurons, as a result of some external stimulus. The findings suggest that learning capabilities of such

networks can be formulated, when designed appropriately. In 1951, Marvin Minsky and Dean Edmonds of Princeton University built a system called **SNARC (Stochastic Neural Analog Reinforcement Calculator)**, the first neural network capable of learning from experience and enhancing its performance over time by trial and error, similar to reinforcement learning algorithms (Parvez, 2023). The conceptual foundations of how machines can “think”, laying the grounds of **Machine Learning (ML)** was first published in Alan Turing’s “**Computing Machinery and Intelligence**” article in 1950 (Turing, 1950).

In 1956, a two-months seminar was organized by John McCarthy (Assistant Professor of Mathematics, Dartmouth College), Marvin Minsky (Harvard Junior Fellow in Mathematics and Neurology), Claude Shannon (mathematician at Bell Telephone Laboratories), and Nathaniel Rochester (Manager of Information Research at IBM Corporation). The aim of the **Dartmouth workshop** was to explore how every aspect of learning and intelligence could be precisely described and simulated by a machine, enabling machines to use language, form concepts, solve problems, and improve themselves (John McCarthy et al., 1955). The outcomes also showed why AI should be treated as a separate field of science, as a technology inherently built on computer systems, yet attempting to demonstrate human-like capabilities (such as creativity, or language use), operating independently under dynamic, changing circumstances.

The years following the Dartmouth workshop were marked by optimism, but the limitations of AI soon became apparent. Early programs could demonstrate clever tricks, yet they relied on very simple computing tools, which could perform mostly arithmetic operations. The ambition of creating “**thinking machines**” was hindered by the restricted capacity of available hardware. This mismatch created a gap between theoretical advances and real-world implementation of AI. At the same time, researchers were experimenting with approaches that began to mimic the process of human problem-solving. While computers could already calculate with speed and accuracy that was above human capabilities, making them “think” required new methods of representing knowledge, setting goals, and breaking down complex challenges into manageable tasks. These first steps provided important basis for further

work, yet it immediately became visible how much else is required to be done to turn AI into a functioning discipline.

One of the earliest milestones was the development of the **General Problem Solver (GPS)** in 1957 by Allen Newell and Herbert Simon (Newell & Simon, 1958). This program used a method called **means–end analysis**, which focused on reducing the difference between the current situation and a desired goal through intermediate steps. GPS was significant because it simulated a way of thinking similar to human cognition, by setting subgoals and testing possible actions that might achieve them. While the system could only tackle relatively simple problems, it offered the basics of a new model for programming machines to reason in ways that resembled human logic. GPS illustrated that machines could be designed not only to execute pre-defined instructions but also to make decisions dynamically, depending on how a problem developed. Although limited in scope, GPS represented an important theoretical breakthrough by modelling a machine’s ability to “think humanly” in an operational form.

In the same period, advances were made in programming languages specifically adapted for AI research. In 1958, John McCarthy introduced **LISP**, a language designed with symbolic processing in mind (McCarthy, 1979). LISP rapidly became the dominant AI language for the next three decades, valued for its flexibility and suitability for handling data structures needed in problem-solving and knowledge representation. Beyond LISP, McCarthy also contributed ideas about how machines could **adapt to new inputs without requiring constant reprogramming**, an idea later formalised in his vision of “Programs with Common Sense” (McCarthy, 1959). These hypothetical models sketched out how a system might use stored knowledge to interpret new situations, a concept that would underpin later developments in knowledge-based systems. These contributions were important to ensure that AI research could build upon a common technical and conceptual foundation, easing subsequent development efforts.

The establishment of dedicated research institutions further strengthened AI as an independent scientific field. In 1963, the **Artificial Intelligence Laboratory at Stanford University** was founded, which soon became (and still is) one of the most influential centres of AI research (Stanford Artificial Intelligence Center, n.d.). The focus of the activities conducted in the centre shifted towards building reasoning and synthesis techniques that could be applied across different domains. Perhaps its most celebrated project was **Shakey the Robot**, developed between 1962 and 1972 (Kuipers et al., 2017). Shakey was the first general-purpose robot that could perceive its environment, reason about its own actions, and plan next steps accordingly. Combining robotics, computer vision, and natural language processing, the system was able to execute a list of available commands and navigate physical space. Although limited in complexity, Shakey demonstrated how AI could integrate multiple disciplines into a functioning physical system.

Despite these achievements, most expectations from AI were not realized by the end of the 1960s. Researchers expected that the new systems developed will be capable to demonstrate human-level intelligence within a decade. Progress was however much slower with major obstacles hindering developments. First, many subject areas were **not sufficiently understood** to allow accurate modelling, as in the case of natural language translation. Second, the **search-based methods** employed in early programs were inefficient, as they relied on trying out different combinations of a large volume of steps rather than finding optimal solutions. As problems to be solved became more complicated, the limitations of such approach surfaced, which couldn't be compensated by the fact that hardware resources continuously evolved and became more powerful. Finally, the **limits of basic neural network structures** became clear, due to their incapability of representing more sophisticated behaviours, despite their ability to learn some patterns. By the end of the 1960s, funding and enthusiasm had declined significantly, leading to a period of reduced investment often referred to as the **first AI winter** (Thorwirth, 2021).

Despite these setbacks, academics kept on working on AI-related projects, with a dedicated branch of research shifting towards developing “**knowledge-intensive**”

**systems.** These were structures that relied less on brute-force methods and more on expert knowledge encoded in detail. What was different in these systems is their focus tilting towards narrow, domain-specific areas, where expertise could be formally represented and applied to real problems. An important example was the **DENDRAL** program, developed in the 1960s to assist chemists in identifying unknown organic molecules from mass spectrometry data (AI World Society, 2025). DENDRAL clearly separated the domain-specific knowledge base from the reasoning engine, making it a highly influential invention in AI development. This separation allowed for solving more complex problems at higher accuracy and created an important basis of future expert systems. Knowledge-based systems also showed potential in areas such as natural language understanding, where linguistic rules and semantic structures could be encoded to improve comprehension. This shift in focus showed a change in direction for AI development, with solutions focusing on achieving results related for more constrained problems, instead of chasing the creation of universal intelligence.

By the late 1970s and into the 1980s, AI became more commercialised and closely associated with practical industry applications. **Expert systems** gained widespread adoption, especially in corporate environments where structured decision-making was required. One of the most successful examples was the **R1 (later called XCON) system** developed for Digital Equipment Corporation, which assisted in configuring computer systems based on customer requirements. Systems like the R1 demonstrated business value derived from these innovations, resulting in major corporations establishing their own AI groups. Vision technologies, robotics, and specialised hardware also showed significant improvements during this period.

Despite all these progressions, the end of the 1980s brought a **second AI winter** triggered by disappointment in expert systems. While such architectures worked well for narrowly defined tasks, they would easily break when faced with new or unexpected situations. The cost of developing and maintaining extensive rule-based knowledge bases also became an obstacle, as these systems required the careful encoding of expert knowledge by specialists. The limitations of these **weak methods** revealed the difficulty of scaling AI solutions to handle broader, more complex

problems. As investment slowed, scepticism towards AI research increased again. However, this drop in optimism was still an important influencing factor, encouraging researchers to refine their methods and rethink the foundations of AI.

During the same period, work on neural networks also continued, with researchers pursuing two distinct directions. On the one hand, they sought to create **effective network architectures and algorithms**, exploring how layers of artificial neurons could be trained with improved efficiency. On the other hand, neuroscientists and computer scientists collaborated on modelling the **empirical properties of biological neurons**, aiming to better understand how ensembles of neurons function in the brain (Russell & Norvig, 2009). This approach helped in advancing both the mathematical understanding of learning algorithms and the biological mechanisms behind those. The findings derived from these initiatives were important in the development of deep learning systems decades later, after the right amount of computational power and data was available to train and operate such architectures.

The late 1980s represented a change in how **scientific methods** were applied in AI research, with stronger connections built between machine learning and other established disciplines. For example, probabilistic reasoning was linked with stochastic modelling, search techniques were tied to optimisation and control theory, and automated reasoning drew upon formal methods. This integration fostered more rigorous experimentation, hypothesis testing, and replication of results. **Shared repositories of test data** and **open-source code** further professionalised the field, creating common standards for evaluation. Expectations towards AI also developed, with researchers focusing more on building **practical frameworks** for tackling specific problems, such as speech recognition or pattern classification. This change in focus towards more pragmatic solutions helped AI regaining credibility.

The mid-1990s saw the emergence of **intelligent agents**, i.e., systems designed to operate autonomously within complex environments, perceiving information, making decisions, and taking actions to achieve predefined goals. The **Internet** provided an

ideal testing environment, offering dynamic and unpredictable conditions that mirrored real-world challenges. While agents were often specialised for narrow tasks, the underlying idea inspired broader discussions in the 2000s about **artificial general intelligence (AGI)** aimed at building systems capable of learning and reasoning across multiple domains. As these discussions evolved, concerns were also started to be raised about how to design **“friendly” AI system** that would align with human values and interests.

An additional significant change in the early 2000s that influenced AI development was the **rising abundance of significantly larger datasets** compared to earlier decades. With the explosion of digital information available on the Internet, the emphasis shifted from refining algorithms in isolation to leveraging these previously unimaginable amounts of data. This shift was also manifested in the popular idea stating that **“data is the new oil,”** with the quality and scale of data becoming just as important as the algorithms chosen to operate on those. This period also resulted in important real-world demonstrations of the technology. In 2005, for example, the **driverless car Stanley** successfully navigated 132 miles through the Mojave Desert, relying on cameras, radar, GPS, and laser sensors. **NASA’s Remote Agent program** further showcased the capabilities of autonomous systems by controlling spacecraft operations without constant human supervision. These examples illustrated the transition of AI from abstract concepts into practical implementations, with significant value creation potential. However, these experiments also highlighted the importance of reliability, safety, and adaptability for such systems to be applied on a larger scale.

Since the 2010s, AI became increasingly embedded in everyday life. Applications such as **spam filtering, automated logistics planning, real-time translation, and household robotics** resulted in the everyday use of AI. These technologies did not necessarily represent human-level intelligence, but they demonstrated how AI could provide concrete benefits by solving specific, well-defined problems. Importantly, they also showed the scalability of AI systems when deployed on a mass level, supported by improvements in computing hardware and cloud infrastructures. By this stage, the field had moved beyond conceptual applications into solutions operating in homes,

businesses, and industries worldwide, becoming an integral part of modern people's lives.

Table 2. Key milestones in AI development from 1940s to 2020s (source: author)

1940-1950s	1960-1970s	1980-1990s	2000s-2010s	2020s
First model of artificial neurons Turing - Computing Machinery and Intelligence Dartmouth workshop SNARC, GPS, LISP	Stanford AI Lab founded Shakey the Robot project DENDRAL and other knowledge-intensive systems First AI winter	Expert systems (R1/XCON) AI groups at corporates Second AI winter Stronger scientific methods Intelligent agents / Internet	Increased amount of data Stanley / driverless car Remote Agents (NASA) Everyday applications Cloud infrastructures and scalability	Mass adoption Debates on AI societal impact Deep learning and data-driven methods' dominance Shift towards responsible AI AGI discussions

To conclude, the history of AI shows a **series of cycles** with periods of heightened optimism and increasing funding followed by disappointments and reduced financial resources available. However, each cycle is left behind with valuable insights, methods, and technologies resulting in the continuous evolution of the field. The key milestones achieved in these are summarized in Table 2. From the early models of artificial neurons and symbolic reasoning, through expert systems and intelligent agents, to today's data-driven and deep learning approaches, the technology consistently improved, extending the capabilities of intelligent machines. Although there was a constant mismatch between initial expectations and the outcomes of developments, the cumulative improvements resulted in **significant innovations**. This historical perspective points out some of the challenges and the transformative

potential of AI, providing context for understanding its role in the present and future in various industries.

## I. 2. AI and other areas of science

AI builds upon a wide range of scientific disciplines that often evolved independently from one another, which will be discussed briefly in this section based on the work of (Russell & Norvig, 2009). The **philosophical basis of AI** explores how machines can mimic different aspects of the human thought process, by following established logical rules and using knowledge to justify actions. At its core, it examines the complex connection between **acquiring knowledge**, **setting goals**, and determining the **appropriate actions** to achieve those goals. This viewpoint raises questions about decision-making, free will, and the relationship between mind and physical systems.

The foundations of AI are deeply rooted in **mathematics**, building upon various subdomains. Firstly, **formal logic** provides a framework for reasoning and representing knowledge, acting as enabler of intelligent systems to make informed decisions, draw inferences, and solve complex problems systematically. Then, **computation** limits what machines can solve, influencing both the scope of potential tasks and the characteristics of AI. Finally, **probability theory** enables decision-making under uncertainty, providing a mathematical framework for evaluating risks, predicting outcomes, and guiding intelligent systems towards optimal choices. Together, these mathematical areas shape how AI systems process information and solve complex problems.

The **economics of AI** explores how individuals and systems make decisions to achieve preferred outcomes, especially in uncertain environments. Domains like **decision theory** and **game theory** provide frameworks to understand how rational agents select strategies, sometimes opting for randomized policies or "good enough" solutions instead of always seeking the optimal outcome. In practice, these approaches reflect the complexities and unpredictable nature of real-world scenarios, where immediate payoffs are rare, and choices are often results of several steps executed. This perspective highlights that both human behaviour and intelligent systems are shaped

by the need to **maximize utility, adapt to changing circumstances**, and sometimes agree on **satisfactory results rather than perfect outcomes**.

Another influential scientific domain influencing the discipline is **neuroscientific research**, examining the brain's network of specialised cells (**neurons**) that transmit information through electrochemical signals. Each neuron connects to tens of thousands of other neurons at junctions known as **synapses**, forming complex networks responsible for learning and information processing activities. While much has been learned about how neurons and the cerebral cortex (the brain's outer layer where most complex cognitive functions -such as perception, reasoning, and voluntary movement- occur) contribute to thought and action, important details about **memory storage** and **other cognitive processes** are still relatively unknown. These questions are still mostly unanswered and the ongoing study in the field continues to inspire the design of AI systems that aim to replicate the abilities of human intelligence.

The **psychology background of AI** draws on the study of how living beings interpret different sources of stimulus and translate those into actions. Early approaches focused on **observable behaviour**, emphasizing the importance of objective measurements. Later, the rise of **cognitive psychology** brought the idea that the brain functions much like an information-processing device, transforming sensory inputs into internal representations and then using these to guide actions. This shift inspired the design of **knowledge-based agents** that can be characterized by the execution of three key steps. First, a **stimulus is received** that is translated into an internal representation (i.e., a system describing how information, knowledge, and data are encoded and organised). In the second step, this representation is manipulated by different procedures to create **new internal representations**, which will be turned into **action** in the final stage. The rise of cognitive psychology also resulted in the development of cognitive science, where computer models are utilized to understand and simulate intelligent behaviour.

**Computer engineering** has also played a crucial role in advancing AI by providing both the hardware and software foundations necessary for its development. Early programmable machines demonstrated the potential for automated control and complex calculations, setting the stage for modern computers capable of universal

computation. Innovations such as **addressable memory**, **stored programs**, and **conditional operations** expanded the possibilities for intelligent systems. The steady increase in computing power, initially driven by improvements in speed and later by the addition of multiple processing cores, has allowed the development of even more sophisticated AI applications. Developments in **programming languages**, **operating systems**, and **software tools** have further empowered researchers to design and implement intelligent algorithms. AI has not only benefited from these advancements but has also contributed innovations that have influenced the broader field of computer science.

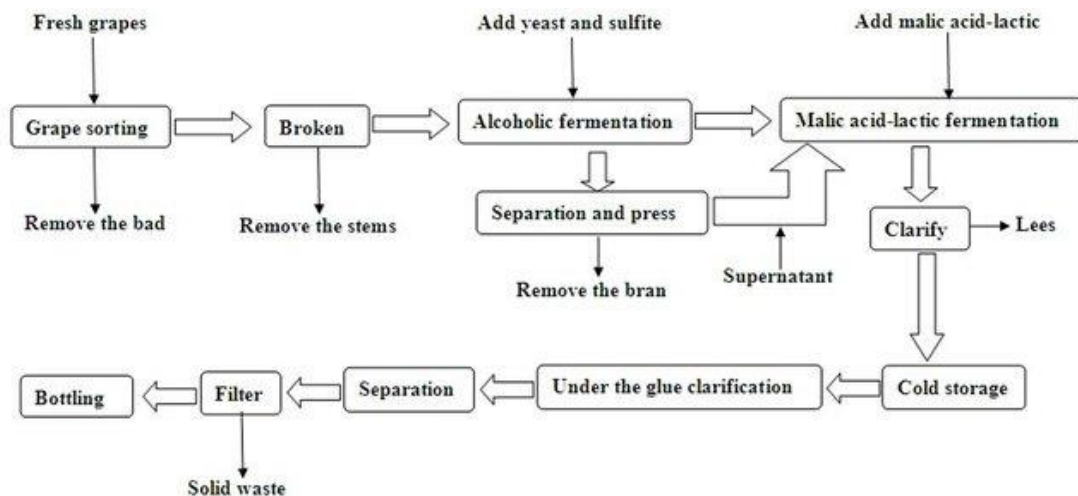
**Control theory and cybernetics** have significantly influenced the development of AI, introducing the concept that intelligent behaviour can arise from feedback-driven systems capable of stable, adaptive actions. **Modern control theory** (particularly in optimal control) seeks to design systems that make the best decisions over time to achieve specific goals by maximizing the so-called **objective function**, an idea that is closely aligned with the goals of AI. Finally, the **linguistic roots of AI** highlight the complexity of language understanding, which requires more than just knowledge of grammar and sentence structure. To truly understand the meaning conveyed by language, intelligent systems must also demonstrate capabilities of **establishing the context and underlying subject** matter in the discourse analysed. Together, these perspectives have shaped AI into a discipline focused on designing systems that can reason, adapt, and interact meaningfully with humans and their environments.

The above summary shows how AI emerged as a discipline shaped by a wide range of scientific foundations, from philosophy, mathematics, and economics to neuroscience, psychology, computer engineering, and linguistics. Each of these domains has contributed to the definition of how intelligent systems can reason, learn, and act in complex environments. Understanding the core contributions of these is important to highlight the multidisciplinary nature of AI. Building on these foundations, the following sections will provide a brief historical overview of the wine industry and AI's development in this sector, illustrating how these theoretical constructs can be turned into practical applications. Further details on the algorithmic background of AI can be found in **Appendix 1**.

### I. 3. An overview of the wine industry and value chain

Archaeological evidence suggests that grape-based fermented drinks were produced as early as 7000 BC in China, marking the first known wine-related discovery in human history. Similar findings from 5000 BC in Iran and 4000 BC in Sicily further support the existence of early winemaking practices. The first organized form of wine production dates back to around 4100 BC in Armenia, where the remains of a winery capable of crushing grapes and collecting juice for fermentation were uncovered (Cuber, 2020). The **process of wine production remains largely unchanged** since these early efforts to domesticate grapes and produce wine on a larger scale. However, as technology evolved, wine production (as shown in Figure 1) became increasingly sophisticated with various technological innovations implemented.

Figure 1. A high-level overview of the 'grape-to-glass' wine production process. (source: (R. Wang et al., 2015))



The wine industry is a **multifaceted and globally dispersed sector**. This complexity makes it an excellent candidate for examining how technology can drive new developments in its business model. The industry's value proposition lies in offering a **diverse range of products** that cater to varying tastes, occasions, price points, and experiential aspects of wine consumption. Products can be categorised by multiple dimensions, such as type (sparkling, still, and fortified wine), flavour (red, white, and rosé wine), or price point (table or jug wine, premium, luxury, or ultra-premium wine).

Winemakers target a **broad customer base**, ranging from casual consumers to connoisseurs, and serve different market segments, including individual consumers, restaurants, bars, wholesalers, and retailers. **Preferences and consumption patterns** vary significantly and are heavily influenced by demographic, economic, and societal factors within individual regions, as well as by innovation activities of wine and other companies in the alcoholic beverages sector.

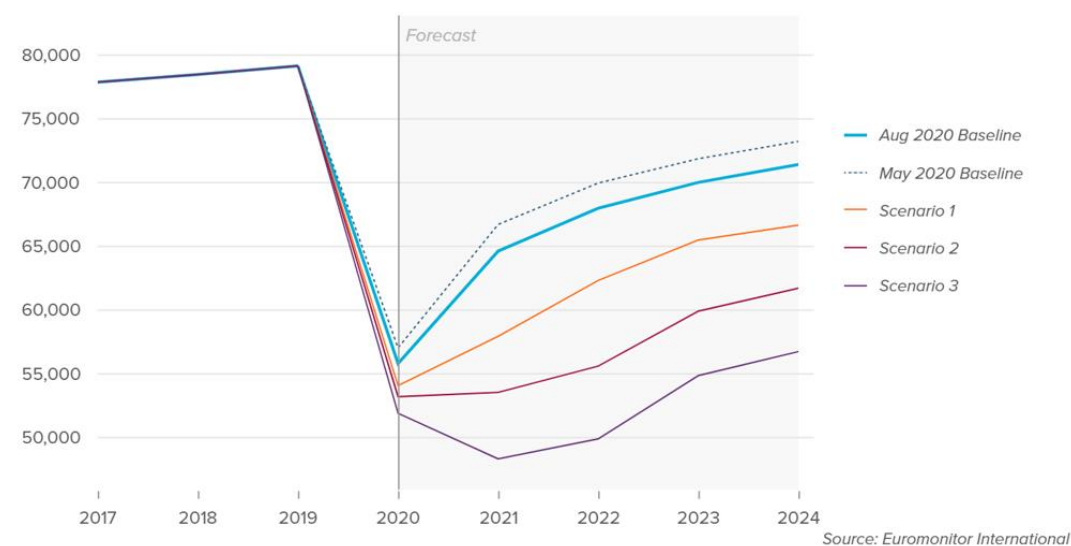
**Distribution channels are diverse**, including direct sales (such as sales at vineyards), online platforms, specialty wine shops, supermarkets (commonly referred to as the off-trade channel), and restaurants or bars (commonly referred to as the on-trade channel). The choice of channel through which wine is sold often reflects the strategic positioning of the brand. Building and maintaining **customer relationships** is essential, often achieved through loyalty programmes, wine clubs, and personalised marketing activities, leveraging digital platforms for customer engagement and feedback. **Premium pricing strategies** are typically employed for high-end wines, while competitive pricing is generally maintained for everyday varieties.

Key resources for producing the final product include **vineyards** and **grapevines**, **winemaking facilities**, **skilled labour** (such as winemakers and viticulturists), and **brand reputation**. Additionally, **technological resources** for production and distribution are increasingly important, helping to address the significant challenges faced by the wine industry and the wider agricultural sector. Key elements of the industry's cost structure are related to vineyard maintenance, production, marketing, and distribution. **Economies of scale** is a significant source of competitive advantage for larger producers, whereas smaller wineries may face higher per-unit costs, often resulting in delays in implementing new technological innovations. These challenges can, to some extent, be mitigated through the formation of **strategic alliances** or entering into various **partnership agreements**.

The **performance of the wine industry** has been sluggish in recent years. The size of the global market (measured at retail sales prices, including applicable taxes)

increasing at a compound annual growth rate (CAGR) of 0.5% between 2016 and 2021, alongside a corresponding volume increase of 0.4% during the same period. This weak growth can be attributed to several factors, the most significant being the **Covid-19** outbreak in 2020, which led to a substantial decline in on-trade sales of alcoholic beverages, following lockdown measures enforced by governments and other authorities (see Figure 2). A meaningful rebound in the industry’s financial performance is yet to be realised, however growth drivers such as ongoing premiumisation, health benefits associated with moderate wine consumption, and innovations in taste can generate expansion, primarily in the United States and Asia-Pacific regions (GlobalData Plc., 2022).

Figure 2. On-trade volume of alcoholic beverages’ sales in million litres (source: (Spiros Malandrakis / Euromonitor International, 2020))



Winemaking is often challenged by **weather conditions**, or other **natural threats** such as fungal infections, which have historically led to close collaboration between scientists and wine producers. For example, in the 1960s and 1970s, winemakers in California began employing extensive quantitative and qualitative analyses, **mechanical harvesting**, **drip irrigation** techniques, and **field grafting** to close the quality gap between European and U.S. wines. Subsequent technological advancements in the California wine cluster focused on **more efficient harvesting**, improved **frost protection**, and the development of grape **varietals with greater**

**resistance** to phylloxera, making the winemaking process more resilient to disruptions and adverse external events. Australian winemaking also experienced a significant rise in wine consumption, with much of this **commercial success** attributed to investments in innovations in viticulture and winemaking technology (Porter & Bond, 1999).

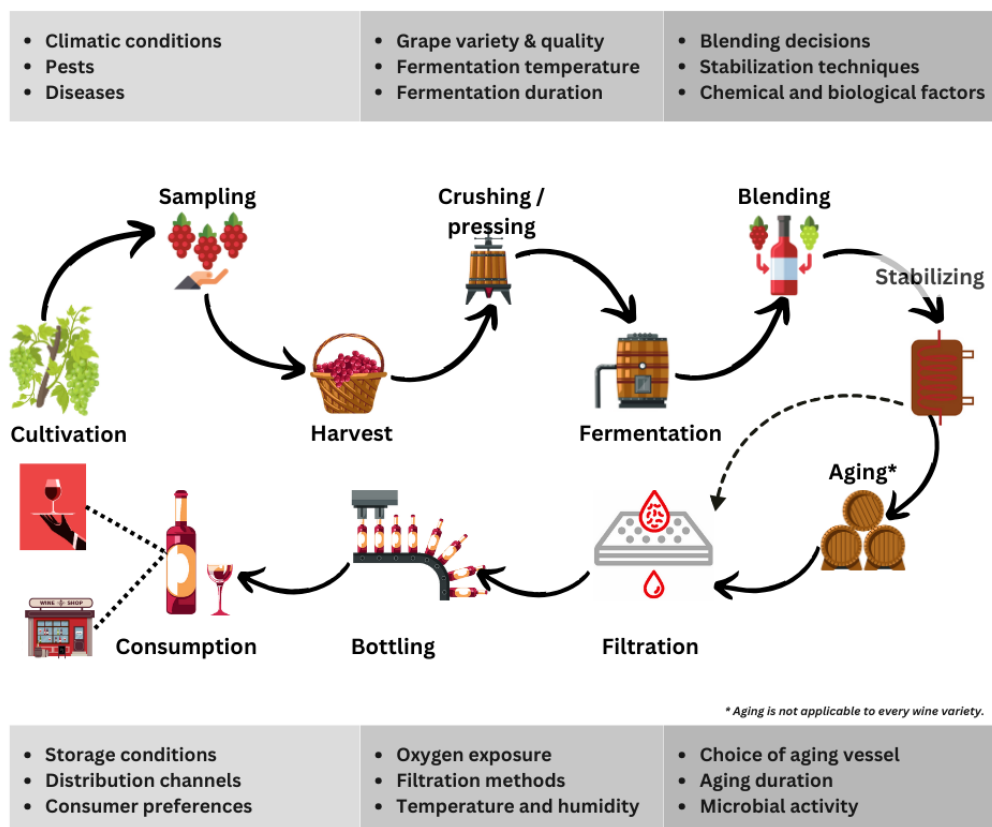
#### I. 4. Use cases of AI in winemaking – potentials and examples

The systematic application of innovations within the wine industry offers multiple benefits. Positive impacts can be realized across the entire grape-to-glass process: from field operations and procurement, through the processes of wine production, fermentation, and ageing, to delivering the final product to consumers and enhancing their overall consumption experience. With the right approach, wineries can reshape their business models, enter new markets, and develop additional channels to reach customers. Further benefits can include the increased resiliency and adaptability of companies with improved financial performance, enhancing their ability to respond swiftly to unexpected challenges and evolving consumer demand patterns. In short, the **systemic application of such innovations** can result in a **transformative disruption to the entire wine value chain**.

Figure 3 includes another depiction of the grape-to-glass process, calling out factors influencing the quality and availability of wine at the different stages of creation. As the image shows, there are various components that can have an impact on the success of winemaking, from **environmental specifics**, through **production and storage conditions**, to **factors affecting demand** for the final product. These items together create a complex and uncertain environment, where the success of any endeavour in winemaking is the outcome of the sophisticated interplay between various, sometimes correlated, but often unrelated components. Each of these factors can be described by a wide range of data points, which become increasingly available for businesses to be utilised. If this data is collected in a structured and systematic manner, the use of the right algorithms and tools can provide significant advantages for entities in the wine industry.

These potential benefits were also recognised by technology developers and industry stakeholders, and the use of AI in winemaking is becoming increasingly widespread. AI systems are now being designed to support a variety of decision-making processes across the grape-to-glass journey, from **optimizing vineyard irrigation** and **predicting yields**, to **enhancing fermentation control** and **designing targeted marketing campaigns**. These applications reflect a broader shift toward data-driven technology transformation in the wine sector, where AI not only improves operational efficiency but also enhances resilience and the ability to act on strategic developments in a more agile manner. In this section, selected case studies will be briefly presented that show how AI-driven innovations are currently used in the wine industry. A structured summary of these cases is shown in Table 3.

Figure 3. Wine value chain and key influencing factors across different stages (source: author)



**Viña Concha y Toro**, a leading wine producer in Latin America, demonstrates interesting examples on how AI can be applied across multiple areas of the wine value chain. Through its dedicated Center for Research and Innovation (CRI), the winery has integrated AI into vineyard management, winemaking processes, and strategic

planning, improving the quality of decision making. AI-driven models can help monitor water loss from soil and plants due to evaporation and plant transpiration, supporting **more efficient irrigation planning** (Viña Concha y Toro, 2024). In parallel, AI-enhanced satellite and sensor-based platforms support **grape yields forecasting** and **grape quality prediction**. This improves harvest planning and resource allocation, as well as helps in the **detection of fungal diseases** via camera-equipped tractors, allowing **earlier intervention** and **targeted treatments** (Vinetur, 2024; Wine-Intelligence, 2024b). Beyond field applications, AI tools also assist in the **bottling process** by predicting equipment failures and optimizing maintenance schedules, reducing disruptions in production. The innovations result in improved operational efficiencies, better adaptation to climate change, and maintaining high-quality production standards, while preserving the human expertise essential to the winemaking process.

Table 3. A summary of selected examples of AI use in the wine industry

Case ID	AI application area	Technology used	Problem addressed	Reported outcomes
Viña Concha y Toro	<ul style="list-style-type: none"> <li>• Yield prediction</li> <li>• Disease detection</li> <li>• Water / environmental stress detection</li> <li>• Quality grading</li> </ul>	<ul style="list-style-type: none"> <li>• Machine learning models</li> <li>• Predictive analytics</li> <li>• Computer vision</li> <li>• Neural networks</li> </ul>	<ul style="list-style-type: none"> <li>• Incorrectly forecast yields resulting in suboptimal production / logistic decisions</li> <li>• Environmental stress reducing grape quality and availability</li> </ul>	<ul style="list-style-type: none"> <li>• Improved production decisions</li> <li>• Better grape and product quality</li> <li>• Improved decision-making accuracy</li> </ul>
E. & J. Gallo Winery	<ul style="list-style-type: none"> <li>• Fermentation monitoring</li> <li>• Quality assurance</li> <li>• Environmental conditions control</li> <li>• Sales mix optimization</li> <li>• Brand building and consumer engagement</li> </ul>	<ul style="list-style-type: none"> <li>• Machine learning models</li> <li>• Predictive analytics</li> <li>• Computer vision</li> </ul>	<ul style="list-style-type: none"> <li>• Traditional fermentation monitoring requiring costly lab tests and manual adjustments</li> <li>• Inconsistent wine quality leading to customer satisfaction problems</li> <li>• Sales foregone due to</li> </ul>	<ul style="list-style-type: none"> <li>• Increased efficiency</li> <li>• Consistency in quality</li> <li>• Decision making backed by data (vs intuition)</li> </ul>

Case ID	AI application area	Technology used	Problem addressed	Reported outcomes
			suboptimal bar and outlet layout	
Pernod Ricard	<ul style="list-style-type: none"> <li>Field work automation</li> <li>Manual labour replacement</li> </ul>	<ul style="list-style-type: none"> <li>Autonomous robots</li> <li>Sensor fusion (infrared and RGB cameras, LiDAR sensors, and radar)</li> </ul>	<ul style="list-style-type: none"> <li>Ongoing labour shortages experienced since the Covid-19 pandemic</li> <li>Deterioration of soil structure and fertility due to the pressure from heavy equipment</li> </ul>	<ul style="list-style-type: none"> <li>Increased precision in manual tasks</li> <li>More efficient operations</li> <li>Enhanced sustainability due to optimized tractor routing</li> </ul>
Vivino	<ul style="list-style-type: none"> <li></li> </ul>	<ul style="list-style-type: none"> <li>Machine learning models</li> <li>Predictive analytics</li> <li>Image recognition</li> <li>Neural networks</li> </ul>	<ul style="list-style-type: none"> <li>Wine selection process is complicated for most end users</li> <li>Wine offering matched to individual preferences</li> </ul>	<ul style="list-style-type: none"> <li>Personalized wine recommendations</li> <li>Simplified wine selection tailored to individual preferences</li> </ul>

**E. & J. Gallo Winery** is one of the largest family-owned wine companies in the world. The entity has become a leader in applying AI across both production and commercial functions in the United States. In winemaking, Gallo uses AI to **monitor fermentation conditions** in real time, analysing a wide range of variables including temperature, sugar levels, and yeast activity. This helps the company in ensuring **consistency of quality** across wine labels, whilst also **optimizing production efficiency** (Marr, n.d.; Sommeliers Choice Awards, n.d.). AI also supports **quality control** by predicting potential equipment failures in bottling lines, allowing for the implementation of proactive maintenance practices and minimizing downtime. On the commercial side, Gallo's Account 360 platform utilizes machine learning to support salespeople in identifying better placement opportunities in bars and retail outlets based on **sales data and visual recognition** of the bar layout (High, 2019). Extensive use of predictive analytics enables the company to **model consumer preferences, optimize brand development activities, and tailor marketing strategies** based on social media insights and regional sales data (Henschen, 2012). Gallo's approach toward the use of

these tools also shows how technological innovations can elevate human expertise, instead of aiming for full replacement of working staff. This also enables the company to make strategic decisions that integrate analytical insights with the intuition and creativity of experienced winemakers.

**Pernod Ricard Winemakers** has emerged as a pioneer in integrating autonomous technologies into vineyard operations, particularly through the deployment of AI-powered **Autonomous Vineyard Tractors (AVTs)** in New Zealand. Developed in collaboration with Smart Machine, the customised Oxin AVTs have been designed to perform **labour-intensive activities** such as mowing, mulching, and defoliating, thereby addressing the problems of widespread **labour shortages** and **enhancing operational efficiency**. These AI-enabled machines operate with high precision and consistency and can complete multiple tasks in a single pass. This has a **favourable environmental impact** by the reduction of fuel use, time, and soil compaction while also **improving productivity and efficiency**. Beyond its current use, Pernod Ricard is actively exploring fully electric and green-energy-powered AVTs, to reduce carbon emissions and improve sustainability of operations. By integrating AI-driven automation into vineyard management, Pernod Ricard is not only advancing precision viticulture but also demonstrates the case of **sustainable innovation in wine production** (Pernod Ricard Winemakers, n.d.; Wine-Intelligence, 2024a).

Finally, **Vivino**, the world's largest online wine marketplace and most downloaded wine app, demonstrates how AI can be utilized in wine retail to enhance consumer experience. The application's **AI-driven algorithms and big data analytics** capabilities form the basis of a recommendation engine that creates **personalised match scores** for each wine once a user has reviewed at least five labels. These scores are generated by analysing a wide range of variables including flavour preferences, grape varietal patterns or contextual cues such as food pairing and value perception. A distinctive feature is the use of **image recognition technology**, allowing users to scan wine labels and receive real-time information, reviews, and price comparisons. This interface transforms the (sometimes overwhelming) wine-buying experience into a **more user-friendly process**, creating a dynamic and adaptive digital sommelier experience. By embedding AI into the consumer-facing end of the wine value chain,

Vivino creates connections between producers and buyers, generating important insights for wineries, and contributing to more efficient product discovery and targeted marketing strategies (Marr, 2021b, 2021a).

Whilst not comprehensive in nature, the reviewed case studies demonstrate some interesting applications of AI across the wine value chain, from autonomous vineyard operations and improvements in production processes to intelligent consumer engagement platforms. While large-scale innovations such as autonomous tractors or drone-based disease detection may require significant investment and infrastructure, solutions like AI-driven recommendation engines or decision support tools based on existing consumer or environmental data offer more accessible entry points for companies in the wine value chain planning to implement the technology. These innovations often build on publicly available data and user-friendly platforms, making them feasible even for smaller wineries with limited resources. This demonstrates the potential that AI holds for varying operating models and technological readiness levels.

## II. Research objective and questions

Building on the discussion of how AI has developed, its connections to other fields of science, and the technology's already emerging influence the wine value chain, the next step in the dissertation is to define the focus of this research. The previous chapter provided a glimpse into how AI can be used in winemaking and the potential offered by the technology, as well as the complexity of widespread application. The aim of this section is therefore to clarify the specific research problem addressed in this study, the objectives of the investigation and the questions guiding further academic inquiries.

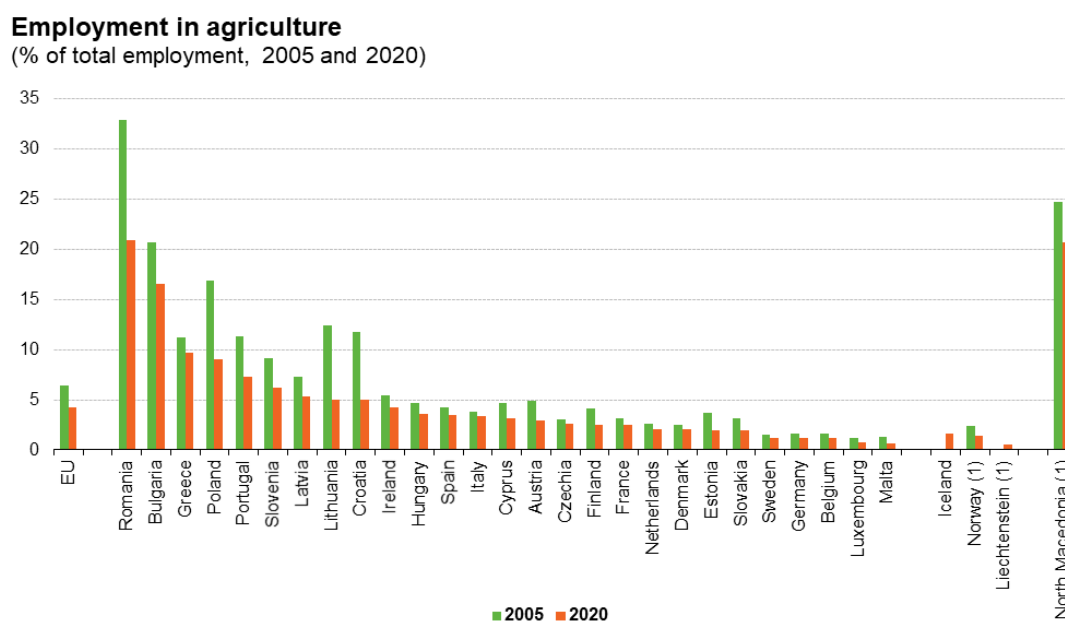
### II. 1. Problem statement

**Agriculture** represents a significant portion of economic activity. While the % of total employment in agriculture shows a decreasing trend in the European Union (Figure 4), in 2020-2021, still a total of 8.7 million people in the EU and an average of 22.86% of the global workforce were employed in this sector alone (Employment in Agriculture by Country, around the World, n.d.; Farmers and the Agricultural Labour Force - Statistics, n.d.-a). The **wine industry** is similarly important, with 333.0 billion USD revenue generated in 2023 and consumption amounting to 232 million hectolitres in 2022 (Wine Consumption Worldwide 2022, n.d.; Wine - Worldwide | Statista Market Forecast, n.d.). Spain, Italy, and France are the leading wine-producing and exporting countries by volume; however, the United States, Australia, South Africa, Germany, Argentina, and Chile are also gaining an increasingly larger share of the global market (see Table 4).

The agricultural sector faces significant difficulties on a global level, due to various factors. The main challenges include **labour shortages**, the impact of **environmental concerns** and the resulting need to comply with different **legislative requirements** related to the preservation of nature, or the overall **economic viability** of the industry (Pinion Global, 2025). These factors exert a similar impact on the wine industry and new technologies can be essential contributors to solve these problems in the long run (Bastard & Chaillet, 2023). Innovative solutions can enhance the **efficiency and**

**sustainability of winemaking**, addressing pressing issues such as environmental degradation, or the rising demand for premium, organic products with limited land available for grape growing.

Figure 4. Employment in agriculture (% of total employment, 2005 and 2020) Source: (Farmers and the Agricultural Labour Force - Statistics, n.d.-b)



(1) 2019.

## II. 2. Research objectives

The objective of this research is to understand the **drivers, enablers, benefits, and barriers to implementing AI** within the wine industry. As the introduction section showed, AI can be considered as a technology with rich historic background, yet the widespread expansion was facilitated by the emergence of generative AI tools such as ChatGPT, Gemini, or Microsoft CoPilot in the early 2020s. Potential use cases uncover a variety of benefits offered, including enhancing the efficiency and sustainability of operations across a wide range of economic sectors. As a result, this technology has a significant potential to provide various solutions to the previously outlined problems the wine industry is facing.

Table 4. Top 10 wine producing countries in 2023 (source: (Wine Producing Countries 2025, n.d.)

Country	Wine production 2023 (million hectolitres)	Percentage of global wine production 2023
France	48	21%
Italy	38	17%
Spain	28	12%
United States	24	11%
Chile	11	5%
Australia	10	4%
South Africa	9	4%
Argentina	9	4%
Germany	9	4%
Portugal	8	3%
Other	35	15%
<b>Total</b>	<b>229</b>	<b>100%</b>

A natural question can be raised about **why it is worth investigating the specific impact of innovation in viticulture**, as opposed to broader agriculture. Winemaking represents a distinctive economic sector where tradition and craftsmanship are essential elements in the business models of individual actors. Technology adoption patterns and barriers to innovation are shaped by cultural heritage and strong product differentiation. A broader study of agriculture would risk overlooking these unique sectoral dynamics, while focusing exclusively on winemaking enables a more precise exploration of how AI can balance efficiency with authenticity in such a traditional sector.

This intentional reduction of scope offers actionable insights for practitioners by helping them better understand **how AI-based innovations can improve primary and secondary value creation activities in winemaking**. Similarly, narrowing the lens to AI rather than all technological innovations avoids dispersion and allows for an **in-depth analysis of how intelligent systems impact** decision-making, operations, and value creation within the industry. Findings derived from such a research design can contribute meaningfully to academic work in business information systems and

wine business studies by providing a clearer view of how innovation is implemented in the wine industry. Additionally, academic research on the implementation of AI in the wine industry is relatively scarce, making this study a valuable contribution to the business informatics and AI knowledge domains, with the potential to provide further scientific and practical insights warranting further research in the field.

### II. 3. Research questions

To reiterate, the objective of this research is to understand the drivers, enablers, benefits, and barriers to implementing AI within the wine industry. The objectives stated are going to be achieved by answering the following research questions:

**RQ 1.** What are the main future use case scenarios of AI in the wine value chain in the next 5-10 years?

**RQ 2.** What are the main future benefits offered by AI in the wine sector?

**RQ 3.** What are the main challenges to the implementation of AI in the wine industry?

**RQ 4.** What are the main drivers of AI adoption in the wine industry?

By addressing these research questions, important conclusions can be drawn regarding the applicability of AI in winemaking. These can provide meaningful contributions to academic discourse in the fields of wine studies and business information systems. The detailed research approach will be outlined in a separate section, but the primary methodologies employed will include a combination of **literature review** and **bibliometric analysis** to assess the current state of academic knowledge on the subject matter. Building on these findings, the **Delphi method** will be employed, asking for the feedback on series of statements presented to a panel of selected experts, using the research questions formulated as a guide when setting up the questionnaire. The results will be analysed using different quantitative tools to examine the interrelationships between the factors and rank their significance. Finally, the findings will be validated through **in-depth interviews** with selected experts to ensure that any underlying factors not identified through quantitative analysis are also uncovered.

This dissertation is structured as follows. **Section III** describes the methodology followed throughout the rest of the study, justifying the choices made to find the most adequate approach aimed at fulfilling the objectives of the research and answering the questions raised. **Section IV** summarises the academic literature focused on the transformation of the wine industry's value chain, using various bibliometric analysis techniques, laying the theoretical foundation for further empirical work. **Section V** and **Section VI** present the research results along with a discussion and analysis of the findings using the Delphi method and in-depth interviews. **Section VII** provides a synthesis of findings and the formulation of a conceptual model describing the application of AI in the wine industry. Finally, **section VIII** concludes the dissertation, pointing out limitations of the current approach and offering directions for future research.

### III. Research methodology

The aim of this section is to describe the overall research design and methodology followed throughout the rest of this study. The methodological considerations in this chapter are mostly based on Earl R Babbie’s “The Practice of Social Research” book (15<sup>th</sup> edition) (Babbie, 2021), a comprehensive guide to the practical application of different research concepts and the various methods available under this domain.

#### III. 1. Research design and paradigms

Table 5. Summary of different types of research purpose (source: author based on (Babbie, 2021))

Research purpose	Goal	Strengths	Limitations
Exploration	To familiarize the researcher with a new topic	Uncovers new insights for under-researched areas and guides future research directions	Lack of representativeness and definitive answers.
Description	Observe and describe a phenomenon systematically	Provides accurate, systematic understanding of observed phenomena	Lacks explanation of underlying causes or broader implications
Explanation	To uncover causal relationships and explain why a phenomenon occurs	Identifies and describes causal relationships effectively	Requires robust data; may oversimplify complex causal factors

**Research design** can be defined as a structured plan guiding the observation, analysis and interpretation of the data in the study. The purpose of research can include **exploration**, **description**, or **explanation**, as summarized in Table 5. Considering that this study’s aim to uncover insights and shape a conceptual framework on AI’s impact in the wine industry, an exploratory research purpose was chosen as most appropriate to be followed. **Research paradigms** are fundamental frameworks that shape how researchers view social phenomena, guiding the development of theory, the formulation of research questions, and the selection of methodologies. The main research paradigms to consider are summarized in Table 6. Because the aim of this study is to identify generalisable laws regarding AI’s impact on the wine industry, a

positivist paradigm is adopted. The conflict paradigm is also considered, due to the hypothesized influence of factors like company size or resources innovation capabilities. Other paradigms are deemed irrelevant for this research and are mentioned only for the sake of academic completeness. Finally, academic research can follow two major logical models, **inductive** and **deductive reasoning**. Inductive reasoning builds theory from observations, while deductive tests theory through hypotheses. This research adopts an inductive stance, due to limited frameworks available on AI's impact on the wine value chain.

Table 6. Various types of research paradigms (source: author based on (Babbie, 2021))

<b>Name</b>	<b>Description</b>	<b>Example application area</b>	<b>Relevance to current research (yes/no)</b>
<b>Positivism</b>	Focuses on objective reality, emphasizing empirical observation and generalizable laws.	Examining the correlation between socioeconomic status and educational achievement through surveys.	Yes
<b>Conflict paradigm</b>	Examines societal power dynamics, emphasizing inequality and its impact on social structures.	Analysing disparities in healthcare access among different income groups.	Yes
<b>Symbolic interactionism</b>	Emphasizes understanding social phenomena through subjective meanings and interactions.	Studying how cultural symbols influence communication patterns within a community.	No
<b>Ethnomethodology</b>	Focuses on uncovering the methods people use to construct social reality in everyday life.	Observing how people maintain conversational norms in workplace interactions.	No
<b>Feminist paradigms</b>	Highlights gendered power imbalances and advocates for equality and inclusivity in research.	Exploring workplace policies to assess their impact on gender equity and inclusion.	No
<b>Critical race theory</b>	Explores how race and systemic racism influence social structures and experiences.	Investigating the impact of racial bias in employment hiring practices.	No

### III. 2. Types of research techniques

Scientific research can be classified along two main techniques: **qualitative and quantitative methods**, focusing on nonnumerical information and numerical output, respectively. Applying both research methods offer complementary insights, combining the benefits of numerical analysis while preserving the depth and context of non-numerical observations.

