THESIS BOOKLET

The Use of Artificial Intelligence (AI) in the Wine Sector

Use Cases, Benefits, Implementation Challenges and Drivers

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1. Introduction and motivation

The rapid evolution of Artificial Intelligence (AI) and its expanding relevance across economic sectors has created new opportunities to rethink how traditional industries operate, including those with deeply rooted cultural and production practices such as winemaking. While AI has a rich scientific history (see for instance (John McCarthy et al., 1955; McCarthy, 1959; Mcculloch & Pitts, 1943)), application into the grape-to-glass value chain is limited. At the same time, agriculture and the wine industry face increasing pressures from environmental volatility, labour shortages, and evolving consumer expectations, increasing the need for innovations that enhance resilience and operational efficiency. These considerations were among the key underlying motivations of this thesis, which will be further explained in this section.

1.1. Background of the research problem

Agriculture remains a strategically significant sector of the worldwide economy, employing over 22% of the global workforce and sustaining a wide range of food-producing activities that underpin economic and societal well-being. Within this broad domain, the wine industry represents a distinctive segment, characterised by strong cultural heritage, production practices tailored to regional conditions and traditions, and a highly complex value chain that integrates viticulture, winemaking, distribution, and consumer engagement. Although the "grape-to-glass" process has remained fundamentally unchanged for a very long time, the complexity of environmental influences, production requirements, and evolving consumer expectations has driven increasing interest in technological solutions that enhance efficiency, sustainability, and resilience of wine production processes.

At the same time, agriculture faces increasing pressures from climate change, labour shortages, economic constraints, and increased regulatory expectations, making digital transformation a critical priority for the sector's long-term viability. (Khanna, 2021; Leal Filho et al., 2022) Recent advances in AI have lowered adoption barriers and expanded opportunities for applications in sectors such as viticulture characterised by traditionally low levels of digitalisation. AI systems are increasingly applied to optimise vineyard management, monitor fermentation, forecast grape yields, detect diseases, and personalise consumer interactions. (Talaviya et al., 2020; Wolfert et al., 2017) These use case examples collectively demonstrate attainable value creation opportunities across the wine value chain.

Despite these advancements, the academic and practical understanding of AI adoption in winemaking remains fragmented and largely focused on technology-centric discussions. (Adamashvili et al., 2024; Bastard & Chaillet, 2023; Truong & Khanh, 2023) Existing contributions tend to emphasise individual use cases or technological capabilities, while less attention is given to how sector-specific cultural norms, authenticity concerns, organisational readiness, or governance structures shape adoption outcomes. (Cortez et al., 2009; Ferrier & Block, 2001; Hanson et al., 2022; Víctor Martínez-Martínez et al., 2020) Moreover, the integration of expert knowledge, empirical evidence, and structured analytical approaches is still limited, leaving gaps in understanding how AI can be effectively embedded into a sector where tradition, craftsmanship, and user experience play significant roles. These knowledge gaps demonstrate the need for a comprehensive, multi-method inquiry that captures both the technological possibilities and the socio-technical considerations shaping AI's impact on the wine industry.

1.2. Motivation for choosing the topic

The decision to examine the impact of AI adoption in the wine industry in this research is based on the sector's significant economic and cultural relevance, as well as the growing set of challenges that threaten its long-term sustainability. Wine production represents a globally dispersed and economically important industry, contributing to agricultural output, employment, and cultural heritage across multiple regions. Despite its deeply traditional character, the sector operates within a complex value chain in which environmental volatility, shifting consumer patterns, labour shortages, and regulatory expectations increasingly shaping production practices and strategic decisions. These pressures highlight the need to identify innovations that can enhance operational efficiency and resilience while preserving the traditional characteristics of winemaking.

At the same time, existing academic discussions on AI in viticulture and winemaking remain fragmented, with limited contributions offering a holistic view of adoption dynamics. (Adamashvili et al., 2024; Bastard & Chaillet, 2023) Despite its rich heritage, studies examining AI's application in winemaking lack an integrated, multi-method approach capturing both technological opportunities and socio-technical constraints.