Table 7. Selected example of qualitative and quantitative research techniques (source: author based on (Babbie, 2021))

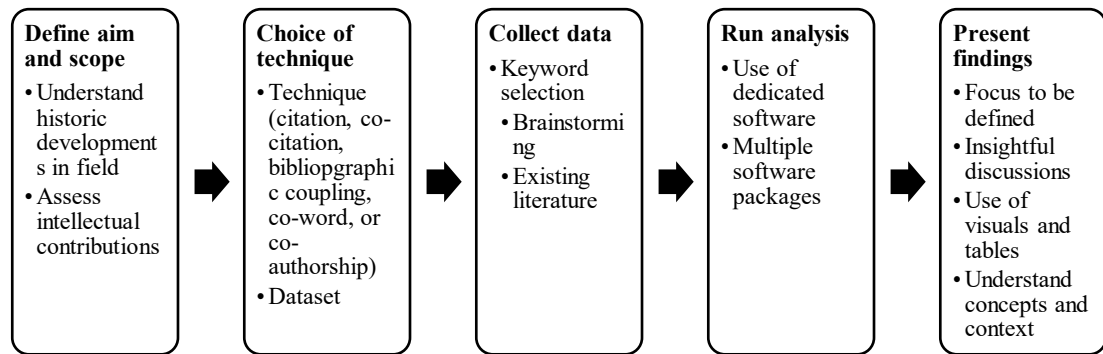
Name	Type	Description	Strengths	Used in current research
Bibliometric analysis	Quantitative	Quantitative examination of scientific literature assessing citation, publication, and collaborations patterns.	Efficient analysis informing later stages of research by revealing trends, collaborations and unexplored areas.	yes
In-depth interview	Qualitative	Open-ended conversations to gain detailed insights into perspectives on the research subject.	Nuanced, context-rich insights provided into stakeholders' views	yes
Focus groups	Qualitative	Facilitated group discussion exploring collective attitudes, perceptions, and insights.	Encourages interaction, revealing shared concerns or divergent views.	no
Survey	Quantitative	Structured questionnaires or interviews to collect numerical data for statistical analysis.	Enables statistical analysis and comparison across groups	no (partially)
Secondary data analysis	Quantitative	Analysis of existing datasets on the research subject to supplement findings.	Enabling researchers to explore new questions or validate findings with existing data.	no

An overview of examples of quantitative and qualitative methods is shown in Table 7. Given the exploratory nature of this research, qualitative techniques are primarily employed, but combined with quantitative methods, to realise the benefits of both

approaches. **Bibliometric analysis** is utilized to establish an understanding of the current knowledge base related to the research objectives. Then, questionnaires will be shared with selected experts, and the **Delphi method** will be used for the analysis of consensus related to a series of statements formulated. Finally, these findings will be corroborated by **in-depth interviews** to establish further depth to the findings and understand nuances not captured when filling out the questionnaires.

### III. 3. The bibliometric analysis method

Figure 5. An overview of the process of bibliometric analysis (source: author based on (Donthu et al., 2021))



**Bibliometric analysis** is a crucial approach for mapping the intellectual landscape of research in a specific field. By systematically examining academic publications, it helps pinpoint influential works, trace topic evolution, and highlight emerging academic trends. In this thesis, bibliometric analysis offers foundational insights into AI's influence on agriculture and winemaking, informing subsequent stages of the research. Key techniques include **citation analysis**, **co-citation analysis**, **bibliographic coupling**, **co-word analysis**, and **co-authorship analysis**, each revealing different aspects of research impact, thematic clustering, and academic collaboration over time. A high-level overview of the bibliometric analysis workflow and the main bibliometric analysis techniques are summarized in Figure 5 and Table 8, respectively. In addition, when for conducting bibliometric analysis, it is important to follow established guidelines maximizing the outcomes of such endeavours. A list of such best practices is summarized in Table 9.

Table 8. A summary of bibliometric analysis methods (source: author)

Method	Description	Focus
<b>Citation analysis</b>	Identifies influential publications by analysing the number of citations, indicating the impact and intellectual connections between academic contributions.	Historical impact and influence
<b>Co-citation analysis</b>	Examines pairs of publications cited together in subsequent studies, revealing thematic clusters and historical knowledge foundations.	Past intellectual relationships
<b>Bibliographic coupling</b>	Analyses publications sharing common references, suggesting a convergence of ideas and helping to understand the present state of research.	Current research convergence
<b>Co-word analysis</b>	Investigates keywords shared across publications, identifying thematic relationships; useful for discovering potential research areas.	Thematic relationships
<b>Co-authorship analysis</b>	Studies collaboration patterns between scholars, highlighting knowledge clusters and the development of intellectual output over time.	Collaboration and research networks

Table 9. Best practices for conducting a bibliometric analysis (source: author based on (Rogers et al., 2020))

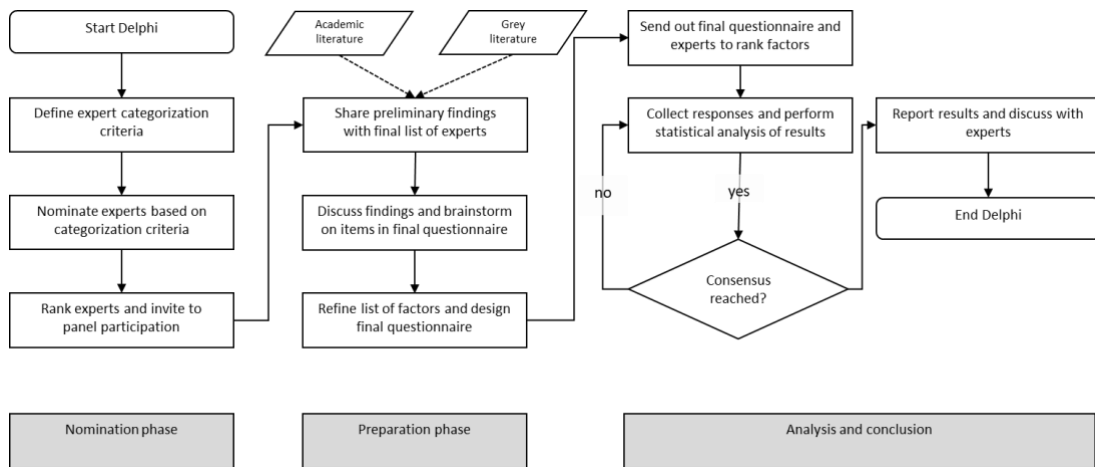
Best Practice	Description
<b>Dataset size</b>	Include at least 500 items to ensure sufficient insights can be derived.
<b>Technique selection</b>	Choose the technique based on research objectives before data collection; consider using multiple techniques for comprehensive analysis.
<b>Database choice</b>	Use one reliable database (e.g., Scopus, Web of Science) to simplify data cleaning and avoid reconciling multiple sources.
<b>Keyword selection</b>	Select keywords carefully to include relevant articles, using literature review and brainstorming as methods.

### III. 4. The Delphi method

The **Delphi method** is used to systematically collect and refine expert opinions, addressing the research objectives when precise data is scarce. Based on insights from the bibliometric analysis, it is a particularly effective approach for exploratory research, bringing together diverse perspectives to identify and align key factors

relevant to the study. The process comprises three phases: nomination, preparation, and analysis, demonstrated in Figure 6. In the **nomination phase**, experts are selected from multiple domains to ensure diversity. During the **preparation phase**, initial findings from literature are shared with a small group of experts to establish a common context. In the **analysis phase**, a refined questionnaire is distributed for experts to rank factors; so that responses can be quantitatively analysed to assess consensus. The results are then fed back to the panel, allowing experts to reconsider their positions, encouraging convergence of opinions through iterative rounds.

Figure 6. A visual depiction of the Delphi method process flow (source: author)



In the absence of specific guidance on the **number of rounds to be used**, experts were requested to provide answers in two iterations, balancing thoroughness with minimising expert fatigue and attrition risks. This approach aligns with established methodologies in high-quality literature sufficient for consensus without excessive time or cost incurred (Aghimien et al., 2020; Höhne & Tiberius, 2020; Kurpjuweit et al., 2021). The **Interquartile Range (IQR)** was used to assess consensus strength, in line with the methodology used by (Höhne & Tiberius, 2020). Decreasing IQR shows convergence, increasing IQR suggests divergence of opinions across rounds. Quartile deviations from the median further illustrate expert response distribution and concentration.

Finally, to assess consensus strength further, the modified **Average Percentage of Majority Opinions (APMO)** calculation is used based on (Mariani & Dwivedi, 2024)

To assess consensus, a modified **Average Percentage of Majority Opinions (APMO)** calculation is used following (Mariani & Dwivedi, 2024), calculated with the formula  $APMO = \frac{Agr+Disagr}{NumOp} * 100$ . *Agr* and *Disagr* represent the total counts of agreement and disagreement responses, respectively, and *NumOp* is the total number of responses. Unlike the traditional method, which is unsuitable for the 6-point Likert scale without a neutral option, this approach focuses on highly polarised responses (*Agr* = 5 and 6; *Disagr* = 1 and 2). Higher modified APMO values reflect strong polarisation, while lower values indicate consensus. By comparing APMO values between Delphi rounds, the method captures whether expert views are becoming more or less polarised, clarifying the evolution of consensus among panellists.

This section intended to provide only the most important methodological details behind the Delphi method, that is necessary for the understanding of the results and the findings derived. Further details on the statements formulated and how the method was executed can be found in **Appendix 2**, while **Appendix 4** shows the pre-engagement material shared with the participants.

### **III. 5. In-depth interviews**

**In-depth interviews** are qualitative conversations allowing participants to share observations, thoughts, and emotions, guided by the researcher to uncover personal insights and interpretive processes (Donatella della Porta, 2014; Roller, 2020). Interview formats vary and can be **structured** (standardised questions for quantifiable data), **semi-structured** (some flexibility with set themes), and **unstructured** (free-flowing, least formal). Another differentiation is to classify in-depth interviews as **standardised/non-standardised** and **respondent/informant** types (Mueller & Segal, 2015). Table 10 summarises these types with their strengths and weaknesses. For this exploratory research, the **unstructured interview** format is adopted, as it enables the discovery of new insights and flexible exploration of themes, which is particularly valuable for understanding complex issues like AI's influence on the wine value chain (Saunders et al., 2007).

Qualitative in-depth interviews effectively **address limitations of other data sources** by enabling the collection of valid, reliable information from experts and allowing participants to elaborate on their responses. This helps providing deeper insights on the topic discussed compared to solely relying on quantitative methods (Milena et al., 2008). Their flexible and customizable format **minimises response bias, strengthens findings**, and **enriches conclusions** derived from numerical data (Roller, 2020). However, the method also introduces risks to the research process due to concerns over **data quality, reliability, and generalisability of findings**, due to the non-standardisation nature of investigation and small sample sizes utilized (Ali & Yusof, 2011). Both **interviewer and interviewee bias** may influence outcomes, while the analysis can be also impacted by the subjective interpretation of findings and the risk of over-fragmenting transcripts. These factors can all potentially compromise the overall coherence of the narrative provided (Donatella della Porta, 2014; Saunders et al., 2007).

Table 10. A summary of the different quantitative interview types using different classification schemes (source: author)

Interview type	Strengths	Weaknesses	Potential use cases
Structured interviews, standardized interviews	Easy to compare data, quantifiable results	Limited flexibility, risk of missing nuanced data	Large-scale surveys, studies requiring standardized responses
Semi-structured interviews	Balance between flexibility and structure	Some variability in responses, potential for interviewer bias	Case studies, exploring specific organizational contexts
Unstructured interviews, non-standardized interviews	Deep insights, allows exploration of complex issues	Time-consuming, harder to analyse and compare	Exploratory research, understanding personal experiences
Respondent interviews	Control over the conversation, directed by interviewer	May limit participant expression	Interviews where specific, directed information is required
Informant interviews	Driven by participant's insights, rich qualitative data offered	Can stray off-topic, more difficult to guide	Understanding subjective perceptions and beliefs, exploratory research

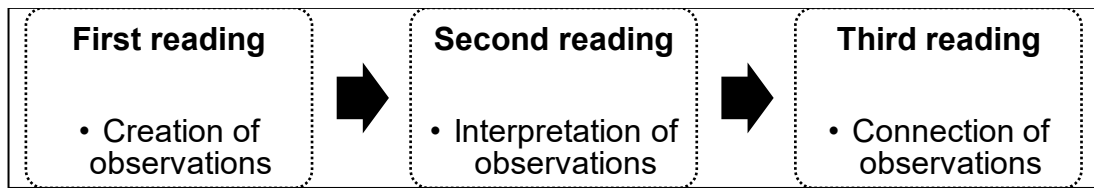
The following sections will provide a high-level overview of the methodological considerations behind the in-depth interviews executed. For additional practical guidance regarding how interviews are to be performed, list of potential pitfalls that can distort the results of the method and ethical considerations to follow during in-depth interviews, refer to **Appendix 3**.

### **III. 5. 1. Interview execution**

The interviews were conducted online, using **Microsoft Teams** as a platform. The meetings were recorded, and the **automatic transcription** functionality was utilized to produce the detailed text of the discussions. Handwritten notes were also taken simultaneously, to ensure that important points are confirmed, and contradictions are identified and reconciled. After the interviews were completed, the transcripts produced were reviewed and cleansed, with some minor modifications processed to the textual output, preparing the content for further analysis

After the transcription was completed, the anonymized output files were loaded uploaded to **Taguette**, an open-source web-based document tagging tool for qualitative data analysis. The **tagging of the information** was done along the same dimensions that the Delphi questionnaires were based on. This method allowed for the comparison of themes, identification of key patterns and contradictions among those, as well as generation of new ideas that were potentially not considered by the preceding research procedures. The coding was executed as an iterative process comprised of multiple readings of the same information, to create observations, interpret those and connect them with each other. The visual depiction of the process is shown in Figure 7. The final codebook used for tagging can be found in **Appendix 5**.

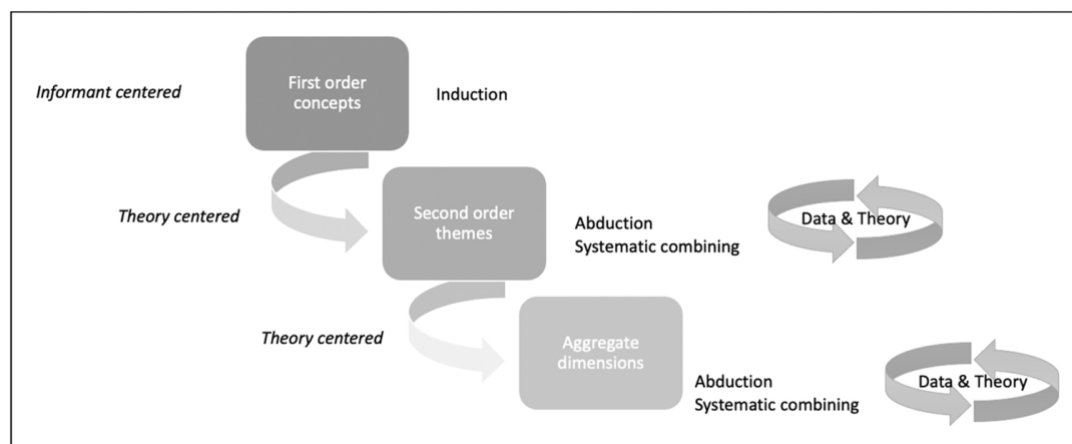
Figure 7. Visual depiction of the interview coding process followed (source: author based on (Donatella della Porta, 2014))



### III. 5. 2. Thematic analysis of interview transcripts

The interview data was first analysed using **Gioia’s methodology** shown in Figure 8. This thematic analysis technique is based on three core principles: **constructing a data structure**, **building a grounded model**, and **presenting the findings** of the analysis. This approach captures the informants' experiences by reflecting their perspectives while also presenting findings from a more theoretical standpoint. This is accomplished through the development of a data structure that organizes informant themes into **first-order concepts**, which are then grouped into broader research themes (**second-order concepts**) and **overarching dimensions**, ensuring the reconciliation of informants’ insights with broader theoretical frameworks (Magnani & Gioia, 2023).

Figure 8. A visual representation of the data structure development under the Gioia methodology (source: (Magnani & Gioia, 2023))

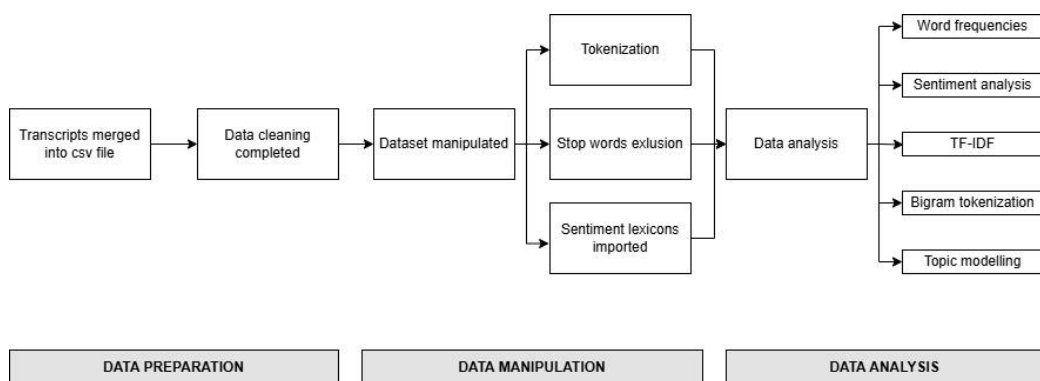


### III. 5. 3. Text mining of interview transcripts

After completing the thematic analysis, the next step was the application of **text mining** using the Python programming language following the flowchart in Figure 9. This semi-automated process extracts knowledge from unstructured text, such as interview transcripts, with human expertise guiding preparation and interpretation of findings (Demeter et al., 2019). Text mining differs from data mining by focusing on the analysis of **unstructured data**. The inclusion of this technique aimed to enhance the research methodology, validate findings, and systematically explore participants' views on the various dimensions of AI implementation in winemaking.

Python is a **flexible, object-oriented programming language** known for its simplicity, modularity, and robust capabilities, making it ideal for extracting insights from unstructured text. Its rich standard library and vast ecosystem of external modules enable the execution of advanced analysis and visualisation tasks (Sanner, 1999). Key libraries in this research used include **Pandas** for data handling, **Natural Language Toolkit (NLTK)** for natural language processing, and **Matplotlib, Wordcloud,** and **Seaborn** for static and graphical visualisations. In addition, **Scikit-learn** was used to support machine learning tasks, **NetworkX** to enable network and graph analysis, and **Gensim** for topic modelling and natural language processing. These tools together contributed to the execution of an efficient, systematic research process and in-depth text analysis.

Figure 9. A flowchart of the text mining process followed (source: author)



First, the interview transcripts were imported into a **CSV file**, so that various data preparation and cleansing tasks could be executed. This involved **removing Taguette software tags, interviewer questions, interpretive questions, and personal data** to have a content available that focus solely on participant insights. The dataset was further manipulated through **tokenisation** (dividing text into words) and the **removal of stop words** (such as ‘an’, ‘and’, ‘or’), using the NLTK library, as these did not contribute to the identification of key themes. After the standard stop words were removed, words appearing at least 50 times were visualized, and additional stop words identified (such as “might,” “could,” or “help”) were manually excluded.

The next step involved the incorporation of **Sentiment lexicons** (lists linking words with sentiments such as positive, negative, trust, or anticipation) to support the analysis. Multiple sentiment lexicons were utilized: **VADER (Valence Aware Dictionary and sEntiment Reasoner)**, a tool within Python’s NLTK library that is well-suited for analysing sentiments in texts from a diverse range of sources (Vader Lexicon, n.d.). The **Bing Lexicon** classifies words into positive and negative sentiments, while the **NRC Emotion Lexicon** encompasses a broader range of attitudes, assigning words into various categories including anticipation, fear, joy, sadness, surprise or trust (Business Analytics in Python and R - Sentiment Analysis, n.d.). Based on the research questions, the analysis focused on the sentiments **‘positive’, ‘negative’, ‘anticipation’, and ‘trust’** from the NRC Lexicon for further exploration.

Table 11. Overview of text mining techniques applied in interview analysis (source: author)

Phase	Objective	Tool / library used	Analytical technique	Output / indicator	Purpose / interpretation
<b>Data preparation</b>	Merge and clean transcripts	Python (Pandas)	Data cleaning, merging	Cleaned CSV dataset	Consistent, relevant text created
<b>Data manipulation</b>	Process text for analysis	NLTK	Tokenization, stop word removal	Tokenized text corpus	Meaningful words analysed
<b>Sentiment analysis</b>	Identify emotional tone	VADER, Bing, NRC Lexicons	Lexicon-based sentiment classification	Positive, negative, anticipation, trust	Evaluates attitudes toward AI in winemaking
<b>Keyword importance</b>	Identify key terms	Scikit-learn	<b>TF-IDF</b> computation	Weighted keyword list	Key AI adoption terms highlighted

Phase	Objective	Tool / library used	Analytical technique	Output / indicator	Purpose / interpretation
<b>Phrase extraction</b>	Detect multi-word patterns	NLTK, Scikit-learn	Bigram tokenization	Frequent bigram list	Reveals contextual expressions
<b>Topic modelling</b>	Discover hidden themes	Gensim, Scikit-learn (LDA)	Probabilistic topic modelling	Main topics discussed	Latent structures identified

The next phase of text mining involved calculating **term frequency–inverse document frequency (tf-idf)** scores for each research dimension. Tf-idf assesses a term’s importance in a document by balancing how often it appears (term frequency) against **how rare it is across all documents** (inverse document frequency), helping to highlight distinctive and significant terms. To enhance robustness of findings, **bigrams** (pairs of consecutive words) were also extracted and their tf-idf scores calculated, enabling the identification of meaningful phrases and multi-word expressions. Finally, **Latent Dirichlet Allocation (LDA)** a probabilistic topic modelling technique was applied to uncover **hidden thematic structures** in the interview transcripts. LDA assumes documents are mixtures of topics, with each topic represented by a distribution of words, thus revealing underlying patterns and themes. For LDA execution, a **document-term matrix (DTM)** was created using the CountVectorizer class in Python’s scikit-learn library. Initially, six topics were considered, but due to the modest transcript size (about 30,000 words), this was reduced to four to ensure each topic added meaningful insight.

The text mining process followed ensures a structured flow of data preparation, manipulation, and analysis, as summarized in Figure 9. Each methodological step serves a distinct purpose in transforming unstructured text into analysable insights (as summarized in Table 11), corroborating the outcomes of the thematic analysis, thereby improving the depth of the investigation. The process validates qualitative findings and helps revealing nuanced linguistic and emotional patterns. This enhances the understanding of how AI adoption is perceived across the different research dimensions in the wine sector.

### III. 6. Research approach summary and outcome sought

To conclude, this study will utilize a selection of different methods aimed to achieve the research objective stated earlier. As discussed in the introduction of this thesis, the use of AI in winemaking received limited focus in academic work in recent years. In fact, to the best of the author's knowledge, there was no previous study that summarized the impact of this technology on this sector in such a holistic manner that this work plans to. Therefore, the research follows an **exploratory approach**, with a **positivist view** and an **inductive stance** primarily, aimed at better understanding this previously uncovered phenomenon.

The objective of the research will be achieved by answering four research questions aimed at understanding the **use cases, benefits, challenges and drivers of AI implementation in the wine industry**. Because of the limited research output available in this field, selected experts will be utilized to provide their views in relation to a series of statements formulated along these dimensions. To ensure that the statements are robust and grounded in the current state of knowledge, the **bibliometric analysis** method will be used. The outputs of this analysis will be then utilized when conducting the next steps of the research, to assess expert consensus on the various themes identified.

Despite its qualitative nature though, the **Delphi method** carries elements of quantitative investigation, due to the use of standardized questionnaires and calculation of scores intended to measure consensus strength. This would introduce the risk of overlooking topics that were not reflected in the original questionnaire or somehow were obscured in the responses received. Therefore, the results of the questionnaires will be corroborated by **in-depth interviews** and the analysis of transcripts recorded during those discussions. The principal approach here is the **thematic analysis of responses**, which is a qualitative method, carrying again the risks of subjectiveness in evaluation. To overcome this, the results of this analysis will be corroborated by a **text mining-based approach**, which is more quantitative in nature.

Figure 10. A summary of the research approach followed in this study (source: author)

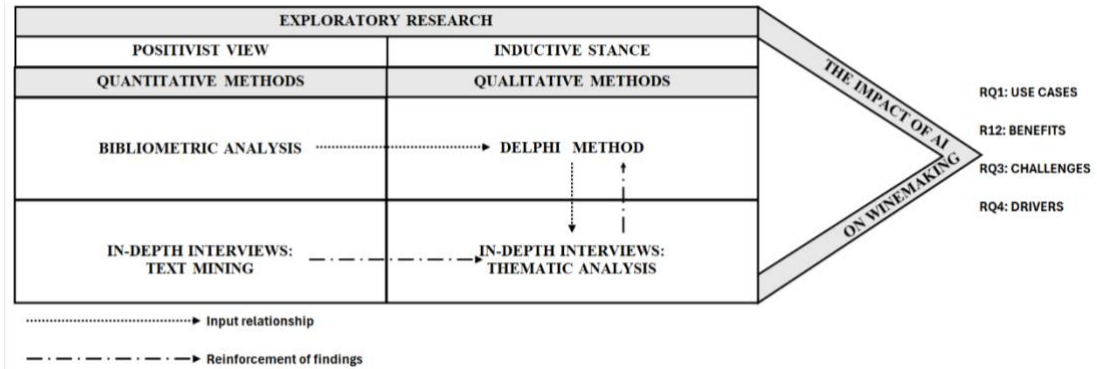


Figure 10 visualizes the structure followed throughout this research, including how the outputs of different inquiries will be used as **inputs for next stages** (round dotted lines), and how the outcomes of those will be utilized to **corroborate or challenge previous findings** (long dash dotted lines). Applying such a mixed methods approach supports the integration of both inductive and deductive research reasoning, allowing for theory development and hypothesis testing within a single study, contributing to the advancement of both theoretical and practical insights. (Donatella della Porta, 2014; Jogulu & Pansiri, 2011)

The expected outcome of this research is threefold. First, the aim is to provide a **comprehensive understanding of how AI can impact the wine value chain**, through the dimensions encapsulated in the research questions. Second, the research is expected to provide **practical insights into the AI implementation process within winemaking**, forming the basis of observations that could be generalised when exploring the impact of technological innovation on traditional industries at the lower end of the digital maturity spectrum. Finally, despite its explorative nature, the research also seeks to formulate a **conceptual framework describing the impact of AI on winemaking**, by the synthesis of results derived from the various methods utilized, providing the basis for further academic inquiry in this field.

## **IV. Bibliometric analysis of academic literature**

In this section, the outcome of a comprehensive bibliometric analysis is provided, exploring the potential impact of AI on viticulture and the wine value chain. This review serves as an essential foundation for understanding how AI and related technologies are transforming practices and business models in the grape-to-glass process, and the findings will be utilised in the later sections when constructing the Delphi questionnaire and the in-depth interview questions.

### **IV. 1. Introduction**

The description of the various bibliometric analysis techniques was provided in the previous section. Following the flowchart shown in Figure 5, the first step of the process was to construct the dataset for this analysis. A structured approach was adopted during the selection of keywords, dividing them into two distinct groups:

1. **AI-related keywords**, such as “artificial intelligence”, “machine learning”, “deep learning”, and “neural network” were included as they are commonly used interchangeably or in conjunction with AI in academic literature. In addition to these terms, expressions reflecting specific AI application methods such as “robot\*”, “intelligent agent”, “predictive analytics”, “computer vision”, “smart farming”, and “precision agriculture” were also incorporated. These keywords reflect the main AI applications in agriculture and wine, based on an initial screening of relevant literature (Cubric, 2020).
2. **Agriculture-related keywords** were chosen to ensure that articles retrieved are relevant to winemaking and agriculture. Using the keyword “wine” alone yielded an insufficient number of items for meaningful bibliographic analysis. By adding “agriculture” and “food,” the dataset expanded to a sufficient number of records, allowing for robust analysis with over one thousand items included.

The final list of keywords used is shown in Table 12. The search was conducted using the **TITLE-ABS-KEY** method within Scopus, scanning titles, abstracts, and keywords for the chosen terms. Publication types were limited to **academic papers** and **conference proceedings** in English language to ensure a focus on high-quality, peer-reviewed sources, reflecting the intellectual structure of the academic knowledge in this area. The subject area was restricted to **Business, Management and Accounting** to align with the business informatics scope of this research.

Table 12. List of keywords and final search term used for bibliographic analysis (source: author)

Keyword used	Rationale
artificial intelligence	Focus of this research
machine learning	Terms used interchangeable with the “artificial intelligence” expression
deep learning	
neural network	
robot*	
intelligent agent	Main application methods of AI in the context of agriculture and wine, based on initial screening of academic studies and grey literature
predictive analytics	
computer vision	
smart farming	
precision agriculture	
wine	
agriculture	
food	
BUSI	Terms restricting results to business and management related studies, academic articles and conference papers
ar	
cp	
<b>Final search term used:</b>	
TITLE-ABS-KEY ( "artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network" OR "robot*" OR "intelligent agent" OR "predictive analytics" OR "computer vision" OR "smart farming " OR "precision agriculture " ) AND TITLE-ABS-KEY ( "wine" OR "agriculture" OR “food”) AND ( LIMIT-TO ( SUBJAREA , "BUSI" ) ) AND ( LIMIT-TO ( DOCTYPE , "ar" ) OR LIMIT-TO ( DOCTYPE , "cp" ) )	

The final search yielded a total of 1,118 documents. These were exported into a CSV file containing citation information (e.g., author(s), document title, source title,

publication year), along with abstracts, keywords (both author and indexed), and reference data. This dataset was prepared for the various types of bibliometric analyses outlined earlier. The analysis was conducted with the **VOSViewer** software, as a reliable tool for creating and visualizing bibliometric maps that is also acceptable to be used in academic studies (van Eck & Waltman, 2010). To enhance the quality of findings, entries that are not connected to the objectives of this research that may arise from the broad scope of keywords were filtered out or manually excluded during the interpretation of the results.

#### IV. 2. General summary of the articles extracted

Table 13 shows that 1,118 items, published from 1983 to 2023 by 160 authors across 80 sources were analysed. Only 6.6% of these were single-authored, highlighting the **collaborative, multidisciplinary nature of AI research** in agriculture and winemaking. The productivity metric of ~7 documents per author indicates a small group of highly productive experts. Figure 11 visualises leading contributors in this field.

Table 13. A general overview of the articles extracted (source: author)

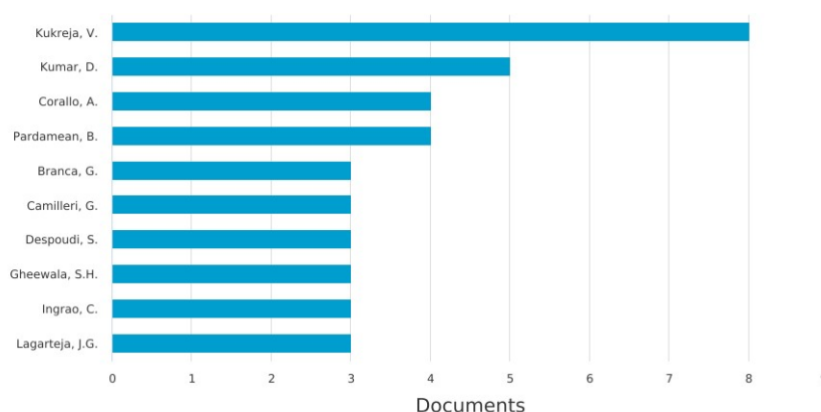
Item	Result
Number of articles extracted	1,118
Conference papers	311
Academic articles	807
Timespan	1983 to 2023
Number of sources	80
Total number of authors	160
Single-authored documents	74
Multi-authored documents	1,044
Documents per author	6.99

Source: prepared by author

The **publication timeline** (Figure 12) shows that most articles in the list extracted appeared after 2011, with a marked rise from 2018. This increase is likely linked to the increased accessibility of data and computational power, as well as evolving use

cases for AI in sectors like agriculture. This surge peaked in 2020 and 2021, possibly driven by the Covid-19 lockdowns, suggesting the accelerating impact of external shocks on technological adoption. Despite the earlier noted corporate use of AI since the 1980s, academic interest lagged in the pre-2010s periods, indicating lower digital maturity in agriculture. The analysis, completed in November 2023, means data for 2023 may be incomplete and later years are not represented.

Figure 11. Most relevant authors in the list of items analysed (source: author, based on Scopus download)



The **geographic focus of publications** analysed in Figure 13 highlights that China and India are the most productive countries in terms of publications, followed by the United States. The prominence of these countries may be attributed to strong government support for AI research, a strategic focus on technology, and international collaborations that promote innovation. Additionally, Italy, Australia, Germany, and France are also significant contributors, which correlates with the importance of agriculture and wine production in the economic output of those countries.

Figure 12. Number of contributions by publication year (source: author, based on Scopus download)

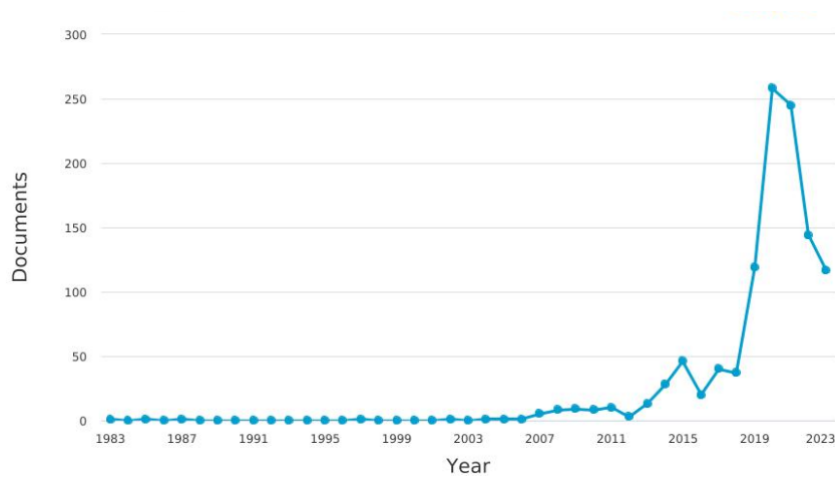


Figure 13. The most productive countries in the list of articles analysed (source: author, based on Scopus download)

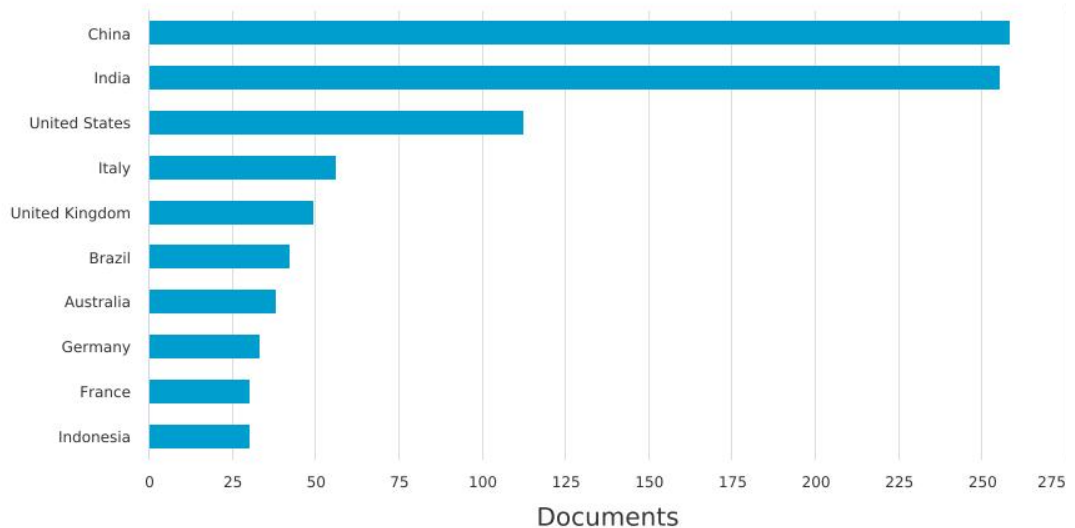


Table 14 lists the **top 20 journals in the dataset**, with the Journal of Cleaner Production accounting for 25% of publications, reflecting the importance of sustainability in the academic discussions. Other notable journals include the International Journal of Recent Technology and Engineering and Technological Forecasting and Social Change. About half of contributions are distributed across various journals, indicating broad research interest and lack of dominating position of other journals.

Table 14. Academic contributions by sources (source: author, based on Scopus download)

Source title	Number of publications	Percentage of total
Journal of Cleaner Production	280	25%
International Journal of Recent Technology and Engineering	49	4%
International Journal of Scientific and Technology Research	29	3%
Technology in Society	24	2%
Technological Forecasting and Social Change	23	2%
Internet of Things (Netherlands)	16	1%
International Journal of System Assurance Engineering and Management	15	1%
International Journal of Energy Sector Management	14	1%
International Journal of Sustainable Agricultural Management and Informatics	14	1%
Clean Technologies and Environmental Policy	13	1%
Lecture Notes in Business Information Processing	11	1%
2023 6th International Conference on Information Systems and Computer Networks	10	1%
Journal of Commercial Biotechnology	10	1%
2022 IEEE Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation	10	1%
International Journal of Computing and Digital Systems	10	1%
2022 International Conference on Data Analytics for Business and Industry	9	1%
2017 6th International Conference on Agro-Geoinformatics, Agro-Geoinformatics 2017	9	1%
Knowledge-Based Systems	8	1%
2011 2nd International Conference on Artificial Intelligence, Management Science and Electronic Commerce	8	1%
Systems Research and Behavioral Science	7	1%
Other	549	49%
<b>Total</b>	<b>1,118</b>	<b>100%</b>

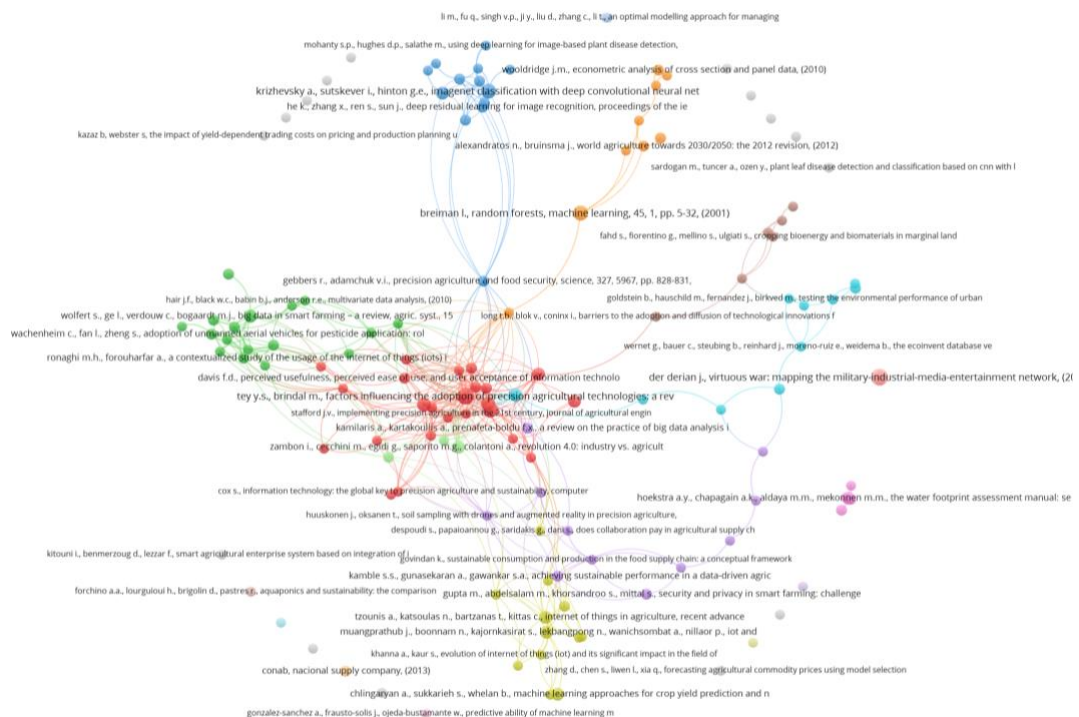
### IV. 3. Co-citation analysis

The aim of the co-citation analysis is to identify **thematical clusters** and **historic knowledge foundations** in the existing corpus, by highlighting academic contributions cited together in various studies. Figure 14 shows the visualization of the

**co-citation network** extracted with VOSviewer, where each node represents a scientific publication. The **sizing of nodes** indicates the significance of those, i.e. citation count, and the connections between nodes reflect citation relationships. The **colour-coding of nodes** identifies clusters of closely related publications.

### IV. 3. 1. Presentation of findings

Figure 14. Co-citation analysis first results ((source: author, based on VOSviewer)



Based on the co-citation network, **six significant clusters** were identified, each colour-coded to illustrate distinct thematic groups within the literature that can broadly be categorized into two groups. The first consists of publications on **general topics in AI, Machine Learning (ML), and neural networks** with no or limited connections to specific industrial applications. These works reflect the technical foundations of ML techniques widely applicable across economic sectors, for instance the random forest method (Breiman, 2001), or convolutional neural networks (CNNs) for image categorization (Krizhevsky et al., 2017). These are important technical contributions

forming the basis of subsequent innovations and AI use cases in various sectors, including agriculture (and winemaking).

In the second group, the focus shifts to **applications of AI within agriculture and food**, providing inspirations on the technology's use cases in winemaking. For example, (Mohanty et al., 2016) explore deep learning's potential for **diagnosing plant diseases** via smartphone-assisted image recognition. (Tzounis et al., 2017) emphasize highlighting how data-driven solutions can optimize precision agriculture practices and improve sustainability. (Wolfert et al., 2017) discuss how big data and predictive analytics drive **smart farming**, and (Muangprathub et al., 2019), provide an overview of a comprehensive IoT-based system for **optimizing agricultural watering**. Table 15 summarizes the key articles, including the cluster where each belongs to, as well as their main findings and limitations.

In VOSviewer an important input to the result of the final outcome is the specification of the **minimum cited references threshold**. Initially, this value was set to three, resulting in a total of 136 references meeting this criterion (total entries: 44,858). This approach can potentially introduce the risk of overrepresenting less impactful studies, which may distort the analysis by including references with limited influence. To filter out outliers and highlight only the most influential cited studies, the analysis was rerun by utilizing higher thresholds for minimum cited references in VOSviewer.

Table 15. Summary of key articles on AI and machine learning: core benefits and limitations in general topics and agricultural applications (source: author)

Main cluster	Theme	Author(s)	Benefits of AI	Limitations of AI
General topics in AI	Random forest method	(Breiman, 2001)	Improved prediction accuracy by combining multiple decision trees.	Risk of overfitting with single trees; dependence on training data diversity.
General topics in AI	Convolutional neural networks	(Krizhevsky et al., 2017)	Enhanced image recognition accuracy.	Infrastructural limitations, training time, dataset size.
General topics in AI	Deep learning architecture	(LeCun et al., 2015)	Features learnt from raw data by avoiding manual feature extraction.	Large, labelled datasets required; computational intensity, network depth.
General topics in AI	Convolutional neural networks	(Simonyan & Zisserman, 2015)	Improved image recognition accuracy with deeper networks.	Training challenges due to increased complexity and computational needs.
General topics in AI	Residual learning framework	(He et al., 2015)	Vanishing and exploding gradient issues in deep neural networks.	High computational intensity; vanishing/exploding gradient problems.
Applications of AI and ML within agriculture	Disease diagnosis	(Mohanty et al., 2016)	Disease detection with smartphone-assisted AI, improved crop yields.	Diverse dataset requirements.
Applications of AI and ML within agriculture	Disease diagnosis	(Sladojevic et al., 2016)	Early disease detection improves agricultural productivity.	Diverse dataset requirements.
Applications of AI and ML within agriculture	Disease diagnosis	(Lu et al., 2017)	Automatic detection of rice diseases, improved crop quality and yield.	Diverse dataset and optimized network parameters requirements
Applications of AI and ML within agriculture	Image segmentation	(Singh & Misra, 2017)	Earlier detection of leaf diseases, sustainable intervention.	Challenges due to varied leaf images and environments.
Applications of AI and ML within agriculture	Precision agriculture and IoT	(Tzounis et al., 2017)	Optimized agricultural practices, quality control, sustainability.	Networking scalability, interoperability issues, and data security concerns.
Applications of AI and ML within agriculture	Circular economy in agriculture	(S. Kumar et al., 2021)	Sustainable agricultural practices and improved yields through IoT and Industry 4.0 technologies.	Workforce skill gaps and policy challenges, especially in developing countries.
Applications of AI and ML within agriculture	IoT-based watering systems	(Muangprathub et al., 2019)	Optimized water usage, increased productivity.	Scalability and adaptability challenges.

Main cluster	Theme	Author(s)	Benefits of AI	Limitations of AI
Applications of AI and ML within agriculture	Precision agriculture	(Tey & Brindal, 2012)	Improved efficiency and sustainability by minimizing resource use.	Adoption influenced by socio-economic and behavioural factors, farmer acceptance.
Applications of AI and ML within agriculture	Big data and smart farming	(Wolfert et al., 2017)	Real-time decision-making, predictive analytics.	Data ownership, privacy, and security issues.
Applications of AI and ML within agriculture	Unmanned aerial vehicle (drone) adoption for agriculture	(Wachenheim et al., 2021)	Reduced pesticide use, safer and more sustainable practices.	Adoption limited by social and economic factors, lack of financing and rural support.
Applications of AI and ML within agriculture	Crop yield estimation	(Gonzalez-Sanchez et al., 2014)	Improved yield predictions, effective agricultural planning.	High sensitivity to data quality; risk of overfitting and limited generalizability.
Applications of AI and ML within agriculture	Precision agriculture	(Chlingaryan et al., 2018)	Enhanced yield estimation and environmental monitoring.	High costs in data collection and equipment CAPEX; data accuracy.

The results are summarized in Table 16. The maximum number of cited references was capped at seven items. The articles meeting this level are presented in Table 17. Of these, (Breiman, 2001; Krizhevsky et al., 2017; Tey & Brindal, 2012) had already been examined in the prior analysis, confirming their central role within the core literature. The remaining reference, (Kutter et al., 2011), introduces an additional perspective by analysing the role of communication and cooperation in adopting precision farming technologies.

Table 16. Robustness testing of co-citation analysis: number of cited references with different minimum thresholds (source: author)

New threshold selected	Number of cited references
4	45
5	17
6	7
7	5

Table 17. List of co-cited articles with minimum cited references threshold of seven selected (source: author)

Authors and year	Title	Source
(Kutter et al., 2011)	The role of communication and co-operation in the adoption of precision farming	Precision Agriculture
(Tey & Brindal, 2012)	Factors influencing the adoption of precision agricultural technologies: A review for policy implications	Precision Agriculture
(Breiman, 2001)	Random Forests	Machine Learning
(Krizhevsky et al., 2017)	ImageNet classification with deep convolutional neural networks	Communications of the ACM

### IV. 3. 2. Discussion of results

The corpus of studies identified through the co-citation analysis encompass a broad range of methodologies and domains. Yet, the findings add important inputs into how digital and AI-driven tools reshape agricultural production systems, providing inspirations to this research assessing the same impact on the wine industry. The dataset mostly covers work from 2009 to 2023, reflecting a period in which digital agriculture evolved from conceptual models to systems deployed on fields. Three methodological families dominate in these studies: **qualitative inquiry** analysing how societal factors can impact the widespread adoption of technologies (see for example, Kutter et al., 2009), **quantitative and engineering experimentation** (Mohanty et al., 2016; Muangprathub et al., 2019), and **conceptual or review-based theorisation** of adoption and data ecosystems (Tey & Brindal, 2012; Tzounis et al., 2017; Wolfert et al., 2017).

In terms of **domain focus**, most studies centre on open-field crops, with limited representation of technology applications in vineyards. The **geographical emphasis** is skewed toward developed economies, especially Europe and North America, where better infrastructure and availability of research funding can be assumed for high-technology experimentation compared to less developed countries. The exception is Muangprathub's study in Thailand that provides a rare example of technology deployment in a smallholder context, highlighting scalability and affordability concerns often missing elsewhere. **Dataset types** also differ substantially: lab-based, public datasets (e.g., PlantVillage in Mohanty et al., 2016) enable standardised

algorithm testing under controlled conditions. These can be good to prove the prospective value added by advanced image recognition technologies, but do not capture the real-world diversity and the heterogeneous nature of agricultural environments. In contrast, research utilising proprietary or locally gathered sensor data (for instance in Muangprathub et al., 2019) covers this gap, with potential generalisability limitations of findings derived.

Taken together, these contrasts reveal **comparability constraints** along the dimensions of controlled versus real-world data, individual versus systemic focus, and high-income versus smallholder contexts. At the same time, such variability also provides rich scientific contributions, allowing for the understanding and synthesis of how various factors (such as **technical capability**, **organisational behaviour**, and **institutional governance frameworks**) can interact in shaping AI adoption in agriculture. The resulting findings therefore align well with the objective of this dissertation, explaining the multifaceted nature of AI adoption in the wine sector.

In the most relevant studies analysed, technology adoption is discussed from **three main perspectives**, influenced by trust, cooperation, and advisory networks that translate innovation into practical use cases (Kutter et al., 2009). Such findings therefore provide the **societal perspective** when analysing the impact of technology transformation in agriculture. In contrast, the same topic can be approached as an **economic decision**, driven by measurable factors such as profitability, education, and farm size, assuming rational behaviour and clear incentives associated with technological transformation (Tey & Brindal, 2012).

Finally, engineering studies (Mohanty et al., 2016; Muangprathub et al., 2019) prioritise **technical feasibility**, suggesting that tangible benefits (such as improved accuracy, or automation of repetitive tasks) offered by new systems will naturally lead to more widespread technology adoption. This assumption is however moderated by multiple factors. The **real-world variability of field environments** can result in solutions developed not working as effectively as they did under lab conditions. In

addition, **limited user readiness** and the **differences in resources available** to various players of different size in agriculture (and thus, the wine industry) also impact how such advantages can be realised.

Together, these viewpoints indicate that technology adoption in agriculture is neither purely a social nor purely a technical decision. Rather, the success of such initiatives depends on how proven technological capabilities can be translated into meaningful potential outcomes that generate interest, spark user confidence and demonstrate tangible value. The findings therefore suggest that the effective diffusion of AI in non-technology native industries (such as the wine sector) requires the **integration of technical feasibility and reliability** with **trust-based advisory structures** and **clear economic benefits**. Taking such a holistic approach can help ensuring that innovation initiatives align with both human factors and organisational characteristics shaping the success of such endeavours. Table 18 summarized these key findings and their relevance to the objectives of this dissertation.

Synthesising the findings from the most relevant contributions, a **multi-level framework of AI adoption in agriculture** can be proposed, overlapping individual, organisational, and systemic dimensions. Each level involves distinct mechanisms of change, yet considering these collectively can ensure that digital transformation happens in a sustainable manner, considering the various interactions among the different layers. These findings can provide important insights into how AI is shaping winemaking, informing both the subsequent research and the findings derived from this study.

Table 18. Summary of different perspectives of AI adoption in food and agriculture (source: author)

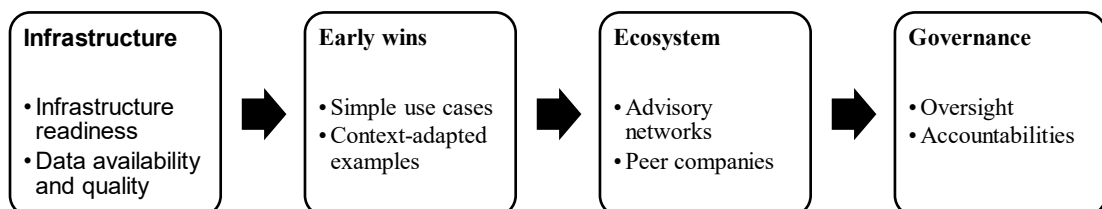
Perspective / lens	Example representative studies	Key transferable insights for AI in the wine sector	Relevance to dissertation objective
Socio-technical perspective	Kutter et al. (2009)	AI adoption in winemaking will depend on trusted intermediaries providing valid insights into the capabilities offered by AI tools.	Social and cultural drivers/barriers influence AI uptake and technology diffusion.
Economically rational perspective	Tey & Brindal (2012)	Demonstrates that economic incentives (ROI, cost savings, efficiency) remain critical motivators, albeit insufficient on their own.	Economic and behavioural determinants shape technology (including AI) adoption decisions in wineries.
Engineering perspective	Mohanty et al. (2016); Muangprathub et al. (2019)	High technical accuracy demonstrates feasibility but does not guarantee real-world success - solutions must be tailored to local realities.	Technological and infrastructural prerequisites to be resolved for successful AI implementation in viticulture.

At the **micro level**, one can emphasize the role of **individual and farm-level characteristics** (such as education and awareness, digital literacy, perceived profitability, and risk tolerance) as the foundation of adoption readiness. These variables explain **who adopts**, but they do not provide insights into **how behavioural changes unfold**. Treating technology adoption as an exercise aimed at realizing one-time utility, rather than as an ongoing process will result in important longer-term factors being overlooked. It is important to recognize the fact that people's experiences with technology can change over time as they receive feedback, encounter challenges, and gradually build trust in using the new tools. At the **meso level**, the **social infrastructure** can be considered, that facilitates the transformation of individual intentions into concrete technology adoption steps. **Advisors, contractors, and peer farmers** act as intermediaries promoting innovations, shaping perceptions, reducing

uncertainty, and providing operational support. These structures can also compensate for capability gaps and act as a legitimate proof of innovation benefits within professional communities. This perspective indicates that without credible intermediaries, technical readiness and benefits offered will rarely generate behavioural change that is required to ensure long-term technology adoption in agriculture. Finally, at the **macro level**, adoption success will depend on **systemic governance** activities, such as data ownership rules, interoperability standards, or value-sharing initiatives.

Building upon these insights yields, a **sequenced AI adoption pathway** in agriculture and winemaking. First, it is essential to build the **appropriate infrastructure** necessary to support technology diffusion. Equally important is to ensure the availability of data in the appropriate quality and quantity, for training and testing newly built AI systems. Second, it is recommended to start the rollout with **simple use cases**, adapted to individual contexts, generating early wins that reinforce commitment towards large scale AI adoption initiatives. Third, it is recommended to utilise **advisory and contractor networks** to scale existing solutions. Finally, as AI-based tools are began to be used pervasively, it is essential to institutionalise these by adopting rigorous **governance frameworks**. The synthesis summarized in Figure 15 directly informs this dissertation’s focus on the wine sector by illustrating that the success of AI adoption in wineries will be not only driven by vineyard-level capabilities, but equally on wider meso- and macro-level factors.

Figure 15. A potential AI adoption framework in agriculture (source: author)



#### IV. 4. Bibliographic coupling review

The next section complements and strengthens the findings from the co-citation analysis by utilizing additional bibliometric review techniques. The aim of the bibliographic coupling review is to examine the most influential contributions through a high citation threshold and uncover any significant work that might not have been captured earlier. By setting a threshold of 100 citations, this analysis isolates the most influential articles in the dataset, aligning with the dissertation's aim to explore the broader knowledge base in AI and ML applied to agriculture.

##### IV. 4. 1. Presentation of findings

The list of articles extracted with the bibliographic coupling method is presented in Table 19. Out of these contribution, only the work of (S. Kumar et al., 2021) was included in the earlier review, providing an opportunity to extend the existing understanding of AI's role in agriculture. Similar to the co-citation analysis, the extracted articles focus on distinct themes such as the use of **predictive ML tools to forecast environmental indicators**, the **management of pollutant sources and risks** associated with them, the **measurement and mitigation of climate risks**, or the **adoption behaviour of complex digital systems** and the barriers to the implementation of those. For example, (Maleki et al., 2019) applied artificial neural networks (ANNs) to predict air pollution levels, while (Liu et al., 2021) examined factors influencing carbon emissions, underscoring the importance of cross-sector cooperation for greener practices. Similarly, (Elahi et al., 2022) investigated the impact of extreme weather events on agriculture, proposing adaptive management strategies to mitigate these effects.

*Table 19. List of academic contributions extracted using the bibliographic coupling method (minimum number of citations threshold = 100) (source: author, based on VOSviewer)*

<b>Authors and Year</b>	<b>Theme</b>	<b>Technology benefits</b>	<b>Technology limitations</b>	<b>Source</b>
(Elahi et al., 2022)	Climate adaptation in agriculture	Reduced crop losses, adaptive farming.	Regional implementation and adaptation challenges	Other journal
(S. Kumar et al., 2021)	Industry 4.0 and circular economy barriers in agriculture	Enhanced supply chain efficiency, sustainable practices	Inadequate policies and support, high implementation costs	JoCP
(Maleki et al., 2019)	Air pollution prediction using AI	Air pollution prediction with ANN-s	Data variability across monitoring locations	CtAEP
(Liu et al., 2021)	Carbon emissions reduction	Sustainability through efficient resource use	Regional disparities in productivity and carbon reduction	JoCP
(Fang et al., 2018)	Carbon dioxide emission forecasting with AI	Improved prediction accuracy for emission	High computational demand for large datasets	JoCP
(Chen et al., 2020)	Water resource management	Improved water management and use	Data availability	JoCP
(Zeng et al., 2020)	Water quality management	Water quality management and sustainable use	High contamination and complex pollutant sources	JoCP
(Aubert et al., 2012)	Precision agriculture adoption	Sustainable farming with IT adoption	Compatibility with existing systems and processes	DSS
(K. Wang et al., 2013)	Soil nitrogen prediction	Predictive insights for soil management	High variability in data quality	Other journal
(Saurabh & Dey, 2021)	Blockchain adoption in agri-food chain / wine	Traceability, trust, and supply chain efficiency	High adoption costs and regulatory challenges	JoCP
(Cortez et al., 2009)	Predicting wine preferences	Enhanced wine quality evaluation	Limited generalizability due to dataset specificity	DSS
(Yazdanpanah & Forouzani, 2015)	Consumer purchase intentions in agriculture	Identification of factors influencing food purchases	Regional, cultural and economic factors impacting consumer adoption	JoCP
(Pham & Stack, 2018)	Data analytics in agriculture	Reshapes decision-making in agriculture	Data privacy and ethical concerns	Other journal

Authors and Year	Theme	Technology benefits	Technology limitations	Source
(R. Kumar et al., 2015)	Optimizing crop yield with AI / ML	Better crop selection decision and yield	Data quality and environmental variability	Other conference
(Caetano, 2014)	Renewable energy from waste	Sustainable fuel alternatives	Material-specific extraction challenges	CTaEP
(Srbinovska et al., 2015)	Environmental monitoring in precision agriculture	Real-time crop monitoring management	High initial cost and limited awareness	JoCP

JoCP = Journal of Cleaner Production; CTaEP = Clean Technologies and Environmental Policy; DSS = Decision Support Systems

Studies on **technology adoption** (Aubert et al., 2012; Saurabh & Dey, 2021) in agriculture emphasise the importance of value perception, costs of integration, compatibility with existing infrastructure, and resource availability as key determinants. Solutions are most likely adopted when they fit existing systems and offer clear benefits, with visible use cases. Other contributions (Cortez et al., 2009; K. Wang et al., 2013) focus on the **predictive capabilities** of technologies used in agriculture, to map soil nitrogen content, or predict wine tasting preferences, highlighting difficulties associated with heterogeneity of local data, making the application of solutions working in lab environments challenging under real-life circumstances. Finally, there are also studies focusing on higher level concepts such as **sustainability** and the utilization of waste as feedstock for subsequent activities (Caetano, 2014), or the **strategic implications** of data analytics on agriculture transformation (Pham & Stack, 2018).

#### IV. 4. 2. Discussion of results

A group of the most influential articles identified in the bibliographic coupling demonstrate a **strong quantitative orientation**, reflecting a preference of data-driven approaches to understand the complex connections between environmental and agricultural factors and technological innovations. Techniques such as ANNs, or Gaussian Process Regression show an emphasis on **measurable efficiency, accuracy, and optimisation** rather than holistic interpretation of technology adoption effects (Liu

et al., 2021; Maleki et al., 2019). These models rely on structured datasets, rigorous quantitative methods and algorithmic refinement to generate results that are credible and can be replicated using other data inputs. In contrast, another group of studies utilize **qualitative or mixed-method designs**, such as the Delphi method, expert surveys, or behavioural models (S. Kumar et al., 2021; Saurabh & Dey, 2021). These contributions complement the quantitative studies by incorporating practitioner insights, institutional factors, and adoption dynamics that numerical approaches tend to overlook. Such methodological diversity exposes the divide between studies focused on technical and policy-related aspects of technology implementation in agriculture, highlighting the need for integrated approaches to address both analytical considerations and real-world AI adoption challenges in winemaking.

The reviewed studies provide a detailed overview of the adoption conditions, capabilities, and impacts of technological innovations in agriculture. Contributions focused on predictive modelling capabilities highlight **technical efficiency benefits** but often overlook organisational and sustainability factors. In contrast, expert-based research reveals **considerations of practical implementation** and the role of **governance and policy features**. This distinction shows that successful implementation of AI in winemaking depends on both technical benefits and organisational, human, and regulatory readiness. Key drivers of AI adoption include **infrastructural readiness, technological maturity, and data availability**, while **behavioural and institutional factors** (such as culture, finances, and skills availability) are also crucial. Factors limiting AI uptake include **weak governance, limited expertise**, and **poor interoperability** of systems. Such resource constraints can be moderated by adequate **policy support** and targeted **training programs**. The findings highlight that effective AI adoption in winemaking requires a combination of robust data infrastructure, regulatory clarity, management capabilities, and cultural acceptance of the technology.

The comparison of methodologies also reveals some important limitations that must be considered when interpreting findings. Most studies **lack longitudinal validation**, relying on cross-sectional data, which hinders understanding of causal relationships

and changes in AI adoption over time. This is crucial in sectors like agriculture and winemaking characterised by fluctuating environmental conditions over various seasons. Quantitative studies often **omit uncertainty assessment**, reducing confidence and transferability of results, while dependence on **self-reported data** in survey-based research makes causal inference difficult. As a result, evidence on AI's impact on agriculture remains fragmented and context dependent. These findings provide further support to the use of a mixed-method approach in this dissertation, combining Delphi analysis with interview-based thematic coding and text mining analysis. By integrating various types of evidence, the validity of findings is enhanced, offering a more reliable picture of AI implementation dynamics in the wine sector.

Overall, the findings provide important insights and actionable lessons into the practical implementation of AI in agriculture. Adoption should be a **sequential process** starting with **policy clarity, infrastructure readiness, and capacity building** before considering the **implementation of advanced analytics or automation solutions**. Establishing **appropriate governance mechanisms** to ensure transparency, validation, and interpretability of AI outcomes is equally important. For the wine sector, this implies that ensuring data quality and interoperability and investing in digital literacy is key to ensure successful AI adoption. Cooperation between wineries, research institutions and policymakers, as well as gaining inspirations on technological innovations from other industries is essential to ensure the adoption of meaningful innovations. These observations are consistent with the socio-technical, economically rational, and engineering perspectives previously identified in the co-citation analysis and the implementation framework defined in Figure 15. Together, they reinforce that AI adoption in winemaking requires balancing technical precision with behavioural and institutional readiness.

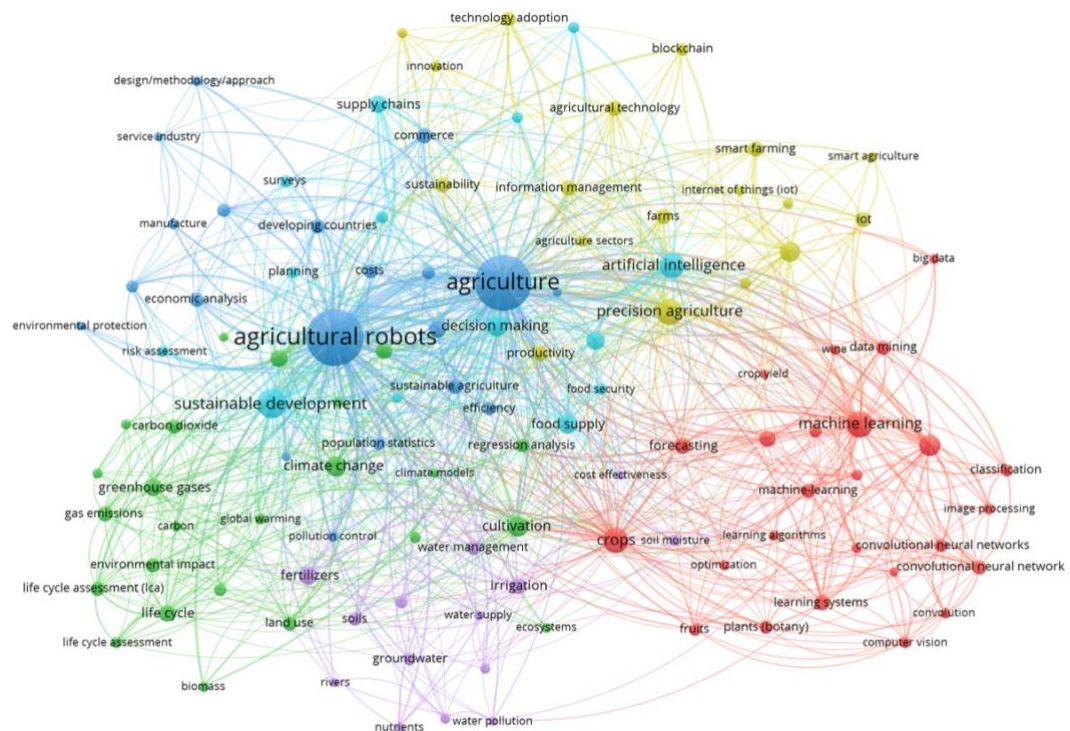
#### **IV. 5. Co-word analysis**

Finally, the outputs of the co-word analysis are presented in this section, aimed at identifying emerging themes and potential future research directions within the academic discourse related to the objective of this study. The method focuses on the

co-occurrence of keywords, allowing for the exploration of **conceptual relationships** between topics. Parameters within the VOSviewer software were set to co-occurrence mode with "all keywords" option selected as the unit of analysis, aimed to capture a comprehensive representation of the keywords in the academic sources extracted. A **minimum occurrence threshold of 15** was chosen to maintain a balance between relevant keywords, while excluding infrequent terms with limited insights provided.

#### IV. 5. 1. Presentation of findings

Figure 16. Co-occurrence analysis, first results (source: author, based on VOSviewer)



The co-word analysis identified a total of 6 clusters, as presented in Figure 16 and in Table 20. The co-word analysis identified six clusters. The first cluster highlights the use of **advanced machine learning and deep learning for agricultural and viticultural data analysis**, focusing on computer vision, data analysis or crop yield enhancement. The second cluster examines **agriculture's link with environmental sustainability**, addressing topics like climate change, carbon footprint, and management of complex ecosystem. It underlines the importance of quantifying

emissions and resource use through life cycle assessment, exploring the intersection of agricultural activities with ecological concerns.

The third cluster explores **economic and technological aspects in agriculture**, with a focus on automation for improved efficiency and financial viability, highlighting the need for environmentally responsible innovation. The fourth cluster addresses **agriculture’s digital transformation**, featuring smart farming, precision agriculture, IoT, and automation. Blockchain and information management also appear to improve traceability, data integrity, and transparency, while technology adoption and innovation reflect the drivers of productivity and the way farm management and operational practices are reshaped.

Table 20. Co-occurrence analysis, table format (source: author, based on VOSviewer)

<b>Cluster 1 Machine learning</b>	<b>Cluster 2 Climate impact and sustainability</b>	<b>Cluster 3 Agri-economics and automation</b>	<b>Cluster 4 Smart farming</b>	<b>Cluster 5 Resource management</b>	<b>Cluster 6 AI in decision support</b>
big data	agricultural practices	agricultural productions	agricultural development	cost effectiveness	agricultural products
classification	biomass	agricultural robots	agricultural technology	fertilizers	artificial intelligence
computer vision	carbon footprint	commerce	agriculture sectors	groundwater	decision making
convolutional neural network	China	cost benefit analysis	automation	irrigation	decision support systems
crop yield	climate change / models	data acquisition	blockchain	nutrients	ecology
crops	climate models	design/methodology/approach	farms	rivers	electronic commerce
data mining	cultivation	developing countries	information management	soil moisture	food security
decision trees	economic and social effects	economic analysis	innovation	water conservation / management	planning

Cluster 1 Machine learning	Cluster 2 Climate impact and sustainability	Cluster 3 Agri-economics and automation	Cluster 4 Smart farming	Cluster 5 Resource management	Cluster 6 AI in decision support
deep learning	ecosystems	efficiency	internet of things	water pollution	risk assessment
forecasting	emission control	energy utilization	precision agriculture	water quality	rural areas
fruits	environmental impact / management	environmental protection	productivity	water resources	supply chains
image processing	forestry	investments	smart agriculture / farming	water supply	surveys
learning algorithms / systems	gas emissions	manufacture	sustainability		sustainable development
machine learning	global warming	pollution control	technology adoption		
neural networks	greenhouse gases	population statistics			
optimization	land use	service industry			
plants (botany)	life cycle (assessment)	sustainable agriculture			
remote sensing	regression analysis				
support vector machines					
wine					

The fifth cluster focuses on **optimising and conserving vital resources**, particularly water and soil nutrients, within agriculture, highlighting issues such as irrigation, nutrient management and water quality. The final cluster centres on **AI-driven decision-making**, examining how artificial intelligence and decision support systems can enhance planning, supply chains, and food security. Keywords like surveys and risk assessments underscore the importance of using structured methodologies for making evidence-based decisions.

## IV. 5. 2. Discussion of results

The co-word analysis underscores that AI adoption in agriculture, including winemaking, integrates **technological, ecological, and socio-economic dimensions**. The core topic of Clusters 1 and 4 is **data-driven optimization**, distinguishing algorithmic processes from technological infrastructure, reflecting AI's cognitive (model training, prediction) and physical (IoT-based) aspects. **Sustainability** appears across Clusters 2–6 from varied perspectives such as climate change adaptation, economics, resource management, and decision support. This variability emphasizes the need for developing AI solutions fitting multiple contexts. Other frequently appearing terms such as **efficiency and productivity** may indicate thematic overlap, yet they also reveal consistently central concepts in how AI impacts agriculture. However, such similarity of keywords across clusters may also reflect a lack of conceptual precision, implying that research often revisits already established ideas rather than expanding theoretical boundaries, which can be an important limitation of findings.

**Comparing the co-word analysis with earlier bibliometric results** reveals both convergence and divergence of themes. The appearance of clusters related to machine learning and smart farming align with **technological aspects**, while decision support and sustainability reflect **behavioural and institutional views**. Unlike prior studies separating algorithmic, socio-economic, and environmental dimensions, the co-word analysis shows growing conceptual integration, where AI and sustainability now appear within the same research networks. Yet, this convergence may also make it harder to distinguish where technological innovation ends and socio-economic transformation begins. A more explicit mapping of causal relationships would further clarify how these domains influence each other. This shift positions AI not merely as a technical tool but as part of interconnected innovation systems spanning **technological, organisational, and societal layers**.

Earlier studies followed a “technology-push” logic, assuming that advanced algorithms, big data, or sensor networks would automatically drive adoption and

efficiency. The co-word analysis shows that **technological readiness alone is insufficient**. Emerging terms like decision making, supply chains, and sustainable development highlight the growing relevance of organisational factors, enterprise ecosystems, and market mechanisms. This contrast underlines a shift towards a more systemic thinking, yet most studies still lack empirical demonstration of how these interactions between socio-technical factors unfold in practice. AI diffusion must therefore be viewed through integrated frameworks aligning **technological, human, and systemic factors** across micro (skills, trust), meso (networks), and macro (governance) levels to ensure sustainable, value-creating implementation of the technology.

As noted above, the co-word analysis shows **sustainability and resilience as central themes** in AI-agriculture research. Whereas earlier studies treated environmental issues as external constraints, terms like climate change, sustainable agriculture, and water conservation appear across multiple clusters in the keyword analysis. These act as conceptual bridges linking technological, economic, and governance studies, reflecting a shift toward **AI as an enabler of sustainability**. In winemaking, this implies using AI not only for efficiency but also for climate adaptation, improved resource management, and reduced environmental impact, aligning innovation with sustainable and circular agriculture goals. However, the frequent use of sustainability-related keywords may also suggest that researchers assume sustainability is always positive, without examining how it might conflict with practical farming goals such as yield or cost efficiency. Future research should test whether AI genuinely enhances resilience (by jointly contributing to climate adaptation and economic performance) rather than simply reframing existing practices.

The co-word analysis reveals the rising relevance of **economic and governance factors** in agricultural AI adoption. Keywords like cost effectiveness, investment, and economic analysis highlight financial viability as a core driver, now balanced with sustainability and transparency goals. The presence of blockchain and information management indicates emerging governance mechanisms ensuring **data reliability and accountability**. Yet, the keyword clusters formed indicate that research may

understate the significance of high upfront costs and skills required for AI systems. Future studies should critically evaluate whether these mechanisms are viable for small and medium-sized wineries, aligning financial objectives with data governance frameworks.

To conclude, the co-word analysis reveals both diversity and fragmentation in AI-agriculture research. **Overlapping clusters** show that algorithmic precision, sustainability, and decision support are studied in parallel but rarely integrated, confirming the bibliographic coupling results. Future research could be therefore conducted to link technical studies with human, organisational, and sustainability perspectives. Gaps also remain in **viticulture-specific data and smallholder representation**, and the method-centric design of current literature offers models with limited real-world validation, limiting the understanding of how context-dependent factors pose challenges to AI implementation. Applying a more cross-disciplinary research designs could enhance generalisability of findings, creating a useful input for shaping agricultural and technological policies. This dissertation is a step towards addressing some of these gaps, by applying a mixed-method approach integrating expert judgment with empirical evidence for a holistic understanding of AI adoption in winemaking.

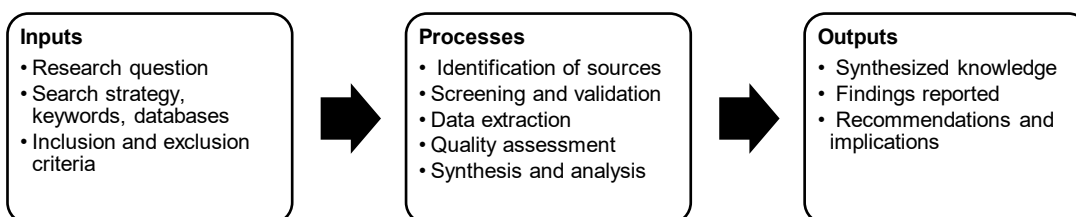
#### IV. 6. Review of grey literature

Because the business application of Artificial Intelligence (AI) is a relatively new phenomenon, it is expected that advancements in practical applications are documented in industry reports, white papers, and government documents before they appear in academic journals. To ensure any such developments not touched in scientific contributions are also captured, **non-academic sources** (collectively referred to as **grey literature**) were also investigated to improve the understanding of the phenomenon, complementing and enriching earlier findings.

*Table 21. Grey literature review process summary of criteria (source: author)*

<b>Research question:</b> To understand the main innovations related to the use of AI in agriculture, the potential benefits offered and implementation challenges	
<b>Sources used</b>	
Deloitte	Leading international consulting firms publishing industry reports on technology trends and novel solutions in agriculture.
PricewaterhouseCoopers	
McKinsey	
International Organisation of Vine and Wine (OIV)	Intergovernmental organization dealing with technical and scientific aspects of viticulture and winemaking.
United States Department of Agriculture (USDA)	United States governmental organisation offering reports on agricultural technology and its economic impact.
Food and Agriculture Organization of the United Nations (FAO)	Agency of the United Nations providing global perspectives on agricultural technologies and trends.
International Society of Precision Agriculture	Professional association on precision agriculture.
Agri-TechE	Business focused membership organisation supporting innovation and technology innovation in the agricultural value chain.
International Food Policy Research Institute (IFPRI)	International research center focusing on transformation of food systems to resolve major challenges
CGIAR	Global partnership focusing on systemic transformation approach for food, land, and water systems.
<b>Search strategy</b>	
Search engine used	Google
Keyword combination used	artificial intelligence agriculture agribusiness + site name (e.g., artificial intelligence agriculture agribusiness site:Deloitte.com)
Hard exclusion criteria	Pre-2020 articles and reports excluded
Soft exclusion criteria	<ul style="list-style-type: none"> <li>• Irrelevant reports excluded</li> <li>• Reports not providing further contribution to earlier identified findings excluded</li> </ul>
<b>Results</b>	
Number of items scanned	54
Final list of items reviewed	21

Figure 17. An overview of the grey literature review process (source: author)



The **grey literature review** process (Figure 17) is driven by the research questions formulated. The main steps involve identifying appropriate keywords, databases, websites, and repositories, screening and selecting relevant documents, and extracting and synthesizing data. Websites utilised were limited to **reliable external sources** including government reports and publications, industry and professional associations, research institutes and think tanks, academic and research centres, consulting firm reports, conference proceedings, trade publications and magazines, white papers, and case studies, and contributions from non-governmental organizations (NGOs). The search strategy was based on **previously identified keywords**, utilizing the **Google search engine**, focusing on documents **dated from 2018 onward** to capture the most recent practical developments in this field. Similarly to the bibliometric analysis, this part of the research was conducted in 2023, therefore the latest articles used in the review process was dated from this year.

When evaluating the different documents, several criteria were applied to enhance the quality of the review process, including the **assessment of the authorship**, the **authority of the publication source** and the evaluation of **content relevance**. The final list of criteria used when executing the grey literature review is summarised in Table 21. The concept of **theoretical saturation** (referring to the point at which no new significant insights emerge from additional sources) was used to determine when to conclude the review process. In practice, this was achieved by systematically recording and analysing overlapping findings between sources. When findings in new documents were not significantly different from those in previous reports, it was taken as an indication of saturation. The final list of articles selected for the review of the grey literature is shown in Table 22.

Table 22. List of articles selected from the review of the grey literature (source: author)

Source	Title
(Deloitte Touche Tohmatsu Limited, 2020)	Transforming Agriculture through Digital Technologies
(Deloitte Touche Tohmatsu Limited, 2021)	Emerging Tech & Innovation in Malaysia's Agriculture Landscape
(World Economic Forum in collaboration with Deloitte and NTT Data, 2022)	Transforming food systems with farmers: A Pathway for the EU

Source	Title
(PricewaterhouseCoopers, 2020)	Unlocking productivity and investment opportunities across Nigeria's agribusiness value-chain
(McKinsey & Company, 2020b)	Agriculture's connected future: How technology can yield new growth
(McKinsey & Company, 2023a)	Agtech: Breaking down the farmer adoption dilemma
(McKinsey & Company, 2022)	How advanced analytics can address agricultural supply chain shocks
(McKinsey & Company, 2020a)	Agriculture supply-chain optimization and value creation
(McKinsey & Company, 2023b)	How agtech is poised to transform India into a farming powerhouse
(McKinsey & Company, 2021b)	Reducing postharvest crop losses
(McKinsey & Company, 2021a)	Building value-chain resilience with AI
(OIV Digital Transformation Observatory Hub, 2021)	Digital trends applied to the vine and wine sector
(Delgrosso, 2021)	OIV Digital Transformation Observatory Hub
(United States Department of Agriculture, 2023a)	Artificial Intelligence For Sustainable Water, Nutrient, Salinity, And Pest Management In The Western U.S.
(McFadden, 2023)	Precision Agriculture in the Digital Era: Recent Adoption on U.S. Farms
(Parsaeian et al., 2022)	Towards the Modeling and Prediction of the Yield of Oilseed Crops: A Multi-Machine Learning Approach
(United States Department of Agriculture, 2023b)	USDA Science and Research Strategy, 2023-2026: Cultivating Scientific Innovation
(Food and Agriculture Organization of the United Nations, 2020)	Is there a potential in adopting Artificial Intelligence in food and agriculture sector, and can it transform food systems and with what impact?   E-Agriculture
(Food and Agriculture Organization of the United Nations, 2021)	Digital Agriculture In Action. Artificial Intelligence For Agriculture
(Santos Valle, & Kienzle, 2020)	Agriculture 4.0 – Agricultural robotics and automated equipment for sustainable crop production
(CGIAR, 2022)	Melisa chatbot - the 'oracle' for Colombian farmers

The findings from the grey literature analysis align with the results of the previous bibliometric review, providing additional perspectives on the research subject. The review highlighted the **transformative role of digital technologies** (mostly AI, IoT, and Blockchain) in modern agriculture and winemaking, aimed at enhancing **productivity**, optimizing **resource usage**, promoting **sustainable practices** through automating tasks, or enabling **real-time monitoring of environmental conditions**. The key challenges listed in the grey literature included **technical limitations** (like

data privacy concerns and infrastructure needs), **skill gaps** and high **initial and maintenance costs**.

The grey literature added practical insights into **current industry challenges** related to precision agriculture and AI applications and the **socioeconomic implications of technology adoption**. Instead of focusing mostly on theoretical advancements, grey literature content emphasized real-world limitations, such as **rural infrastructure** and **skill deficits**, and highlighted the critical role of **supportive policies** for successful integration of AI in agriculture. The main points extracted from these reports are summarized in

Table 23. The findings will be utilized in the next stages of this research when developing the Delphi questionnaire in line with the research questions formulated.

Table 23. Summary of main findings from grey literature review (source: author)

<b>Technology benefits and use cases</b>	<b>Technology limitations</b>	<b>Technology adoption hurdles</b>	<b>Drivers of technology adoption</b>
Enhanced productivity through AI-driven yield prediction and disease detection	Data privacy and security concerns, particularly with IoT and Blockchain implementations	High initial costs for tech adoption, making it inaccessible for small to medium-sized farms	Increased profitability pressure due to economic challenges (cost inflation, high interest rates)
Optimized resource usage via IoT-enabled precision farming	Insufficient rural infrastructure limiting technology deployment	Skill gaps in the workforce, creating a need for training and development in AI and IoT systems	Climate change-induced challenges (availability of natural resources, weather conditions)
Improved supply chain efficiency and transparency using Blockchain	Limited interoperability between systems and technological platforms	Need for clear policies on data management and governance to protect sensitive agricultural data	Shifting consumer preferences towards high-quality, traceable, and organically certified products
Sustainability and reduced environmental impact	Technical servicing infrastructure required to support complex digital solutions	Resistance to change and reluctance to abandon traditional practices in certain farming communities	Increase in global demand for food and agriculture products due to population growth

Technology benefits and use cases	Technology limitations	Technology adoption hurdles	Drivers of technology adoption
Increased resilience to climate change effects through AI-based solutions	Varying levels of digital literacy among farmers, affecting ease of technology use	Dependence on consistent regulatory support, particularly within EU policy frameworks	The intensification of both domestic and international competition

#### IV. 7. Concluding remarks

The aim of this section was to provide a multidimensional view of how AI is conceptualised and applied in agriculture and the wine value chain, by the combined use of co-citation, bibliographic coupling, and co-word analyses. The outcomes revealed AI's **layered architecture** underpinned by a cognitive component (represented by machine learning, deep learning, and neural networks) and a physical-enabling layer (driven by sensors, and IoT devices, with application cases in precision agriculture). The co-word analysis revealed that the various layers are increasingly integrated. This represents a shift from seeing AI implementation in agriculture as a purely algorithmic experimentation, toward a more systemic digital transformation approach.

A recurring theme across the outcomes of all bibliometric techniques was the centrality of sustainability. Rather than being seen as a purely external constraint, sustainability now appears as a goal that drives AI development and implementation in agriculture. Research is no longer treating environmental, economic and resource management aspects separately. Instead, these dimensions are integrated into decision-making and governance frameworks, showing that sustainability and AI adoption are interconnected across technical, managerial, and policy levels. This evolution highlights AI's role as an enabler of **adaptive sustainability**, capable of improving climate resilience and efficient resource use in agriculture and viticulture.

The analysis also highlights the **socio-economic and institutional levels** to be considered in the process of AI adoption. Just because a solution is technologically feasible, doesn't necessarily mean that it will be implemented. Instead, the success of adoption is shaped equally by the impact organisational culture, corporate and advisory ecosystems, and various layers of governance mechanisms. In addition, the growing attention to blockchain, interoperability, and data governance reflects a shift towards transparency and accountability dimensions. Overall, results indicate that the effective integration of AI in winemaking requires the simultaneous consideration of engineering, behavioural and institutional readiness, aligning technological capabilities with human and organisational factors.

The review of grey literature complemented these findings by providing a **practice-oriented and up-to-date perspective**. The evidence confirmed the previously identified benefits of AI in agriculture and winemaking, such as greater efficiency, improved operational control, and enhanced decision-making. At the same time, the grey literature also exposed some key barriers of adoption, including data privacy concerns, infrastructural readiness, skill shortages, and the cost of AI implementation and maintenance. These findings reinforce the need for policy environments supporting technology adoption and long-term investments in digital capacity.

Synthesising findings from both literature domains, a multi-level framework for AI adoption can be proposed. At the **micro level**, adoption readiness depends on individual and farm-specific factors such as education, digital literacy, and perceived profitability, determining not only who adopts new innovations, but also how adoption develops. At the **meso level**, ecosystem and wider infrastructure considerations play a role, with advisors, contractors, and cooperatives acting as intermediaries that facilitate diffusion, increasing the success of new initiatives introduced. Finally, at the **macro level**, governance and regulatory frameworks provide systemic support through clear rules on data ownership, interoperability, and value-sharing. These factors together lead to the sequenced adoption pathway recommended (infrastructure and data establishment, early wins through simple initial use cases, ecosystems formulation and governance mechanism) as depicted earlier in Figure 15.

Despite the wide coverage achieved, the existing literature clearly has some important **methodological and contextual gaps**. Most studies rely on cross-sectional data, limiting the ability to draw causal inference and to track changes of patterns identified over time. Quantitative models often lack uncertainty assessment and findings derived under controlled conditions are difficult to be implemented in real-life settings. Also, surveys depend heavily on self-reported data, raising concerns over the validity and generalisability of findings. Moreover, the heavy focus on large, well-funded farms in developed regions leaves smallholder producers underrepresented, which can be significant in the context of the wine industry. The limited number of viticulture-specific datasets used places further constraints on drawing conclusions that are specific to the context of winemaking. Some of these gaps can be addressed by the mixed-method approach applied in this dissertation, to provide a more balanced overview of how AI can impact the wine value chain.

## V. Analysis of the Delphi questionnaires

This section presents the empirical findings derived from the questionnaire responses and their subsequent analysis. Initially, descriptive statistics will be used to give an overview of the dataset and indicate potential variations in responses across the two survey rounds. Following this, the degree of consensus among participants is assessed to determine the extent to which the Delphi method achieved its objectives, complemented by a detailed comparison of responses across both rounds.

### V. 1. Descriptive statistics

The **descriptive statistics** (number of responses, mean, median, variance, skewness and kurtosis) for the answers received in the questionnaire are presented in Table 24. The overall results show **high mean values** (ranging from 4.22 to 4.83) for all groups (use cases, benefits, challenges, and transformation drivers), indicating positive perception of participants across categories of the individual elements in the questionnaire. The medians of 4.50 to 5.00 suggest a **strong consensus** toward agreement with most statements. **Variance** values differ between groups, with the greatest variability in responses observed in transformation drivers (2.03). **Skewness** is negative for all groups, implying a slight tendency toward higher scores, while **excess kurtosis** values are close to zero, indicating close-to normal distribution with minor deviations.

In **round 1**, the responses exhibit similar trends, with mean scores across groups remaining high (ranging from 4.19 to 4.83), coupled with relatively consistent variance figures, negative skewness and low excess kurtosis values. **Round 2** shows minor increases in mean scores for use cases (4.90) benefits (4.84) and AI adoption drivers (4.25), while challenges (4.45) experienced a slight decline compared to the first round. Variance decreased in all groups, suggesting greater consensus among participants. Skewness becomes more negative for use cases (-0.96), indicating a higher proportion of responses demonstrating stronger agreement in this dimension. Excess kurtosis patterns vary, with use cases exhibiting the highest value (0.55),

suggesting a shift towards a leptokurtic distribution, with a higher likelihood of stronger agreement or disagreement within the dataset in this dimension.

Table 24. Descriptive statistics of the different Delphi rounds for the various categories of research (source: author)

Group name	Statistic	Overall results	Round 1	Round 2
Use cases	Responses	504	266	238
	Mean	4.82	4.75	4.90
	Median	5.00	5.00	5.00
	Variance	1.33	1.46	1.19
	Skewness	-0.88	-0.80	-0.96
	Kurtosis	0.17	-0.11	0.55
Benefits	Responses	360	190	170
	Mean	4.83	4.83	4.84
	Median	5.00	5.00	5.00
	Variance	1.01	1.11	0.91
	Skewness	-0.68	-0.75	-0.58
	Kurtosis	0.04	0.12	-0.15
Challenges	Responses	252	133	119
	Mean	4.50	4.54	4.45
	Median	5.00	5.00	5.00
	Variance	1.63	1.78	1.47
	Skewness	-0.68	-0.72	-0.65
	Kurtosis	-0.33	-0.38	-0.21
AI adoption drivers	Responses	180	95	85
	Mean	4.22	4.19	4.25
	Median	4.50	4.00	5.00
	Variance	2.03	2.18	1.88
	Skewness	-0.68	-0.68	-0.69
	Kurtosis	-0.27	-0.30	-0.21

Overall, these results indicate **increasing consensus** in round 2, as reflected by reduced variance across all groups. The noticeable improvements in expert agreement, especially for challenges and transformation drivers suggest progress in aligning participants' views, thereby meeting a key objective of the Delphi method. The decrease in mean scores for challenges suggests a shift toward a more sceptical stance

on these statements during the second round of the study that may indicate areas requiring further discussion.