A further motivation lies in the need to develop a conceptual model that reflects the specific characteristics of AI application and technology diffusion in traditional agri-food ecosystems. Winemaking is shaped by long-standing production practices, regionally embedded knowledge, and strong product differentiation. These characteristics create an ideal context in which to investigate how AI can be aligned with sectoral values while supporting operational improvements and capabilities to adapt to new circumstances. (Wolfert et al., 2017) Finally, the societal relevance of the topic is underscored by broader concerns related to sustainability, labour availability, and environmental resilience. Innovations such as precision viticulture, improved resource management, and automated field operations can support more sustainable practices and resolve challenges related to labour shortages, offering pathways toward a more resilient and competitive wine sector. Together, these considerations provide a strong rationale for undertaking a systematic and academically grounded investigation of AI's role in transforming winemaking.

1.3. Research objectives and research questions

The central objective of this research is to understand how AI can influence the wine industry by examining the drivers, enablers, benefits, and barriers associated with its adoption across the grape-to-glass value chain. The increasing pressures that the sector faces create a need for technologies capable of supporting more efficient, resilient, and sustainable production systems . At the same time, the distinctive characteristics of winemaking shape unique adoption dynamics that require focused academic inquiry. (Aubert et al., 2012; Tey & Brindal, 2012)

To address the earlier noted gap caused by the lack of a comprehensive perspective that integrates technological, organisational, and socio-cultural factors, the research is structured around four main questions that guide the empirical and conceptual development of the study:

1. **What are the main future use case scenarios of AI in the wine value chain in the next 5–10 years?**
2. **What are the main future benefits offered by AI in the wine sector?**
3. **What are the main challenges to the implementation of AI in the wine industry?**
4. **What are the main drivers of AI adoption in the wine industry?**

Answering these questions enables the formulation of a structured problem statement centred on the need to understand how intelligent systems can be effectively embedded into a sector characterised by deep-rooted practices and complex environmental dependencies. This research contributes at three levels. **Theoretically**, it advances knowledge in business informatics and wine business studies by offering a sector-specific view of AI adoption that captures both technological opportunities and socio-technical constraints. **Methodologically**, it employs a multi-method design (combining bibliometric analysis, Delphi surveys, in-depth interviews, and text mining) to generate integrated and empirically grounded insights. **Practically**, the findings support wineries, policymakers, and technology developers in identifying feasible use cases, anticipating implementation barriers, and understanding how AI can enhance operational efficiency, sustainability, and long-term resilience within the wine value chain.

2. Introduction and motivation

2.1. Research design overview

The research follows a hybrid, multi-phase design structured to generate conceptually rich, empirically grounded insights into the role of AI in the wine industry, harnessing the benefits of various scientific approaches. (Jogulu & Pansiri, 2011) Given the limited academic work available on this topic and the **exploratory nature** of the research problem, the overall design is rooted in an **inductive logic**, enabling theory development through the systematic observation and integration of qualitative and quantitative evidence. The study adopts a **positivist paradigm**, as the objective is to identify generalisable patterns and relationships shaping AI adoption within the wine value chain, while elements of the conflict paradigm are also acknowledged due to differences in resource availability and innovation capabilities across producers. (Babbie, 2021)

The research design progresses through multiple interconnected phases. First, a **bibliometric analysis** is conducted to map the existing academic landscape on AI in agriculture and winemaking. This phase establishes the intellectual foundations of the study by identifying influential publications, thematic clusters, and research gaps. Its outcomes inform the development of the subsequent empirical stages, particularly the formulation of Delphi statements and the identification of topics requiring expert evaluation.

Building on this foundation, the second phase employs the **Delphi method** to collect and refine expert judgments on future use cases, expected benefits, implementation challenges, and key drivers of AI adoption in the wine sector. The Delphi process follows a structured sequence of nomination, preparation, and analysis, enabling iterative convergence of expert views while preserving anonymity and minimising group influence. Quantitative indicators such as medians, interquartile ranges, and the modified APMO (Average Percentage of Majority Opinions) measure are used to assess consensus strength across rounds.

The third phase consists of **in-depth interviews**, designed to add depth and nuance to the findings generated by the Delphi study. Using unstructured interview formats, this step enables the exploration of contextual, cultural, and experiential dimensions that structured questionnaires may not capture. The interview transcripts are analysed through **thematic coding** supported by qualitative analysis software, followed by **text mining and topic modelling techniques** to identify latent patterns and reinforce reliability of the qualitative insights.

The **integration logic** across these phases is central to the research design: the bibliometric analysis informs the Delphi instrument; Delphi findings shape the interview focus; and interviews, in turn, corroborate, refine, or challenge earlier results. This sequential and iterative structure ensures a robust synthesis of evidence, supporting the development of a comprehensive conceptual understanding of AI's impact on the wine value chain.