Table 25. Results of the Delphi questionnaires across round 1 and round 2(source: author)

Question no.	Question	First round (N=19)				Second round (N=17)				DIFFERENCE			
		Q1	Q2	Q3	IQR	Q1	Q2	Q3	IQR	Q1	Q2	Q3	IQR
<b>Section 1: use cases</b>													
1	Automated disease diagnosis and classification	5.00	6.00	6.00	1.00	5.00	6.00	6.00	1.00	0.00	0.00	0.00	0.00
2	Forecasting soil and climatic conditions	4.00	5.00	6.00	2.00	4.50	5.00	6.00	1.50	0.50	0.00	0.00	-0.50
3	Optimal harvest time definition	4.00	5.00	6.00	2.00	4.00	5.00	6.00	2.00	0.00	0.00	0.00	0.00
4	Automated water control systems	4.00	5.00	6.00	2.00	4.00	5.00	6.00	2.00	0.00	0.00	0.00	0.00
5	Targeted pesticide spraying and irrigation	5.00	5.00	6.00	1.00	5.00	5.00	6.00	1.00	0.00	0.00	0.00	0.00
6	Automated steps of farming operations	4.00	4.00	6.00	2.00	4.00	5.00	6.00	2.00	0.00	1.00	0.00	0.00
7	Controlling barrel aging conditions	5.00	5.00	6.00	1.00	5.00	5.00	5.50	0.50	0.00	0.00	-0.50	-0.50
8	AI-based wine blending	4.00	5.00	6.00	2.00	4.00	5.00	6.00	2.00	0.00	0.00	0.00	0.00
9	AI-based production scheduling	4.00	5.00	6.00	2.00	4.00	5.00	6.00	2.00	0.00	0.00	0.00	0.00
10	Predicting wine quality by leveraging sensory analysis and maturation data	4.00	4.00	5.00	1.00	3.50	4.00	6.00	2.50	-0.50	0.00	1.00	1.50
11	Forecasting outcomes of wine tasting experiences	2.00	4.00	5.00	3.00	3.00	4.00	5.00	2.00	1.00	0.00	0.00	-1.00
12	Virtual sommelier services	4.00	5.00	6.00	2.00	5.00	5.00	6.00	1.00	1.00	0.00	0.00	-1.00
13	Marketing strategies developed with generative AI	4.00	5.00	6.00	2.00	5.00	5.00	6.00	1.00	1.00	0.00	0.00	-1.00
14	Wine fraud prevention	4.00	5.00	6.00	2.00	4.50	5.00	6.00	1.50	0.50	0.00	0.00	-0.50
<b>Section 2: benefits</b>													
15	Earlier intervention against diseases and pests	5.00	5.00	6.00	1.00	5.00	5.00	6.00	1.00	0.00	0.00	0.00	0.00
16	Improvement in grape yields	4.00	5.00	5.00	1.00	4.00	5.00	5.00	1.00	0.00	0.00	0.00	0.00
17	Targeted farming practices	4.00	5.00	6.00	2.00	4.00	5.00	6.00	2.00	0.00	0.00	0.00	0.00
18	Higher profitability due to lower use of inputs	5.00	5.00	6.00	1.00	4.50	5.00	5.50	1.00	-0.50	0.00	-0.50	0.00
19	Price premiums paid, improved quality	3.00	4.00	5.00	2.00	3.00	4.00	5.00	2.00	0.00	0.00	0.00	0.00
20	Better anticipation and service of customer demand	4.00	5.00	6.00	2.00	4.50	5.00	6.00	1.50	0.50	0.00	0.00	-0.50
21	Stricter quality control and transparency	4.00	5.00	6.00	2.00	4.00	5.00	5.00	1.00	0.00	0.00	-1.00	-1.00
22	More sustainable operations due to reduction in inputs	5.00	5.00	6.00	1.00	4.50	5.00	6.00	1.50	-0.50	0.00	0.00	0.50
23	More flexibility to cope with global challenges (climate change and other disruptions)	4.00	5.00	6.00	2.00	4.00	5.00	6.00	2.00	0.00	0.00	0.00	0.00
24	More meaningful jobs created	4.00	4.00	6.00	2.00	3.00	5.00	6.00	3.00	-1.00	1.00	0.00	1.00
<b>Section 3: challenges</b>													
25	Infrastructural constraints	2.00	3.00	5.00	3.00	2.50	3.00	4.00	1.50	0.50	0.00	-1.00	-1.50
26	Lack of awareness and knowledge	5.00	5.00	6.00	1.00	4.00	5.00	6.00	2.00	-1.00	0.00	0.00	1.00
27	Shortage in skilled workforce	4.00	5.00	6.00	2.00	4.00	5.00	5.00	1.00	0.00	0.00	-1.00	-1.00
28	Lack of acceptance towards new technologies	4.00	5.00	6.00	2.00	4.00	5.00	6.00	2.00	0.00	0.00	0.00	0.00
29	Cost implications of investments	4.00	5.00	5.00	1.00	4.50	5.00	5.00	0.50	0.50	0.00	0.00	-0.50
30	Farm size, economies of scale	4.00	5.00	6.00	2.00	4.00	5.00	5.00	1.00	0.00	0.00	-1.00	-1.00
31	Gaps in governmental policies and incentives	3.00	4.00	5.00	2.00	3.00	4.00	5.00	2.00	0.00	0.00	0.00	0.00
<b>Section 4: transformation drivers</b>													
32	Economic pressures, inflation and high interest rates	4.00	5.00	6.00	2.00	4.00	5.00	5.50	1.50	0.00	0.00	-0.50	-0.50
33	Growth in population	1.00	2.00	3.00	2.00	2.00	2.00	3.50	1.50	1.00	0.00	0.50	-0.50
34	Climate change-induced challenges	4.00	5.00	6.00	2.00	4.00	5.00	5.50	1.50	0.00	0.00	-0.50	-0.50
35	Shifting consumer preferences	3.00	4.00	5.00	2.00	4.00	4.00	5.00	1.00	1.00	0.00	0.00	-1.00
36	The intensification of both domestic and international competition	5.00	5.00	6.00	1.00	4.50	5.00	6.00	1.50	-0.50	0.00	0.00	0.50

Q1 = Lower quartile  
Q2 = Median  
Q3 = Upper quartile

IQR = Interquartile range (Q3 - Q1)

Reduction of IQR  
Increase of IQR

Approximation of quartile towards median  
Deferral of quartile from median

Table 26. Modified APMO Calculation for both Delphi rounds (source: author)

Question no.	Question	First round (N=19)		Second round (N=17)		Consensus change
		APMO - Delphi 1	APMO - Delphi 2	APMO - Delphi 1	APMO - Delphi 2	
<b>Section 1: use cases</b>						
1	Automated disease diagnosis and classification	84.2%	94.1%	84.2%	94.1%	more polarized
2	Forecasting soil and climatic conditions	68.4%	76.5%	68.4%	76.5%	more polarized
3	Optimal harvest time definition	68.4%	64.7%	68.4%	64.7%	less polarized
4	Automated water control systems	73.7%	64.7%	73.7%	64.7%	less polarized
5	Targeted pesticide spraying and irrigation	84.2%	100.0%	84.2%	100.0%	more polarized
6	Automated steps of farming operations	52.6%	58.8%	52.6%	58.8%	more polarized
7	Controlling barrel aging conditions	84.2%	82.4%	84.2%	82.4%	less polarized
8	AI-based wine blending	63.2%	64.7%	63.2%	64.7%	more polarized
9	AI-based production scheduling	52.6%	58.8%	52.6%	58.8%	more polarized
10	Predicting wine quality by leveraging sensory analysis and maturation data	52.6%	58.8%	52.6%	58.8%	more polarized
11	Forecasting outcomes of wine tasting experiences	68.4%	52.9%	68.4%	52.9%	less polarized
12	Virtual sommelier services	78.9%	88.2%	78.9%	88.2%	more polarized
13	Marketing strategies developed with generative AI	68.4%	82.4%	68.4%	82.4%	more polarized
14	Wine fraud prevention	84.2%	82.4%	84.2%	82.4%	less polarized
<b>Section 2: benefits</b>						
15	Earlier intervention against diseases and pests	84.2%	94.1%	84.2%	94.1%	more polarized
16	Improvement in grape yields	73.7%	70.6%	73.7%	70.6%	less polarized
17	Targeted farming practices	68.4%	70.6%	68.4%	70.6%	more polarized
18	Higher profitability due to lower use of inputs	78.9%	76.5%	78.9%	76.5%	less polarized
19	Price premiums paid, improved quality	47.4%	58.8%	47.4%	58.8%	more polarized
20	Better anticipation and service of customer demand	68.4%	76.5%	68.4%	76.5%	more polarized
21	Stricter quality control and transparency	73.7%	52.9%	73.7%	52.9%	less polarized
22	More sustainable operations due to reduction in inputs	78.9%	76.5%	78.9%	76.5%	less polarized
23	More flexibility to cope with global challenges (climate change and other disruptions)	68.4%	58.8%	68.4%	58.8%	less polarized
24	More meaningful jobs created	52.6%	52.9%	52.6%	52.9%	more polarized
<b>Section 3: challenges</b>						
25	Infrastructural constraints	57.9%	41.2%	57.9%	41.2%	less polarized
26	Lack of awareness and knowledge	78.9%	70.6%	78.9%	70.6%	less polarized
27	Shortage in skilled workforce	73.7%	64.7%	73.7%	64.7%	less polarized
28	Lack of acceptance towards new technologies	84.2%	70.6%	84.2%	70.6%	less polarized
29	Cost implications of investments	68.4%	82.4%	68.4%	82.4%	more polarized
30	Farm size, economies of scale	78.9%	76.5%	78.9%	76.5%	less polarized
31	Gaps in governmental policies and incentives	47.4%	47.1%	47.4%	47.1%	less polarized
<b>Section 4: transformation drivers</b>						
32	Economic pressures, inflation and high interest rates	73.7%	70.6%	73.7%	70.6%	less polarized
33	Growth in population	52.6%	52.9%	52.6%	52.9%	more polarized
34	Climate change-induced challenges	63.2%	64.7%	63.2%	64.7%	more polarized
35	Shifting consumer preferences	36.8%	52.9%	36.8%	52.9%	more polarized
36	The intensification of both domestic and international competition	84.2%	76.5%	84.2%	76.5%	less polarized

## V. 2. Discussion of results: first round

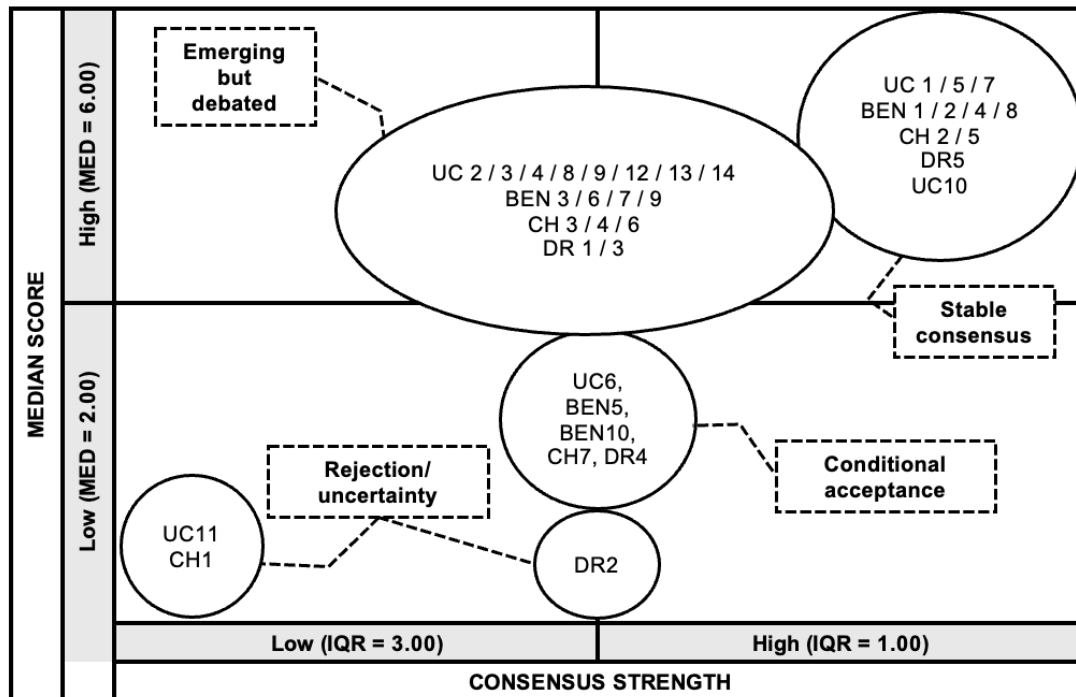
The aggregated results (three quartiles and the interquartile range / IQR) of the two Delphi rounds and the modified APMO calculations are presented in Table 25 and Table 26, respectively. The following section will provide an analysis of expert responses gathered in the **first round of the Delphi questionnaire** utilizing both of these metrics. The results were visualized first using the IQR and median scores, with the resulting layout presented in Figure 18, and the explanation of the different abbreviations shown in

The above findings can be compared and contrasted with earlier results. The main discoveries of the various bibliometric methods included five overarching themes that describe how the academic understanding of the impact of AI on agriculture and

winemaking has evolved. First, the literature shows a clear **evolution from a technological to a socio-technical focus**, shifting attention from algorithmic accuracy and automation toward the interaction between technology, people, and institutional frameworks. Second, there is a growing **importance of sustainability and resilience as central goals** to AI adoption, with the technology being increasingly viewed as a tool to support resource efficiency, environmental protection, and adaptation to changing climate conditions. Third, studies emphasise **economic and governance dimensions as critical enablers of adoption**, where financial benefits, investment capabilities, and data accountability determine implementation success. Fourth, the field is moving from **fragmented research streams toward integrated innovation ecosystems**, linking technological, behavioural, and policy perspectives. Finally, a **multi-level adoption framework** has emerged, highlighting the need for alignment across micro-level user skills, meso-level collaboration networks, and macro-level governance. Collectively, these findings indicate that AI adoption has matured beyond technical experimentation, evolving into a complex, system-level process that connects technology, sustainability, and governance dimensions.

Table 27. The different statements can be separated across four distinct themes. The top right quadrant (stable consensus with high median and low IQR) represents **mature and validated expectations** that are widely agreed upon among experts, indicating well-understood (and potentially practically proven) implications of AI in winemaking. The top middle group (**emerging but debated** themes with high median and moderate IQR) captures areas of strong interest but mixed interpretation, where experts recognise the potential but differ in assessing the feasibility or long-term value delivery potential of those. The bottom middle quadrant (**conditional acceptance**, with moderate median and moderate IQR) reflects topics viewed as relevant only under specific circumstances, such as favourable policies, market incentives, or resource availability. Finally, the bottom left quadrant (**rejection or uncertainty**, with low median and high IQR) gathers items that experts either considered less significant or about which opinions remain scattered, suggesting limited perceived importance or conceptual ambiguity in the current phase of AI adoption.

*Figure 18. Summary of the results of the first Delphi round by consensus strength and median score (source: author)*



The above findings can be compared and contrasted with earlier results. The main discoveries of the various bibliometric methods included five overarching themes that describe how the academic understanding of the impact of AI on agriculture and winemaking has evolved. First, the literature shows a clear **evolution from a technological to a socio-technical focus**, shifting attention from algorithmic accuracy and automation toward the interaction between technology, people, and institutional frameworks. Second, there is a growing **importance of sustainability and resilience as central goals** to AI adoption, with the technology being increasingly viewed as a tool to support resource efficiency, environmental protection, and adaptation to changing climate conditions. Third, studies emphasise **economic and governance dimensions as critical enablers of adoption**, where financial benefits, investment capabilities, and data accountability determine implementation success. Fourth, the field is moving from **fragmented research streams toward integrated innovation ecosystems**, linking technological, behavioural, and policy perspectives. Finally, a **multi-level adoption framework** has emerged, highlighting the need for alignment across micro-level user skills, meso-level collaboration networks, and macro-level governance. Collectively, these findings indicate that AI adoption has matured beyond technical experimentation, evolving into a complex, system-level process that connects technology, sustainability, and governance dimensions.

Table 27. Key to the summary of results of the first Delphi round by consensus strength and median score (source: author)

Stable consensus	Emerging / debated	Conditional acceptance	Rejection / uncertainty
UC 1 - Disease diagnosis UC 5 - Targeted spraying UC 7 - Barrel control BEN 1 - Early intervention BEN 2 - Yield improvement BEN 4 - Higher profit BEN 8 - Sustainability CH 2 - Awareness gap CH 5 - Investment costs DR 5 - Market competition UC 10 - Quality prediction	UC 2 - Climate forecasting UC 3 - Harvest timing UC 4 - Water control UC 8 - Wine blending UC 9 - Production scheduling UC 12 - Virtual sommelier UC 13 - Marketing strategies UC 14 - Fraud prevention BEN 3 - Targeted farming BEN 6 - Customer insight BEN 7 - Quality control BEN 9 - Climate resilience CH 3 - Skilled workforce CH 4 - Tech acceptance CH 6 - Farm size DR 1 - Economic pressure DR 3 - Climate pressure	UC 6 - Automated farming BEN 5 - Price premiums BEN 10 - Meaningful jobs CH 7 - Policy gaps DR 4 - Consumer trends	DR 2 - Population growth UC 11 - Tasting forecast CH 1 - Infrastructure limits

The findings from the first round of the Delphi questionnaire both support and challenge the outcomes of the bibliometric analysis. A clear alignment can be observed in the pattern of **expert consensus around operational and technically mature AI applications**. Similar to the early technology-focused phase identified in the literature, experts expressed the strongest agreement on use cases such as automated disease detection, targeted pesticide spraying and irrigation, or benefits such as the ability to intervene earlier against diseases and pests, or improvement in yields. These are areas where technological feasibility and tangible benefits of precision agriculture solutions were already proven. This reflects a shared understanding among experts in the panel about AI's ability to generate value through precision and efficiency. Yet, these findings also highlight that professionals primarily perceive AI's impact in

winemaking within the **technological layer of adoption**, while the literature has evolved toward a more holistic perspective.

The **sustainability dimension** also shows a high degree of convergence between academic and practitioner viewpoints. Benefits such as reduced input use and the potential to enhance the environmental sustainability of operations achieved strong consensus. This confirms the trends identified in bibliometric analysis, suggesting that **sustainability** has evolved into a **centre element of AI discourse**. However, these answers also suggest that experts predominantly interpret sustainability through the lens of efficiency and resource optimisation rather than as part of a broader resilience or social responsibility framework. This indicates that the operational side of the theme is well understood, but the transformative potential of AI as a driver of long-term sustainability transitions remains underrecognized among practitioners.

The assessment about the importance of **economic factors** also showed similarities between the Delphi results and the bibliometric findings. The expert panel confirmed that cost implications of investments and competitive pressures are decisive in driving the adoption of AI solutions in winemaking. These findings are consistent with the literature's emphasis on cost-effectiveness and value creation promises offered by AI in agriculture. Yet, while the outcomes of the bibliometric analysis show that academics increasingly link these economic aspects to governance and institutional frameworks, the participants in the expert panel treated them largely as **stand-alone considerations**, as the consensus around the impact of governmental policies, skills shortages, or acceptance of new technologies were conditional, or debated by the respondents. The divergence indicates a separation between economic and systemic governance considerations from the practitioners' perspectives.

Similarly, experts showed only conditional acceptance of **social or policy-related dimensions of AI adoption**, such as creation of more meaningful jobs, or innovation driven by consumer requirements. The importance of structural barriers (such as infrastructure or population growth) was also generally downgraded. These findings suggest that respondents perceive constraints of AI adoption in winemaking as institutional (due to lack of awareness and knowledge, or high costs) rather than

technological. Overall, the Delphi Round 1 findings confirm much of the academic understanding of AI's potential in agriculture. Yet, divergences reveal that expert perceptions still **prioritise immediate technical and financial feasibility** over the systemic, multi-level integration that characterises the more advanced scholarly models of AI-enabled transformation in agriculture and winemaking.

The modified **Average Percentage of Majority Opinions (APMO)** score provides an additional layer of insight by measuring the significance of how experts agreed or disagreed with each statement. High APMO scores, combined with favourable median values, identify themes where consensus is not only strong but also confident. This applies particularly to operational use cases such as **automated disease diagnosis, targeted spraying, and controlling barrel aging conditions** (all 84.2%), as well as key benefits like **earlier disease intervention, higher profitability, and more sustainable operations** ( $\geq 78.9\%$ ), and the driver linked to market competition (84.2%). These results reinforce the “stable consensus” quadrant, confirming that experts see these areas as proven, high-priority use cases and benefits of AI application in winemaking. A second group of items (such as **forecasting soil and climatic conditions, automated water control, quality control, and climate-related challenges**) recorded lower levels of polarization (APMO varying between 63.2–73.7%), aligning with the “emerging but debated” quadrant, where agreement is positive but still evolving. In contrast, low APMO scores (below 55%) highlight themes with uncertain or context-dependent relevance, including social or policy factors like the **impact of consumer preferences on AI adoption, creation of more meaningful job, the impact of population growth, or the importance of gaps in governmental policies**, recorded in the “conditional acceptance” or “rejection/uncertainty” areas. The only exception is **infrastructural limitations** that showed moderate decisiveness (57.9% APMO score) but low consensus, suggesting divided views that generally dismiss the impact of these constraints. Overall, the results derived from the analysis of the APMO scores confirm that expert confidence is strongest in technologically mature and economically justified domains, while social, governance, and policy dimensions continue to generate mixed or ambivalent responses.

To conclude, the results of the first-round Delphi analysis confirm several key patterns identified through the bibliometric review while also revealing areas where academic and practitioner perspectives diverge. Experts demonstrated strong and consistent consensus around AI applications driven by **operational and economic considerations**. These findings validate the literature's emphasis on efficiency and productivity improvements enabled by technological innovations. Similarly, **sustainability** emerged as a core theme, though the view demonstrated by experts was mostly focused on practical terms (e.g., input reduction and profitability improvements), as opposed to more systemic dimensions (such as improvements in social resilience). Economic factors and competitive pressures were seen as decisive adoption drivers, confirming the literature's view that **financial justification in technology implementation** remains critical. In contrast, **governance-related factors** such as policy alignment, data accountability, and institutional readiness received less agreement, suggesting a continuing gap between theoretical frameworks and industry practice. Overall, the synthesis indicates that while AI in winemaking has moved beyond conceptual experimentation with a potential shift towards integration in everyday operations, its strategic, policy, and governance dimensions are still evolving. This requires further coordination between technological, economic, and institutional domains to achieve full socio-technical alignment.

### V. 3. Discussion of results: second round

This section provides a similar analysis to the previous one, using the results of the second Delphi round. The questionnaire was completed by 17 respondents. Out of the 36 statements evaluated, no changes were observed in 15 statements for the strength of consensus (IQR equal in both rounds). For 16 statements, the consensus strengthened (decreasing IQR in round 2), while a weakening was noted for the remaining five (increasing IQR in round 2). The high-level results therefore indicate that the **Delphi method was successful as consensus strengthened** for almost 50% of the statements. The output and the explanation of the different abbreviations are shown in Figure 19 and Table 28, respectively.

Figure 19. Summary of the results of the second Delphi round by consensus strength and median score (source: author)

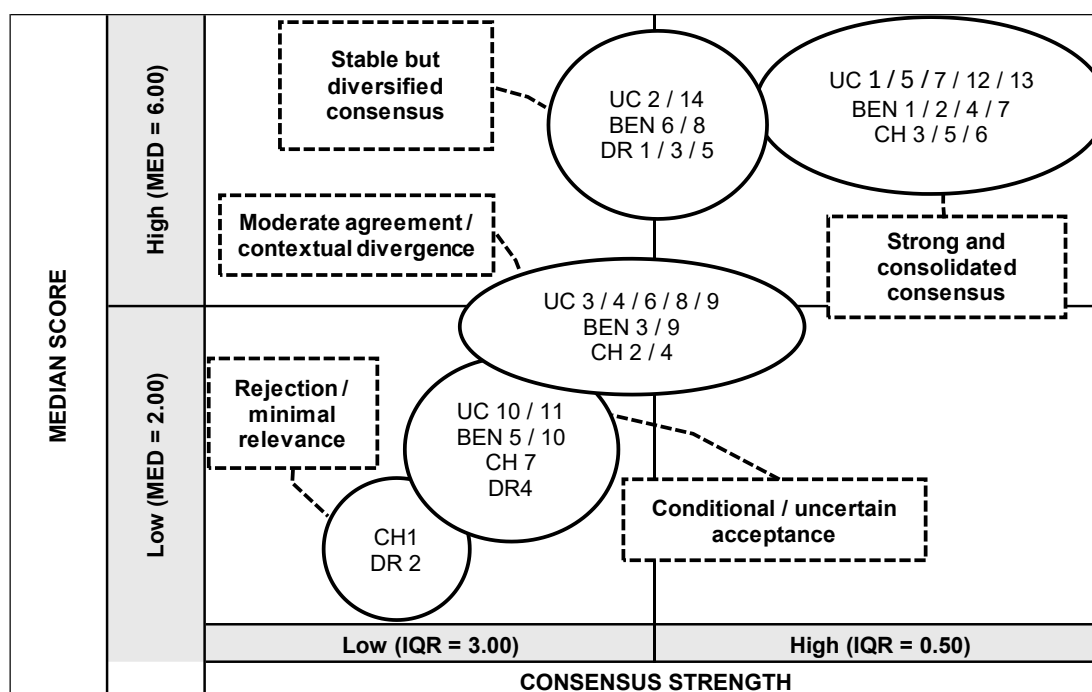


Table 28. Key to the summary of results of the second Delphi round by consensus strength and median score (source: author)

Strong and consolidated	Stable but diversified	Moderate agreement / contextual divergence	Conditional / uncertain acceptance	Rejection / minimal relevance
UC 7 - Barrel control	DR 4 - Consumer trends	DR 3 - Climate pressure	BEN 9 - Climate resilience	UC 10 - Quality prediction
CH 5 - Investment costs	BEN 8 - Sustainability	CH 1 - Infrastructure limits	CH 4 - Tech acceptance	BEN 10 - Meaningful jobs
UC 1 - Disease diagnosis	DR 5 - Market competition	DR 2 - Population growth	UC 6 - Automated farming	
UC 5 - Targeted spraying	UC 2 - Climate forecasting	CH 2 - Awareness gap	BEN 5 - Price premiums	
BEN 1 - Early intervention	UC 14 - Fraud prevention	UC 3 - Harvest timing	CH 7 - Policy gaps	
BEN 2 - Yield improvement	BEN 6 - Customer insight	UC 4 - Water control	UC 11 - Tasting forecast	
BEN 4 - Higher profit	DR 1 - Economic pressure	UC 8 - Wine blending		
UC 12 - Virtual sommelier		UC 9 - Production scheduling		
UC 13 - Marketing strategies		BEN 3 - Targeted farming		

Strong and consolidated	Stable but diversified	Moderate agreement / contextual divergence	Conditional / uncertain acceptance	Rejection / minimal relevance
BEN 7 - Quality control				
CH 3 - Skilled workforce				
CH 6 - Farm size				

The different statements can be separated into five distinct categories of themes. The top right quadrant (**strong and consolidated consensus**, with high median and very low IQR) represents mature and validated expectations that are widely accepted among experts. The second quadrant (**stable but diversified consensus**, with high median and moderate IQR) captures areas where experts broadly agree but differ slightly in emphasis or perceived scope, typically reflecting issues that are accepted, but require more careful consideration and analysis. The third group (**moderate agreement with contextual divergence**, with high median but higher IQR) includes topics that experts generally support but evaluate differently depending on context, such as organisational readiness or environmental variability. The fourth quadrant (**conditional or uncertain acceptance**, with moderate median and mixed IQR) represents issues seen as relevant only under certain conditions, including market or policy dependencies. Finally, the bottom left quadrant (**rejection or minimal relevance**, with low median and higher IQR) contains statements that experts consistently rated as less significant, indicating limited perceived importance for current AI adoption in winemaking.

The findings from the second round of the Delphi questionnaire reinforce several patterns identified in previous sections of this research, while also demonstrating a higher degree of convergence among expert opinions. The strongest consensus emerged around **operational and technically mature applications** of AI in winemaking. Use cases such as controlling barrel aging conditions, automated disease diagnosis, targeted spraying, and virtual sommelier services achieved the most stable agreement combined with an optimistic view. These results underscore the practical implementation opportunities of AI in monitoring, process optimisation, and product differentiation activities in the wine industry. The findings align with the observation from the bibliometric analysis, showing AI's potential in agriculture evolving from experimental models to tools that are embedded in everyday operations and used systematically. It is also apparent that experts still emphasised the technological layer

of adoption more strongly than its organisational or governance dimensions, indicating that the socio-technical interpretation found in academic research is yet to be fully reflected in practice.

**Sustainability and environmental performance** continue to serve as central connecting themes between the Delphi results and bibliometric findings based on the outcomes of the second round. Benefits such as higher profitability through reduced inputs, improved yields, and more sustainable operations received consistent endorsement from experts in the panel, confirming the literature's view that sustainability has become an integral part of the AI innovation agenda in agriculture. Nevertheless, the answers continue to indicate that sustainability is still viewed as a driver towards operational efficiency improvement rather than the enhancement of systemic resilience, confirming earlier results. This suggests the strategic and institutional dimensions of sustainability-driven innovation in winemaking are still emerging within the professional discourse.

**Economic and governance-related aspects** also show alignment with bibliometric insights, but the depth of consensus remains differentiated. Investment costs and market competition received high median ratings and consensus, confirming that financial viability and competitive pressures are key determinants in the AI adoption process in winemaking. However, responses received for items related to policy incentives, consumer trends, and social impact (such as the creation of more meaningful jobs) uncovered mixed or divergent views. These provide further confirmation that wider contextual considerations (such as institutional and policy frameworks) are still perceived by experts as secondary in nature, compared to immediate financial or operational priorities. This diverges from the academic perspective, which views economic and governance mechanisms as interconnected enablers of large-scale AI adoption, yet the views converge with the broader Delphi findings showing that experts continue to prioritise technological and economic dimensions over systemic, governance-driven layers.

Finally, similar to earlier bibliometric findings, low consensus was found for **traditional structural constraints**, including infrastructure and population growth,

which were considered minor contributing factors to AI adoption in winemaking. This supports the idea that the adoption barriers in winemaking are no longer technological but organisational and institutional. Overall, the second-round Delphi results confirm that expert thinking is converging around the same economic, technological, and environmental dimensions identified in the literature. Yet, they also reveal that the deeper socio-technical and governance integration patterns identified in academic research remain at an early stage in professional understanding. These findings point to a gradual (but still, incomplete) alignment between theoretical and practical perspectives on AI-enabled transformation in winemaking.

The analysis is concluded by reviewing the modified Average Percentage of Majority Opinions (APMO) scores from the second Delphi round, as these provide additional insights into how strongly experts agreed or disagreed with each statement. High APMO values (such as those for **automated disease diagnosis** (94.1%), **targeted pesticide spraying** (100%), **early intervention against diseases** (94.1%), and **cost implications of investments** (82.4%)) confirm that these items represent areas with the least polarized views, reinforcing the “strong and consolidated” quadrant identified earlier. Similarly, consistently high scores for **virtual sommelier services**, **marketing applications**, and **sustainability-related benefits** (each above 76.5%) demonstrate growing confidence in the commercial and environmental value of AI applications in winemaking. Moderate APMO results (between 60–70%) point to topics that remain agreed in principle but show inconsistent strength of agreement (mainly issues related to **workforce themes**, **governance questions**, and **climate resilience**). Lower APMO values, such as those for **infrastructural constraints** (41.2%), **policy gaps** (47.1%), and **population or consumer-related factors** (52.9%), highlight weakly formed or potentially inconsistent opinions, confirming their limited perceived relevance. Overall, APMO outcomes strengthen the conclusion that expert consensus regarding AI adoption in winemaking in Round 2 is not only stronger but also more centred around operational, economic, and sustainability-related aspects.

#### V. 4. Comparison of findings between Delphi Rounds 1 and 2

The comparison of the results across the two Delphi rounds reveals how expert judgment evolved. Movements can be classified as **positive** (e.g., stable consensus changing to strong and consolidated), **negative** (e.g., conditional acceptance changing to rejection), or **neutral** (e.g., emerging and debated themes changing to moderate agreement), with most statements exhibiting positive or neutral movement across the consensus spectrum. Out of all 36 statements, a significant majority advanced toward higher agreement and lower uncertainty, demonstrating that the Delphi approach achieved its objective and the iterative process followed was effective in refining and stabilising expert views. Positive shifts were most visible among **technically mature and economically relevant items**. Use cases related to earlier disease diagnosis, targeted pesticide spraying, and controlling of barrel conditions moved from “stable” to “strong and consolidated consensus”, confirming experts’ growing confidence in well-established operational applications of AI in winemaking. Similarly, **benefits linked to productivity and profitability** (earlier intervention against diseases, improvement in yields, or higher profitability) and the challenge related to high upfront investment costs reinforced the central importance of efficiency and return-on-investment considerations in AI adoption decisions. These developments correspond with the findings of bibliometric analysis results, indicating a move from simple conceptual consideration to practical applications of AI in winemaking.

The sentiment also advanced positively across a second group of statements, but the convergence was more nuanced, moving from categories such as “emerging or debated” to “stable but diversified.” Examples include **winemaking relevant AI use cases** in forecasting climate conditions, or fraud prevention, benefits harnessed due to improved consumer insights generated, or economic pressures acting as driving forces of AI adoption. These patterns indicate that experts are becoming more confident in higher-order analytical and market-driven applications of AI in the wine sector, although the associated opinions are still somewhat dispersed. The movement of previously rejected or uncertain items (such as infrastructural limitations as implementation challenges, population growth as drivers of AI adoption, or using the technology for forecasting tasting experiences) into moderate or conditionally

accepted categories further shows that experts view these as potentially relevant factors, depending on the context. These positive shifts demonstrate that round 2 brought experts closer to the **multifaceted understanding of AI adoption in winemaking**, particularly by recognizing that such endeavour cannot be viewed as a purely technological effort, rather than an initiative shaped by wider (environmental and economic) conditions.

Neutral movements were mostly relevant for items where consensus was in the mid-range. Items such as use cases related to automated farming, the benefits recognized from improved ability to charge price premiums, or challenges related to policy gaps remained conditionally accepted, while several other operational and environmental statements stayed within the “moderate” zone. These patterns indicate that whilst there is a continuing consensus on the impact of these themes in principle, but the **interpretation depends heavily on contextual factors**, such as the availability of policy support, cost structures, or technological readiness of individual companies in the wine value chain. This consistency also means that, while understanding of the basic layers of the impact of AI on winemaking is improving, the **wider social and organisational drivers and implications** of the technology is **yet to be fully appreciated** by practitioners. This is also in line with the findings of the bibliometric analysis suggesting that systemic alignment across micro-, meso-, and macro-levels is still incomplete.

Negative movements were limited to few items yet still provide meaningful insights for the purpose of this research. The consensus related to benefits due to the improvement in sustainability and intensifying market competition as adoption driver slightly weakened. The patterns suggests that while these issues remain relevant, their interpretation became more diversified among respondents. The view around the benefits associated with the creation of more meaningful jobs, challenges related to awareness gaps, and wine quality prediction use cases declined further. The patterns confirm that expert opinions are fragmented around **social** (AI’s impact on job market), **cognitive** (the importance of AI knowledge among practitioners), and **trust-related** (AI’s ability to reliably replicate sensory or human-judgment-based evaluation) factors. These variations add further confirmation that, despite the overall

convergence in expert opinions, socio-technical and human-centred aspects of AI adoption are yet to progress further, compared to the operational and financial implications. These findings mirror the observations derived in various earlier stages of this research, with academics transitioning towards integrated, governance-driven models of AI adoption in winemaking (agriculture), whereas expert practice still focuses primarily on technological and economic feasibility.

In conclusion, the comparison of the two Delphi rounds demonstrates a clear **progression toward stronger and more stable expert agreement**, particularly in areas linked to operational efficiency, profitability, and technical feasibility of AI in winemaking. Most statements moved positively across the consensus spectrum, confirming that professional understanding has become more confident and consistent around mature, economically justified applications. However, several neutral and negative shifts reveal fragmentation in socio-technical and governance-related themes. These findings indicate that while experts increasingly recognise AI in winemaking as a practical enabler of productivity and resource efficiency, its broader role as a catalyst for institutional transformation and social value creation remains underdeveloped. Achieving full alignment with the academic vision of AI-driven sustainability transitions will therefore require stronger integration between technological, economic, and governance layers.

## **V. 5. Concluding remarks**

This section aimed to assess and validate the impact of AI adoption within the wine sector along the research questions formulated. 36 statements were developed to represent potential applications and effects of AI across the wine value chain, informed by an extensive bibliometric and literature review. The Delphi method was applied with a panel of experts from various fields to reach informed consensus on these items across two iterative rounds. The process provided a rigorous, evidence-based understanding of where AI can realistically generate value in viticulture and winemaking, as well as the barriers that may limit its widespread adoption. Together, the results clarify the maturity of expert thinking on AI in winemaking and identify domains where theoretical and practical perspectives converge or diverge.

The first Delphi round confirmed strong optimism toward AI's capacity to **enhance core operational and technical processes** in winemaking. The findings reflected high confidence in AI's utility to achieve higher precision and efficiency in operations. These conclusions are consistent with earlier academic discourse focused mostly of technological phases of AI adoption in agriculture / winemaking. **Sustainability** appeared as an important topic, though it's viewed mainly through the lens of efficiency and input reduction, as opposed to positioning as a systemic transformation objective. **Economic viability and competitive pressures** were also key themes, confirming that financial considerations remain central to AI adoption decisions in winemaking in practice.<sup>1</sup> Meanwhile, areas such as workforce impact, policy gaps, and social value creation were characterized by weaker and more debated consensus, indicating limited integration of broader governance and institutional dimensions. Overall, round 1 revealed a **strong technical-economic orientation** and **partial alignment with the socio-technical and sustainability-driven frameworks** observed in academic literature.

Round 2 produced clearer and more consolidated patterns of agreement, indicating that the Delphi method successfully achieved its objective by facilitating convergence among expert opinions. Consensus strengthened for almost half of all statements, especially for **technologically mature and commercially viable applications**, including operational automation, quality control, and capabilities of AI in digital marketing activities. Similarly, **environmental and efficiency-related benefits** achieved continuously high scores, reflecting growing professional confidence in AI's ability to optimise resources and improve sustainability performance. However, some areas saw declining consensus, particularly around **social impacts, awareness, and trust-dependent applications**. These findings indicate that the evaluation of human-centric and organisational domains of AI adoption in winemaking can be still characterized with elements of uncertainty. The variations imply that while experts

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<sup>1</sup> Further context on these constraints is provided in **Appendix 7**, where the cost of selected AI-enhanced equipment is presented.

recognise AI's transformative potential, they continue to interpret its role primarily through the lenses of **technical feasibility and economic return**, with governance, cultural readiness, and ethical considerations remaining less prioritized areas in practice.

Across both Delphi rounds, expert perspectives consistently validated the technological and economic foundations of AI adoption. The growing consensus around operational and sustainability-linked themes demonstrates that the industry is transitioning **from experimentation to practical deployment**. At the same time, **continuous fragmentation** in views on the importance of education, policy, and social implications suggests that AI integration in winemaking is yet to achieve full institutional maturity. To ensure successful AI implementation in the wine industry, following a phased approach adjusted to individual contexts is essential, where **technological advancement** is integrated with **organisational readiness** and **human capability development**. Efforts should prioritise targeted education and reskilling programmes to address workforce gaps, alongside the creation of collaborative data-sharing frameworks that enable transparency and trust across the value chain. Policymakers and industry associations should focus on **supportive governance structures** and **financial incentives** to reduce the cost barriers associated with digital transformation. Equally, attention must be paid to **ethical and cultural factors**, ensuring that technology adoption complements rather than disrupts the artisanal and tradition-based identity of winemaking.

## VI. In-depth interviews with experts

In the final section of this research, the results of the in-depth interviews executed with selected experts from the panel used in the Delphi rounds will be presented. The list of participants interviewed is shown in Table 29. Selection was guided by the principle to achieve a reasonable coverage across **academia**, **policymaking** and **practice**, with the latter category including experts from various parts of the spectrum relevant to the objective of this research (including wine practitioners, AI professionals or other technology specialists). This inclusive approach ensured that multiple viewpoints were accommodated, enriching the analysis and supporting a more comprehensive understanding of the impact of AI on winemaking.

Table 29. Interview respondents' details (source: author)

Respondent number	Respondent profile
R1	Machine learning leader and business/finance graduate
R2	Aviation expert specializing in agricultural drone applications
R3	Professor specializing in agricultural economics and wine business
R4	CEO of an online wine discovery platform
R5	Wine business consultant, sommelier, and tourism expert
R6	Agriculture official, associate professor, origin protection and wine business
R7	Founder of award-winning, handcrafted Hungarian winery
R8	Academic expert and co-owner in small-scale winery
R9	Strategy consultant with expertise in technology transformation
R10	President and co-owner in viticulture equipment and solutions

The transcripts of the conversations recorded were analysed in detail first using **Gioia's method**, as discussed in the research methodology section, establishing first order concepts, second order themes and aggregate dimensions related to the different research questions. The current section will only provide the summaries of these aggregations, with more details included in **Appendix 6**. Then, a detailed content analysis was performed utilizing various **text mining** techniques, to establish a systematic view of the key themes being discussed, complementing the outputs of the previous research techniques.

## VI. 1. Thematic analysis of in-depth interviews

The interviews revealed **general agreement on AI's transformative potential** in the wine industry, particularly in **automating tasks** like text generation, error detection, customer service, and social media personalization. While already embedded in digital tools, some respondents were **sceptical about AI's long-term** significance, seeing it as a passing trend. The industry itself faces shrinking demand, inflation, and rising costs, with global production outpacing consumption. Experts distinguished between **large producers** adopting AI for efficiency and **smaller, artisanal wineries** resisting it to maintain authenticity. **New consumer trend** (sustainability, traceability, and lower-alcohol preferences) further reshape strategic priorities, highlighting both opportunity and fragmentation within the sector.

### VI. 1. 1. Presentation of findings

Regarding **the future use cases of AI in winemaking** (Table 30), multiple similar records were identified that reflect the participants' real-world experiences and views on this topic. Statements related to vineyard operations, such as disease detection and monitoring soil moisture levels to improve irrigation practices were grouped under the theme **AI for vineyard management and precision agriculture**. Similarly, references made to forecasting weather conditions and recommending practices adapted to local microclimate were assigned to the theme **AI for weather prediction and vineyard protection**. Comments about optimizing the fermentation process and enhancing quality control were categorized as **AI for process optimization in winemaking**. Other themes identified included **AI for personalized consumer engagement**, capturing insights about how wine recommendation systems driven by AI can be utilized in the future. Finally, the **AI for sustainability** theme reflected the technology's potential to reduce the (hazardous) input use of the wine industry. At a higher level, these emerging themes were aggregated into core concepts of **operational efficiency, commercial activities** and **sustainability** themes.

Table 30. Emerging themes and dimensions of AI's potential use cases in the wine value chain (source: author)

1st Order Concepts (Participant Statements)	2nd Order Themes (Emerging Patterns)	Aggregate Dimensions (Core Concepts)
"AI can detect diseases early in the vineyard" "AI monitors soil moisture and irrigation levels"	AI for vineyard management and precision agriculture	Operational efficiency
"AI forecasts weather conditions to prevent vineyard damage" "AI can monitor large areas and recommend adaptations to microclimate"	AI for weather prediction and vineyard protection	Operational efficiency
"AI optimizes the fermentation process" "AI facilitates consistency of wine quality"	AI for process optimization in winemaking	Operational efficiency
"AI personalizes wine recommendations for consumers" "AI supports targeted marketing practices and better decision making"	AI for personalized consumer engagement	Commercial activities
"AI reduces pesticide and water usage significantly" "AI can recommend climate-resistant grape varieties"	AI for sustainability	Sustainability

For the **future benefits of AI use in the wine sector**, multiple participants called out how the technology can improve water usage, reduce labour through automation, or define optimal harvest time based on weather data. These statements were grouped under the theme **operational efficiency enhancement**. Responses also highlighted AI's role in cost reduction and the optimization of different processes to ensure consistent wine quality, which were assigned to the **cost and resource optimization** and **product quality improvement** themes. Enhancing the understanding of consumer preferences and improving marketing efforts were categorized under the **consumer engagement and personalization** heading. Finally, **sustainability and environmental benefits** was also assigned a distinct category in this subsection. At a higher level, these themes were combined under the **efficiency and cost reduction**,

**product quality and consistency, market insights and consumer engagement and sustainability and environmental impact** core concepts (Table 31).

Table 31. Emerging themes and dimensions of AI's potential benefits in the wine value chain (source: author)

<b>1st Order Concepts (Participant Statements)</b>	<b>2nd Order Themes (Emerging Patterns)</b>	<b>Aggregate Dimensions (Core Concepts)</b>
"AI improves water usage in vineyard management" "AI reduces labor through automation of tasks" "AI optimizes harvesting times based on weather data"	Operational efficiency enhancement	Efficiency and cost reduction
"AI enables precision in applying chemicals" "AI supports logistics, reducing transportation costs"	Cost and resource optimization	Efficiency and cost reduction
"AI detects vine diseases early, preventing spread" "AI monitors fermentation for consistent wine quality"	Product quality improvement	Product quality and consistency
"AI enhances understanding of consumer data " "AI improves marketing strategies "	Consumer engagement and personalization	Market insights and consumer engagement
"AI assists in achieving sustainability goals" "AI will have a positive impact on sustainability"	Sustainability and environmental benefits	Sustainability and environmental impact

When discussing the key **challenges to AI implementation in the wine industry**, the main themes were centred across cultural resistance on accepting new technologies, knowledge gaps on the potential use cases and the benefits of AI in winemaking, as well as infrastructural limitations. These items were grouped under the **cultural and traditional barriers** and **technological and infrastructural constraints** concepts. Financial and legislative concerns were grouped under the aggregate dimensions of **economic and financial constraints** and **regulatory and legal challenges** headers, respectively. The results are summarized in Table 32.

Table 32. Emerging themes and dimensions of AI's potential application challenges in the wine value chain (source: author)

1st Order Concepts (Participant Statements)	2nd Order Themes (Emerging Patterns)	Aggregate Dimensions (Core Concepts)
"Winemakers resist AI due to cultural beliefs" "Winemakers fear AI reduces authenticity"	Cultural conservatism hindering AI adoption	Cultural and traditional barriers
"Traditional methods favoured over technology" "Winemakers lack knowledge about AI benefits"	Knowledge gaps and traditional winemaking methods	Cultural and traditional barriers
"Infrastructural limitations of winemaking machinery" "Concerns about existing equipment compatibility with AI"	Infrastructural limitations and outdated equipment	Technological and infrastructural constraints
"AI implementation too costly for small wineries" "High costs of AI maintenance and training"	High initial investment and other economic barriers	Economic and financial constraints
"AI adoption slowed by legal uncertainties" "Different legislation landscape across regions"	Legal and regulatory challenges in AI implementation	Regulatory and legal challenges

Finally, the analysis of transcripts about the **drivers of AI adoption and technological transformation in the wine industry** revealed themes around efficiency improvement and climate change adaptation needs. These were grouped under the **economic and environmental pressures** concept. Outputs of discussions about the increased need for digital and personalized experiences from younger wine consumers were assigned to the **consumer demand for innovation** dimension. Comments related to how innovations in other industries can influence adoption of new technologies (such as AI) in winemaking were allocated to the **cultural factors and drivers** heading. Finally, observations on how the increasing accessibility of technological innovations can provide solutions to common operational problems (such as labour shortages) in winemaking, were categorized under the **technological advancements and accessibility** construct.

Table 33. Emerging themes and dimensions of the potential drivers of AI adoption and technology transformation in the wine value chain (source: author)

1st Order Concepts (Participant Statements)	2nd Order Themes (Emerging Patterns)	Aggregate Dimensions (Core Concepts)
“Efficiency improvements through technology adoption” “Economic pressures drive cost-cutting innovations”	AI improves operational efficiency in vineyards	Economic and environmental pressures
“Winemakers need to adapt to climate change” “AI helps reduce water and energy usage”	Climate change and sustainability goals push winemakers to innovate	Economic and environmental pressures
“Younger consumers expect digital wine experiences” “AI can personalize wine recommendations”	Consumer expectations drive digital innovation	Consumer demand for innovation
“External tech companies drive AI adoption” “Wine industry slow to adopt technology”	Inspirative innovation pushes technological transformation in winemaking	Cultural factors and drivers
“AI tools become easier to implement” “Labor shortages push vineyards towards automation”	Tech accessibility improves adoption and response to operational challenges	Technological advancements and accessibility

The interviews provided additional insights beyond earlier phases, summarized in Table 34. New use cases included **AI-driven gene editing** for disease-resistant grape varieties and **AI-as-a-service models** offering ready-made, low-cost solutions for wineries. Related benefits involved improved climate adaptation and broader AI accessibility through **generative tools**. Challenges included **data quality**, **limited cooperation** among wineries, and **general risk aversion** that categorizes the industry. Emerging drivers (**simplified implementation**, **falling costs**, and **labour shortages**) further encourage adoption. Though not part of the original questionnaire, these findings conceptually align with previous themes, reinforcing the completeness and reliability of earlier results.

Table 34. Summary of additional findings uncovered during the in-depth interviews (source: author)

AI use cases	AI benefits	Implementation challenges	AI adoption and transformation drivers
Enhancing gene editing for drought-resistant rootstocks and disease-resistant clones.	AI enables vineyards to adapt to climate change by assisting in selecting grape varieties with lower pesticide needs and higher resilience to environmental challenges.	Data availability and reliability remain significant concerns, particularly in consumer-facing AI applications.	Generative AI innovations push the wine industry towards digital transformation by reducing complexity and cost barriers.
'AI as a service' lowers investment barriers, offers advanced AI tools, and provides comprehensive support packages.	Generative AI democratizes access to advanced tools, making them more affordable and usable for non-experts.	Limited cooperation in regions like Eastern Europe and reluctance to share resources slow adoption.	Labour shortages and competitive pressures drive adoption of accessible and user-friendly AI solutions.
		The risk-averse nature of winemaking due to annual harvest cycles creates resistance to new technologies.	External market conditions and advancements in AI tools ease resistance to technological innovation.

## VI. 1. 2. Discussion of results

Earlier phases in the research showed that the academic discourse has evolved from the simple discussion of technological evolution (**technology-push determinism**) to the interactions between people and new innovations (**socio-technical integration**). The Delphi analysis revealed strong optimism about technical feasibility of AI solutions in winemaking, with limited maturity in governance, skills and institutional readiness. The interview outcomes give further insights into how these issues are understood, prioritised, and interpreted by industry experts. This can be an important basis for contrasting operational aspects with theoretical frameworks, better identifying the conditions under which AI adoption in winemaking can succeed or fail. In particular, the outcome of these discussions gives a good opportunity to test whether wineries are looking at **AI as a collection of isolated tools**, or as part of a **wider integrated system**. Also, more insights could be gathered about how technological

efficiency aligns or conflicts with the **preservation of artisanal authenticity** of winemaking, and whether **sustainability** could be observed as a central theme in decision making.

The analysis of findings derived from interviews confirms and extends several key insights from previous rounds. Respondents consistently emphasized AI's transformative potential across the wine value chain, yet with clear differentiation between technological feasibility and institutional readiness. The **most frequently mentioned use cases** (disease detection, vineyard monitoring, weather forecasting, and process optimization) reinforce the **strong and consolidated consensus around operational and technical dimensions** identified when using the Delphi method. Recall that the bibliometric analysis noted the high representation of studies related to precision agriculture, with methodology dominated by quantitative and engineering approaches. Therefore, participants' descriptions of these as areas where AI is already providing value in winemaking support observations that adoption maturity is highest among **data-rich, repetitive, and quantifiable tasks**. At the same time, interviewees highlighted the **need for contextual adaptation**, noting that vineyard-specific microclimates, varying infrastructure, and data quality constraints limit the generalizability of many AI-driven solutions in the wine sector.

Beyond operational efficiency, several respondents pointed to emerging commercial and sustainability-related applications, such as **personalized consumer recommendations** or **optimized pesticide and water usage**. These findings also align with the Delphi results where benefits related to resource efficiency and environmental performance gained strong consensus, with experts continuously interpreting sustainability primarily through the lens of productivity and cost savings. Themes related to **consumer engagement and marketing** received more cautious endorsement, mirroring the moderate Delphi consensus and revealing concerns about the subjective nature of wine appreciation and the challenges associated with the availability of relevant data. Overall, the interviews support the Delphi's conclusion that AI in winemaking is transitioning from **experimentation to practical deployment**. Also, the **strong focus on operational benefits** underscores that

discussions about the socio-technical and governance-related integration of technology remains at an early stage, reflecting a pattern consistent with both the bibliometric and Delphi findings.

The discussions on the **perceived benefits of AI adoption** provide a more detailed understanding of how experts assess the technology's value. The most prominent themes (efficiency enhancement, cost reduction, and quality improvement) closely mirror the areas of strongest consensus observed in the Delphi results, particularly regarding benefits such as **earlier disease intervention, improved yields, and higher profitability**. Respondents emphasized that automation and data-driven decision-making can significantly **reduce waste, optimize resource use**, and enhance the **consistency of wine quality**. The findings also reveal that such positive effects are more relevant in **large-scale operations** where precision and standardization are critical (and potentially more advanced). These findings reinforce the bibliometric analysis, which identified a growing body of research connecting AI adoption to measurable productivity gains and economic performance improvements. However, several interviewees cautioned that efficiency improvements are only sustainable when accompanied by **long-term investments in data architectures, analytics capabilities, and human expertise**.

**Sustainability** emerged as a recurring benefit, though once again it was interpreted through an operational rather than systemic lens. Interviewees associated AI with water conservation, reduced pesticide use, and climate adaptation, aligning outcomes with the Delphi panel's strong support for environmentally linked applications. Yet, few respondents extended this perspective to broader sustainability-related issues such as **social responsibility** or **circularity**. Conversely, the interviews revealed more **scepticism about the economic and social benefits of AI** use identified in earlier rounds. For instance, the potential for AI to generate price premiums or create more meaningful jobs received mixed reactions. Many participants saw limited consumer willingness to pay more for technologically optimized wines, while others argued that automation could initially displace, rather than enhance, human roles, unless accompanied by targeted upskilling and reskilling initiatives.

The interview findings provide further insight into the **implementation challenges** identified through the Delphi rounds. Cultural and traditional factors emerged as particularly significant barriers, with interviewees highlighting that winemaking's **deep-rooted traditions foster resistance to change**. Recall that the consensus in the Delphi rounds related to awareness gaps (CH 2) and technology acceptance (CH 4) moved from stable / emerging consensus to moderate agreement / uncertain and conditional acceptance. This minor decline in agreement and certainty is therefore potentially explained by the cultural divide between traditional and progressive actors, differing levels of digital literacy, and the perceived inapplicability of AI for smaller, artisanal wineries. Together, these factors confirm that views about the relevance and feasibility of AI in winemaking are fragmented, suggesting that while the technology's potential is widely acknowledged, its **acceptance remains uneven and context-dependent** across different segments of the wine industry.

Technological and economic constraints were also emphasized by the respondents, supporting earlier findings that the feasibility of AI adoption in winemaking is largely dependent on **economies of scale** and **capital availability**. Respondents described outdated equipment, fragmented data systems, and the small operational size of many wineries as key bottlenecks to technological innovations. These insights validate why obstacles related to cost of investments (CH 5) remained a strong and consolidated challenge. At the same time, new insights emerged regarding **data availability** and **reliability** (especially for consumer-facing applications) which were identified as previously underacknowledged, but critical barriers. Finally, **legal and regulatory uncertainty**, represented by policy gaps in the questionnaire (CH 7), persisted as a conditionally accepted issue. Interviewees cited inconsistent legislation across markets and stringent European wine regulations as blockers to technology experimentation in the sector. These findings reinforce the view that **institutional and policy readiness** can **hinder technological progress** and the implementation of new innovations (such as AI) in the wine sector.

The interview results provide additional layers to the understanding of the **drivers that shape AI adoption in winemaking**. Economic and environmental pressures were

confirmed as primary motivators of technological transformation, as respondents repeatedly emphasized the necessity of efficiency improvements in response to **rising costs, labour shortages, and sustainability imperatives**. These findings reinforce the Delphi results, where economic and climate-related drivers (DR 1 and DR 3) achieved stable or moderately positive consensus, indicating that practitioners view AI as an important tool to mitigate financial and ecological risks. **Consumer demand** for innovation also emerged as a potential driver of adoption. Experts noted that younger generations increasingly expect **personalized, digital experiences**, while traditional wine consumers remain less influenced by such factors, highlighting the context-dependent relevance of those. These findings correspond to the conditional acceptance pattern observed for the same driver (DR 4) in the Delphi analysis.

The results indicate that some experts see AI as essential for maintaining cost competitiveness, and others view its advantage limited to technologically advanced wineries only. These insights provide potential clarification about why the consensus for **competitive pressure (DR 5)** weakened slightly between the Delphi rounds. Finally, a new and transformative driver (**technological accessibility through generative AI**) emerged strongly in the interviews. Multiple respondents emphasized the **commoditization of technological innovations** and the significant drop in barriers to entry with the appearance of accessible user friendly chatbots based on adequately trained and tested Large Language Models (LLMs). As the appearance of these became widespread since early 2023, it is normal that such dynamic was not captured in the Delphi questionnaire, as the scientific articles covered didn't place emphasis on this topic. Yet, these findings offer a plausible explanation for growing optimism and stabilizing consensus around digitally enabled use cases such as improved marketing strategies (UC 13) or virtual sommelier services (UC 12).

## VI. 2. Text mining results

The final element in the overall research methodology is the text mining of interview transcripts, and this section presents the key findings derived from the application of this technique. The analysis covers the outputs of multiple methods, including frequency counts, lexicon-based sentiment analysis, term frequency - inverse document frequency (**tf-idf**) scores and Latent Dirichlet Allocation (LDA) analysis. The aim is to better understand underlying thematic structures and topic distributions present in the interviews, corroborating or challenging earlier results. Together, these approaches offer a comprehensive understanding of the main themes, sentiments, and patterns shaping the discourse on AI in the wine industry.

### **VI. 2. 1. Presentation of findings**

The first step in the text mining exercise was to analyse the frequency count of relevant terms in the interview transcripts. Following several iterations, words appearing at least 30 times in the dataset were visualized on a horizontal bar chart and a word cloud. The outputs are shown in Figure 20 and Figure 21.

As the word counts shows, the data can be separated into **three major clusters**. The first cluster includes the words “**AI**,” “**wine**”, and “**data**” which appear more than 100 times in the cleansed dataset, aligning with the objective of this study and the research questions. The second batch of words includes the terms “**industry**”, “**technology**”, and “**winemaking**” appearing at least 50 times in all the transcripts. Following this cluster, there is a gradual decline in word frequencies. Examples from the three quartiles include “**know**”, “**significant**”, “**change**”, “**believe**”, “**solutions**”, “**better**”, and “**first**”. These words suggest a positive and transformative view among participants on AI’s impact on winemaking, which will be explored further in the next section.

*Figure 20. Most frequent words appearing in the cleaned dataset (Frequency  $\geq$  30) (source: author)*



outcome of the sentiment analysis is presented in multiple outputs. Table 35 shows the **40 most frequent words and associated sentiments** based on the NRC Lexicon. Figure 22 presents the binary outcome of the sentiment analysis, showing the **frequency of positive and negative words**, while Figure 23 provides further insights by displaying the **top five positive and negative words** in the interview transcripts.

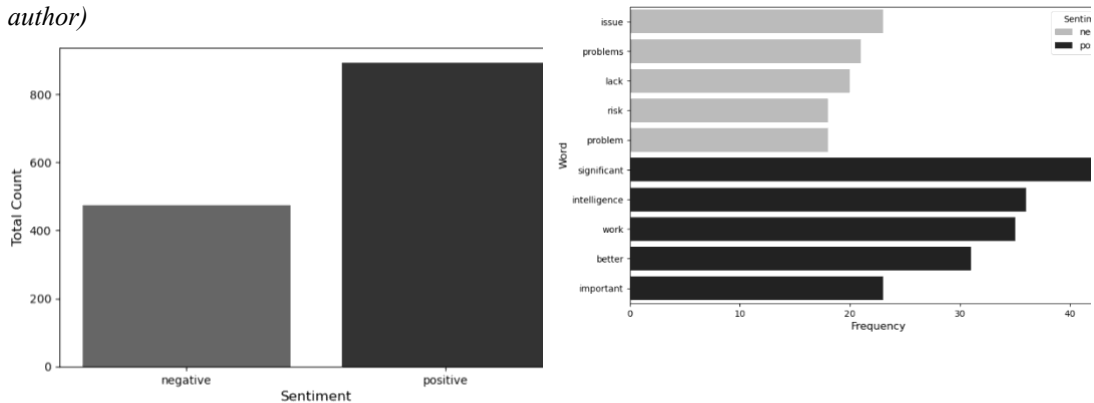
*Table 35. Sentiment analysis of the 40 most frequent words using the NRC Lexicon (source: author)*

Word	Count	Sentiment	Word	Count	Sentiment
production	40	anticipation	technology	78	positive
time	30	anticipation	production	40	positive
risk	18	anticipation	intelligence	36	positive
harvest	17	anticipation	knowledge	32	positive
wont	16	anticipation	question	31	positive
labour	15	anticipation	information	26	positive
efficient	14	anticipation	understanding	23	positive
long	13	anticipation	important	23	positive
result	13	anticipation	crucial	21	positive
start	12	anticipation	model	18	positive
small	22	negative	intelligence	36	trust
lack	20	negative	understanding	23	trust
problem	18	negative	important	23	trust
risk	18	negative	crucial	21	trust
case	16	negative	labour	15	trust
drone	15	negative	efficient	14	trust
challenge	14	negative	provide	13	trust
bad	13	negative	achieve	12	trust
soil	13	negative	system	12	trust
disease	12	negative	management	12	trust

The next step was the calculation of the term frequency - inverse document frequency (**tf-idf**) scores for the five main categories in the final codebook used for tagging the interview transcripts. The **first four categories** (use cases, benefits, challenges, and AI implementation drivers) correspond to the research questions formulated at the start of this study. The **last category** (other) captured emergent themes that were not part of the initial Delphi questionnaire. For the purposes of this calculation, a **revised version of the dataset was used**, showing tags from the Taguette software alongside

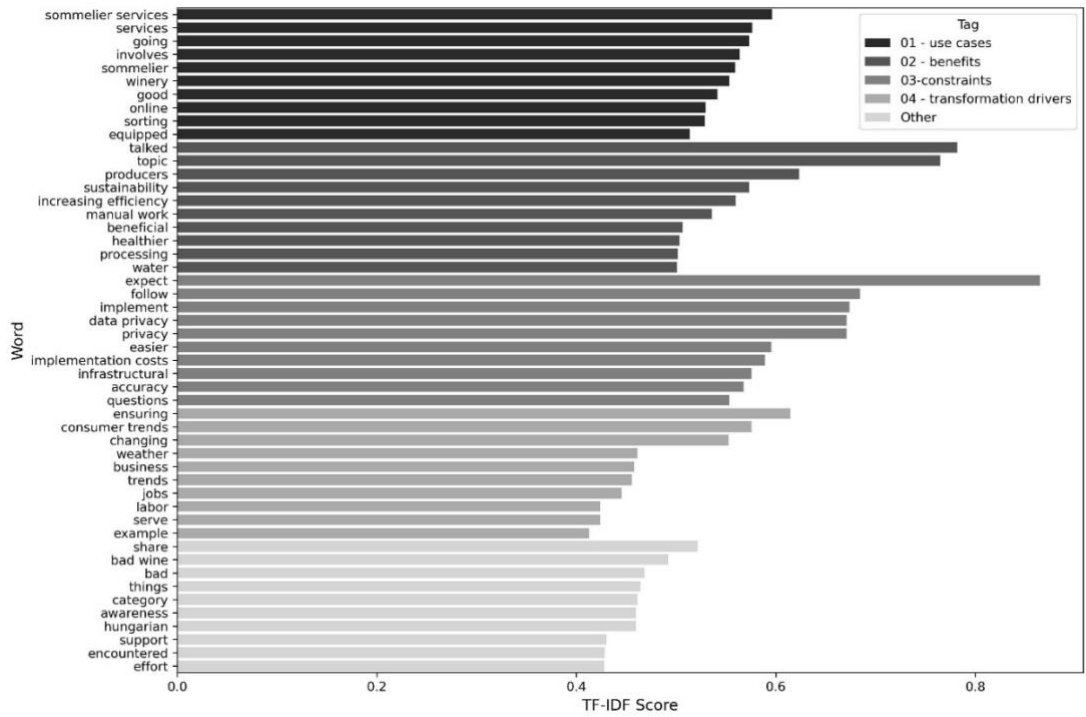
these five categories and the comments made by participants assigned to those. The final outcomes of the tf-idf score calculations are presented in Figure 24.

Figure 22. Binary sentiment analysis of Figure 23. Top five positive and negative words transcripts using the Bing dictionary (source: author)



In the **use cases category**, terms with the highest tf-idf scores include “**sommelier services**“, “**winery**“, “**online**“, or “**sorting**“. In the benefits category, high scoring terms such as “**sustainability**“, “**increasing efficiency**“, “**beneficial**“, or “**healthier**” align with earlier findings. In the challenges category, highest ranked terms like “**data privacy**“, “**implementation cost**“, “**infrastructural**“, and “**accuracy**” highlight barriers to AI adoption, including data security concerns, financial constraints, and limited infrastructure readiness. For the adoption drivers category, terms such as “**consumer trends**“, “**changing**“, “**weather**“, or “**jobs**” emphasize external pressures like shifting consumer preferences and climate unpredictability, which can act as forces driving companies in the wine value chain to adopt AI or other technological innovations. Finally, in the other category, words like “**awareness**“, “**Hungarian**“, “**support**“, or “**effort**” provide region-specific insights, including challenges in Hungary and broader observations about AI awareness and support mechanisms.

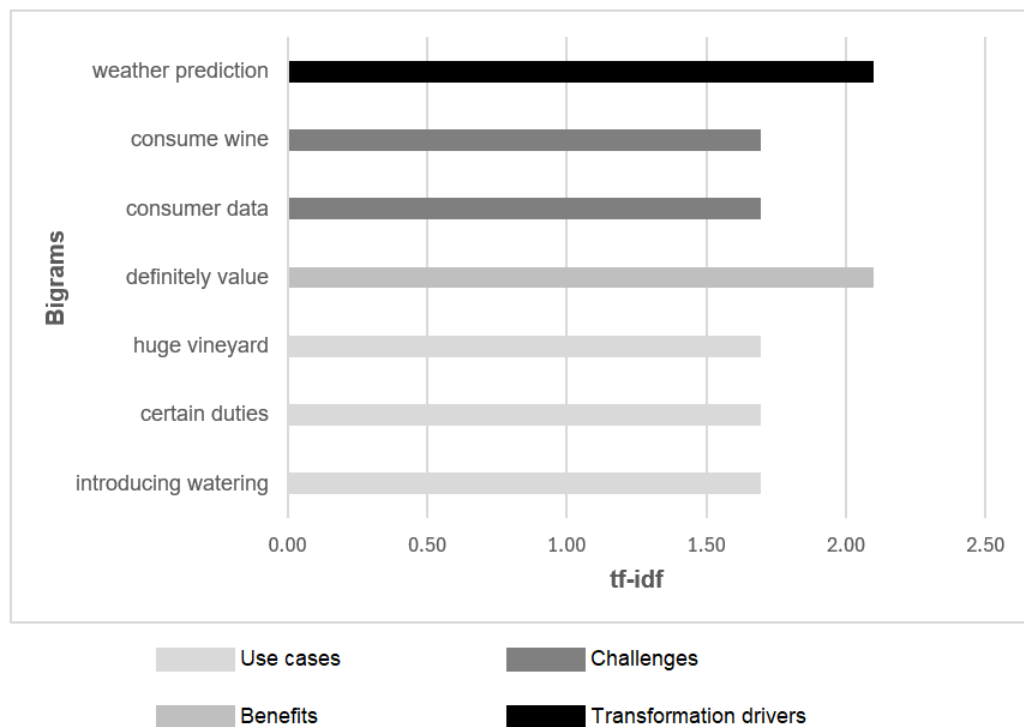
Figure 24. Top 10 words by tf-idf score for the different dimensions used in the research (source: author)



As described in the research methodology section, **bigrams** were also extracted and their respective tf-idf scores were calculated to enhance robustness of results. The bigrams with the highest tf-idf scores per response category are visualized in

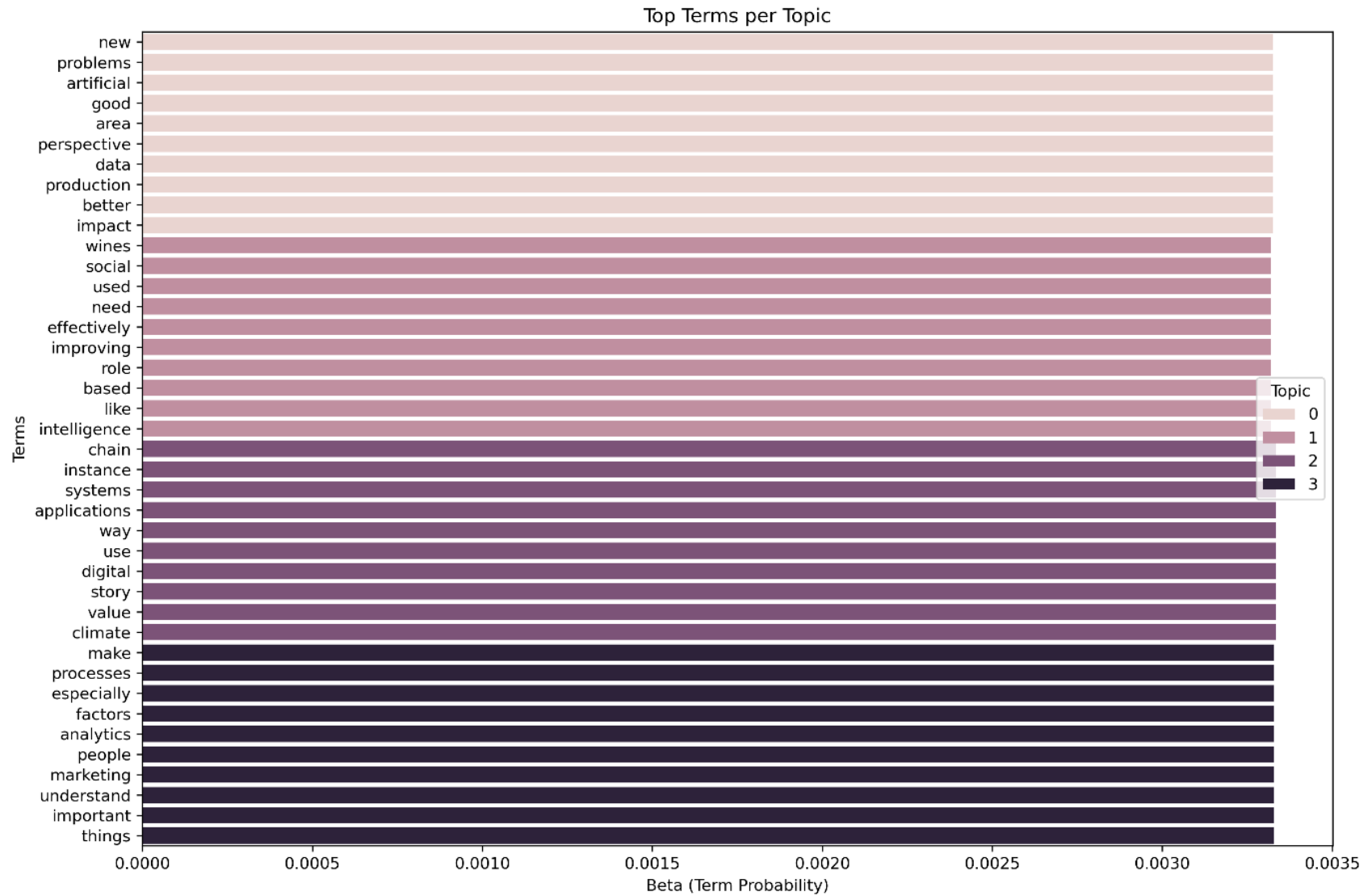
Figure 25. For the use cases category, bigrams such as “introducing watering”, “**certain duties**” and “**huge vineyard**” suggest frequent discussions around AI’s impact on field operations and jobs across the wine value chain. The reference to vineyard size can indicate AI’s capability to facilitate repetitive tasks on large land areas or that the implementation of the technology is more viable in larger plots. In the benefits dimension, the term “**definitely value**” reflects participants’ positive views on the advantages AI can bring to the wine value chain. In the challenges category, bigrams like “**consume wine**” and “**consumer data**” highlight complexities in the consumer journey and challenges in obtaining suitable datasets to train AI tools. The term “**weather prediction**” in the transformation drivers category underscores climate unpredictability as a major driver for adopting AI in winemaking.

Figure 25. Bigrams with highest tf-idf score per response category (source: author)



Finally, the **Latent Dirichlet Allocation (LDA) analysis** was employed to uncover and summarise the main themes arising from the interview transcripts, offering structured insight into the key topics discussed. The final output is presented in Figure 26. The first topic includes the words “new”, “**problems**”, “**artificial**”, “**good**”, “**area**”, “**perspective**”, “**data**”, “**production**”, “**better**” and “**impact**”. These keywords suggest a central theme among participants that is focused on innovation and challenges associated with adopting AI in the wine industry. The words also indicate a theme centred on improving production efficiency and understanding the wider implications of integrating technological innovations in the sector.

Figure 26. Output of topic modelling using Latent Dirichlet Allocation (LDA) (source: author)



The second topic includes the keywords like “wines”, “social”, “used”, “need”, “effectively”, “improving”, “role”, “based”, “like” and “intelligence”. These terms indicate the existence of a topic that is skewed towards the social dynamics and human-centred aspects of winemaking, as well as discussions about how AI can be leveraged to enhance existing practices and fulfil industry needs. The third cluster consists of the words “chain”, “instance”, “systems”, “applications”, “way”, “use”, “digital”, “story”, “value” and “climate”. These terms suggest that parts of the discussions are centred around the practical implementation of digital tools and technologies within the wine sector, highlighting the importance of addressing climate-related challenges and creating value through innovative approaches. The last topic consists of the words “make”, “processes”, “especially”, “factors”, “analytics”, “people”, “marketing”, “understand”, “important” and “things”. These terms highlight again the significance of understanding and optimizing processes within winemaking, through technology implementation, as well as the importance of leveraging data analytics to better understand consumer behaviour and enhance marketing strategies. The topics identified were labelled and summarized in Table 36 to ease interpretation.

Table 36. Summary of topics generated using the LDA method (source: author)

Topic number	Topic label	Brief description of topic
0	Technology and production impact	The topic explores how AI, and technological innovations can enhance <b>efficiency in wine production</b> , and <b>integration</b> of those in the wider wine value chain.
1	Social dynamics and intelligence	The theme focuses on the role of <b>social dynamics</b> in winemaking, and how AI can <b>enhance intelligence</b> and <b>improve decision making</b> in the wine value chain.
2	Digital transformation and climate adaptation	The cluster highlights the importance of <b>implementing digital systems</b> in the wine value chain, to enhance <b>sustainability, resiliency</b> and <b>value creation</b> .
3	Process optimization and consumer insights	The proposition covers <b>process improvements</b> , <b>consumer analytics</b> , and development of <b>marketing strategies</b> through the use of AI and other technological innovations.

## VI. 2. 2. Discussion of results

The text mining analysis confirms that discussions about AI use cases in winemaking are primarily centred on **operational and process-oriented applications**, reflecting a continuation of the patterns identified through the bibliometric and Delphi analyses. The most frequent words in the corpus underscore a strong technological and production-oriented focus of the themes discussed, suggesting a view of looking at AI as an enabler of precision, monitoring, and optimization. These findings mirror the earlier findings that AI adoption maturity is high in **data-rich environments**, looking at the implementation as a question of technological feasibility. Interview participants continuously associate AI with vineyard and cellar-level efficiency gains, with strategic or governance-related transformations lacking widespread representation.

The tf-idf analysis further underscore these tendencies, where top-ranked terms indicate that experts see valid use cases of AI across both **production and customer-facing functions**, including application examples such as automated quality control and personalized wine recommendations. Yet, participants' continuous emphasis on questioning AI's ability to replicate human judgement in sensory or experiential dimensions **moderates this optimism**. These findings provide support to the Delphi panel's limited consensus on consumer-oriented use cases of AI in winemaking. Similarly, themes identified in bigrams reinforce earlier findings about the perception of AI's feasibility and advantage in **large-scale, repetitive operations**, while smaller producers may remain constrained by resource and infrastructure barriers. LDA results reinforce these interpretations further, where Topic 0 ("**Technology and production impact**") and Topic 3 ("**Process optimization and consumer insights**") both indicate that professional discourse is dominated by underlying themes related to production efficiency, automation, and quality enhancement. Together, these results confirm that AI's perceived role in winemaking remains **strongly tied to operational dimensions**, further reinforcing the observations derived from the bibliometric that technological rather than socio-organizational themes dominate the AI adoption landscape in winemaking.

The text mining results reveal that the perceived benefits of AI in winemaking are strongly concentrated around themes of **efficiency, cost reduction, sustainability, and quality enhancement**. These mirror earlier findings derived from the Delphi rounds and the thematic analysis of interviews. In the frequency and sentiment analyses, terms dominating the **positive and anticipation categories**, underscore participants' overall optimism toward the integration of AI technologies into winemaking. The results also imply that participants perceive AI primarily as an enabler of **productivity improvement**. This is consistent with the bibliometric conclusion showing how the technology has evolved from conceptual innovation toward **practical efficiency enhancement** within the agricultural domain. The distribution of sentiments shown in Figure 22 and Figure 23 further confirms this interpretation. Positive emotions outnumber negative ones by a wide margin, indicating that there is a prevailing belief among participants about AI's ability to contribute to measurable performance gains in the wine sector.

The tf-idf and LDA analyses reinforce this pattern, with terms related to **sustainability** and **efficiency improvement** receiving high tf-idf scores. These align closely with Delphi statements showing strong and strengthening consensus, such as BEN1 (earlier intervention), BEN2 (improved yield), and BEN4 (profitability). Likewise, the LDA Topic 2 ("**Digital transformation and climate adaptation**") highlights sustainability, resilience and value creation as emerging benefit domains. The sentiment distributions reinforce this optimism, indicating confidence in AI's capacity to generate various benefits. Yet, it is clear that the language remains predominantly **operational and instrumental**, focusing on immediate gains rather than systemic or governance-level outcomes. Overall, the text mining evidence supports the conclusion that **AI's perceived benefits in winemaking are performance-oriented**, reinforcing earlier findings that industry expectations are tilted towards efficiency improvement, as opposed to transformative changes in the value chain.

The results highlight that implementation challenges and barriers form one of the most complex and versatile themes in the interview corpus. The most recurrent challenge-related words reveal that the difficulties in adopting AI in winemaking are understood

as both **structural** (limited scales and resources, less formalised processes) and **behavioural** (knowledge and awareness gaps, risk perception and aversion). This finding is somewhat contradictory with the Delphi outcomes, where consensus weakened between rounds for awareness gaps (CH2), or received only moderate agreement for technology acceptance (CH4). The tf-idf analysis adds further layers to this interpretation, with high-scoring terms highlighting three dominant clusters of constraints: **data governance** considerations, **financial limitations**, and **technical readiness**. Similarly, the **bigrams** indicate the importance of difficulties in accessing or managing datasets related to consumption patterns or consumer preferences. These findings underscore interviewees' concerns about **data privacy**, **fragmented data ownership**, and **regulatory ambiguity** when assessing the feasibility of AI implementation in winemaking.

Combining these findings with the **sentiment analysis results** (Figure 22) reveals that expressions related to challenges contribute disproportionately to the negative sentiment category. The results indicate that while participants see AI's potential in winemaking, they are aware of the industry's structural weaknesses hindering the technology's widespread adoption. Combining these with the LDA topics (especially, Topic 0, "Technology and production impact" and Topic 1, "Social dynamics and intelligence"), underscore that the barriers in the wine sector are deeply connected with **cultural conservatism**, **cost constraints**, and **infrastructural readiness**. Overall, the text mining results confirm that the industry's main bottlenecks to AI adoption are **institutional and socio-technical** rather than purely technological, reinforcing earlier findings from both Delphi and qualitative analyses.

Finally, the text mining results reveal that the drivers of AI adoption and transformation in the wine sector are primarily shaped by **economic pressures**, **environmental challenges**, and **shifting consumer expectations**. High-frequency terms with high tf-idf scores suggest that wineries are motivated to explore AI solutions mainly as a response to **market volatility**, **climate unpredictability**, and **labour shortages**. This interpretation aligns with the Delphi findings, where the strongest consensus on what was triggering AI implementation in the wine sector was reached for external drivers

(e.g., DR1 – economic pressure and DR4 – consumer trends) rather than internal organisational initiatives. The appearance of “**weather prediction**” among the top bigrams further reinforces the growing recognition of AI’s value in enhancing climate resilience through predictive analytics, or adaptive vineyard management.

The LDA Topic 2 (“Digital transformation and climate adaptation”) provides additional support for this interpretation, highlighting the **convergence between digitalisation and sustainability goals**, suggesting that experts view AI as a tool to future-proof the industry against environmental and operational risks. Similarly, the presence of “consumer”, “marketing”, and “analytics” in Topic 3 underscores that **changing consumer preferences and demand for personalised experiences** are also shaping technological adoption pathways. Sentiment analysis complements these insights by showing that words linked to drivers often fall within the anticipation and trust categories, reflecting cautious optimism about AI’s ability to enhance competitiveness in the winemaking sector. However, the absence of strong governance or policy-related vocabulary suggests that these adoption forces remain market-led rather than shaped by institutional factors. Taken together, the text mining results reinforce earlier findings from the Delphi and interview analyses by confirming that AI-driven transformation in the wine industry is driven by **external factors** (necessity and opportunity), such as **climate adaptation** and **consumer-driven innovation**.

### VI. 2. 3. Concluding remarks

The aim of this section was to explore how experts see the impact of AI in winemaking using **in-depth interviews** to uncover fine-grained insights that supplemented or contradict findings from the previous sections of this study. The **qualitative nature of the interviews** allowed for the exploration of technological aspects of AI adoption, as well as the social, cultural, and operational factors influencing AI’s implementation in the wine industry. The use of various **text mining approaches** adequately complemented unstructured format of the interviews and highlighted common topics discussed during those, as well as the sentiment towards the impact of AI in winemaking among participants.

The interviews revealed a diverse range of AI use cases that could have a transformative impact on the wine industry. The most discussed topics included **optimized vineyard management practices** through precision agriculture, **enhancement of fermentation, blending and quality control** procedures, and **improvement in consumer engagement** through a more in-depth analysis of consumption preferences. The expected benefits of AI in winemaking include the technology's potential to **improve operational efficiencies** and **achieve cost reduction**, leading to enhanced competitiveness in an industry facing significant economic pressures. Another commonly discussed benefit was AI's ability to improve and ensure **product quality and consistency**, which could be highly valuable in premium wine production, where maintaining a steady flavour profile is essential for brand reputation. Additionally, AI offers significant opportunities for **improvements in sustainability**, reducing the wider environmental footprint of winemaking, satisfying the demands of the increasingly environmentally conscious consumers.

Despite its potential, AI adoption in the wine industry faces significant challenges, including winemaking's deeply rooted nature in **heritage and craftsmanship**, creating resistance to technological innovations. **Financial constraints** were also identified as a major hurdle, along with ongoing **maintenance and staff training requirements**. Technological and **infrastructural barriers**, the **lack of knowledge and education** about AI's capabilities and **regulatory and legal challenges** also received confirmation as key obstacles to implementation. Finally, regarding the key drivers of AI implementation in the wine industry, **economic and environmental pressures** as well as **consumer demand for innovation** were noted as key forces pushing vineyards to adopt new technologies to improve efficiency and reduce costs. These highlight that the nature of technological transformation in the wine industry is mostly driven by external, "push" factors, instead of organic evolution of business models and operations.

The results of the interview analysis and text mining further consolidate the multi-dimensional view of AI adoption in winemaking developed throughout this dissertation. The outcomes underscore that the discourse around AI in winemaking is shifting from conceptual exploration to practical implementation, with a growing focus on **efficiency, cost reduction, and product quality enhancement**. However, consistent with the Delphi findings, these results also reveal that discussions remain concentrated in the **technological and economic dimensions**, while broader socio-technical and governance aspects (such as regulatory adaptation, collaborative data ecosystems, and trust-building) are still underdeveloped. Convergence with the bibliometric and Delphi results is particularly strong in three areas: the dominance of **operational and efficiency-related themes**, the recurring emphasis on **sustainability** as an embedded (yet, still operational) goal, and the recognition of **economic viability** as key factor in AI adoption. However, emerging findings indicate that **cultural resistance, risk aversion, and limited collaboration** remain persistent barriers to widespread AI use in the wine industry. The interview and text-mining results thereby enrich the Delphi outcomes by providing further context behind the objection against AI adoption, revealing a **lack of institutional support structures** (like regulation, cooperation, and funding) **and unified vision** across the industry. Moreover, these weaknesses are more pronounced among smaller producers, leading to **fragmented adoption patterns and uneven progress** across the sector.

## VII. Research output – summary conceptual model formulated

This penultimate section of the dissertation summarizes the outcomes of the different methods used in the previous sections. The result is twofold: first, a conceptual framework is formulated, to provide a structured representation of how AI impacts winemaking across the research dimensions used. Then, a practical implementation model is devised, aiding practitioners and policy makers to decide how to embark on the AI introduction journey in the wine sector. These models are reconciled, to ensure that practical recommendations are embedded in the theoretic constructs identified.

### VII. 1. Conceptual integration of evidence collected

The development of the final conceptual model is based on the integrated outcomes of the bibliometric review, the Delphi study, and the analysis of the in-depth interviews complemented by text-mining techniques. Each methodological phase resulted in distinct, yet connected insights, creating a gradually refined understanding of how AI adoption impacts winemaking. The joint interpretation of these findings enables the formulation of a conceptual framework that captures the relationships among drivers, use cases, benefits, and challenges of AI implementation in the wine industry.

The **bibliometric analysis** established the theoretical base for the study by mapping the intellectual structure of AI research in agriculture and the wine value chain. Co-citation, bibliographic coupling, and co-word analyses revealed a multifaceted knowledge base covering technical, operational, economic, environmental, and governance domains. Key clusters highlighted the **progression from algorithm-centric studies** (dominated by machine learning, deep learning and IoT-supported precision agriculture) towards **more integrative, socio-technical and sustainability-oriented perspectives**. This phase set the wider conceptual boundaries of AI adoption and identified typical application areas such as disease detection, irrigation optimisation, and predictive analytics. Sustainability and resource efficiency appeared as key concepts within these clusters. The analysis also revealed structural gaps in existing research, such as limited viticulture-specific evidence and underrepresentation

of smallholders, reinforcing the need for a multi-method empirical design, providing a theoretical justification to the data collection and analysis conducted in this study.

Building on this foundation, the **Delphi analysis** contributed by providing an assessment of the practical relevance, feasibility and perceived impact of AI across the wine value chain, validated by a wide range of experts. The outcomes indicate that **applications focused on economic benefits** (such as earlier disease diagnosis, targeted spraying, climatic forecasting, fermentation support, and quality prediction) dominate potential use cases of AI in winemaking. The results also suggest that AI performs most effectively in **data-rich, repetitive, and precision-oriented task**. Benefits such as **earlier intervention against diseases, yield improvement, higher profitability, and sustainability gains** achieved strong and consolidated consensus, reflecting alignment with the technical and environmental priorities observed in the literature. At the same time, challenges related to **investment costs** received strong agreement, whereas **governance-related aspects** (policy gaps, awareness, workforce skills, data accountability) generated more variable responses. These results therefore validated the technological and economic themes identified through bibliometric evidence, while revealing **divergences** between academic and professional interpretations of **socio-technical and institutional factors**. Having a consolidated view of where expert agreement was the strongest and most stable helped identifying the key central constructs that formed the core base of the conceptual model to be defined.

The **interviews** and the associated **text-mining analyses** provided the third layer of insight, enhancing the understanding of how contextual and behavioural factors, and practical constraints shape AI adoption in winemaking. The core themes identified confirmed the priority of operational efficiency as the main rationale for AI use in winemaking. The outcomes also highlighted how differences between large, technologically advanced producers and smaller, tradition-oriented wineries can have different opportunities in adopting advanced technologies. The thematic analysis and core text mining outputs (frequency analysis, sentiment scoring, tf-idf metrics, bigram analysis, and LDA topic modelling) reinforced three recurring patterns: (1) AI is primarily viewed as an enabler of **precision, quality, and cost reduction**; (2)

**sustainability** is interpreted through an **operational lens** rather than as systemic transformation; and (3) **cultural conservatism, data quality issues, risk aversion,** and **limited regional cooperation** present persistent barriers to widespread adoption. New insights also emerged, including the role of generative AI in lowering barriers to entry and the emergence of AI-as-a-service models, adding further details to the understanding of adoption drivers and highlighted recent technological innovations not yet reflected in the academic literature at the time the bibliometric study was executed.

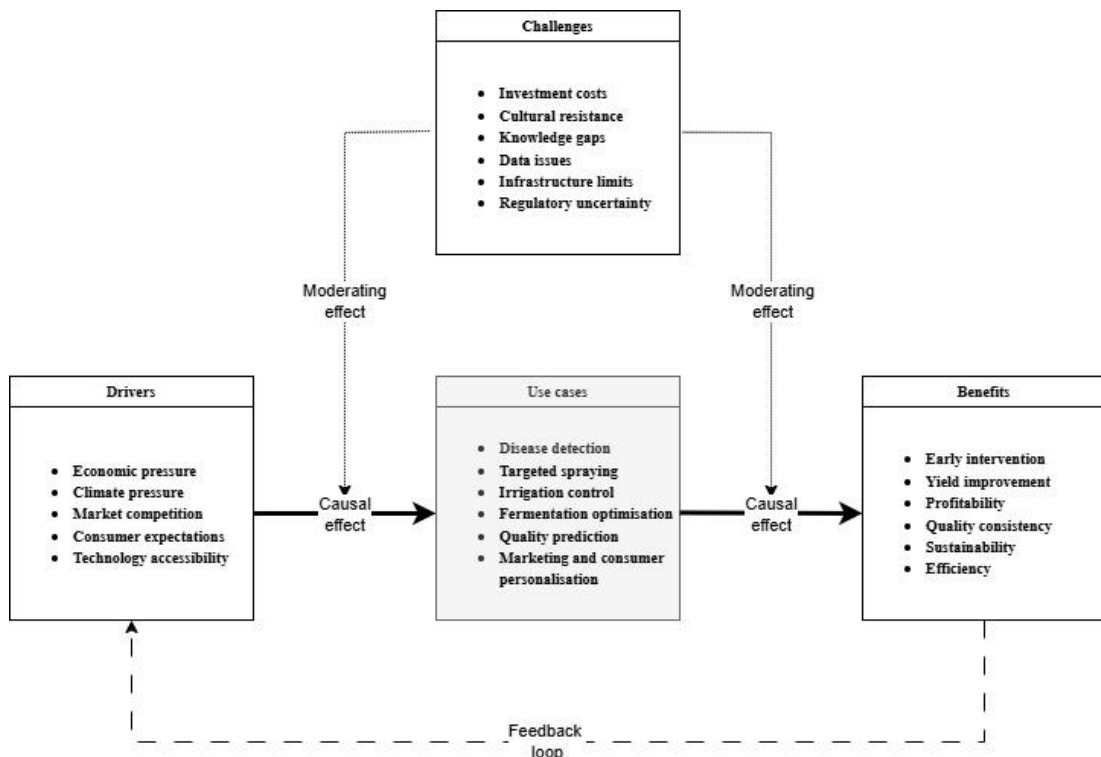
The triangulation of these three layers of evidence reveals areas of convergence and divergence simultaneously on the impact of AI in winemaking. **Convergence** is most prevalent in areas related to operational use cases, benefits aimed at efficiency improvement, and the importance of economic and environmental pressures as primary adoption drivers. Sustainability also appeared as a core recurring theme, though the interpretation from practitioners is much narrower and process-driven, compared to the academic viewpoint. **Divergence** emerges more clearly in the socio-technical and institutional dimensions, where academic literature increasingly emphasises governance, data ecosystems, and systemic alignment when assessing the impact of AI on agriculture and viticulture. Practitioners appear to assign less importance to these factors. The interview findings also expose important barriers specific to the wine industry (such as cultural resistance, limited cooperation, infrastructural disparities) that help explain some of the moderate / less agreed expert opinions observed in the Delphi responses

The integration of theoretical constructs (derived from the bibliometric insights), expert consensus (Delphi results) and the mechanisms, contingencies, and contextual factors identified (in-depth interviews) provide the empirical justification for the structure of the **final conceptual model**. By synthesizing the findings, a framework can be constructed where drivers act as enablers of use cases that generate benefits, moderated by various challenges at each link, with realized benefits feeding back into drivers. This approach helps the formulation of an **iterative adoption cycle**, while also providing a **practice-oriented implementation** recommended that builds on the core theoretical foundations identified.

## VII. 2. Conceptual framework of AI Adoption and impact in winemaking

The integrated findings from the preceding analysis allow the formulation of a comprehensive **conceptual framework** that explains how AI adoption unfolds in winemaking and the background mechanisms playing a role in this process. The framework synthesizes the core constructs derived from the research dimensions analysing the use cases, benefits, challenges and drivers of AI implementation in winemaking. These are arranged into an **ordered sequence** reflecting cause-and-effect relationships where **drivers enable use cases** and **use cases generate benefits**, which are **moderated by the various challenges** noted. The model also incorporates a **feedback loop for benefits realized**, which can either reinforce, or reshape the drivers of AI implementation. Together, these elements provide a coherent theoretical structure that captures both the logic and the dynamics of AI-enabled transformation in the wine sector. The visual representation of the framework is shown in Figure 27.

Figure 27. Theoretical conceptual framework for AI impact on winemaking (source: author)



Starting the framework from the left-hand side, **drivers** represent the **external and internal pressures** that initiate or accelerate interest in AI. The bibliometric review

identified several continuously mentioned drivers in agriculture and winemaking, including economic pressures, sustainability initiatives, and the impact of increasing environmental variability. These findings were reinforced in both Delphi rounds, where economic pressure, climate pressure, and the driving forces of market competition received strong or stable consensus, underscoring the central importance of these concepts. The in-depth interviews provided further details, by illustrating how labour shortages, cost inflation, and changing consumer expectations create additional incentives for wineries to seek digital and AI-based solutions. Emerging trends (such as greater accessibility of AI tools through generative AI and the proliferation of AI-as-a-service solutions) were also identified as new forms of technological push that lower barriers to adoption. Taken together, drivers form the **motivational foundation** of the framework, explaining why companies in the wine sector begin to explore and implement AI.

**Use cases** represent the various **application areas** through which AI addresses the pressures captured in the drivers construct related to operational, commercial, and sustainability-related concerns. The bibliometric evidence reveals that agriculture and winemaking research has concentrated heavily on precision agriculture, disease diagnosis, water management, climate forecasting, and process optimisation. These topics were also prominently represented in the Delphi questionnaire, with the strongest and most consolidated consensus demonstrated for AI's use in disease diagnosis, targeted pesticide spraying and water control, forecasting of climate conditions, determining optimal harvest timing, predicting wine quality and controlling barrel aging conditions. Taken together, these findings indicate that practitioners recognise these as the most technically mature and feasible applications of AI in the wine industry. The interviews added further confirmation to this domain, by identifying AI-supported fermentation, consumer personalisation tools, marketing analytics, and emerging applications such as gene editing for climate-resilient grape varieties and AI-as-a-service solutions as further key application areas. These diverse use cases confirm that AI plays a role across the **end-to-end wine value chain**, not just to subsets of specific activities.

**Benefits capture the positive effects produced** when AI-enabled use cases are successfully implemented. The bibliometric results emphasised measurable performance improvements across agriculture, including higher yields, improved resource efficiency, sustainability gains, and more accurate decision-making. These outcomes strongly aligned with Delphi consensus results that were reinforced by interview findings, with participants highlighting improvements in operational efficiency, cost reduction, product consistency, better market insights, and enhanced environmental performance. The text-mining results further supported this construct, where words linked to these benefits had high tf-idf scores and appeared frequently in positive sentiment categories. Overall, these outcomes indicate that experts increasingly associate AI in winemaking with performance-enhancing outcomes. In the framework, benefits also act as an essential **reinforcing mechanisms** within the system.

**Challenges** represent the factors that moderate the relationship between core drivers, use cases, and benefits of AI in winemaking identified with the different methods. The bibliometric analysis and grey literature highlighted the key structural barriers as data quality, interoperability issues, high initial costs, infrastructure limitations, and skills shortages. The Delphi analysis revealed differentiated consensus on these items, where investment costs for instance showed strong, consolidated agreement as a key obstacle blocking widespread adoption of AI in winemaking. In contrast, factors such as awareness gaps, technology acceptance, shortages in relevant policies, and skilled workforce limitations received mixed or conditional assessments. Interview findings added more details to this picture, where respondents described cultural conservatism, fear of losing authenticity, fragmented data ecosystems, risk aversion, limited cooperation among wineries, and regulatory complexity as key impediments to AI application in the wine sector. These insights indicate that such barriers (moderating the feasibility and effectiveness of use cases and determining the extent to which benefits can be realised) are **predominantly socio-technical and institutional rather than technological**.

The final element of the conceptual model is the **feedback loop** that links benefits back to drivers. After synthesizing findings across the multiple layers of evidence, a picture

can be drawn where the realisation of AI-generated benefits in winemaking (such as improved profitability, resource management, and sustainability, or more precise decision-making) reinforces organisational readiness, strengthens economic justification for further investments, and increases confidence in AI tools. This is underscored by interviewees' statements emphasizing how early successes in simple, easy to implement operational areas (e.g., disease detection, or irrigation optimisation) can build internal support and reduce resistance towards technology transformation among traditional winemakers. Similarly, Delphi results suggest that technology-driven performance gains increase the perceived importance of AI adoption drivers such as competitiveness and environmental pressures, which is also confirmed by different interviewee statements. This loop thus reflects a **dynamic implementation cycle**, where benefits realized are not the end of the AI adoption process. Rather, these gains act as forces that reinforce the underlying drivers, increasing confidence in new solutions, and enhancing the perceived relevance of the original drivers. This strengthens organisation motivation and justification for continued AI use in the various process steps across the wine value chain.

### VII. 3. Practice-oriented model of AI implementation in winemaking

The final step in this research process is translating the conceptual framework into a **practice-oriented scheme** that reflects both the causal relationships identified in the theoretical model and the real-world considerations highlighted by experts. The aim is to provide a sequenced, actionable pathway for companies operating in the wine industry seeking to implement AI for the first time in their operations. This section draws conclusions mostly from the interview findings, particularly the implementation-focused discussions. The summary model is captured in Table 37 articulating elements of a practical roadmap that aligns with the constructs identified in the theoretical model.

The first stage of the practical implementation model is focused on the **main prerequisites** required for any AI initiative to succeed highlighted by interview participants. Respondents emphasize **data availability** and **data preparation** as key pre-conditions to any successful AI implementation project. These constructs also

reflect the moderating influence of challenges in the conceptual framework, as data-related obstacles are key moderators that determine whether AI drivers can realistically lead to implementation of those and if benefits can be achieved. Thus, the practical model mirrors to the moderating role of challenges in the conceptual framework. Responses indicated that technical readiness is determined less by the type of AI tools applied than the ability to generate, structure, and maintain relevant datasets. Addressing this topic can also mitigate barriers linked to infrastructural problems, compatibility of outdated equipment with new solutions, and limited analytics capabilities, which were repeatedly emphasised in both the interview and Delphi results.