2.2. Bibliometric analyses

Bibliometric analysis forms the foundational phase of the research design, helping to identify influential contributions, thematic evolutions, and gaps requiring further empirical investigation. This research applies three complementary bibliometric methods (co-citation analysis, bibliographic coupling, and co-word analysis) to obtain a comprehensive view of the intellectual structure and current directions of research in this domain. (Donthu et al., 2021)

Co-citation analysis examines how frequently pairs of publications are cited together in subsequent academic work, revealing historical intellectual connections and underlying knowledge foundations. This method is highly useful for identifying seminal works and understanding how earlier contributions shaped the evolution of research themes relevant to AI adoption in agriculture and viticulture. **Bibliographic coupling**, focuses on shared references among publications, highlighting emerging discussions and providing insights into present-day research clusters central to the study's objectives. (Weinberg, 1974) **Co-word analysis** complements these approaches by examining the co-occurrence patterns of keywords within publications, identifying thematic relationships, revealing dominant and emerging topics, and supporting the discovery of underexplored research areas.

All bibliometric procedures follow established best practices, including careful keyword selection, reliance on a single major database (Scopus) for consistency, and compilation of a sufficiently large dataset to ensure robustness of insights. The analyses are conducted using **VOSviewer** for visualization and clustering, enabling the systematic handling of publication metadata and keyword structures.

2.3. Delphi study

The **Delphi method** forms the second major phase of the research and is used to systematically collect, refine, and converge expert opinions on the future impact of AI in the wine industry. This method is a suitable choice for exploratory research areas where empirical data is limited, and where expert insight is required to assess complex, multidimensional phenomena. The process follows a structured sequence with nomination, preparation, and analysis phases, ensuring rigor, transparency, and iterative refinement of expert views. (Gordon, 1994; Okoli & Pawlowski, 2004)

A **two-round Delphi structure** was employed to balance analytical depth with the need to minimise expert fatigue. Experts were selected using purposive sampling, reflecting the method's focus on specialised knowledge rather than population representativeness. **Five categories of experts** were included: winemaking professionals, academic researchers in wine business and agricultural economics, technology consultants, AI specialists, and representatives from governmental or non-governmental organisations connected to agriculture or viticulture. This diversity ensured that insights captured technological, operational, strategic, and regulatory dimensions of AI adoption. The final panel consisted of **nineteen experts** representing a broad geographical distribution and a wide range of professional backgrounds.

Statement generation drew directly from the preceding bibliometric analysis and literature review, ensuring that all projections were firmly anchored in existing academic and grey literature. A total of **36 statements** were developed and organised into **four clusters** aligned with the research questions: (1) future AI use cases in the wine value chain, (2) expected benefits, (3) implementation challenges, and (4) key drivers of technological transformation. These statements formed the basis of the questionnaire distributed in both Delphi rounds.

Consensus metrics included the median as the central indicator of agreement, supported by the interquartile range (IQR) to capture the dispersion of responses. Additionally, a modified Average Percentage of Majority Opinions (APMO) was used to assess **polarisation** and the evolution of consensus between rounds, a technique appropriate for a **6-point Likert scale** without a neutral option. (Höhne & Tiberius, 2020; Mariani & Dwivedi, 2024) Together, these metrics provided a transparent and robust assessment of convergence across experts' perspectives. The **quantitative and qualitative insights** generated directly informed subsequent interview design aimed at refining the conceptual understanding of AI adoption in the wine industry.

2.4. In-depth interviews

In-depth interviews constitute the third major phase of the research design, providing qualitative depth to complement the findings of the previous sections, selected for their ability to capture **nuanced, experience-based insights** that couldn't be fully extracted using structured questionnaires. The method allows participants to articulate observations, interpretive processes, and sector-specific reasoning in their own words, enriching the understanding of AI adoption across the wine value chain. (Donatella della Porta, 2014; Saunders et al., 2007)

The interview design followed an **unstructured format**, consistent with established qualitative research recommendations for exploring complex and emergent topics. (Milena et al., 2008; Mueller & Segal, 2015) While each interview was guided by a **preparatory script** reflecting themes derived from earlier research phases, flexibility was maintained to enable participants to expand on topics they considered important. This format helped uncovering new perspectives related to winemaking practices, technological readiness, cultural considerations, and organisational challenges, not captured in structured survey responses. Interviews were conducted with **ten participants**, including winemakers, winery owners, viticulture experts, and other professionals affiliated with the wine or technology sectors.