Table 37. A summary model for AI implementation in winemaking (source: author)

Pre-requisites				
Data availability		Data preparation		
Value-driven AI implementation strategy				
Opportunity sizing	Capability assessment		Prioritized action list	
<ul style="list-style-type: none"> <li>Linking potential AI applications to economic value drivers</li> <li>Estimate the potential economic impact of applying AI in various parts of the wine value chain</li> </ul>	<ul style="list-style-type: none"> <li>Assess the availability and quality of data</li> <li>Evaluate how the existing data can be analysed</li> <li>Identify how the data and insights can be used in practical business scenarios</li> <li>Assess the organizational and operational model and skills available</li> </ul>		<ul style="list-style-type: none"> <li>Create a prioritized list of actions</li> <li>Focus on initiatives with the highest impact and the least efforts required</li> <li>Develop a three to five years roadmap outlining the areas and use cases to start with</li> <li>Focus the start on smaller pilots</li> </ul>	
Potential areas of first-time implementation of AI				
Monitoring and spraying	Automated fermentation processes	Weather- and disease prediction	Understanding consumer profiles	Marketing
Success factors				
Team-based approach		Focus on incremental progress		

Once foundational conditions are in place, experts recommended a **value-driven AI implementation strategy**, consisting of three sequential components: opportunity sizing, capability assessment, and prioritised action planning. Each stage reflects a direct alignment with the constructs of the conceptual framework.

**Opportunity sizing** involves linking AI applications to economic value drivers such as yield improvement, reduced production loss, enhanced quality consistency, or optimised pricing. This step connects the drivers of adoption to practical AI applications by showing how industry pressures (e.g., climate variability, cost inflation, labour shortages, competitive positioning) can be addressed with specific use cases. Respondents agreed that ideally, the potential impact of applying AI across the entire value chain has to be estimated, to ensure that operational needs and strategic pressures are simultaneously prioritized when deciding on implementation paths. This stage therefore reflects the core logic of the conceptual framework, with drivers generated by opportunity estimates provide the **motivation for adoption** that is then continued in the identification of specific use cases to realize the expected benefits.

After the benefits are estimated, the next step to execute is the **capability assessment**, corresponding to evaluation of the key moderating variables identified in the conceptual framework. Experts noted the importance of assessing data quality, accessibility, analytical readiness, and organisational skills when pursuing AI implementation endeavours. This stage also includes evaluating the existing organisational and operational model to ensure the availability of relevant staff capabilities and internal processes that drive sustainable adoption and deep integration of AI in corporate routines. The interviews highlighted that wineries differ significantly in their readiness, with larger and technologically mature producers better positioned than smaller artisanal estates. Overall, this stage ties back to the conceptual framework identified by highlighting **how challenges** (such as data fragmentation, limited digital literacy, cultural conservatism, or infrastructural constraints) may **weaken the link** between use cases and benefits realised.

Finally, after capability assessment is complete, companies in the wine industry should create a **prioritised list of actions** based on the size of the opportunity and the effort required to implement those. Experts recommended focusing initially on small pilots - use cases that deliver tangible benefits which can be implemented with minimal effort and changes required to existing ways of working. Once evidence is available on the value creation a potential of AI, a longer (three- to five-year) roadmap can be developed to scale successful the potential applications across the wider value chain. This step mirrors the **feedback loop** in the conceptual framework, as successful pilots generate demonstrable value, reinforce stakeholder confidence, reduce cultural resistance, and create momentum for further adoption, while requiring moderate efforts to implement, due to their small-scale nature.

Experts identified several use cases that are good candidates for **first-time implementation**, reflecting the parts of the value chain with strong drivers, clear benefits and manageable challenges. Examples include using AI to improve monitoring and spraying activities, earlier prediction of adverse weather effects or quicker reaction to diseases, or better understanding consumer profiles, improving the effectiveness of marketing activities. These reflect important drivers identified with strong consensus among experts, such as climate pressure and resource optimisation, quality control and consistency, or changing consumer expectations and digital engagement.

Finally, the model for practical implementation covers the **key organisational enablers** that support long-term and successful implementation of AI in winemaking. Respondents consistently highlighted two critical success factors. First, the importance of a **team-based approach** was highlighted, with a collaborative environment, where learning is distributed and embedded easily in everyday practice. This can involve very simple steps, where AI is implemented through a series of weekly experiments, by assigning small tasks, and building capability through practice rather than widespread redesign of processes. Second, the significance of **incremental progress** was emphasized, where the adoption journey is broken into manageable steps, starting with pilots, and scaling only when benefits have been demonstrated and internal confidence has developed. These success factors directly reinforce the **feedback loop** again in the

conceptual framework, where team-based learning reduces cultural resistance, while incremental progression strengthens the impact of drivers by producing visible benefits that justify adoption. Together, they help ensure that AI implementation is seen not as a disruptive, one-time effort, rather as a continuous, adaptive process aligned with the traditions and operational realities of winemaking.

#### **VII. 4. Concluding remarks**

To conclude, this section presented the final conceptual framework developed in this dissertation, by bringing together empirical findings from a wide range of sources and methodologies, integrating them into a systematically organised model. This combined structure contributes both to the academic understanding of AI's impact on winemaking, as well as to managerial considerations by providing practical insights on the technology's adoption path. The theoretical framework explains the interactions between drivers, use cases, benefits, and challenges in the AI-enabled transformation process in winemaking, highlighting the iterative nature of adoption through a reinforcing feedback loop. Using a multi-construct presentation of findings also reflect the evolution of the literature from technology-focused experimentation toward holistic, socio-technical interpretations that recognise the importance of economic, environmental, and governance dimensions in AI adoption. The framework therefore synthesises different strings of academic research, demonstrating that AI adoption in winemaking is shaped by pressures and enabling conditions at micro-, meso-, and macro-levels. The success of such initiatives depends not only on technical feasibility but also on organisational readiness, resource capabilities, and institutional support.

Complementing this theoretical contribution, the practice-oriented model provides a structured, actionable blueprint for companies in the wine sector seeking to implement AI for the first time. Derived directly from expert interviews, the model translates theoretical constructs into a structured series of operational steps starting from establishing essential data pre-requisites, followed by value-driven opportunity sizing, assessing organisational and analytical capabilities, and prioritising small-scale pilots before moving toward a multi-year adoption roadmap. The practical model also identifies feasible first-use applications where industry pressures, technological

maturity, and tangible benefits align, maximising the probability of AI implementation's success. Other success factors highlighted mirror the reinforcing mechanism defined in the conceptual model, showing how realised benefits strengthen organisational drivers and facilitate ongoing adoption. The practical model thus offers a credible pathway that aligns with the operational circumstances of wineries, especially those lacking advanced digital infrastructures or specialised expertise in the area.

## VIII. Conclusion and future research directions

The aim of this dissertation was to explore the **transformative potential of AI in the wine industry**, with a focus on understanding the **drivers, use cases, benefits, and challenges** of the technology's implementation in the sector. To achieve this objective, the research was conducted in three distinct stages. In the first part, a **bibliometric analysis** (complemented with a review of grey literature) was conducted to map the academic landscape of AI applications in agriculture and winemaking. Conclusions derived from this section provided the baseline for establishing the knowledge base guiding subsequent stages of the study. In the second phase, the **Delphi method** was utilized, by constructing a questionnaire to gather expert opinions in the wine value chain, assessing consensus on the statements formulated. This approach provided important inputs into validating (or challenging) the main constructs defined in the previous phase. The third building block of the study involved conducting **in-depth interviews** with a selection of experts to understand behavioural, contextual and other factors shaping the perception of AI's impact on the wine sector, not captured in the questionnaire used. Results were evaluated with two distinct, yet complementary approaches. The thematic analysis conducted using Gioia's methodology helped uncovering the key themes and aggregate dimensions underlying the professional discourse reflected in the interview transcripts. Due to the method's qualitative and subjective nature, various text mining techniques were also used to validate these findings, enriching previous results.

The outputs of the results of various academic methods were summarized in a conceptual model, explaining the interaction between and the feedback loop across the different dimensions describing the impact of AI on winemaking. In addition, a practical adoption framework was developed, supporting wine industry practitioners in designing strategies on projects aimed at the first-time implementation of the technology. Together, these elements contribute on two levels. Academically, this dissertation provides a **robust conceptual framework of AI adoption in winemaking**, grounded in empirical results, providing a better understanding of the interplay between technological, behavioural, organisational, and policy-related dimensions. From a practical point of view, the research delivers a **realistic**

**technology adoption roadmap** based on experiences, challenges and expectations noted by industry experts from a diverse range of fields. This ensures that the gap between academic concepts and practical implementation is bridged adequately.

This dual approach also highlights the **originality of this research**. Earlier literature on AI in agriculture and winemaking focused on narrower aspects, such as standalone technological use cases, or certain phases of the adoption process. In contrast, this study provides a **comprehensive synthesis and understanding of the full adoption cycle**, from drivers, through use cases to benefits, whilst incorporating the moderating effect of challenges impacting the relationship between these factors. The mixed-method design strengthens the validity of the framework and ensures the combined theoretical and practical relevance of findings. This provides an integrated framework as a foundation for AI adoption in the wine sector, capturing the complexity of digital transformation initiatives.

### **VIII. 1. Summary of individual findings**

The **bibliometric analysis** used a dataset of 1,118 articles extracted from the Scopus database, applying various techniques (co-citation analysis, bibliographic coupling, and co-word analysis), to identify key trends in academic research, influential contributions, thematic relationships and emerging topics not yet captured in citation patterns. The thematic clusters and core themes revealed (such as AI applications in precision agriculture, disease detection, and predictive analytics) demonstrated the technology's diverse and evolving role in agriculture and winemaking. Beyond technical applications, the bibliometric results indicated a broader conceptual shift in the academic discourse, highlighting the importance of **socio-technical factors** (such as organisational behaviour, advisory networks, trust, data governance, and policy frameworks) as other key elements of AI adoption. Across the various themes identified, **sustainability** appeared as a central concept, impacting various dimensions including efficiency consideration, resource optimisation, climate resilience, and environmentally responsible production practices. Finally, results also showed a

**structural bias**, with much of the existing research focusing on large, well-resourced farms in developed regions, where the smallholders and viticulture-specific datasets were underrepresented.

In the second part, the **Delphi method** was used to derive consensus with an international panel of experts on the impact of AI in the wine industry. Using two rounds of questionnaires, the approach allowed for the evolution and refinement of opinions, reflecting the collective understanding of participants on the topic investigated. The projections formulated were focusing on the use cases, benefits, challenges, and drivers of AI adoption in the wine sector. The strongest and most consistent insights were related to **operational and technically mature applications** (like use cases in field operations, production conditions monitoring or consumer preferences assessment), confirming that practitioners perceive AI's most immediate value in efficiency-enhancing and automation-oriented tasks. Similarly strong agreement emerged for benefits linked to **operational and environmental performance**, reflecting the consensus that AI enables tangible improvements in productivity, cost efficiency, and product consistency.

In contrast, the results revealed more mixed or divided views for **socio-technical and governance-related themes**. Benefits tied to social outcomes (such as the creation of more meaningful jobs through innovation) or consumer-driven factors received more variable scores. Similarly, use cases related to sensory evaluation or high-level market predictions attracted dispersed opinions, while governance-related challenges (such as **policy gaps, technology acceptance, or limited awareness**) remained in the conditional or moderate-agreement zones across both rounds. These patterns reflect a recurring finding across the entire dissertation, where experts prioritise technological and economic dimensions of AI adoption, assigning less weight to the importance of institutional, policy, and cultural considerations. A similar hierarchy was highlighted among **challenges**, with the only investment costs achieving strong and stable agreement, compared to infrastructure limitations or other structural constraints. The evolution of opinions across the two rounds highlighted experts' growing confidence in AI's operational value and economic justification. In contrast, the weakening or

fragmented nature of social, policy-related, and consumer-driven statements, reflect continuing uncertainty about AI's broader organisational and institutional implications.

In the final part of the research, **in-depth interviews** were conducted with ten participants to corroborate findings, enabling the identification of theoretical concepts and practical considerations that were not anticipated in earlier phases of the study. Thematic clusters were identified using the **Gioia methodology** which were confirmed by the application of various **text mining techniques**, to add a more systemic analysis of the interview outcomes. Findings about **use cases** and **benefits** highlighted regarding operational performance aspects, efficiency and sustainability improvement were in line with those highlighted in the Delphi questionnaire rounds. Main **challenges to AI adoption** identified included financial considerations, cultural resistance, technological readiness and data quality as well as the lack of AI expertise. Finally, the interviews also added further details on the **drivers of technology adoption and transformation** in the wine industry, highlighting the impact of consumer demand for sustainability and innovation, competitive pressures, and external support through partnerships with technology providers. These findings not only confirmed earlier results, but also highlighted how cultural, economic and technological factors influence technology implementation in the sector, strengthening the research's overall conclusions.

## **VIII. 2. Summary of dissertation outcome**

The outcomes of the multi-method research design were culminated in the development of a conceptual framework and a practice-oriented implementation model, jointly forming the primary theoretical and managerial contributions of the study. The **conceptual framework** developed integrates the diverse findings into a coherent, empirically grounded structure that explains how AI adoption unfolds in winemaking. The structure is organised around four core constructs along the research questions defined (the use cases, benefits, drivers and challenges of AI implementation

in winemaking). These are linked through a progression path that reflects both the academic foundations and the practical insights gathered through expert engagement. The framework considers **drivers** (including economic pressures, climate variability, labour shortages, market competition, consumer expectations, and increased technological accessibility) initiating the consideration and exploration of AI solutions in winemaking. These are then translated into feasible **use cases**, such as disease detection, irrigation optimisation, targeted spraying, climate forecasting, fermentation control, quality prediction, and consumer personalisation. The building blocks within these dimensions emerged consistently across all research phases as the most prominent and widely accepted elements of AI adoption, reflecting strong agreement in the Delphi rounds and repeated confirmation in the interview findings regarding their potential in the wine sector.

Successful implementation of the use cases produces **measurable benefits**, including earlier intervention against diseases, yield improvements, cost reduction, operational efficiency, improved product consistency, enhanced sustainability performance, and deeper consumer insights. The framework highlights that these benefits are not merely operational outcomes but are rather to be seen as reinforcing mechanisms. Once such benefits are demonstrated, they reduce organisational resistance against innovation, strengthen internal motivation, and support further investment in new technologies. This is illustrated by the **feedback loop** built into the final conceptual model. At the same time, the framework recognises that a **series of challenges moderate AI adoption** in the wine sector. The barriers identified act as moderating factors that influence the strength and feasibility of the links between drivers, use cases, and benefits. Such a moderating effect can explain why adoption remains uneven across wineries and why smaller producers may encounter greater obstacles.

The conceptual framework is complemented by a **practice-oriented implementation model** that translates theoretical insights into a roadmap for practitioners. Key building blocks of the model include **foundational pre-requisites** (such as data availability, data preparation, and digital readiness), followed by a **value-driven implementation strategy**, consisting of opportunity sizing, capability assessment and the creation of

prioritised actions. It is important to ensure that **small, high-impact pilots** are initiated first with the potential to demonstrate early wins, gradually scaling successful initiatives into multi-year transformation roadmaps. The careful selection of **initial application areas** (such as automated monitoring and spraying, or AI-driven weather- and disease prediction) is also key, and the importance of the **team-based learning** and **incremental progress** cannot be overlooked, if sustained adoption is to be ensured.

Together, the conceptual framework and the practical implementation model offer a unified contribution, by explaining simultaneously how AI adoption in winemaking is structured and how it can be effectively achieved in practice. By integrating academic insights with empirically validated practitioner perspectives, the dissertation provides a comprehensive and actionable foundation for understanding AI-enabled transformation in the wine sector.

### **VIII. 3. Limitations and future research directions**

When assessing the contributions of this study, it is also important to discuss the various **limitations inherent in this research** due to the underlying methods used. **Citation analysis and bibliographic coupling** can be constrained by factors such as limitations in the underlying database, citation errors, multi-authorship challenges, journal indexing biases, or inconsistencies introduced by uncontrolled citation practices (Weinberg, 1974; Worrall & Cohn, 2023). These shortcomings were partially addressed with the way how the bibliometric analysis was executed, the inclusion of grey literature and the text mining methods utilized in the in-depth interview section. The limitations of the **Delphi method** also cannot be overlooked, with potential challenges including panel fatigue, or decline in participant engagement and response quality reducing consensus reliability. This obstacle was addressed by limiting the number of questionnaire distributions to two rounds, with the relatively low dropout rate (17 respondents completing the second round compared to the initial 19 participants) suggesting that the risk was adequately mitigated. Finally, the

shortcomings of **in-depth interviews** (including **interviewer bias**, **interviewee bias** and **response bias**, or the relatively **small sample size**) should be also highlighted, despite the safeguards put in place.

Beyond these methodological considerations additional limitations include the **degree of interpretive judgement** exercised when formulating the final conceptual framework from the Delphi responses, and interview data. Also, the relatively **high proportion of experts with technology exposure** in the interview panel introduced the risk of small wineries' underrepresentation in less digitised regions. The views highlighted by experts on AI application in the wine sector may be also **aspirational or hypothetical**, whilst the **rapid pace of technological change** in this field may also outpace the relevance of some of the findings derived.

Future research could address these limitations and the gaps or incomplete evidence identified during the study. By increasing the representation of actors in underdeveloped regions with lower digital maturity could enhance the understanding the **AI adoption pathways available to small wineries**, focusing on how these producers combat cultural resistance, the process behind prioritising use cases under financial constraints, and the role of support mechanisms in technology transformation. Cross-sectional, or cross-country comparisons could add insights about the impact of structural differences on adoption feasibility, perceived benefits, and risk tolerance, yielding important academic contributions by enabling more generalisable theories of AI adoption in agriculture adjusted to different contexts. From a practical point of view, such approach could support the development of tailored implementation models, policy interventions, and capability-building initiatives targeted at small wineries, helping these actors to recognize the benefits of digital innovations.

Future research could also address the structural and contextual gaps related to data quality and infrastructure, and governance practices limiting the effectiveness of AI implementation. Exploring how **shared data ecosystems could be designed and**

**regulated** within the wine sector, or the examination of **collaborative sensing networks** with standardized data collection practices for disease detection and microclimate monitoring could be interesting avenues for later studies. In addition, analysing **incentives and barriers for wineries to participate** in regional or cooperative data platforms, investigating models for secure data sharing, or mechanisms for improving data quality could be also explored. Such studies would not only contribute to the academic understanding of digital transformation by highlighting the moderating effect of data governance but would also deliver practical insights by examining how such practices shape and influence the effectiveness of AI adoption in the wine sector.

While the technical and economic arguments for AI adoption were widely acknowledged and confirmed in this dissertation, the **socio-technical and cultural dimensions** could be explored further to extend the knowledge base on this topic. Insights gathered from experts during the Delphi rounds and the in-depth interviews demonstrated fragmented views on cultural acceptance, trust, workforce readiness, and the perceived compatibility of AI with the artisanal nature of winemaking. Future research could therefore investigate the **behavioural and organisational mechanisms shaping acceptance or resistance to AI** adoption in winemaking, including comparative analyses across regions, winery sizes, or cultural contexts to add further insights into the influencing impact of these differences. From a practical perspective, these studies could be valuable basis by supporting decisionmakers in designing interventions addressing behavioural and cultural barriers.

The analysis of AI adoption factors could be also extended to a broader level to understand the **higher-level dynamics influencing technology uptake** in the wine industry, focusing on micro-, meso- and macro-level factors revealed by the bibliometric analysis. Future research could explore how policy incentives and regional governance structure influence technology uptake in wineries. As part of that, the impact of differences in regional conditions, resource and ecosystems availability as influencing factors impacting AI implementation in the wine industry could be also explored. By developing an all-round understanding of the adoption approach would

not only enrich academic knowledge but provide useful inputs for practitioners and decision makers to design action plans that positively influence AI readiness across the wine sector.

Finally, future research could also address the **uncertainties, transparency needs and other trust-related issues** impacting AI adoption in winemaking. The risk averse nature of the wine sector and limited trust in the reliability of AI-driven solutions in an industry characterised by the importance of craftsmanship, tradition, and product authenticity makes this a highly relevant field to explore. Future studies could focus on addressing transparency requirements, or explainable AI (XAI) techniques that make model outputs interpretable for various participants in the sector, to improve the understanding of how factors related to risk, trust and interpretability of results shape adoption in the wine industry. Results could also provide valuable inputs to the development of preventive mechanisms and communication strategies that could enhance confidence in AI tools, thereby increasing technology uptake in the industry.

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## **Appendix 1. Summary of key machine learning concepts**

This dissertation is focused on the implementation of AI in the wine sector, and it is recognized that some of the related concepts might be vague, or difficult to understand without having the right background knowledge. The aim of this appendix is to provide a high-level introduction into some of the key theoretical constructs underlying this domain. The theoretical foundation for this overview is mostly drawn from "The Hundred-Page Machine Learning Book" by Andriy Burkov (Burkov, 2019), complemented by additional materials and explanations as needed.

### **Artificial Intelligence, Machine Learning and related concepts**

**Artificial Intelligence (AI)** including its historical development, and the relationship of this domain to other fields of science was introduced in the first section. AI is a broad concept that is aimed at creating machines or systems capable of exhibiting human-like intelligence, reasoning, and problem-solving abilities. It is a multidisciplinary field that draws on various subfields, including Machine Learning (ML), which primarily involves the development of algorithms that enable computers to learn from data and make predictions or decisions without being explicitly programmed for each task. ML serves as a fundamental component of AI, providing the practical tools to achieve AI's overarching objective of creating intelligent systems.

**Machine Learning** is a branch of AI and data science that has evolved significantly over recent decades, progressing from basic statistical analysis techniques to highly sophisticated algorithms capable of learning from data without explicit programming. The core aim of ML is to develop algorithms that can identify patterns and make predictions, allowing machines to perform tasks that traditionally required human intelligence. (Jordan & Mitchell, 2015) An overview of the various types of ML methods, the training data required to use those, their goals and selected example use cases of those in the wine industry is summarized in Table 38.

In **supervised learning**, a model learns to recognize patterns and relationships within data by using a labelled dataset (a dataset where each data point is paired with a known outcome or target variable). The model generalizes from these labelled examples to make predictions on new, unseen data, mirroring the way humans learn from examples provided by a teacher (Cunningham et al., 2008). Supervised learning algorithms can be divided into classification and regression models, each designed to solve different types of problems. **Classification** involves predicting discrete categories, where the output represents one of a set of predefined classes. In contrast, **regression** aims to predict a continuous numerical value based on input features.

Table 38. Overview of machine learning types and applications in the wine industry (hypothetical examples) (source: author)

Type	Training data required	Goal	Common applications (including wine industry analogies)
<b>Supervised</b>	Labelled data	Predict specific outcomes from labelled inputs	Predicting grape quality based on environmental factors; classifying wine types based on flavour profiles
<b>Unsupervised</b>	Unlabelled data	Identify patterns or groupings in raw data	Segmenting consumer preferences for targeted marketing; identifying quality issues in bottling processes
<b>Semi-supervised</b>	Partially labelled data	Leverage limited labelled data to refine models	Classifying wine reviews with minimal human intervention; optimizing vineyard layout based on mixed data
<b>Reinforcement</b>	Feedback from environment	Optimize actions through trial and error	Training robots for automated harvesting; refining cellar climate control systems

Supervised learning can also be categorized into model-based and instance-based learning. In **model-based learning**, the algorithm uses training data to develop a generalized model that can make predictions about new data. For example, linear regression is a model-based learning approach that finds the best-fit line through the data points to predict outcomes. On the other hand, **instance-based learning** relies on using the entire dataset to make predictions for new data points. An example of this is the k-nearest neighbours (k-NN) algorithm, which classifies new data points by comparing them to similar instances in the training data, based on the majority label of its nearest neighbours in the dataset. The kNN algorithm and linear regression will

be discussed later in detail. In short, model-based learning generalizes from the data to form predictions, while instance-based learning uses the data directly for prediction.

Supervised learning algorithms are also categorized as shallow learning or deep learning approaches, depending on the complexity of the models. **Shallow learning** involves algorithms with minimal processing stages, often consisting of only a single layer without hidden layers. These models learn parameters directly from the features in the training dataset, making them suitable for simpler tasks. **Deep learning**, on the other hand, involves neural networks with multiple layers, where each layer represents a processing stage that transforms the input data into more complex representations. Deep learning models use these hidden layers to capture complex patterns and relationships within the data, making them suitable for tasks that require the understanding of more complicated data structures. The detailed architecture of neural networks and deep learning model will be discussed in a later section of this appendix.

Supervised learning can be applied to a wide range of problems. A simple example is a spam detection model, which classifies emails as "spam" or "not spam" using a shallow learning classification algorithm. For a regression example, consider predicting property prices based on features such as square footage, number of rooms, property age, and building materials. This task uses a regression model to estimate continuous property values. If this same problem was approached using deep neural networks with multiple hidden layers to identify complex patterns, it would demonstrate a deep learning approach. More complex applications, such as autonomous driving, involve deep learning classification models that detect objects in images by analysing features through several processing stages.

In contrast to supervised learning, **unsupervised learning** operates without labelled data. Rather than being guided by predefined outcomes, unsupervised algorithms identify inherent structures and relationships within raw data, uncovering hidden groupings or anomalies. This method resembles how humans naturally detect patterns and differentiate elements in their environment (Tyagi et al., 2022). Example domains

with use cases of unsupervised learning methods include healthcare (e.g., analysing patient databases), e-commerce (e.g., customer segmentation for targeted marketing), cybersecurity (e.g., intrusion detection), finance (e.g., fraud detection), retail (e.g., shopping cart analysis for product recommendations), and computer vision (e.g., image segmentation) (Naeem et al., 2023).

Combining elements of both supervised and unsupervised learning, **semi-supervised learning** algorithms leverage a mix of labelled and unlabelled data to refine predictions. This approach is especially useful when labelling data is costly or time-consuming, as it maximizes the utility of available information. In semi-supervised learning, labelled data provides an initial framework, while unlabelled data enhances the model's understanding of the problem. Semi-supervised learning has found practical applications in various domains, including natural language processing, text document classification, or image categorization (C A Padmanabha Reddy et al., 2018).

**Reinforcement learning** is distinct from other ML types in that it relies on trial and error to make sequential decisions by interacting with an environment. Here, an "agent" (e.g., a robot or software entity with capabilities to make decisions aimed at achieving a target state by interacting with its environment) learns by receiving feedback on its actions, known as rewards or penalties. This process of interaction and feedback enables the agent to develop optimal strategies over time. An example scenario where reinforcement learning is used is robot motion, where the device has no prior knowledge of the route and must explore various paths and actions, through a process of trials and errors and feedback loops, ultimately leading to optimal strategies executed for reaching its goal. Reinforcement learning is a useful method in situations where decision-making involves a sequence of actions and where the consequences of those actions may not be immediately apparent, such as game playing, disease detection or autonomous vehicles. (Brooks, 2021)

Table 39. A summary of key datasets used in Machine Learning (ML) applications. Source: author

Dataset type	Purpose	Function in model development	Key role
Training set	Builds the model by adjusting weights and parameters	Exposes the model to examples for pattern recognition	“Teaches” the model through repeated exposure
Validation set	Refines the model after initial training	Helps select algorithms and fine-tune hyperparameters	Prevents overfitting by adjusting model tuning
Test set	Evaluates final model performance	Provides unbiased assessment after training and tuning	Assesses generalization to unseen data

Machine learning algorithms are developed using data captured, relying on three distinct datasets: the training set, validation set, and test set. Each of these fulfil a specific function in model development and assessment. The **training set** is used to construct the model by iteratively determining the optimal values of weights and parameters to minimize errors, often through an objective function known as the model’s cost function. This dataset effectively “teaches” the model by exposing it to a broad range of examples, allowing it to learn patterns that will guide predictions. The **validation set** serves as an intermediary dataset that helps refine the model. After the initial training, the validation set allows data analysts to select the most appropriate learning algorithm and fine-tune hyperparameters -settings that govern the learning process itself. This also supports in preventing the model from becoming too specific to the training data (also referred to as overfitting) by offering an independent dataset for adjustments without influencing the training process directly. Finally, the **test set** is used strictly for evaluating the final model's performance, allowing for an unbiased assessment of its effectiveness, and providing insight into how well the model will generalize to unseen data. The purpose, function and key role of each dataset is summarized in Table 39.

### Common notation and terms

In this subsection, the key mathematical concepts and notation commonly used in machine learning are introduced. These foundational elements are important to understand some more advanced algorithms and methods discussed in academic

literature focused on the application areas of these solutions. By becoming familiar with these terms, it is easier to grasp the principles that drive ML techniques, particularly those related to model optimization and training.

The first concept introduced is the **derivative**, denoted as  $f'(x)$  for function  $f(x)$ . Derivatives characterize the rate of change of a function, which is essential in machine learning for optimizing model parameters. Many algorithms, such as **gradient descent** (an optimization method used in ML to find the minimum of a function) rely on derivatives to adjust parameters in a way that minimizes the model's error or loss. For example, if the derivative of a function  $f(x) = 3x + 2$  is  $f'(x) = 3$ , this indicates a constant rate of change, meaning the function is linear and has a constant slope of 3, regardless of the input value  $x$ . Conversely, if the derivative equals to zero at a point  $x$ , it signifies that the function has a horizontal slope at that specific point, which can indicate an optimal point (e.g., a minimum or maximum) in optimization contexts. In summary, the derivative is a tool for understanding how rapidly a function changes, which is foundational for optimizing model behaviour in machine learning.

In cases where the derivative of a function varies at different points, this implies a non-linear relationship. Calculating derivatives in these cases requires **differentiation**, a process that allows us to find the rate of change for more complex functions. For instance, to find the derivative of a complex function, the *chain rule* is applied as shown in Equation 1 and Equation 2, respectively.

*Equation 1. Example of a complex function.  $F(x) = f(g(x))$*

*Equation 2. The derivative of a complex function  $F'(x) = f'(g(x)) * g'(x)$ .*

For example, if  $F(x) = e^{(3x^3+2x)}$ , then  $F'(x) = (9x^2 + x) * e^{(3x^3+2x)}$ . This principle enables the differentiation of layered functions, which is particularly relevant for complex machine learning models.

When working with functions that have multiple inputs, the concept of **gradients** extends derivatives to account for each input. Gradients are especially relevant in machine learning as they help optimize parameters in multi-dimensional spaces, often

associated with cost function minimization. The **partial derivative** focuses on how a function changes with respect to one specific input variable while keeping others constant, yielding a vector of derivatives across dimensions. For instance, consider the function  $f([x^{(1)}, x^{(2)}]) = a * x^{(1)} + b * x^{(2)}$ . The partial derivatives with respect to  $x^{(1)}$  and  $x^{(2)}$  are  $\frac{\partial f}{\partial x^{(1)}} = a$  and  $\frac{\partial f}{\partial x^{(2)}} = b$ , respectively. In machine learning, gradients guide the adjustments of parameters across multiple inputs, enhancing model accuracy and efficiency.

Machine learning models also rely on two critical types of variables: parameters and hyperparameters. **Parameters** are internal variables learned from training data, such as weights in a linear regression model, and are directly adjusted through training to fit the model to the data. **Hyperparameters**, on the other hand, control the training process itself and are set prior to training. Examples include the learning rate, which determines the step size during optimization, and the regularization strength, which manages the model's complexity to prevent **overfitting** (which refers to a problem where a model learns patterns specific to the training data, thereby reaching highly accurate predictions on the training set, whilst performing poorly on new, unseen data). Unlike parameters (intrinsic to the model's structure and are learned from data), hyperparameters (external configurations that direct the model's training approach) are not learned but rather **predefined settings** that guide the learning process. In

### Fundamental algorithms in machine learning

**Linear regression** is a fundamental supervised learning algorithm widely used in predictive modelling due to its simplicity and interpretability. It is ideal for understanding and quantifying the relationship between input features and a continuous target variable by assigning weights to each predictor, to best approximate the target value. In a linear regression model, predictions are made using the formula presented in

Equation 3:

*Equation 3. Linear regression formula*       $f_{w,x}(x) = wx + b$

In the above equation,  $\mathbf{x}$  is a feature vector that represents the attributes of each training example,  $\mathbf{w}$  is a weight vector that assigns importance to each feature, and  $\mathbf{b}$  is the intercept term. By tuning these weights, linear regression aims to model the relationship between the features and target labels, allowing for accurate predictions on new data.

The effectiveness of a linear regression model is assessed by minimizing the **error**, i.e., the difference between predicted and actual values. This is accomplished using an objective function that quantifies total error across all examples in the dataset. The **loss function** represents the error for each individual prediction, while the **objective function** minimizes this error across all instances. Specifically, in linear regression, the **squared error loss** is commonly used as a loss function, as shown in Equation 4:

*Equation 4. Squared error loss formula* 
$$\frac{1}{N} \sum_{i=1}^N (f_{\mathbf{w}, \mathbf{b}}(x_i) - y_i)^2$$

In this equation,  $y_i$  denotes the observed values in the dataset. The **cost function** often refers to the average loss across the dataset and may be used interchangeably with the loss function in certain contexts, although they can be distinct depending on the model's configuration. Minimizing the cost function is key to achieving the best model fit in machine learning. To find the optimal values of  $\mathbf{w}$  and  $\mathbf{b}$ , linear regression often employs **gradient descent**, an iterative optimization algorithm that fine-tunes parameters to minimize prediction error. Gradient descent adjusts the weights in small steps to gradually reduce the cost function. In each step, or **epoch**, the algorithm runs through the entire training data, during which parameters are updated based on the calculated errors. The **learning rate** (denoted by  $\alpha$ ) controls how big each adjustment step is, balancing speed and accuracy in the process of reducing errors through solving an optimization problem. Through each epoch, gradient descent updates parameters by computing partial derivatives of the cost function with respect to each parameter, thereby “descending” towards values that minimize error.

Although gradient descent is highly effective, it has limitations, such as sensitivity to learning rate selection and slow convergence for large datasets. **Various advanced**

**methods**, including mini-batch stochastic gradient descent (SGD), AdaGrad, RMSprop, and Adam, offer improvements to address these challenges, particularly in neural network applications. Explaining these methods in detail are beyond the scope of this thesis.

In summary, gradient descent is a fundamental optimization method that adjusts model parameters to minimize the cost function, aligning predictions more closely with actual values. By guiding the iterative adjustment of weights, this process enhances model accuracy and ensures the best fit to the training data.

To illustrate, consider a practical scenario where a winery's commercial team wants to develop a model that forecasts weekly sales (in bottles) based on historical demand, price promotions, marketing spend, and weather conditions during the tourist season. The team decides to use a linear regression function of  $f_{w,x}(x) = wx + b$ . The independent variables are captured in an input feature vector  $\mathbf{x}$ , while the model's goal is to predict future sales. Linear regression assigns a weight of  $\mathbf{w}$  to each factor, reflecting each one's importance. For example, the weight for "temperature during weekend periods" may be high if warmer weather strongly increases sales volumes (by boosting tasting-room visits). During model training, the algorithm compares predicted sales to actual revenue and calculates the error using the loss function (the difference between the two values). The gradients then indicate how each weight should be adjusted to reduce this error. If the model repeatedly overestimates sales during rainy periods, the gradient with respect to the weather variable will point downward, indicating that its weight should be reduced. Gradient descent uses these signals to adjust the parameters incrementally, moving the model toward an optimal configuration.

Hyperparameters (such as the learning rate) shape how quickly the forecasting model adapts. If these are set too high, the updates will result in optimal values being overshoot. Conversely, with a learning rate that is too low, the training process becomes inefficient. Each epoch gradually refines these parameters, guided by the learning rate, until the algorithm achieves convergence, which is a point where further adjustments result in negligible improvements in errors reported. This example shows how

complex mathematical tools are utilized in practice that can support decisionmaking regarding pricing, inventory planning, and marketing budget allocation in the context of an individual winery.

### Other key supervised learning algorithms

Supervised learning encompasses a variety of algorithms that tackle classification and regression tasks in unique ways. Each algorithm applies different techniques to learn from labeled data, using distinct methods and optimization goals to achieve accurate predictions.

**Logistic regression** is a widely used algorithm for classification tasks that predicts binary or multiclass outcomes. It models the relationship between features and a categorical output  $y(i)$ , expressed as either binary or one of a finite set of outcomes. The **logistic function**, or **sigmoid function**, used in logistic regression is defined in Equation 5:

Equation 5 Logistic function. 
$$f_{\mathbf{w},b}(x) = \frac{1}{1+e^{-(\mathbf{w}x+b)}}$$

Where  $\mathbf{w}$  represents the weight vector,  $\mathbf{x}$  the feature vector, and  $\mathbf{b}$  the intercept. This function maps predictions to a range of (0,1), making it ideal for probability-based classification.

The optimization criterion for logistic regression is the **likelihood function**, which maximizes the probability of the observed labels given the model parameters. The likelihood function for logistic regression is represented as:

Equation 6. Likelihood function for logistic regression

$$L(w, b) = \prod_{i=1}^N (f_{(w,b)}(x_i)^{y_i} \cdot (1 - f_{(w,b)}(x_i))^{(1-y_i)})$$

Where  $\left(f_{(w,b)}x_i = \frac{1}{1+e^{-(wx+b)}}\right)$  is the predicted probability for each instance  $x_i$ ,  $y_i$  represents the actual label (0 or 1) for instance  $i$ , and  $N$  represents the total number of instances in the dataset.

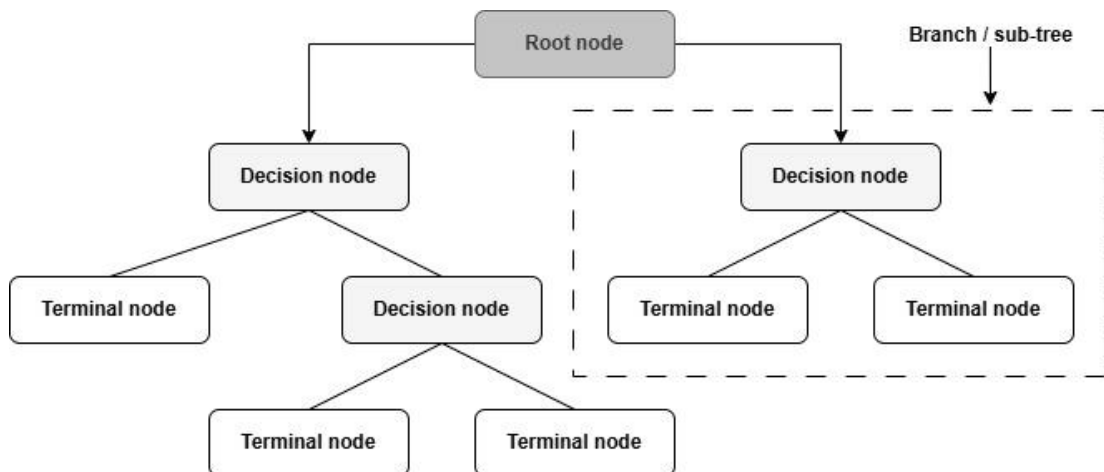
For practical purposes, the **log-likelihood function** is often used (that is taking the logarithm of the likelihood function), as it simplifies computation by converting the product into a sum:

Equation 7. Log-likelihood function

$$\log L(w, b) = \sum_{i=1}^N \left( y_i \log \left( f_{(w,b)}(x_i) \right) + (1 - y_i) \log \left( 1 - f_{(w,b)}(x_i) \right) \right)$$

The goal of logistic regression is to find the parameters  $\mathbf{w}$  and  $\mathbf{b}$  that maximize this log-likelihood, making it more likely that the model’s predictions align with the observed outcomes. However, a detailed explanation of this optimization process falls beyond the scope of this thesis.

Figure 28. A visual depiction of the decision tree model (source: author)



**Decision tree learning** is another widely used algorithm for both classification and regression tasks, which structures data into a tree format to facilitate decision-making. The algorithm constructs a hierarchical model where each node represents a decision based on a feature of the dataset. These nodes are organized hierarchically, starting from the **root node** at the top of the tree as the first decision point, where the data is

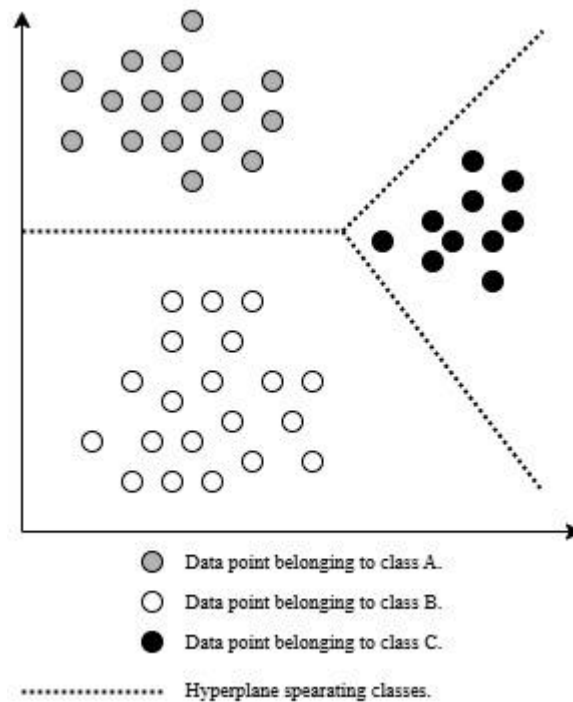
initially split based on the feature that provides the most informative separation of classes. From the root node, branches lead to additional **internal nodes**, each representing further decisions that split the data into more refined subgroups based on other features. This process continues until the algorithm reaches **leaf nodes** (or **terminal nodes**), where final class predictions are made. Leaf nodes are associated with specific outcomes or class labels, meaning that any data point reaching a particular leaf node will be assigned that node's label. This hierarchical structure of decision trees allows for a straightforward, step-by-step approach to decision-making, where each branch narrows down possibilities, ultimately classifying or predicting based on the paths taken through the tree. A visual depiction of the model is presented in Figure 28.

**Support vector machines (SVM)** are classification algorithms that separate classes using a hyperplane. In binary classification, SVM aims to find a hyperplane that maximally separates positive and negative classes. The decision boundary is represented as:

Where  $\mathbf{w}$  and  $\mathbf{x}$  are weight and feature vectors, respectively and  $b$  is the offset. The algorithm optimizes two main objectives: maximizing the **margin** between classes and ensuring clear separation of examples (leading to better generalization of results). Additionally, **SVM kernels** can be incorporated, to allow for the separation of complex, non-linear cases that are distorted by outliers or other noise. This adapts the use of the algorithm for more complex datasets. An illustration of a simple case of the SVM algorithm is provided in Figure 29.

The final learning algorithm covered in this subsection is **k-Nearest Neighbours (kNN)**, which is a non-parametric, instance-based algorithm used for classification and regression. Due to its non-parametric nature, kNN doesn't assume a specific mathematical model for the distribution of the underlying data. Instead, the algorithm makes predictions based on the similarity of new data to stored instances in the training dataset. When classifying an unlabelled data point, the algorithm identifies the  $k$  nearest neighbours (based on distance metrics like Euclidean distance) and assigns the class label most common among those neighbours.

Figure 29. A visual representation of the Support vector machines (SVM) algorithm (*source: author*)



Equation 8. Decision boundary formula  $w x - b = 0$

To summarize, these supervised learning algorithms each utilize unique methodologies and optimization goals, providing flexible solutions across a range of classification and regression tasks. While logistic regression and SVM focus on maximizing separation, decision trees prioritize data partitioning, and kNN leverages similarity to classify new data. Together, these algorithms offer a wide range of flexible solutions for various types of machine learning applications.

Awareness about the above supervised learning algorithms is highly useful as they serve as the basis of valuable practical applications. Consider for instance that a winery's direct-to-consumer sales team wants to predict whether a customer will purchase a premium wine during an online promotion. As this problem can be translated into a binary classification or not (decision of purchase, or no purchase), logistic regression is well-suited for this task. Input features might include prior buying frequency, average basket value, responsiveness to past promotions, seasonality, or

website browsing behaviour. The sigmoid function then can be used to convert these inputs into a probability estimate between 0 and 1, indicating how likely each customer is to buy. Marketing teams can then set a probability threshold (for example, only targeting customers with a predicted probability above 0.65), to support the efficient allocation of promotional budgets, or provide personalized offers based on individual characteristics and behaviours.

In vineyard operations, SVM can help classify grape batches as “healthy” or “disease-affected” based on sensor readings or hyperspectral imaging data. Because SVM seeks the hyperplane that maximizes separation between classes, it performs well when the distinction between healthy and diseased samples is subtle, but still detectable through algorithmic methods. Features used for such detection might include leaf moisture levels, colour indices, canopy temperature, or fungal-infection markers. For vineyard managers, this can serve as an important aid for the early identification of disease risks, reducing crop losses and enabling more targeted and sustainable interventions.

An example use case of the decision tree algorithm in the wine sector could be to classify bottles into quality categories (e.g., standard, reserve, premium) based on chemical properties and production parameters. Each internal node of the tree represents a decision rule, by answering questions such as, “Is the acidity above a certain threshold?” or “Is residual sugar below a pre-defined value?”. By executing the algorithm, the data could be split into homogeneous groups. Because decision trees classify products through explicit, rule-based steps, managers can easily review how each quality decision was reached. This clarity and traceability is valuable for audits and quality control certifications, as every classification can be traced back to clear, interpretable criteria. This interpretability also helps identify which production factors most strongly influence quality outcomes, supporting improvement initiatives or creating more consistent wines.

Finally, an example use case of kNN-s could be personalizing wine recommendations in a winer’s tasting room. Suppose that a new visitor enters their taste preferences (e.g., sweetness level, body, aroma notes) into a digital kiosk at the start of their visits. An appropriately designed and trained algorithm could compare this new profile to

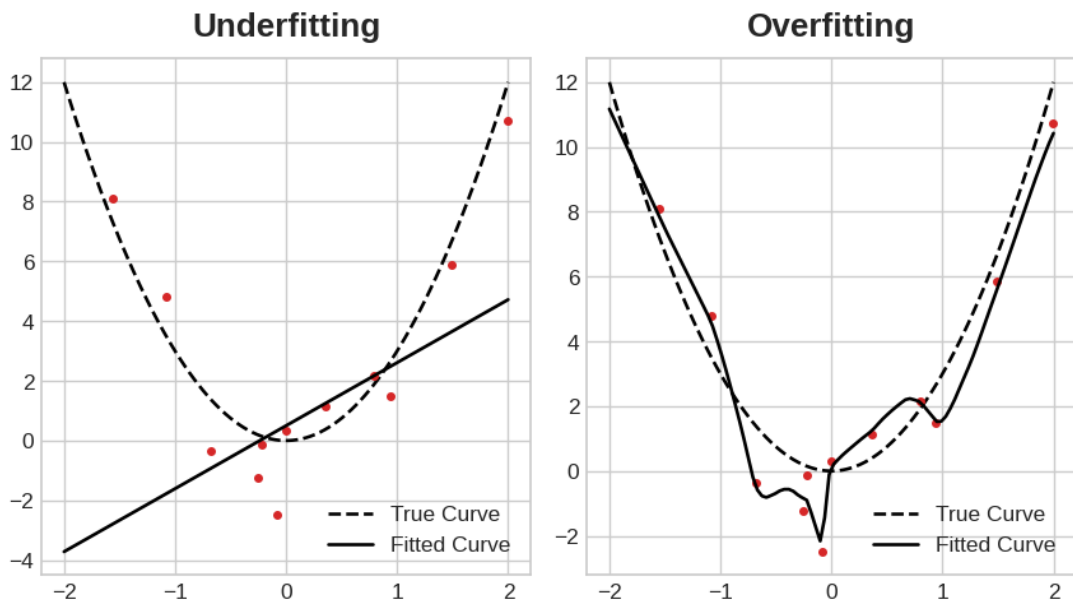
historical data from previous visitors whose preferences and purchase choices are stored. By identifying the k-number of most similar past customers, the algorithm can provide wine recommendations based on those customers' most frequent purchases. Because kNN requires no predefined model and learns directly from stored examples, it adapts naturally as customer databases grow. This helps wineries enhance customer experience and potentially increase sales by providing personalized, data-driven recommendations.