Interview execution included several **procedural safeguards**. Discussions were held online using Microsoft Teams, with informed consent obtained and anonymity assured. Sessions were recorded and automatically transcribed, with transcripts subsequently reviewed and corrected to ensure accuracy. Handwritten notes were taken during each meeting to identify contradictions, clarify points of interpretation, and support later analytical steps. (Knott et al., 2022) After the interviews were complete, **thematic analysis** was executed based on Gioia's methodology. (Magnani & Gioia, 2023) The Taguette open-source qualitative analysis tool was used to execute an iterative coding process for the transcriptions, along the same dimensions applied in the Delphi study. This enabled the systematic comparison of themes and identification of both convergences and divergences. Emerging concepts not captured earlier were added as new codes, following a structured numbering logic to ensure analytical clarity. This approach provided the basis for higher-order thematic interpretation and facilitated the integration of expert narratives into the broader conceptual development of the study.

2.5. Text mining and NLP techniques

Text mining and natural language processing (NLP) techniques were employed as an additional analytical layer to enhance and corroborate the qualitative findings derived from the in-depth interviews. This phase aimed to extract structured insights from unstructured textual data, allowing the identification of linguistic patterns, sentiment orientations, and latent thematic structures that may not be immediately evident through manual interpretation. The corpus consisted of **anonymised interview transcripts**, which collectively included approximately 30,000 words. Prior to analysis, all transcripts were merged into a unified dataset and cleansed of redundant and personal data to ensure that only participant-derived content were analysed.

The data preparation stage involved tokenisation and the removal of stop words using **Python's Natural Language Toolkit (NLTK)**. (Sanner, 1999) Frequently occurring but analytically uninformative terms were filtered out, while additional stop words identified during initial frequency checks (such as modal verbs and auxiliary expressions) were manually excluded. The processed corpus served as the basis for multiple NLP techniques, including keyword extraction through term frequency-inverse document frequency (tf-idf), bigram identification, and topic modelling.

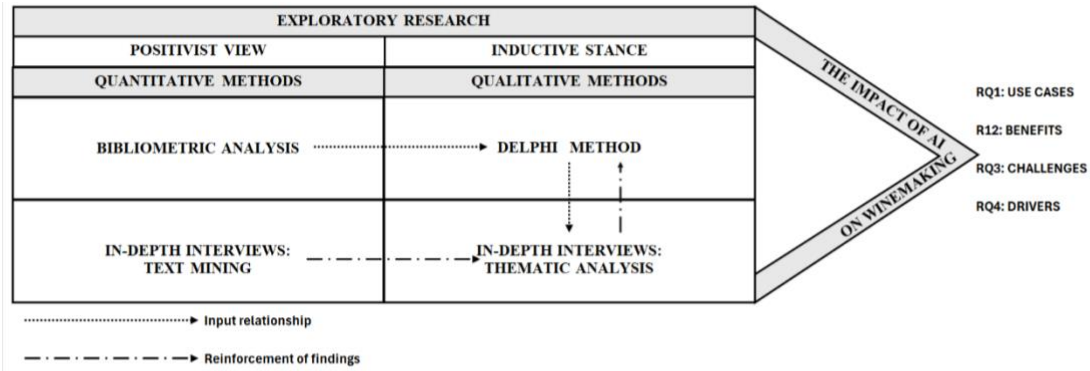
Tf-idf analysis enabled the identification of distinctive terms across the research dimensions, while bigram extraction revealed recurrent multi-word expressions that provided deeper contextual meaning. Topic modelling was performed using **Latent Dirichlet Allocation (LDA)**, implemented via Python's scikit-learn and Gensim libraries. A document–term matrix was constructed using CountVectorizer, and four topics were ultimately selected to ensure interpretability given the corpus size. LDA supported the identification of latent thematic structures by modelling transcripts as mixtures of topics represented by probabilistic distributions of words.

Throughout this process, **triangulation with qualitative evidence** was central. Text mining results were compared with themes emerging from the Gioia-based coding of interview transcripts, enabling validation of findings and reinforcing analytical robustness. Sentiment lexicons such as VADER, Bing, and NRC were also applied to assess emotional tone across the corpus, supporting a more granular interpretation of expert perceptions. (*Vader Lexicon*, n.d.) Collectively, these techniques deepened the empirical grounding of the study by integrating computational and interpretive approaches into a cohesive analytical framework.