### **Bias, variance, overfitting and regularization**

In machine learning, bias and variance are two fundamental sources of error that significantly influence a model's predictive accuracy. **Bias** represents the error introduced by approximating real-world data with a simplistic model. A model with high bias tends to make assumptions that oversimplify the underlying data patterns, often resulting in poor performance on both training and validation sets. This can lead to **underfitting**, where a model is too simple to capture the underlying structure of the data. The high bias in the model leads to low performance on both training and test data, as it makes incorrect or overly simplistic and too generalized predictions based on the underlying datasets.

On the other hand, **variance** refers to the sensitivity of the model to fluctuations in the training data. A model with high variance is overly complex and adapts closely to the training data, including its noise and other irrelevant details. While this may lead to high accuracy on the training data, the model performance will likely degrade on new training and validation sets. This phenomenon is known as **overfitting**, which can be visualized as a model that precisely fits the training data points but produces irregular, fluctuating predictions for new data. The difference between underfitting and overfitting is visualized on Figure 30.

Figure 30. Visualization of underfitting and overfitting (source: (Ryan Holbrook, n.d.)



There are different techniques used in machine learning aimed at addressing overfitting. **Regularization** aims to simplify the model and mitigate overfitting by introducing a penalty for complexity in the objective function. The two most common regularization methods are L1 regularization, also known as Least Absolute Shrinkage and Selection Operator (LASSO), and L2 regularization, commonly referred to as ridge regression.

**L1 regularization** modifies the objective function by penalizing the absolute values of the model's parameters. This approach encourages that the model prioritizes only the most significant features, setting less important feature weights closer to zero. L1 regularization is therefore useful in feature selection, as it helps to identify and emphasize the most critical factors for prediction. **L2 regularization**, on the other hand, applies a penalty to the squares of the parameter values. This method discourages large parameter weights, stabilizing the model and reducing its sensitivity to individual data points without the removal of features altogether. L2 regularization is thus suitable in cases where all features are valuable, but their impact needs to be moderated to prevent overfitting

The strength of these regularization methods is controlled by a **hyperparameter**, often denoted as  $C$ . This hyperparameter balances the trade-off between fitting the training

data closely and maintaining simplicity in the model. A lower value of  $C$  applies stronger regularization, which simplifies the model by increasing bias and decreasing variance. Conversely, a higher value of  $C$  reduces regularization, allowing for a more complex model that may better fit the training data but with the risk of higher variance. In mathematical terms, consider a basic regression model where the objective function is to minimize the error, expressed as:

*Equation 8. Error function, basic regression model*

$$\frac{1}{N} \sum_{i=1}^N (f_{\mathbf{w},b}(x_i) - y_i)^2$$

where  $f_{\mathbf{w},b}$  represents the model's prediction function,  $x_i$  denotes the input features,  $y_i$  represents the actual output values,  $\mathbf{w}$  denotes the weight parameters,  $b$  denotes the bias term, and  $N$  is the number of samples in the training dataset. In the case of L1 regularization, the objective function is modified to:

*Equation 9. Modified objective function, L1 regularization*

$$\min_{\mathbf{w},b} \left[ C|\mathbf{w}| + \frac{1}{N} \sum_{i=1}^N (f_{\mathbf{w},b}(x_i) - y_i)^2 \right]$$

The L1 penalty term promotes **sparsity** (emphasizing only the most essential features by setting others to zero) by focusing on fewer, more relevant features. For L2 regularization, the objective function changes to:

*Equation 10. Modified objective function, L2 regularization*

$$\min_{\mathbf{w},b} \left[ C\|\mathbf{w}\|^2 + \frac{1}{N} \sum_{i=1}^N (f_{\mathbf{w},b}(x_i) - y_i)^2 \right]$$

Here, the L2 penalty prevents large weight values, allowing for a model that generalizes better by maintaining stable predictions across different datasets.

The concepts of bias and variance lead to what is known as the **bias-variance trade-off**, an essential aspect of machine learning model design. The aim is to find a balance where the model is neither too simple (leading to high bias and underfitting) nor too complex (leading to high variance and overfitting). The earlier demonstrated regularization techniques help to manage this trade-off by moderating the complexity of the model, although they inherently increase bias as they reduce variance.

### Neural networks and deep learning

Similarly to other machine learning models, **neural networks** are often represented mathematically to provide a clear description of how data flows through the network. In this representation, the network is seen as a function that takes an input and transforms it into an output through a series of operations. In this context, neural networks are commonly denoted with the equation:

*Equation 11. Neural networks, standard function*

$$y = f_{NN}(x)$$

Where  $f_{NN}$  represents the overall function of the network. This notation describes the sequential transformations applied to the input  $x$  as it passes through each layer in the network, ultimately yielding the output  $y$ .

A neural network typically consists of multiple layers, each performing a specific role in the processing of data. The first layer, known as the **input layer**, receives the initial data. **Hidden layers** then transform this data through a series of operations, such as linear transformations and non-linear **activations**, allowing the network to model complex relationships within the data. By combining these simpler functions or transformations hierarchically, the network can learn complex patterns and dependencies embedded in the training data. To mathematically describe this layered structure, we can express a three-layer neural network with the following equation:

*Equation 12. Three-layered neural network, standard function*

$$y = f_{NN}(\mathbf{x}) = f_3\left(f_2(f_1(\mathbf{x}))\right)$$

Where each function, such as  $f_1$  and  $f_2$ , corresponds to transformations occurring within a specific layer. These layers are composed of **vector functions** that receive a vector input and produce a vector output, gradually transforming the data through each stage of the network.

Each layer's transformation can be further specified as:

*Equation 13. Transformation of layers of neural networks, standard function*

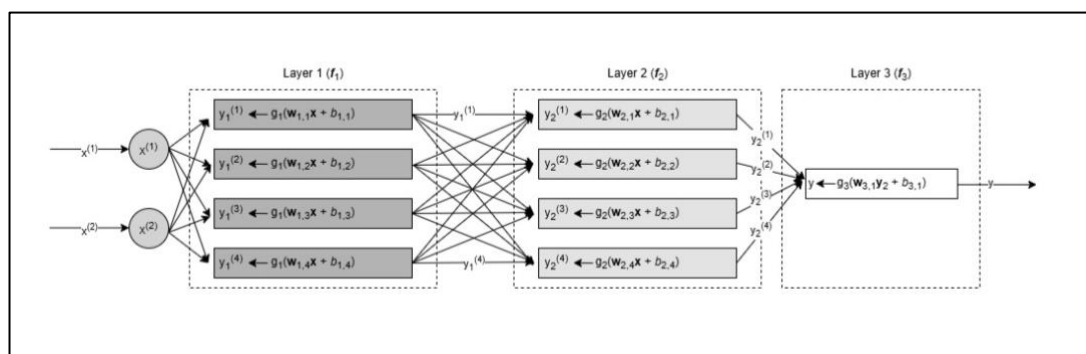
$$f_l(\mathbf{z}) \stackrel{\text{def}}{=} \mathbf{g}_l(\mathbf{W}_l \mathbf{z} + \mathbf{b}_l)$$

Where  $l$  is the **layer index** (in this example, up to three layers) and  $\mathbf{g}_l$  represents the **activation function**, which plays a critical role by introducing non-linearity into the network. Common activation functions include the **Rectified Linear Unit (ReLU)**, which outputs the input directly if it is positive and zero otherwise, the **Sigmoid function**, which maps values between 0 and 1, and the **Hyperbolic Tangent (Tanh)**, which maps values between -1 and 1. Each of these activation functions contributes to the flexibility and capacity of neural networks by enabling them to generalize across a wide array of data patterns. However, a more detailed mathematical description of these functions and their operations is outside of this thesis's scope.

A particular type of neural network configuration, known as the **multilayer perceptron (MLP)**, is commonly used and serves as a fundamental example of how these networks operate. An MLP belongs to the broader category of **feed-forward neural networks (FFNNs)**, an architecture where data passes sequentially from one layer to the next, without any backward connections. MLPs are typically composed of three types of layers: the input layer, which receives and represents the input features; one or more hidden layers, where data undergoes transformation through weighted connections and activation functions; and the output layer, which generates the network's final prediction. The hidden layers, situated between the input and output layers, perform the critical work of representing complex patterns within the data by applying transformations through weights and biases.

Figure 31 offers a visual representation of a three-layer MLP architecture, demonstrating the flow of data from input to output layers. In this example, the input is represented as a two-dimensional feature vector, which enters the first hidden layer containing four neurons. Each neuron in the hidden layer applies an activation function (such as  $g_1$ ), transforming the data before passing it to the next layer. The second hidden layer also contains four neurons, performing additional transformations with a distinct activation function  $g_2$ . The final output layer consists of a single neuron, which applies the activation function  $g_3$  to generate a real-valued output. This flow of information from layer to layer, with each neuron performing a weighted sum of its inputs plus a bias, illustrates how MLPs process data through interconnected layers to produce a prediction.

Figure 31. An example layout of a three-layer MLP. (source: *The Hundred-Page Machine Learning Book* (Burkov, 2019))



Following the discussion on neural networks, it's essential to understand a specialized area within this field known as deep learning. **Deep learning** is a subset of machine learning and neural networks that focuses on training models with many hidden layers, allowing for greater complexity and capability in learning patterns from data. This unique depth has enabled deep learning models to excel in fields that require complex pattern recognition, such as image classification, natural language processing, and speech recognition. These advances have positioned deep learning as a transformative branch within AI, significantly pushing the boundaries of what machine learning can accomplish.

The word “deep” in deep learning refers to neural networks that contain multiple (usually, more than two) hidden layers between the input and output layers. Unlike traditional machine learning models, which may rely on simpler architectures, deep learning networks use this layered structure to capture hierarchical representations within the data. Each layer in a deep network builds on the information extracted by the previous one, learning more abstract and complex features as the data passes through. This ability to model complicated data relationships and uncover patterns that are difficult to capture manually is a key advantage of deep learning methods.

Training these deep networks, however, poses unique challenges due to their complex, multi-layered structure. Special techniques, such as backpropagation, are essential for adjusting the weights and biases of each layer in response to errors. **Backpropagation**, short for “backward propagation of errors,” is a fundamental algorithm that enables the model to minimize the difference between predicted and actual values by iteratively updating the model’s parameters. This iterative process is crucial for learning in deep networks, as it ensures that the model’s predictions improve over time. Despite its effectiveness, backpropagation introduces specific limitations when applied to deep learning architectures, primarily through the issues known as exploding and vanishing gradients. The **exploding gradient problem** arises when gradients (the values used to update the model's parameters) become excessively large as they are propagated back through the network, leading to unstable updates and often preventing the model from converging. In contrast, the **vanishing gradient problem** occurs when these gradients become very small, particularly in networks with many layers. This diminishes the model’s ability to learn long-range dependencies and limits its overall performance. These challenges have led to the development of methods like the **ReLU (Rectified Linear Unit) activation function**, which helps alleviate vanishing gradients, and **gradient clipping**, which controls the size of gradients to address exploding gradient issues. The detailed discussion of these methods is outside the scope of this thesis.

The capabilities offered by deep learning were instrumental in creating more complex applications based on the method. In image classification, for example, deep learning models can distinguish complex visual patterns, allowing systems to recognize and

categorize images with high accuracy. In natural language processing, deep learning enables applications like machine translation and sentiment analysis, where understanding context and nuanced meaning is essential. Through these applications, deep learning has demonstrated its ability to transform tasks that were once considered impossible to be performed by machines, highlighting its critical role within the wider AI domain. Previously demonstrated practical examples provide a glimpse into how more advanced deep learning-based algorithms can be utilized in business scenarios specific to the wine industry.

### **Convolutional neural networks**

Finally, the concept of **convolutional neural networks (CNNs)** is introduced in this section. CNNs are a specialized type of feedforward neural networks (FFNNs) particularly effective for tasks in image recognition, text processing, and computer vision. CNNs excel in their ability to handle spatial hierarchies within data, meaning they can recognize how different parts of an image are organized relative to each other. The characteristic to capture spatial hierarchies (such as the arrangement of edges, shapes, and textures) allows CNNs to build a layered understanding of images. As a result, they are exceptional tools in identifying simple patterns and then combine these to detect more complex structures, like shapes or objects, as they move through deeper layers in the network. This hierarchical approach makes CNNs effective for tasks that involve high-dimensional data, like images, where understanding the relative positions of features is crucial. Unlike traditional multilayer perceptrons (MLPs), where adding more layers can lead to exponential growth in the number of parameters, CNNs utilize a unique structure that helps manage computational complexity. By using local receptive fields and shared weights, CNNs significantly reduce the number of parameters, making them more efficient for processing high-dimensional data.

In CNNs, the **convolution operation** is central to feature detection. Filters, or small matrices of weights, slide over the input image in a systematic way, identifying specific patterns or features, such as edges and textures. Each filter is trained to respond to a particular type of feature within the image. For example, an edge-detecting filter would yield high activation values when encountering a sharp contrast

between pixels, indicating the presence of an edge. This feature-detection capability enables CNNs to build complex representations of visual data in successive layers.

The **convolution process** is illustrated in Figure 32 and Figure 33, which help to visualize how a filter operates over different parts of an image. In Figure 32, a sample convolution operation between matrices  $F$  and  $P$  shows the element-wise multiplication and summing steps that result in a single value representing similarity between the filter and the image patch. Figure 33 shows how a filter moves across an image, performing this operation over various sections to produce a feature map, or a matrix of values representing different features detected in the image. For instance, in a simple black-and-white image, a patch  $P$  could be represented as follows, where 1 denotes black pixels and 0 denotes white pixels:

$$P = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Each convolutional layer in a CNN also includes a **bias term**, which allows for adjusting the output independently of the specific input. Adding bias enables the network to learn patterns more flexibly, as it shifts the output values to better capture the data's underlying structure. After applying the convolution and bias, an activation function is typically used to introduce nonlinearity. The rectified linear unit (ReLU) is commonly applied here, as it effectively captures non-linear relationships without significantly increasing computational load. ReLU transforms the output by retaining positive values and discarding negative ones, enhancing the network's capacity to learn complex patterns.

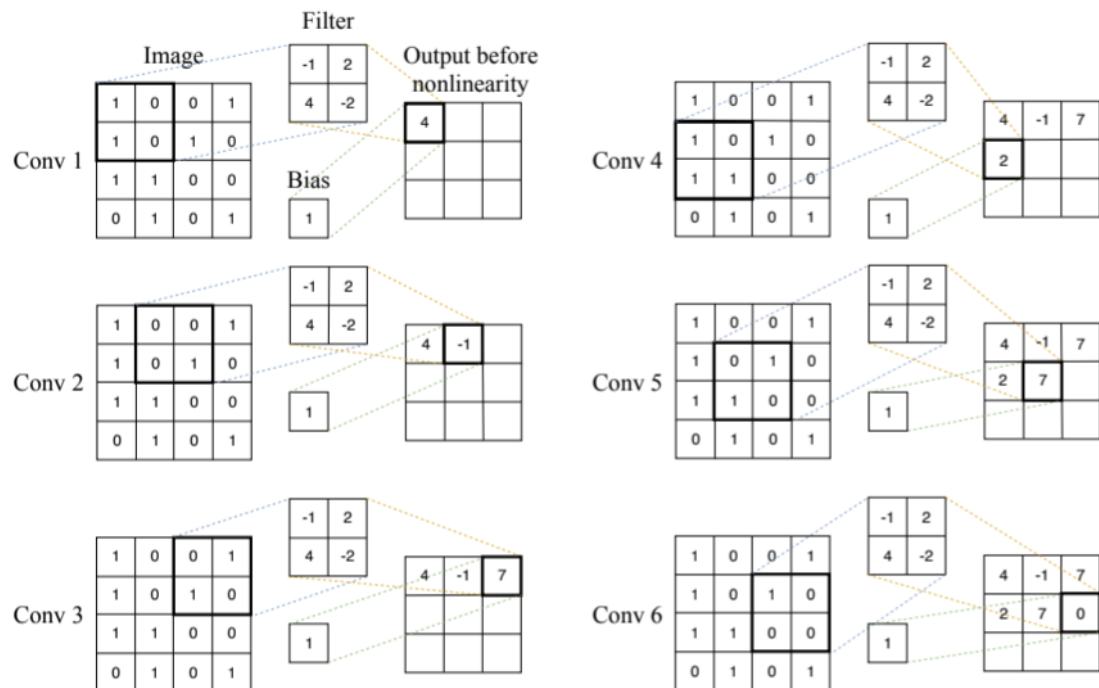
Figure 32. An example of convolution between matrices  $F$  and  $P$ . (source: *The Hundred-Page Machine Learning Book* (Burkov, 2019))

$$P = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \xrightarrow{\text{convolution}} F = \begin{bmatrix} 0 & 3 & 7 \\ 6 & 2 & 4 \\ 1 & 0 & 0 \end{bmatrix} \xrightarrow{\text{overlay}} \begin{bmatrix} 1 * 0 & 0 * 3 & 0 * 7 \\ 0 * 6 & 1 * 2 & 0 * 4 \\ 0 * 1 & 0 * 0 & 0 * 0 \end{bmatrix} \xrightarrow{\text{sum}} 2$$

**Pooling** is another crucial component in CNNs, acting as a dimensionality reduction technique that follows the convolutional layer. Pooling, often using max or average

pooling operations, by applying a moving window over the convolutional output to reduce its spatial dimensions. This process preserves the depth (the number of feature maps) but reduces the width and height, thereby lowering computational requirements and helping the network focus on the most relevant features by discarding less important details. Pooling thus improves both model accuracy and training efficiency.

Figure 33. An illustration of a filter convolving across an image. (source: *The Hundred-Page Machine Learning Book* (Burkov, 2019))



## **Appendix 2. Execution of Delphi method – operational details**

The use of the Delphi method required careful consideration about the expert panel setup, data collection methods used, the statements formulated and how to analyse the data collected. The aim of this section is to provide further context about these themes that was not included in the main body of the research.

### **Expert panel setup and data collection**

The Delphi process flow is split into three main phases: nomination, preparation, and analysis and conclusion, as demonstrated in Figure 6. In the **nomination phase**, experts are selected to ensure a diverse and representative panel. The process begins by defining criteria to categorize experts, following established approaches used in similar studies. This method aims to assemble a balanced group, including practitioners, academics, government officials, and representatives from non-governmental organizations (NGOs) (Okoli & Pawlowski, 2004). Such diversity is critical to capture a broad spectrum of perspectives, as individuals from different backgrounds can offer unique insights based on their varying experiences with the topic. Once the list of potential experts is compiled, they are ranked based on relevance and expertise, contacted, and invited to participate in the panel.

When executing this research, the data collection process began with defining the categories of experts to be included in the Delphi panel. The aim was to develop a **sampling strategy** where the data generated is sufficient to answer the research question and thus ensure that the objectives of the study are met. When deciding on this, it was important to consider the various sampling methods and techniques available in social research, in line with the sampling logic considerations in (Babbie, 2021).

Sampling methods can be categorized into two groups. **Nonprobability sampling** is suitable for exploratory and qualitative research, when full population data is not

available. In contrast, **probability sampling** allows for the compilation of a panel that is representative of the entire population and thus enables statistical generalization. Due to the exploratory nature of this study, the nonprobability sampling method was deemed appropriate to meet the research objectives. The associated sampling techniques are summarized in Table 40.

Table 40. Nonprobability sampling techniques available (source: author based on (Babbie, 2021))

<b>Sampling technique</b>	<b>Description</b>	<b>Use cases</b>	<b>Weaknesses</b>
Convenience sampling	Selects participants based on accessibility or availability.	Pretesting instruments, exploratory research.	Highly biased; does not generalize to the broader population.
Purposive sampling	Researcher selects participants with specific characteristics.	Studying niche groups or deviant cases.	Limited generalizability; prone to researcher bias.
Snowball sampling	Participants recruit others within their network.	Hard-to-reach populations like undocumented immigrants.	Limited representativeness; depends on participants' willingness to recruit others.
Quota sampling	Ensures sample distribution matches specific population attributes.	Studying subgroups, e.g., gender and age distributions.	Requires accurate population data; sampling within quotas may introduce biases.

Out of the different nonprobability sampling techniques identified, the **purposive sampling** was used, as a method inherent in the design of the Delphi approach. The weaknesses were acknowledged, yet this was deemed the most suitable technique to identify and engage knowledgeable experts whose insights were essential for addressing the specific research questions and achieving the study's objectives. The goal was to assemble a group of professionals from diverse fields to achieve the objectives of this research, thereby ensuring a comprehensive understanding of the topic. The main selection criteria included extensive professional experience (at least 5 years) in winemaking, viticulture or the wider alcoholic beverages industry, significant exposure to AI development and implementation and technology-driven transformation, faculty membership at a higher education institution focusing on wine

business research, or a member of a governmental or non-governmental organization with ties to the wine industry.

*Table 41. Categories of experts to be included in the Delphi panel studying the impact of the application of AI in the wine industry (source: author)*

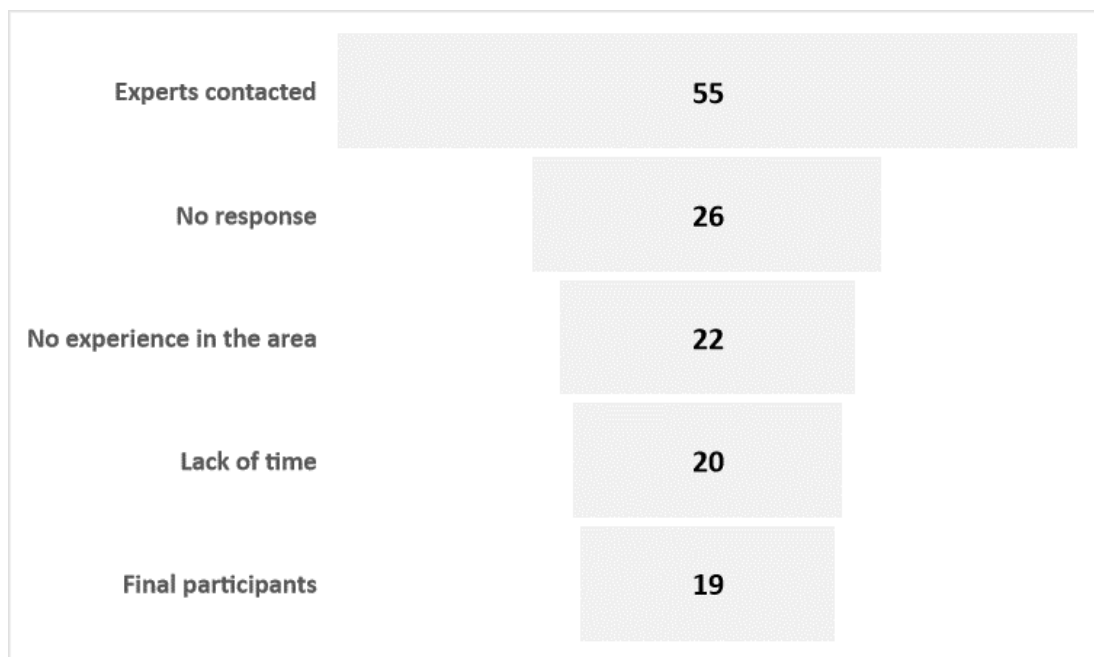
Title	Description
Winemaking experts	Owners, managers or employees with significant decision-making authority in companies in the wine value chain, with an in-depth practical experience in the wine industry, understanding of current opportunities and the challenges the sector is facing.
Technology consultants	External advisers employed by reputable consulting firms with a specific focus on the agricultural sector, or technology transformation (with a particular interest in AI).
Technologists and AI specialists	AI and technology experts specializing in machine learning, data analytics, and AI applications that can provide insights into the implementation of technological innovations relevant to the wine industry.
Academic professionals	Research staff employed by academic institutions with an up-to-date understanding of how the body of scientific knowledge in wine business evolved in the last years, with a particular focus on technology implementation trends.
Governmental or non-governmental organisations representatives	Professionals employed by regulatory authorities or other policy setting bodies knowledgeable about the technology implementation trends, benefits and hurdles in the wine industry, or the wider agricultural sector.

Table 41 lists the five categories of experts included in the panel. These categories were designed to represent a wide range of perspectives, each offering unique insights into the study's subject. **Winemaking experts**, actively engaged in various stages of the wine value chain, were expected to contribute insights based on their practical experience and understanding of industry challenges and opportunities. **Technology consultants** from reputable advisory firms specializing in either agriculture or technology (with a particular focus on AI), offered a broader perspective on technological innovation patterns with potential consequences to the wine sector. **Technologists and AI specialists** provided technical and interdisciplinary insights, ensuring a comprehensive understanding of different considerations and viewpoints relevant to the objective of this research. **Academic professionals** offered research-driven insights, adding valuable knowledge that strengthens the study's findings. Lastly, **representatives from governmental and non-governmental organizations**

provided an understanding of additional dimensions related to AI adoption in the wine industry. Selecting such a range of experts contributed to a holistic understanding of the research problem laid out at the start of this thesis.

The **recruitment of the expert panel** began with the identification of professionals who met the criteria outlined in Table 41. Fifty-five experts were initially contacted via email or LinkedIn message. A total of twenty-nine candidates did not respond after sending a reminder to them. Four potential participants indicated that their expertise was more focused on viticulture rather than technology transformation in winemaking, reflecting a narrow specialization in the field. Two prospects cited time constraints as a reason for non-participation, while one agreed initially but subsequently declined to participate. The funnel showing how the final expert panel was reached in this study is shown in Figure 34.

Figure 34. The funnel showing how the final expert panel was collated in the Delphi study (source: author)



*Figure 35. Geographical spread of participants in the final expert panel (source: author)*



The final expert panel presented in Table 42 included seven wine professionals, five academic professionals, three technology consultants, two AI specialists, and two representatives from governmental or non-governmental organizations. To utilize the Delphi method's strengths, the recruitment approach consciously targeted experts from various geographic regions, as shown in Figure 35. This geographic diversity was intended to capture insights that reflect not only technological trends but also potential regional variations in regulatory, cultural, and operational factors that influence AI adoption in the wine industry.

Table 42. Details of the members in the final expert panel (source: author)

<b>Respondent ID</b>	<b>Category</b>	<b>Summary of experience</b>
1	Academic professional	Associate professor in viticulture and oenology with research in technology use in viticulture.
2	Wine professional	Finance director in global beverage industry; Non-Executive Director at an online wine retailer.
3	Academic professional	Researcher in agricultural economics and wine business model innovation with 30+ publications.
4	Wine professional	CEO of an online wine discovery platform, 15+ years' experience in launching wine-related startups.
5	Wine professional	Co-owner of a small-scale winery and researcher in wine business models.
6	Technologist and AI specialist	Machine Learning lead with a finance and math background; wine enthusiast and hobbyist.
7	Wine professional	Founder of an AI-powered platform designed for wine industry professionals to enhance their sales materials.
8	Academic professional	Business administration professor with 50+ contributions in wine business and agricultural economics.
9	Technology consultant	Partner at strategy consultancy specializing in tech transformation and data analytics.
10	Wine professional	Wine consultant and certified sommelier with experience in wine tourism, reviews, and sales.
11	Technologist and AI specialist	Group leader in AI-based automotive solutions with a master's in robotics and management.
12	Wine professional	Founder of a renowned Hungarian winery with multiple international awards.
13	Wine professional	President of a wine region's organization and co-owner of a viticulture solutions company.
14	Technology consultant	PhD in Transportation Science with focus on drones and UAVs in agriculture.
15	Technology consultant	CEO of an IT consulting firm; lecturer and researcher in AI and cybersecurity in agriculture / viticulture.
16	Academic professional	Associate professor in data analytics with interests in digital transformation and smart farming.
17	Academic professional	Head of System Development at a nonprofit, focusing on robotics in grape pruning.
18	Governmental or non-governmental organisations representative	Department head in agriculture ministry; assistant professor in wine business.
19	Wine professional	Co-owner of a leading winery, awarded "Wine Producer of the Year in Hungary."

## Questionnaire and projections formulated

Table 43. Delphi projections used in the final questionnaire (source: author)

<b>Cluster 1: future use cases of AI in the wine industry in the next 5-10 years include...</b>	
1	Automated disease diagnosis and classification through image recognition
2	Forecasting soil and climatic conditions through data obtained from sensors
3	Optimal harvest time definition, based on environmental conditions analysis
4	Automated water control systems
5	Targeted pesticide spraying and irrigation
6	Automated steps of farming operations such as planting, pruning, harvesting, and grape sorting
7	Controlling barrel aging conditions, biological and chemical processes affecting wine quality
8	AI-based wine blending
9	AI-based production scheduling to improve winemaking efficiency
10	Predicting wine quality by leveraging sensory analysis and maturation data
11	Forecasting results of wine tasting experiences, using the physiochemical properties of wine
12	Virtual sommelier services, offering customized recommendations and wine selection
13	Marketing strategies developed with generative AI
14	Wine fraud prevention by authenticating packaging, or analysis of chemical composition
<b>Cluster 2: main benefits of the use of AI in the wine industry in the next 5-10 years include...</b>	
15	Earlier intervention against diseases and pests
16	Improvement in grape yields
17	Targeted farming practices based on vineyard characteristics
18	Higher profitability due to lower use of input materials
19	Price premiums paid by end consumers due to improved quality
20	Better anticipation and service of customer demand
21	Stricter quality control and product lifecycle transparency
22	More sustainable operations due to reduction in hazardous and other input materials
23	More flexibility to cope with global challenges (climate change and other disruptions)
24	More meaningful jobs created through the automation of labour intensive and repetitive tasks
<b>Cluster 3: main challenges to the adoption of AI in the wine industry in the next 5-10 years include...</b>	
25	Infrastructural constraints (network availability, lack of computational resources)
26	Lack of awareness and knowledge of technological innovations among decision makers
27	Shortage in skilled workforce
28	Lack of acceptance towards the implementation of new technologies
29	Cost implications of investments
30	Farm size making the implementation of new innovations economically non-viable
31	Gaps in governmental policies and incentives
<b>Cluster 4: AI adoption and technological transformation in the wine industry is driven by..</b>	
32	Increased profitability pressure due to economic challenges (cost inflation, high interest rates)
33	Increase in global demand for wine and grape-based products due to population growth
34	Climate change-induced challenges (availability of natural resources, weather conditions)
35	Shifting consumer preferences towards high-quality, traceable, and organically certified wines
36	The intensification of both domestic and international competition

In line with the research questions laid out at the beginning of this study, the final Delphi questionnaire is split into four sections. The aim is to understand the **future use case scenarios of AI** in the wine value chain in the next 5-10 years, the main **benefits offered by those technologies**, the key **challenges to the implementation of AI in the wine sector** and the main **drivers of AI adoption and technological transformation** in the industry. Based on the detailed review of academic and grey literature, a total of 36 statements were formulated and validated with the Delphi method. The final questionnaire shared with the expert panel is shown in Table 43.

### **Future use cases of Artificial Intelligence (AI) in the wine value chain**

The first section of the Delphi questionnaire includes fourteen statements about the potential applications of AI in the wine value chain over the next five to ten years. Each statement represents a specific use case scenario, offering insights into how AI can support various stages of vineyard management, winemaking processes, and consumer engagement, grounded in current research and expert perspectives, that were deduced from the bibliometric analysis and grey literature review conducted in the previous section and corroborated by additional academic articles to strengthen robustness of the statements formulated. The following sections will explain the rationale behind these and other statements, with references to academic literature where such application areas were covered.

#### **S1 Automated disease diagnosis and classification through image recognition**

Grapevines are vulnerable to diseases and pests, with exposure levels varying by climate, region, and viticultural practices. The typical growing season from bud break to harvest lasts five to seven months, during which pest and disease management is essential for grape quality. Machine learning algorithms can assist in early detection of such anomalies, offering a proactive approach to disease management, as shown by research on other crops using similar technology (Deepalakshmi et al., 2021; Ganatra & Patel, 2020; Hidayatuloh et al., 2018, 2018; Loey et al., 2020).

## **S2 Forecasting soil and climatic conditions through data obtained from sensors**

Advances in agricultural technology now enable real-time monitoring of soil and climatic conditions through sensors and IoT applications. This capability supports targeted farming techniques and mitigates grape losses caused by environmental stressors, improving both harvest yields and grape quality (Murlidharan et al., 2021; Vennila et al., 2020).

## **S3 Optimal harvest time definition, based on environmental conditions analysis**

Selecting the optimal harvest time is critical, as it impacts wine quality attributes such as body, acidity, tannins, and sugar levels. AI-based algorithms can analyse environmental data to determine the ideal harvest window, maximizing grape quality and supporting sustainable production through reduced emissions.

## **S4 Automated water control systems**

Grapevines are generally resilient to heat and drought, especially certain European varieties. Smart irrigation systems can ensure that vines receive appropriate water levels, promoting growth while addressing challenges related to freshwater scarcity and efficient water management (A. Kumar et al., 2014).

## **S5 Targeted pesticide spraying and irrigation**

Weed growth in vineyards can significantly impact crop yield by competing for nutrients and water. Advanced drone technology, combined with deep learning, can support more precise weed detection, allowing for targeted herbicide application and reducing chemical usage while enhancing productivity (Tiwari et al., 2019).

## **S6 Automated steps of farming operations such as planting, pruning, harvesting, and grape sorting**

AI can streamline labour-intensive vineyard tasks, enhancing precision and operational efficiency. These automated processes improve grape quality and yield by minimizing human error and variability, contributing to consistency in wine production (Raman et al., 2023).

### **S7 Controlling barrel aging conditions, biological and chemical processes affecting wine quality**

AI technologies can precisely control barrel aging conditions by monitoring and adjusting factors that influence essential biological and chemical processes, affecting quality of the wine produced. Additionally, AI can assist in selecting and assembling barrel staves for optimal oxygen transmission, enhancing wine aging and quality (V́ctor Mart́nez-Mart́nez et al., 2020).

### **S8 AI-based wine blending**

Artificial neural networks and AI models can facilitate the complex process of wine blending by managing nonlinear interactions among compounds to achieve desired sensory characteristics. By modelling sensory data from initial blends, AI enables winemakers to create blends that closely align with targeted flavour profiles (Ferrier & Block, 2001).

### **S9 AI-based production scheduling to improve winemaking efficiency**

Predictive analytics and Machine Learning (ML) support optimized scheduling of winemaking processes, coordinating resource allocation and timing to enhance operational efficiency. This approach streamlines the “grape-to-glass” production cycle, improving resource use across winemaking stages (Truong & Khanh, 2023).

### **S10 Predicting wine quality by leveraging sensory analysis and maturation data**

Machine learning can revolutionize wine quality prediction by analysing sensory and maturation data. This method reduces dependence on labour-intensive expert evaluations, enhancing prediction accuracy and efficiency (Athanasiadis & Ioannides, 2021).

### **S11 Forecasting results of wine tasting experiences, using the physiochemical properties of wine**

Machine learning models can predict wine type and quality based on physiochemical properties by modelling complex interactions among variables. This approach provides an efficient alternative to traditional sensory evaluations, maintaining high accuracy in quality assessments.

### **S12 Virtual sommelier services, offering customized recommendations and wine selection**

AI-powered virtual sommelier services analyse wine characteristics at a molecular level to generate detailed flavour and aroma profiles. Using consumer preference data, these services offer tailored wine recommendations to match individual preferences with high accuracy (Eads, 2024).

### **S13 Marketing strategies developed with generative AI**

Generative AI can enhance marketing activities by personalizing customer interactions and automating the generation of data-driven insights. These applications, commonly

adopted across industries, are well-suited for improving consumer engagement and satisfaction within the wine sector (Kshetri et al., 2024).

#### **S14 Wine fraud prevention by authenticating packaging, or analysis of chemical composition**

AI, combined with IoT and blockchain, can improve transparency and traceability throughout the wine supply chain. By authenticating wine packaging and analysing chemical composition, these technologies reduce fraud risks and ensure product authenticity (Adamashvili et al., 2024; da Costa et al., 2021).

#### **Benefits of Artificial Intelligence (AI) use in the wine sector**

The second section of the Delphi questionnaire identifies key benefits of AI in the wine sector, focusing on the technology's potential for improving operational efficiency, product quality, sustainability, and workforce satisfaction.

#### **S15 Earlier intervention against diseases and pests**

Traditional pest and disease detection methods in agriculture are both costly and time intensive. Digital imaging combined with Machine Learning (ML) can provide faster and more accurate detection of pests and diseases, outperforming conventional approaches (Abbaspour-Gilandeh et al., 2022).

#### **S16 Improvement in grape yields**

AI technologies enhance crop yield predictions by integrating data from remote sensing and advanced analytics. These technologies enable precise, efficient, and cost-

effective farming, allowing for optimized resource allocation and improved crop management (Murugesan et al., 2019).

### **S17 Targeted farming practices based on vineyard characteristics**

Precision agriculture, utilizing tools such as GPS, autosteer, satellite imagery, and variable rate applications (technologies that adjust inputs based on field variability), can tailor farming practices to specific vineyard characteristics. This targeted approach increases resource efficiency and enhances profitability by aligning practices closely with vineyard needs (Hanson et al., 2022).

### **S18 Higher profitability due to lower use of input materials**

AI applications ranging from ground-based robots to aerial drones can optimize resource use by targeting irrigation and pesticide application. These efficiencies reduce labour costs and improve profitability, making farming practices more sustainable economically (Talaviya et al., 2020).

### **S19 Price premiums paid by end consumers due to improved quality**

Wine prices are influenced by a variety of factors, including tasting scores, region, and vintage. AI's role in improving wine quality can increase product value, potentially allowing producers to charge price premiums to consumers (Bombrun & Sumner, 2003).

## **S20 Better anticipation and service of customer demand**

Advancements in AI can enhance demand prediction by combining multiple forecasting models. This enables more accurate demand anticipation and improves operational efficiency, allowing for better alignment of production with consumer needs (Watanabe et al., 2019).

## **S21 Stricter quality control and product lifecycle transparency**

Machine learning-based predictive models can authenticate wine by identifying key chemical markers that classify wine by geographic origin and variety. This capability enhances quality control and provides transparency throughout the product lifecycle (Adamashvili et al., 2024; da Costa et al., 2021).

## **S22 More sustainable operations due to reduction in hazardous and other input materials**

AI improves resource management, reducing water usage and pesticide application. These efficiencies support more sustainable farming practices by minimizing environmental impact and reliance on hazardous materials (Talaviya et al., 2020).

## **S23 More flexibility to cope with global challenges (climate change and other disruptions)**

AI technologies enhance resilience against global challenges such as climate change by enabling precise climate monitoring, thereby allowing for more efficient disaster response. These capabilities support adaptation strategies crucial for vineyard sustainability (Leal Filho et al., 2022).

## **S24 More meaningful jobs created through the automation of labour intensive and repetitive tasks**

The adoption of AI in winemaking is projected to shift manual, repetitive tasks to automated processes, creating opportunities for more meaningful roles focused on strategic activities. This shift could increase job satisfaction by allowing employees to engage in higher-value work (Khogali & Mekid, 2023).

### **Challenges to Artificial Intelligence (AI) implementation in the wine sector**

The third section of the Delphi questionnaire identifies significant challenges associated with implementing AI in the wine sector, highlighting specific barriers that could hinder AI adoption.

**S25 Infrastructural constraints (network availability, lack of computational resources)**

**S26 Lack of awareness and knowledge of technological innovations among decision makers**

**S27 Shortage in skilled workforce**

**S28 Lack of acceptance towards the implementation of new technologies**

**S29 Cost implications of investments**

**S30 Farm size making the implementation of new innovations economically non-viable**

The main barriers to wider AI adoption in agriculture include integration challenges with existing practices, limited technical expertise among farmers, and resistance to technological change. High initial investment costs also pose a significant obstacle, particularly in the wine industry, where vineyards are often small, family-owned operations with limited economies of scale. This condition makes it difficult for

smaller vineyards to absorb the potential financial losses associated with new technologies, further complicating AI adoption efforts in the wine sector (Adamashvili et al., 2024; Chiaraluce et al., 2024; Malisic et al., 2023; Talaviya et al., 2020; Truong & Khanh, 2023).

### **S31 Gaps in governmental policies and incentives**

The absence of standardized policies and regulatory frameworks for AI integration in agriculture creates uncertainty, which can slow down technological transformation in winemaking. Government initiatives, such as training programs or policies introduced, could encourage adoption by rewarding farmers for implementing digital technologies and helping to bridge skill gaps specific to agriculture and winemaking (Heussner et al., 2023; Khanna, 2021).

### **Drivers of Artificial Intelligence (AI) adoption in the wine sector**

The final section of the Delphi questionnaire outlines the key drivers for AI adoption and digital transformation in the wine sector.

### **S32 Increased profitability pressure due to economic challenges (cost inflation, high interest rates)**

Recent economic pressures, including rising interest rates and inflation in raw material costs, have increased the need for productivity gains in winemaking. Precision agriculture utilizing AI and other solutions offers a way to boost efficiency and reduce environmental impact, showcasing how digital technologies can help winemakers adapt to economic challenges (Khanna, 2021).

### **S33 Increase in global demand for wine and grape-based products due to population growth**

With the global population projected to rise from 8.0 billion in 2022 to approximately 9.7 billion by 2050, demand for grape-based products could potentially grow as well. Precision agriculture can help improve crop yields, making AI adoption and the more widespread use of digital innovations in winemaking an attractive solution to meet this potentially anticipated increase in global demand (Nations, n.d.).

### **S34 Climate change-induced challenges (availability of natural resources, weather conditions)**

AI supports climate change adaptation in agriculture by using data and predictive analytics to manage environmental shifts. In winemaking, these capabilities drive technological transformation as wineries seek to mitigate the impacts of climate-driven challenges (Leal Filho et al., 2022)

### **S35 Shifting consumer preferences towards high-quality, traceable, and organically certified wines**

Consumers increasingly value traceability and organic certification in wine, viewing these attributes as indicators of quality and environmental responsibility. As younger generations show a preference for organic wine, the wine sector may turn to AI and digital technologies to enhance product traceability and align with these evolving consumer preferences (Ingrassia et al., 2017; Rachel Arthur, 2022).

### **S36 The intensification of both domestic and international competition**

Digitization has lowered trade costs and intensified global competition, while accelerating innovation cycles. The intensification of competitive landscape pushes wine producers to adopt advanced technologies to improve their market positions and stay ahead in a rapidly evolving industry (Barholomae, 2018).

#### **Questionnaire distribution**

After confirming their participation, each expert panel member was provided with a **standard pre-engagement material** before the first questionnaire round. This material detailed the research objectives, outlined the methodology, described the questionnaire structure, and covered privacy and data protection considerations. It also included an introduction to AI, discussing potential applications across the wine value chain and providing examples of solutions in agriculture and viticulture. This information was tailored to accommodate the background knowledge of both wine professionals and representatives from governmental and non-governmental organizations (with an assumed lower level of familiarity with AI-based innovations) and technology experts (who were introduced to agricultural processes and the operation of the wine value chain). The pre-engagement material was reviewed with a research assistant, an AI expert, and an academic professional specializing in the wine business, incorporating their feedback to ensure clarity and simplicity, following recommendations of (Mariani & Dwivedi, 2024). **Appendix 4** of this thesis includes the final version of the pre-engagement material shared with the panel members. Additionally, each participant was offered an individual meeting to discuss any questions about the research or technological innovations covered. None of the panellists requested such meeting, so the process continued with the survey distribution.

Following the pre-engagement phase, the survey was distributed via email, with each participant receiving a personalized link using the **Qualtrics tool**. All the links were

personalized and visible only to the author, whilst maintaining anonymity, thereby preventing dominant opinions from influencing results. During the research, participants' names and email addresses were securely stored in a password-protected Excel file, accessible solely by the author, with all personal data deleted after the research concluded.

### **Measurement considerations**

When considering the measurement of responses provided, multiple options were evaluated. **Composite measures** refer to the combination of multiple indicators into a single variable, used when complex constructs (for example, attitudes or orientations) cannot be captured with a single indicator. **Indexes** are ordinal measures constructed by the simple accumulation of scores from individual indicators. **Scales** are also ordinal measures that assign scores to responses, and (contrary to indexes) they also consider the intensity of different indicators. Finally, **typologies** refer to classification based on two or more variables that can be used both in quantitative and qualitative research (Babbie, 2021).

Scales are ideal for measuring complex variables with nuanced indicators. Examples of scales include the **Likert scale**, which is a suitable measurement tool for the purpose of this research for multiple reasons. The Likert scale can capture subtle attitudes, perceptions, and levels of agreement across multiple dimensions, which are critical for understanding the complexities of AI adoption in winemaking. Unlike simple indexes or composite measures, the Likert scale highlights the degree of agreement or disagreement among respondents, providing a clearer understanding of differing stakeholder views. Additionally, its ordinal nature enables combining data into clear patterns, supporting the identification of important trends and shared views among participants on the impact of AI on winemaking.

The questionnaire consisted of 36 statements, each rated on a 6-point Likert scale ranging from **1 (Strongly disagree)** to **6 (Strongly agree)**. The choice of a 6-point

scale was intentional, designed to remove a neutral option and encourage definitive responses, thereby generating more decisive data. Each section also allowed for open-ended comments, enabling participants to provide insights beyond the structured questions. A two-week deadline was set for responses and communicated to participants initially.

After the first round was completed, responses were analysed to assess group consensus for each statement. To measure the strength of agreement among participants, **first, second, and third quartiles** were calculated for each question. The **median (second quartile)** was selected as the primary indicator of consensus, as it minimizes the influence of outliers more effectively than the mean, in line with (Gordon, 1994). The **interquartile range (IQR)**, covering the middle 50 percent of data between the 25th and 75th percentiles, was used to measure consensus strength, a method supported by studies such as (Höhne & Tiberius, 2020).

After the analysis was completed, a document was prepared summarizing overall results, median values for each question, and consensus levels indicated by the responses after the first round. Then, each participant received a **personalized document** highlighting any variances between their responses and the group consensus. These documents, along with a link to the updated questionnaire, were shared with panellists from the first round, allowing them to revise their responses in light of group consensus. An additional two-week period was provided for the second survey round, with 17 of the original 19 participants submitting responses.

### **Additional quantitative analysis considerations**

Despite the appropriateness of the Delphi method for exploratory research, it is often complemented by **quantitative techniques suited for descriptive or explanatory research**. For instance, (Rezaei et al., 2021) applied confirmatory factor analysis (CFA) to empirically validate conceptual models derived from expert discussions on ethical challenges in digital healthcare, using a sample of 210 respondents. (Aghimien

et al., 2020) supplemented the findings from discussions with the Delphi panel on critical success factors for digital transformation in construction organizations by calculating Cronbach's alpha to assess the internal consistency of questionnaire items and evaluate variations in responses across expert groups. (Kurpjuweit et al., 2021) utilized the Wilcoxon–Mann–Whitney tests to identify pairwise differences in expert subgroup views on blockchain technology's implications for additive manufacturing and supply chains, based on data from 41 panellists. Additionally, (Fundin et al., 2018) combined the Delphi method with exploratory factor analysis (EFA) to uncover themes related to quality management challenges, leveraging responses from 188 participants across 10 observed factors.

*Table 44. Minimum sample sizes for Cronbach's alpha calculation (source: author)*

Round	Dimension	Desired coefficient alpha	Estimated coefficient alpha	Number of questions	Minimum Sample size
1	Use cases	0.7	0.84	14	62
1	Benefits	0.7	0.80	10	135
1	Challenges	0.7	0.62	7	452
1	Transformation drivers	0.7	0.19	4	30
2	Use cases	0.7	0.84	14	63
2	Benefits	0.7	0.84	10	66
2	Challenges	0.7	0.80	7	159
2	Transformation drivers	0.7	0.24	4	34

While consideration was given to integrating similar quantitative techniques into this study, it was ultimately decided not to apply them when analysing the research results. For Cronbach's alpha, a commonly used metric for assessing the internal consistency of a questionnaire, the limited sample sizes in rounds 1 (n = 19) and 2 (n = 17) of the Delphi study presented significant challenges. According to (Bonett, 2002) the minimum sample size required for reliable Cronbach's alpha calculations depends on several variables, such as the number of questions per dimension, the estimated value of Cronbach's alpha in the population, the desired statistical power, and the predefined significance level (commonly 0.05 for a 95% confidence level). Using the IBM SPSS Statistics software (version 29), Cronbach's alpha values were computed for each

research dimension per round, and the minimum sample sizes were estimated using the recommended formula. The estimate sample sizes are presented in Table 44.

As shown, the estimated required sample sizes are significantly larger than the available respondents. Therefore, it was decided that the use of Cronbach's alpha in this study is not feasible. Other statistical tests, such as the Wilcoxon signed-rank test and Welch's ANOVA were conducted in SPSS to evaluate variations in responses across Delphi rounds and pairwise differences in mean responses for research dimensions. While the results indicated potential differences, the small sample size was insufficient to derive clear insights into statistically significant variations that could effectively test or extend existing theories. As a result, these findings were excluded from the final research. The significant differences in sample sizes highlighted between the studies cited at the beginning of this section and this research further reinforce the decision to exclude additional quantitative techniques in this dissertation.

### **Appendix 3. Execution of in-depth interviews– operational details**

In-depth interviews are highly suitable for adding depth to research by capturing data that cannot be reflected in questionnaires, or other quantitative approaches. However, the method involves several potential pitfalls that, when not considered adequately, can significantly distort the outcomes, adversely impact the execution of the process, undermining confidence in the results extracted. The aim of this section is to explain some of the best practices to be followed, when using in-depth interviews and how these were addressed during the research.

#### **Guidance on how to execute in-depth interviews**

When conducting in-depth interviews, it is essential to first establish clear expectations regarding the **time commitment** required from participants and confirm their **consent** to participate. It is important to ensure that participants retain the right to refuse to answer any specific questions. In such instances, it is useful to document the **reasons for non-responses**, as this information may drive the revision of questions or the development of new interview guides for future discussions. Due to the qualitative and non-standardized nature of the method, it is recommended to **document and retain detailed notes** throughout the research design process to ensure that the rationale behind the chosen strategies and methodologies can be clearly explained later. (Saunders et al., 2007)

Before executing the discussions, it is important to identify **key interview themes**. This, along with other relevant details, can be shared with participants in advance to aid them in their preparation. In addition, it is advisable to create an **interview grid** prior to the interview, with the questions to be raised and the basic details about the interviewee's context, to ensure that responses are better understood and interpreted. The use of **general questions** in a non-directive manner is preferred, to allow for the in-depth expression of one's thoughts, as well as encouraging interviewees to elaborate or clarify their responses when the discussions are held. (Donatella della Porta, 2014;

Saunders et al., 2007). The summary of the steps to create a robust interview grid is provided in Table 45.

During an interview, it is essential to phrase questions clearly to ensure that the interviewee fully understands the topic under investigation. **Open-ended questions** are recommended, to facilitate the provision of comprehensive and developmental responses, as well the smooth and natural start to the conversation. These should be followed by well-constructed **probing questions**, which can further enhance the exploration of specific points in greater depth or can help clarifying responses that may be unclear to the interviewer. On the other hand, **leading questions** should be avoided, as they may influence the interviewee's answers and introduce bias. In addition, **long or multi-part questions** should be avoided and should be broken up into a simpler and more digestible format for clarity. (Knott et al., 2022; Saunders et al., 2007)

Table 45. A three-step approach recommended to the preparation of an interview grid (source: author based on (Donatella della Porta, 2014))

	<b>Identification of themes</b>	<b>Formulating questions</b>	<b>Improving phrasing</b>
<b>Purpose</b>	<ul style="list-style-type: none"> <li>List the relevant themes to guide the conversation.</li> <li>Order themese by importance to maintain focus and structure.</li> </ul>	<ul style="list-style-type: none"> <li>Transform themes into clear and targeted questions.</li> <li>Ensure questions align with the research objectives.</li> </ul>	<ul style="list-style-type: none"> <li>Refine poorly constructed questions to ensure clarity.</li> <li>Maintain relevance, and ease of understanding for the interviewee.</li> </ul>
<b>Relevance</b>	<ul style="list-style-type: none"> <li>Provides a structured foundation for the interview.</li> <li>Ensures all key topics are addressed systematically.</li> </ul>	<ul style="list-style-type: none"> <li>Ensures that the conversation remains aligned with the research theme.</li> <li>Avoiding irrelevant or redundant topics.</li> </ul>	<ul style="list-style-type: none"> <li>Enhances the quality of data collected.</li> <li>Reducing confusion, unease, or misinterpretation of the questions.</li> </ul>
<b>Example</b>	<b>Themes:</b> AI use cases, future benefits, adoption barriers and cultural challenges and digital transformation drivers in the wine industry.	<b>Initial question (example):</b> "What do you think of challenges when integrating AI into winemaking?"	<b>Revised question:</b> "Can you share specific challenges faced during AI integration into winemaking?"

During the interviews, the significance of **notetaking** is vital, as it can contribute to the execution of a more effective discussion. Taking notes supports the interviewer to focus on the participant's perspective relevant to the research questions. It also helps in identifying **contradictions**, newly **emerging insights**, or **topics requiring further exploration**. Notes serve as a valuable tool for immediate reflection during the interview and for later analysis. Handwritten notes are generally preferred, as they encourage deeper conceptual engagement with the material, enhancing the integration of key insights uncovered (Roller, 2020).

### **Execution process of in-depth interviews conducted**

The in-depth interview execution started by **contacting the prospective participants** after the second Delphi round was completed. The email message emphasized the purpose of the discussion planned and consent was requested to continue with the interview process. To ensure that any uncertainties about sharing information is adequately addressed, every detail was clarified if requested. To establish rapport and enhance credibility, a **personalized summary of the research findings** was shared before the meeting.

As preparation for the interactions, an **interview guide** was prepared for each meeting separately. This was used as a tool to establish the directions of the individual discussions. Deviations from the script were allowed, in case there were points raised by the interviewees that required further elaboration. The content was based on the insights derived from the findings of the research so far. When preparing the documents, attention was devoted to ensuring that the questions are phrased in a way that is easily understood by the interviewees, by **minimizing the use of jargon**, or **overly theoretical concepts**. The interview guide included open-ended questions to facilitate meaningful discussions, and respondents were encouraged to provide explanations grounded in real-life experiences. Whilst using standard and recurring questions, the interview scripts were tailored to each participant, depending on the nature of their responses as well as their association with the wine value chain, or the AI domain.

Several **preparatory steps** were performed to ensure that the planned execution method is adequate. Firstly, the scripts were reviewed by other academic personnel before those were used. A mock interview was performed before the start of the process, providing an opportunity to test the interview grid, fine-tune the questions and prepare for potential pitfalls during the discussions. Also, a list of potential difficulties was identified using findings from (Saunders et al., 2007) that could potentially hinder the interview process, with mitigation actions planned against those. These, together with the corresponding mitigation actions are summarized in Table 46.

*Table 46. A list of potential pitfalls during the interview process with mitigation actions suggested (source: author based on (Saunders et al., 2007))*

<b>Potential difficulty</b>	<b>Mitigating actions</b>
Participant provides only brief, monosyllabic responses	• Begin the interview with warm-up questions to ease the participant into the discussion.
	• Use open-ended questions and pauses to encourage more detailed answers.
Participant gives lengthy, off-topic answers	• Gently guide the conversation back to the main topics by referencing previous relevant points.
	• Politely ask for clarification on points directly related to the research.
Participant starts asking the interviewer questions	• Reinforce that the research is based on the formulation of interviewees' opinions and offer that questions are answered at the end of the discussion.
	• Acknowledge their questions, but gently steer the focus back to them.
Participant shows superiority and criticizes the research approach	• Stay respectful and actively listen to their input without appearing defensive.
	• Reinforce the research design and rationale when appropriate, through additional explanation.
Participant becomes emotional or upset	• Allow time for the participant to gather themselves and avoid rushing through the discussion.
	• Reassure that questions can be skipped where the participant feels uneasy about those.
Participant is reluctant to speak due to privacy concerns	• Assure confidentiality and remind them of their anonymity in the study.
	• Start with less sensitive questions to build trust and comfort.

Potential difficulty	Mitigating actions
Participant misunderstands questions	• Rephrase the question to simplify the language or ask in a different way.
	• Use examples or prompts to clarify the intended meaning of the question.
Cultural or language barriers affect communication	• Use simple, clear language and avoid jargon.
	• If possible, use a translator or provide additional context for questions that may be culturally sensitive.

To increase the level of confidence and the sense of trustworthiness, each interview started with a **standard introductory script**. This included expressing gratitude towards the participant for agreeing to the meeting, highlighting the purpose of the discussion, and the main points to be covered. The introduction also included statements assuring anonymity of the results and emphasizing the confidentiality exercised in analysing the responses. The right to not answer questions where participants felt uncertain was also highlighted, to further ease any potential uncertainties associated with the interview process.

The interviews were conducted online, using **Microsoft Teams** as a platform, in a timeframe that was adequate for the participants. The meetings were recorded, and each interviewee was required to give consent to such activity before proceeding with the discussion. To ensure that no unnecessary personal data is processed, participants were asked to disable their camera during the interview, which also helped mitigating any potential interviewer bias caused by facial expressions or non-verbal reactions during the discussion. The recordings were stored in a personalized Microsoft SharePoint folder, to which only the author had access, and these were deleted after the processing was complete.

There is no hard rule defined for how to determine the number of interviews to be conducted. An increase in the number of participants enhances the understanding of the phenomena investigated, whilst causing a rise in the time and other logistical constraints created. Lacking universal guidance, the criterion adopted was related to the measurement of the **saturation of knowledge**, which can be defined as the point

where further discussions do not uncover new insights that are worth the investment and the time commitment to performing additional in-depth interviews. This was measured by constantly reviewing the outputs of the discussions, the insights uncovered, and the new information revealed that could have warranted further investigation. The initial plan was to do a total of 10 interviews, which was adhered to, due to the knowledge saturation experienced in the responses.

The respondent profiles are summarised in Table 29. Interviewees were given adequate time to develop their responses, but the discussion was steered when it was required, to ensure that **time constraints** are adhered to, and planned topics are covered. The explanations provided were summarized periodically by the researcher throughout the sessions, to mitigate the risk of differences in the understanding of the topics discussed. As the responses were provided, appropriately worded **probing questions** were also used, to follow up on important topics highlighted by the interviewee. Additional tools applied included the use of interpretations offered and asking the interviewee to comment on those or confronting the interviewees with views that were opposite to their own. Collectively these measures contributed to the fuller exploration of the research topic analysed and the underlying themes behind the individual research questions.

As the interviews were conducted online, the **automatic transcription** functionality of Microsoft Teams was utilized to produce the detailed text of the discussions. Handwritten notes were also taken simultaneously, to ensure that important points are confirmed, and contradictions are identified and reconciled. After the interviews were completed, the transcripts produced were reviewed and cleansed, due to the limitations of the automatic solution not producing fully accurate outputs. In some instances, the text was slightly modified, ensuring that the overall meaning is maintained, and that important information is not removed, so that the context of the discussion is not distorted.

After the transcription was completed, the anonymized output files were loaded uploaded to **Taguette**, an open-source web-based document tagging tool for qualitative data analysis. The **tagging of the information** was done in this platform, along the same dimensions that the Delphi questionnaires were based on. This method allowed for the comparison of themes, identification of key patterns and contradictions among those, as well as generation of new ideas that were potentially not considered by the preceding research procedures. The coding was executed as an iterative process comprised of multiple readings of the same information, to create observations, interpret those and connect them with each other.

The final codebook used during the analysis is presented in **Appendix 5**. As the analysis progressed, **new themes emerged** that were not included in the Delphi questionnaire. These themes were first classified under the appropriate main category and subsequently assigned new tags, beginning with the number 9, to distinguish them from the tags originating from the Delphi study. This provided further ease to the analysis of results and the comparison of those across respondents and research dimensions.

### **Ethical considerations in research**

Ethics in research involves the protection of contributors' rights, ensuring honesty and maintaining the integrity of the overall research process. An important ethical issue to consider is **providing appropriate information** to participants about the nature, purpose and potential risk of the study, before requesting consent to participate in the process. Participation in the research must be voluntary and situations where implied authority between participants may distort findings must be avoided.

Researchers must make every effort to **mitigate any hypothetical physical, psychological, or social harm** to participants arising from the execution of the research. **Anonymity and confidentiality** must be maintained throughout the process, ensuring that data cannot be linked to participants, except by the researcher, who must

make sure that those linkages are not disclosed. **Deception** (which was not employed as part of this research) might be used sparingly and with care, if justified by the study's potential benefits.

Table 47. Key ethical concepts to be employed in the research process (source: author based on (Babbie, 2021))

Concept	Definition	Application in own research
Voluntary participation	Participation without coercion or undue influence.	Detailed explanation provided to experts participating in Delphi study and in-depth interviews about the objectives, procedures applied and duration of the study.
No harm to participants	Ensuring physical, emotional, and psychological safety.	No methods were applied in the research that could result in such potential harms.
Anonymity vs. confidentiality	Anonymity: No identifiable links to participants. Confidentiality: Links kept private.	Personal data of experts was not disclosed in the final research report. Access to records where linkages to participants could be established was limited to the author.
Informed consent	Participants understand and agree to risks and benefits.	Instructions before survey responses and interviews included comprehensive consent clauses.
Institutional review boards (IRBs)	Panels ensuring ethical compliance in studies involving humans.	Proposals were submitted early for feedback and approval to the supervisors of this dissertation.
Deception and debriefing	Concealing purpose during study; clarifying post-study.	No such technique applied in this study.


When the results are available, researchers must **present data honestly**, without fabrication or the application of selective reporting. **Transparency about limitations** of the selected processes should be disclosed, to strengthen credibility of the findings presented. It is also advisable to set up an **institutional review board (IRB)**, ensuring that research proposals are reviewed for compliance and that ethical viewpoints are appropriately considered in the overall research design. The research proposals must

be sufficiently detailed, so that the IRB can assess if the various ethical risks inherent in the different methods chosen were identified and appropriate plans were put in place to mitigate those.

To ensure that the research results are not only robust from a theoretical perspective, but also meet the tests of validity and integrity, following these guidelines is critical. The key ethical concepts to consider, and the explanation of how those were applied in this research are summarized in Table 47.

## Appendix 4. Pre-engagement material used before first round of Delphi questionnaire


This appendix provides the extracts of the pre-engagement materials shared with the experts in the Delphi panel that was shared after the acceptance to participate in the research, before the first round of questionnaire was shared.



# Use of Artificial Intelligence in the Wine Industry

## Drivers of Transformation, Expected Use Cases, Benefits and Challenges

Attila Loibl, Doctoral School of Economics, Business and Informatics, Corvinus University of Budapest

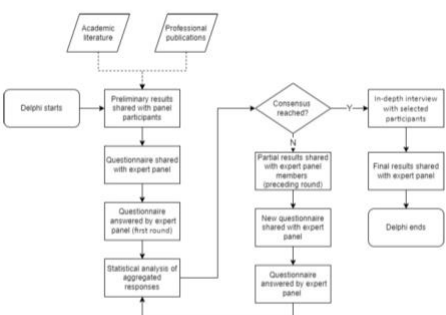


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### Summary


**Aim:** the aim of the research is to reach expert consensus on the future impact of artificial intelligence (AI) on the wine industry.

**Methodology:** an iterative research process, based on the Delphi method, using a questionnaire and following the flowchart below:




```


graph TD
    Start[Delphi starts] --> Prelim[Preliminary results shared with panel participants]
    Prelim --> Q1[Questionnaire shared with expert panel]
    Q1 --> Q2[Questionnaire answered by expert panel (first round)]
    Q2 --> Stat[Statistical analysis of aggregated responses]
    Stat --> Cons{Consensus reached?}
    Cons -- No --> Resh[Partial results shared with expert panel members (preceding round)]
    Resh --> Q3[New questionnaire shared with expert panel]
    Q3 --> Q4[Questionnaire answered by expert panel]
    Q4 --> Cons
    Cons -- Yes --> Int[Int-depth interview with selected participants]
    Int --> Resh2[Final results shared with expert panel]
    Resh2 --> End[Delphi ends]
    
```




**Partial results:** a summary of the results of a literature review based on academic research sources and other professional publications to present technological innovations in the agricultural sector.




**Questionnaire:** 36 statements, covering four main dimensions (expected areas of use of AI, impacts and related challenges in the wine sector, drivers of technological transformation in the industry), using a 6-points Likert scale, and one open-ended question.




**Number of rounds:** the same questionnaire should be answered in a total of 2 rounds. A summary of the first round's results will be shared before the second round.




**Time commitment:** the questionnaire takes about 15-30 minutes to fill once. No more than 90 minutes of time commitment is expected to be required over a total period of 1.5-2 months to participate in the research.




**Outcome:** use and publication of aggregated results in a doctoral dissertation at the Corvinus University of Budapest Doctoral School of Economics, Business and Informatics.



**Data protection:** email addresses are stored in a dedicated password protected storage area and are permanently deleted after the research is completed.





2

## Introduction: research objectives and methodology

**Research objectives:** The purpose of this presentation is to support the empirical research of the PhD dissertation titled "Use of Artificial Intelligence in the Wine Industry: Drivers of Transformation, Expected Use Cases, Benefits and Challenges", which the author is writing as a student at the Corvinus University of Budapest, Doctoral School of Economics, Business and Informatics. The aim of the research is to understand how artificial intelligence (AI), as a technology innovation that has received elevated attention in recent years, is expected to change the broader wine value chain, from grape cultivation, through winemaking, to the sale of the final product to end customers.

**Research methodology:** the empirical research is conducted using the Delphi method, which involves collecting different expert opinions through a series of questionnaires shared and reaching a consensus among the participants of the research panel. As the aim is to reach a common viewpoint, the questionnaires are expected to be answered in two consecutive rounds. Before the second round, participants will receive a summary of the answers to the previous questionnaire, helping to either revise or further confirm previous viewpoints developed towards the subject matter. The information is collected, and feedback is provided in writing, with each participant being contacted separately, so that anonymity is fully ensured. The aim is to allow the members of the expert panel to reach their final position on the topic independently, facilitating the consideration of multiple viewpoints and formulating objective thinking, without resistance to accept new ideas and sticking to earlier developed preconceptions.

**Questionnaire structure:** the questionnaire consists of 36 statements in total, divided into four main sections. The questions examine the expected future use cases of AI, the potential benefits offered by the technology and the main challenges to its widespread adoption in the wine sector, as well as the drivers of technological transformation in the industry. Answers are given on a six-point Likert scale. Responses to the questions will be summarised and the calculated average (as an indicator of group consensus) will be shared with participants before the next survey is launched. The statements included in the questionnaire have been developed using the results of a detailed review and analysis of the scientific and professional literature. This method which carries the risk that some important factors may have been omitted. Therefore, a final, open-ended question has been included in the questionnaire, where participants can name and rate up to three other factors as described above. Answering this question is optional.

**Privacy and data protection:** in order to contact the participants in the expert panel to fill in the questionnaire, it is necessary to record the email addresses where the members can be reached. These will be recorded in a password-protected Excel file in a separate folder, to which only the author has access. The folder can only be shared with new people by the author, so there is minimal risk of any other third-party having access to its contents. Depending on the consensus reached, the entire research is expected to take 60 to 90 days. Once the research is completed, the stored personal data (email addresses) will be permanently deleted. Research participants have the right to request that their email address is deleted at any time before the end of the research.

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## Artificial Intelligence (AI) - a short overview <sup>(1)</sup>

**The definition of Artificial Intelligence (AI)**

AI encompasses machine capabilities that mimic human cognition, including reasoning, learning, planning, and displaying traits of creativity. AI enables technology to perceive its environment, process sensory input, solve problems, and strategize actions to achieve predefined objectives by analysing extensive datasets.

**Potential categorization of AI solutions**

Software-based tools	Hardware-based solutions
Image recognition	Robots
Virtual assistant	Self-driving cars
Search engines	Drones

**Hardware infrastructure enables AI, software executes algorithms and actualizes computational intelligence,**

**Use cases of AI in our everyday lives <sup>(2)</sup>**

Data analytics, decision support

Search engines, generative AI

Recommender algorithms

Navigation optimization

Advanced driver assistance systems

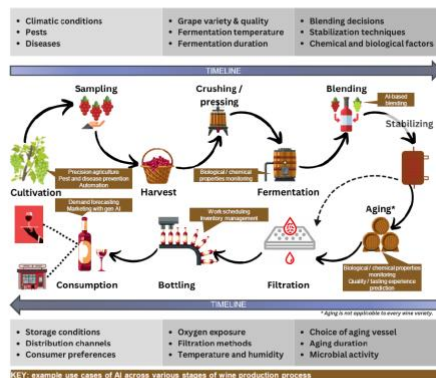
Predictive maintenance

<sup>(1)</sup> Source: What is artificial intelligence and how is it used? | Topics | European Parliament. (09:17:00.0). <https://www.europarl.europa.eu/topics/en/article/20200827/STO85804/what-is-artificial-intelligence-and-how-is-it-used>

<sup>(2)</sup> Images generated by ChatGPT

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## Wine value chain – a high level overview of operations and main influencing factors in each stage



- Winemaking starts from the cultivation activities in the vineyard, through different processing steps, until the final product is sold to the end consumers.
- Whilst in the vineyard, availability of grapes and the quality of the final product is significantly impacted by external forces, including climatic factors (such as rainfall, humidity, hours of sunshine), soil composition and condition, pests and diseases.
- The wine production is a complex process spanning multiple steps during which the grapes are pressed and crushed, fermented and blended, stabilized (to ensure it is chemically and physically stable for bottling in later stages), filtered and bottled. Certain wine varieties are also aged in different types of vessels (e.g., oak barrels, or stainless-steel tanks).
- The end consumers are usually reached on two main channels: on-trade (selling through restaurants, bars, or hotels) and off-trade (selling through intermediaries like wine shops). Recently, direct-to-consumer sales experienced a significant rise in share of wine sales.

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## Selected examples of existing technology innovations in agriculture



**Leaf disease diagnosis:** AI-based systems enabling the early detection of leaf diseases.

**Benefits:** improving crop yield, more secure supply, earlier intervention, lesser use of pesticides and input materials.

**Challenges:** lack of available training data (quality images), infrastructural challenges.



**Remote monitoring of environmental factors:** monitoring of soil and climatic conditions through sensors and wireless networks.

**Benefits:** optimized growth conditions, precision agriculture solutions, improved decision-making capabilities.

**Challenges:** energy usage, lack of network capacity, infrastructural challenges.



**Automated agriculture:** automation and remote control of tasks and processes.

**Benefits:** monitoring vegetation properties, directed cultivation, higher value-added work.

**Challenges:** lack of organizational knowledge, capital investment requirements and uncertain returns.



**Agricultural drones:** automated and remotely controlled processes.

**Benefits:** remote monitoring of large lands, performing other activities (irrigation, spraying), reduced water usage.

**Challenges:** quality and accuracy of imagery equipment, capital investment requirements and uncertain returns.



**Yield prediction:** more accurate forecast of expected output using AI-based systems.

**Benefits:** more efficient resource usage, improved decision making, mitigation of risks associated with weather fluctuations, pests, and diseases.

**Challenges:** highly complex models, lack of organizational knowledge, infrastructural and financial challenges.

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## Selected examples of existing, AI-based technology innovations in winemaking



**Controlling barrel conditions:** prediction of wine maturation processes with data collected through monitoring.

**Benefits:** improved and more consistent wine quality, better service of consumer demand.

**Challenges:** lack of organizational knowledge, infrastructural and financial challenges.



**Harvest planning:** determine optimal time to harvest based on different environmental factors.

**Benefits:** enhanced quality, better anticipation and mitigation of risks associated with external factors.

**Challenges:** variability in local vineyard conditions and microclimate, loss of human expertise, ethical concerns.



**Predicting wine quality:** sensory experience forecasting using biological and chemical properties of wine produced.

**Benefits:** better service of consumer demand, improvement in sales, waste reduction.

**Challenges:** data availability, subjective and multifaceted nature of wine quality, diminished role of human intuition.



**Virtual sommelier:** platforms offering wine recommendations, pairings, and advice, emulating a wine expert's guidance.

**Benefits:** constant accessibility, tailored recommendations, continuous learning and improvement, cost efficiency.

**Challenges:** data privacy concerns, difficulties in interpreting user preferences and providing relevant recommendations.



**AI wine blending:** optimized combination of different wine components using technology.

**Benefits:** ability to analyse vast amounts of data, consistent quality, innovation, better service of consumer demand.

**Challenges:** data accessibility, lack of human expertise, dealing with subjectivity, complexity in winemaking processes.

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## Next steps in the research

**Structure of questionnaire:** the questionnaire consists of 36 statements along the four main dimensions, based on the research objectives:

- Future application areas of AI in the wine industry
- Anticipated benefits from the use of AI in the wine industry
- Main challenges to the application of AI in the wine industry
- Drivers of technological transformation in the wine industry

**Answers:** answers should be given on a six-point Likert scale, as follows:

- 1 – Strongly disagree
- 2 – Disagree
- 3 – Somewhat Disagree
- 4 – Somewhat Agree
- 5 – Agree
- 6 – Strongly Agree

**Free text answers:** when answering the questionnaire, it will be possible to provide free text answers to help better highlight individual opinions. As a last question, a final free text response will allow for the inclusion and evaluation of any factors related to the above dimensions that were omitted from the questionnaire.

**Results sharing:** the processing of data is performed in a way that anonymity is fully maintained. The aggregated results are provided to the panel participants, with possible explanations, showing the current state of the expert consensus.

**Multiple rounds:** panel participants will be invited to complete the questionnaire in two rounds. Before the second round, the aggregated results of the first round will be shared, which can be used to either change or reinforce previous viewpoints in relation to the question analysed. Consensus in the various statements among participants will be measured in both rounds.

**Conclusion:** the results will be shared with the panellists and the findings will be analysed and discussed in detail during a series of in-depth interviews with selected participants. The final outcome will be shared with the panellists upon request.

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## Appendix 5. final codebook used during the analysis of in-depth interviews

The below list shows the codes used in the Taguette software when tagging the interview transcripts. The naming convention followed captures the theme that the tag relates to, according to the four research dimensions, followed by a sequentially increasing identification number (ranging from 1 to 36) corresponding to the place of the individual statement in the original questionnaires. Newly arising concepts not identified in the list of questions were assigned an identifier starting with the number 9, thereby easing the analysis of novel emerging themes.

Table 48. List of codes used during the thematic analysis of the in-depth interviews (source: author)

Tag	Highlights	Tag	Highlights
01 - use cases. 01 - diseases diagnosis and classification	6	02 - benefits. 20 - consumer demand anticipation	2
01 - use cases. 02 - soil and climatic conditions	1	02 - benefits. 21 - quality	10
01 - use cases. 03 - optimal harvest time definition	2	02 - benefits. 22 - sustainability	14
01 - use cases. 04 - automated water control	7	02 - benefits. 23 - climate change adaptation	3
01 - use cases. 05 - targeted pesticide and water	1	02 - benefits. 24 - job transformation	17
01 - use cases. 06 - automated field operations	7	03-constraints. 25 - infrastructure	9
01 - use cases. 06 - cultivation	1	03-constraints. 26 - knowledge	32
01 - use cases. 06 - drones	9	03-constraints. 28 - technology acceptance	22
01 - use cases. 07 - aging conditions	4	03-constraints. 29 - cost implications	6
01 - use cases. 08 - blending	2	03-constraints. 30 - farm size	11
01 - use cases. 09 - production	12	03-constraints. 31 - government grant schemes	3
01 - use cases. 10 - quality prediction and control	3	03-constraints. 91 - data availability	13
01 - use cases. 12 - sommelier	13	03-constraints. 92 - data privacy and security	4
01 - use cases. 13 - brand awareness	2	03-constraints. 93 - data reliability and quality	7
01 - use cases. 13 - commercial	9	03-constraints. 94 - Cooperation	3

Tag	Highlights	Tag	Highlights
01 - use cases. 13 - competitive information	8	03-constraints. 95 - external factors	4
01 - use cases. 13 - consumer preferences	13	03-constraints. 96 - complexity of wine value chain	9
01 - use cases. 13 - customer experience	5	03-constraints. 97 - service provider reliance	2
01 - use cases. 13 - marketing	13	03-constraints. 98 - geographical influences	8
01 - use cases. 14 - fraud prevention	2	04 - transformation drivers. 32 - economic	9
01 - use cases. 91 - decision support	3	04 - transformation drivers. 33 - population growth	1
01 - use cases. 92 - clones	1	04 - transformation drivers. 34 - climate change	6
01 - use cases. 92 - gene editing	3	04 - transformation drivers. 35 - consumer preferences	8
01 - use cases. 92 - resilient variety selection	1	04 - transformation drivers. 91 - social	1
01 - use cases. 93 - wine selection and recommendation	5	04 - transformation drivers. 92 - external circumstances	7
01 - use cases. 95 - AI as a service	4	04 - transformation drivers. 93 - generative AI	3
02 - benefits. 15 - early disease intervention and prevention	6	04 - transformation drivers. 94 - wine industry specifics	1
02 - benefits. 16 - crop yields	1	other.AI first use	15
02 - benefits. 17 - targeted farming practices	2	other.AI generic benefits	8
02 - benefits. 18 - profitability improve	9	other.AI implementation steps	7
02 - benefits. 19 - price premiums	8	other.wine industry general	13

## **Appendix 6. In-depth interview backup details**

This section provides backup details to the first order themes, second order concepts and aggregate dimensions identified in the interview analysis sections, presented in Table 30 to Table 33 under section VI. In-depth interviews with experts.

### **Future use cases of AI in the wine value chain**

Regarding the **optimization of vineyard management practices** through AI, Respondent 1 highlighted that vineyards consist of "a very large area to be monitored," therefore tools utilising AI-based solutions (such as drones), can enhance the effectiveness of viticultural techniques, by gathering vast amounts of data on soil, plant health, and weather conditions, and assisting in decision-making. Respondent 5 noted that "AI-based solutions can diagnose leaf diseases, optimize water usage, and manage pesticide spraying," improving resource efficiency and sustainability. However, Respondent 8 raised concerns about the limitations of AI in this field, due to "unpredictable weather conditions that might not be easily addressed by algorithms." Drones' potentials in precision agricultural practices were praised on multiple occasions, with Respondent 2 mentioning that they apply pesticides "with square meter accuracy," minimizing waste and usage of hazardous input materials.

Under the theme of "**AI for process optimization in winemaking**" Respondent 2 noted that AI can "support the winemaker with intervention by analysing data about when to stop the fermentation" by optimizing key parameters. This confirms that the technology can provide high added value in different steps of the winemaking operations. However, some of the respondents noted that certain, labour-intensive tasks such as bottling and crushing are "hard physical activities that require the active participation of human resources", limiting the usability of the technology (Respondent 2).

Interviewees expressed a wide range of views regarding **AI's potential to improve personalization of customer interactions** and to **increase consumer engagement**.

As Respondent 5 noted, "AI can help consumers find wines they like by understanding their preferences and buying habits". Others, such as Respondent 4 felt that AI could only act as an "information delivery mechanism," rather than offering the nuanced recommendations of a human sommelier. Respondent 6 also added the challenge of converting sensory characteristics into measurable data, emphasizing the limited feasibility of such solutions due to winemakers' reliance on heavily subjective evaluation. Respondent 3 also confirmed that "AI can drive decisions in these [areas, such as virtual sommelier services], but not sure how reliable the technology is".

There was also a consensus that AI could play a key role in helping wineries **target specific market segments more efficiently**. As Respondent 7 highlighted, "AI could potentially help in market discovery, more so than relying on instinct" as well as "AI can aid in precisely targeting marketing efforts," making it easier for winemakers to tackle market complexities and reach consumers more effectively. Yet, some respondents were less optimistic about AI's reliability in capturing the various nuances of wine consumption behaviour. For instance, Respondent 1 noted that " you have to collect data on wine consumption, and I think to have good data on that is a very complex task the more and more I think about it,".

Finally, respondents highlighted AI's potential in **sustainable winemaking**, particularly in optimizing resource use and improving efficiency. Several interviewees pointed out that AI-based solutions can assist in deciding "when and how to spray pesticides or manage water supply" (Respondent 8). There was a consensus that AI's role in monitoring vast vineyard areas and providing real-time data is vital for improving decision-making processes. However, the answers also emphasized the challenge of integrating AI with the unique microclimates found in individual vineyards, making universal solutions difficult to implement.

## **Benefits of AI use in the wine sector**

Regarding AI's abilities in **cost and resource optimization**, Respondent 8 noted that "AI will definitely improve profitability in the long run, despite the initial implementation costs.". Other respondents echoed this sentiment, suggesting for instance that AI could help in producing healthier, more secure crops, leading to better profitability through a different route. In terms of operational efficiency enhancement, respondents agreed that AI can help easing the challenges posed by labour shortages and existing processes inefficiencies. Respondent 5 explained that AI "will primarily take over the boring jobs that most people don't want to do," Although some concerns were expressed that AI might lead to job losses, others (Respondent 1, Respondent 2, Respondent 3, Respondent 5, Respondent 8) were more optimistic, emphasizing that AI would eventually create more meaningful roles in the industry.

Interviewees generally agreed that AI has the potential to significantly **enhance product quality and consistency in winemaking**. As Respondent 4 stated, "the quality of wine is going to go up," though some (such as Respondent 2) expressed caution, noting that achieving this requires "a very large amount of historical data." Respondent 7 pointed out that AI's precise analytical capabilities can help replicate desired quality standards across different years, by providing an understanding of how different materials involved in the wine production process interact to produce the final taste profile. Many respondents emphasized that AI could ensure the maintenance of consistent quality across different vintages, particularly when dealing with uncertainties in weather and other external factors.

Respondents had mixed views on AI's role in **increasing consumer engagement and improving interaction**. Respondent 4 noted that "AI will help increase price if it does some really smart price elasticity equations.". However, the return on investment for wineries in applying such solutions can be questioned, due to the general economic conditions of the sector and the complexity of different environmental factors across regions. Also, responses were somewhat ambiguous in relation to AI's ability in improving pricing positions due to enhanced wine quality. As Respondent 10

explained, "even if AI improves quality, that doesn't necessarily mean the price will go up." Respondent 4 noted the same by stating "the majority of people that buy wine cannot distinguish between the quality of a \$25 and a \$30 wine." The impact of other external factors like geographical origin, brand equity and marketing efforts were emphasized, underscoring the complexity of using AI for consumer engagement and market positioning in the wine industry.

Respondents overall agreed on AI's positive **contribution to sustainability in winemaking** by optimized resource usage reducing environmental impact. The statements generally echo those made in the previous section. Several participants emphasized AI's role in sustainable water management (Respondent 10), or in managing diseases and preventing crop loss (Respondent 8). However, when looking at the sustainability impact holistically, there were opinions expressing concerns about the energy intensity of the underlying computer architectures. As Respondent 10 remarked, "AI is incredibly energy-intensive, which significantly increases environmental impact." Respondent 3 echoed this, adding that while AI helps make operations more efficient, "the causality is very difficult to establish" when considering the technology's net environmental impact. Despite these concerns, participants highlighted the potential for AI to improve both environmental and economic sustainability by reducing resource inputs and increasing production security. By using AI to forecast weather patterns and manage plant protection, winemakers can "save a lot on plant protection costs while also improving crop yields," strengthening both pillars of sustainability. (Respondent 10)

### **Challenges to AI implementation in the wine sector**

Many respondents expressed the potential for **reluctance towards AI adoption** in the wine sector, due to deep-rooted cultural traditions. Respondent 2 emphasized that many winemakers "follow beliefs and previously learned solutions" in an industry that "associates itself with old-world heritage". Potential generational differences were also noted, with Respondent 10 calling out that the "younger generation of winemakers ... are progressive, especially in terms of technology". Respondent 1 added that "it will

take a generational change” for more traditional wineries to embrace AI fully. The level of cultural conservatism might differ across regions, with some responses indicating a potentially stronger presence in European countries.

**Knowledge gaps** also play a critical role in the slow adoption of AI, with Respondent 1 stating that “lack of knowledge probably [is a main challenge to AI adoption]”. Several interviewees (Respondent 2, Respondent 6) emphasized the need for education and awareness, as “only those who have this basic knowledge [of AI and its impact on winemaking] will be able to use it well.” A common theme was that the resistance to AI implementation in winemaking could be potentially reduced, if the users became more familiar with the technology’s capabilities.

Many respondents identified **significant infrastructural** limitations as barriers to AI implementation in winemaking. Respondent 10 noted that “the winemaking technology ... is often not advanced enough to support automation” adding that “a winery with [outdated equipment] can't be automated in the same way” as those with a modern infrastructure. Winery size can be a moderating factor, with the same respondent also noting that “AI becomes more relevant for operations starting at around 20 hectares or for those producing several thousand hectolitres or more”.

The theme of **financial constraints** was also frequently mentioned, with Respondent 1 highlighting that AI use can be too costly for small wineries due to “the cost implication of that, the maintenance and the fact that you have to train your staff”. Financial support through dedicated support programs could potentially ease these constraints according to Respondent 2, stating that “capital does not have to be a problem ... because the current government grant schemes<sup>2</sup> are specifically linked to these types of developments.” Respondent 6 agreed but emphasized that technological transformation in winemaking still relies mostly on farmers’ understanding AI's

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<sup>2</sup> The interviewee referred to the situation in Hungary specifically with this point.

capabilities. In addition, Respondent 10 stated concerns about the effectiveness of targeted subsidies, as “they can do as much harm as they do good for any sector”.

Many respondents highlighted the **regulatory and legal concerns** as a challenge towards the implementation of AI in winemaking. Respondent 10 noted that the European Union’s strict regulatory framework makes it harder for winemakers to introduce new technologies, due to the “natural and almost sacred” nature of wine creating obstacles to adapt more advanced solutions. This indicates the potential for spatial differences in regulations (across the main economic regions globally, as well as country-level regulations) slowing down adoption of new technological innovations in winemaking across different regions.

### **Drivers of AI adoption in the wine sector**

Regarding **economic and environmental pressures**, Respondent 3 highlighted that "the pressure to increase profitability is very high" emphasizing the necessity of implementing more efficient processes in winemaking. Respondent 5 linked AI's financial impact directly to cost savings, stating, "Solutions must translate to financial savings for the wine industry; otherwise, they won't see the value." Respondent 6 noted that “the real challenge now is labour shortage”, and Respondent 8 introduced the perspective of financial pressures faced by wine businesses from reduced consumer budgets due to rising costs. Finally, Respondent 10 noted that new technologies "can help create more efficient production systems ... while reducing environmental impact," demonstrating the industry's growing focus on sustainability.

**Consumer demand for innovation** acts as another key driver of technological transformation and AI adoption in the winemaking sector. These drivers can be manifested in expectations from younger generations to receive personalized services, external disruptions (such as the Covid-19 era) shifting consumers towards digital interfaces for purchasing (Respondent 9), or the increased desire to learn about wine through applications (Respondent 1). In addition, shifting consumer preferences,

especially towards non-alcoholic products may drive innovation in product development in the wine value chain, where AI can be of further use (Respondent 10).

**Cultural factors** seem to play a dual role in the technological transformation of winemaking. Respondent 5 highlighted how innovations from external industries are driving AI adoption in winemaking, stating that “AI is being pushed by external technology companies rather than being developed internally within the wine industry.” However, a key challenge arises from the disconnect between these external innovators and the wine sector, as external companies often "seem to be speaking different languages, metaphorically" and "do not fully understand the nuances of the wine industry, and vice versa."

Finally, a key factor driving the implementation of AI in the wine industry is **technological advancement and accessibility**, which is mostly manifested by the widespread penetration of Large Language Models (LLMs)-based generative AI tools. With the recent rise of ChatGPT, barriers for vineyards to adopt new AI-based technologies were significantly lowered. As Respondent 4 highlighted “technology becomes a commodity at a rate that is unprecedented.”, and Respondent 9 also confirmed that “One doesn't need to be a skilled data scientist or able to code in programming languages to use AI.” However, opinions diverged on how quickly this accessibility would lead to a more pervasive adoption of AI in winemaking, if wineries fail to overcome their reluctance to innovate (Respondent 5).

### **Additional points to consider**

The interview transcripts highlighted multiple AI use cases in the wine industry that were not originally considered in the research. According to several interviewees (Respondent 1, Respondent 6, Respondent 7) an important use case for AI to enhance **gene editing** by helping vineyards source grape varieties tailored to specific climate conditions, such as drought-resistant rootstocks and disease-resistant clones. Respondent 6 emphasized, "AI can assist in selecting grape varieties with lower

pesticide requirements and higher resilience to environmental challenges," illustrating the technology's additional potential in supporting wineries in their adaptation to climate change.

Additionally, **AI as a service** emerged as a significant theme in the interviews, pointing out both opportunities and challenges for the wine industry. Respondent 6 emphasized the importance of service providers, offering AI as a "comprehensive package". Respondent 7 confirmed that this would bring in the necessary knowledge about the technology not available in the wine industry, lower the barriers to access advanced AI tools, reduce the initial investment needs in infrastructure and the risks associated with implementation. However, Respondent 6 voiced concerns that "once you depend on an external provider, you become vulnerable to them". Respondent 10 added that continuous support systems can benefit more the "machinery and software vendors rather than truly helping the spread of technology" and that there can be "many bugs and issues because these technologies are not widely used or mass-produced; they're often the result of small startup efforts".

The interview transcripts revealed several key challenges to the implementation of AI in winemaking that were not previously considered in the research. **Data availability and reliability** emerged as the most significant concern, with Respondent 1 highlighting that "gathering consumer data...is a very complex task... If someone picks up a bottle of wine from a shop you don't really know where that bottle is going to end up ". Respondent 4 added that "wine is an infrequent purchase at infrequent times for an infrequent seller ... so, all of these different factors make the complexity of the Machine Learning (ML) or any kind of AI tools to follow the consumer in the system very challenging".

Another challenge revolves around **data privacy and security**, particularly in the context of consumer-facing AI applications. Interviewees expressed concerns about the implications of AI on customer data, with Respondent 1 warning that "there is a data privacy topic there" when using social media apps to understand consumer

profiles and influence consumption decisions. Additionally, geographical influences and cooperation barriers were noted as challenges, particularly in regions like Eastern Europe. As Respondent 10 stated “in Hungary, collaboration is not exactly a national sport ... when it comes to sharing or merging our own resources, we’re much more reluctant” despite the benefits offered by such settings as “cooperation and forming cooperatives would be ideal for achieving the scale necessary for investments and innovations”. The barriers created by such mindset can further slow the adoption of AI and other technological innovations for (smaller) wineries, particularly in (Eastern-) European regions.

The interview transcripts revealed additional drivers of AI implementation and technology transformation in the winemaking sector, which were not initially considered. **Generative AI** was a key recurring topic not captured by the original questionnaire and literature review completely, highlighted as a democratizing force that makes AI tools more accessible to non-experts. As Respondent 9 mentioned, “in business applications, such as running a business rather than operations” AI will be used more in the future as a result of these innovations. These comments suggest the more pervasive use of the technology across various dimensions in the wine business model in the future.

Overall, winemaking is “not a rapid-fire business” as farmers need to “think on an annual basis ... [having] one harvest” to do what is required for their businesses to prosper, making the industry **highly risk averse** (Respondent 4). Yet, the combination of labour shortages discussed in the earlier sections of this research, the external market conditions, and advancements in user-friendly AI technology are likely to push the winemaking industry towards a more broad-based digital transformation. The **ubiquitous nature of generative AI solutions** can alleviate the risk averse attitude towards technology innovation in the sector, easing some of the concerns caused by labour shortages or competitiveness problems in wineries.

Finally, the interview guide included open-ended questions about **how respondents would implement AI** in the operations of a winery, if they oversaw one. The aim was to understand the factors to be prioritised by different experts and potential implementation steps to follow as a first-time user of AI in a traditional business setting. The results of these discussions are summarized in Table 37.

Interviewees emphasized the importance of **data preparation** as a critical first step, with Respondent 2 noting that "the first task is ... to capture and clean the data and integrate it to the same platform." AI applications in viticulture would likely begin with monitoring and spraying phases, followed by automation of fermentation processes, depending on the size and the financial capabilities of the winery. Respondent 6 highlighted the need to focus on "weather-related data and disease prediction" as well as on "market analysis" that could be significant areas of interest in such transformation programmes. Respondent 3 added further that "wineries need to better understand their consumer profiles", making marketing also as one of the first areas of implementation, without losing focus on field operations, or improvement in quality management processes.

In terms of implementation strategy, Respondent 9 suggested the use of a **value-driven AI execution framework**, following a series of logically arranged steps. The implementation should start with **opportunity sizing** that links AI applications to economic value drivers such as improving grape yield, reducing production loss, or optimized pricing practices. This should be followed by a high-level assessment to estimate the economic impact of those across the entire value chain. The next step is **capability assessment** where the evaluation of the availability, accessibility and quality of data, as well as the related existing analytics capabilities is performed. This should be followed by an assessment of the organizational model and skills needed to ensure that AI adoption recommended are sustainable and create long-lasting benefits. Once this evaluation is complete, a **prioritized action list** should be created, based on the size of the opportunity and required capabilities. The aim is to start with small pilots, prioritizing those with the highest impact and the least capability uplift or investment required. Once the business case is demonstrated through such trials, a

three to five years roadmap should be developed to scale successful AI applications across the entire value chain of the winery or other company participating in the wine value chain.

Finally, when discussing AI implementation strategy, the importance of a **team-based approach, leadership support** and **incremental progress** was frequently emphasized. Respondent 4 shared an example from a large winery, where the team learned AI “by doing a little bit every week, assigning a bit of homework, and having meetings about it”, gradually making it part of their everyday toolset. This comment also highlighted the need to break down the AI implementation task into manageable steps, starting with smaller pilots and scaling up as the team builds capability.

## Appendix 7. Cost implications of AI solutions in winemaking

The objective of this section is to provide some insights into the financial implications of AI application in winemaking. Whilst the assessment of financial feasibility of such solutions should be done on the level of individual wineries, certain benchmark figures can be obtained to demonstrate the level of these expenditures. Table 49 shows **indicative financials for implementing and using different AI-based tools in winemaking**, including autonomous tractors, vineyard robots, smart valves or robotic arms. Whilst the cost of some of these solutions are in par with existing machinery (e.g., conventional tractors can cost \$50,000 to \$80,000 based on engine capacity), these values clearly show that newest technological innovations are more likely to be utilized by larger wineries with more financial resources at their disposal.

Table 49. Potential costs of AI implementation in winemaking (source: author, based on multiple other sources)

Technology	Cost consideration	Source
Autonomous tractors performing conventional farming functions	Investment cost: \$60,000 to \$70,000 Operating expenses: N/A	<i>(Robotic Vehicles Are Driving into the World's Vineyards   Meininger's International, n.d.)</i>
Vineyard robots, optimised for pruning and harvesting. weed management, grape picking, soil work and canopy management	Investment cost: €20,000 to €200,000 Operating expenses: N/A	<i>(Latest Vineyard Robots, n.d.)</i>
Smart valves enabling automatic irrigation based on typical water use learnt	Initial investment: \$600 per valve Operating expenses: \$150 per acre	<i>(AI Made Its Way to Vineyards. Here's How the Technology Is Helping Make Your Wine, n.d.)</i>
Robotic arms for palletizing wine cases	Initial investment: new device (\$2,000 to \$500,000), tooling (\$5,000 to \$50,000), new safety equipment (\$5,000 to \$30,000) Operating expenses: integration (\$10,000 to \$50,000), warranty (\$5,000 to \$20,000)	<i>(The 3 Best Palletizing Robot Arms in 2025 - Standard Bots, n.d.)</i>