2.6. Integration of research phases

The research was designed as a structured and integrated, multi-phase process in which each methodological component informs, strengthens, and validates the next. The visual demonstration of the different building blocks in the process and the interactions among those is demonstrated in Figure 1. This sequential logic and the triangulation of findings across these distinct phases ensures that the final contributions are grounded in a coherent synthesis of quantitative and qualitative evidence. Together, these phases produce a robust, multi-angle synthesis that supports the formulation of a comprehensive conceptual framework on AI's impact on the wine value chain.

Figure 1. A summary of the research approach followed in this study (source: author)



3. Scientific results of the dissertation

3.1. AI adoption drivers in the wine sector

The first scientific contribution of the dissertation is the empirical identification and consolidation of the core drivers shaping the adoption of AI in the wine sector. Across the bibliometric review, Delphi analysis, and in-depth interviews, consistent patterns emerged indicating that AI adoption is primarily motivated by external pressures rather than internal digitalisation initiatives. **Economic constraints**, such as rising production costs, labour shortages, and intensifying competitive pressures appear as dominant drivers, pushing wineries to seek efficiency-enhancing and cost-reducing technological innovations. **Environmental variability and climate-related risks** further reinforce the need for predictive analytics, precision agriculture solutions, and adaptive vineyard management. **Shifting consumer expectations**, particularly the demand for digital experiences and personalised wine recommendations, constitute an additional market-driven stimulus for transformation.

These empirically derived drivers demonstrate that adoption decisions in traditional agri-food ecosystems depend not only on technological readiness and organisational capabilities but also on broader ecological, market, and cultural pressures. The findings emphasise that wineries rarely pursue AI for its own sake; instead, the motivation emerges from a combination of operational necessity, resource constraints, and evolving consumer dynamics, situating AI adoption within a multi-layered and externally shaped innovation environment.

3.2. Use case taxonomy for AI in the wine sector

The second scientific contribution of this dissertation is the development of a systematised taxonomy of AI use cases across the wine value chain. Drawing on the integrated findings of the bibliometric analysis, Delphi study, and in-depth interviews, the taxonomy organises AI applications into three overarching layers (operational, strategic, and consumer-facing), providing a structured representation of how the technology is currently utilised and highlighting future opportunities for adoption.

Operational use cases emerged as the most mature and widely recognised category. Evidence across all research phases consistently highlighted applications in vineyard management, disease detection, irrigation optimisation, microclimate forecasting, fermentation control, and quality assurance. These reflect AI's strong feasibility in data-rich, repetitive, and precision-oriented tasks, and correspond to the core theme of operational efficiency.

Strategic applications include process optimisation and sustainability-related functions, such as resource efficiency improvements, yield prediction, and climate adaptation measures. These use cases respond to environmental and economic pressures and illustrate AI's potential contribution to long-term resilience. **Consumer-facing applications** form the third layer, including personalised wine recommendations, targeted marketing, and enhanced digital engagement. While technically feasible, these were met with more cautious expert views, reflecting uncertainty about AI's ability to replicate sensory and experiential aspects. The resulting taxonomy offers an empirically grounded classification that clarifies how AI supports value creation across viticulture and winemaking.

3.3. Benefits of AI adoption in the wine sector

The third scientific contribution of the dissertation is the empirical identification of the key benefits associated with AI adoption in winemaking, together with the formulation of a causal feedback mechanism that links realised benefits back to the drivers of adoption. Across all methodological phases, the most consistently recognised benefits relate to **efficiency gains**, **cost reduction**, and **product quality enhancement**. Experts highlighted improvements in water and resource use, labour optimisation through automation, earlier disease detection, more accurate climate forecasting, and greater consistency in fermentation and quality control. These outcomes converge around the broader themes of operational efficiency, sustainability, and product consistency, indicating strong performance-enhancing potential.

A distinctive contribution of the study is the demonstration of how these benefits function as a **reinforcing feedback loop** within the adoption process. When wineries begin to realise measurable gains (such as yield improvement, reduced input use, or stronger market insights), the benefits realized strengthen confidence in AI technologies, reduce cultural resistance, and increase organisational willingness to invest further in new technologies. This reinforcement mechanism mirrors the structure of the final conceptual model, where demonstrated value reshapes or amplifies initial drivers such as economic pressures, climate challenges, and consumer expectations. The findings therefore show that AI benefits are not only outcomes but also catalysts that accelerate subsequent adoption decisions.

3.4. Barriers to AI adoption in the wine sector

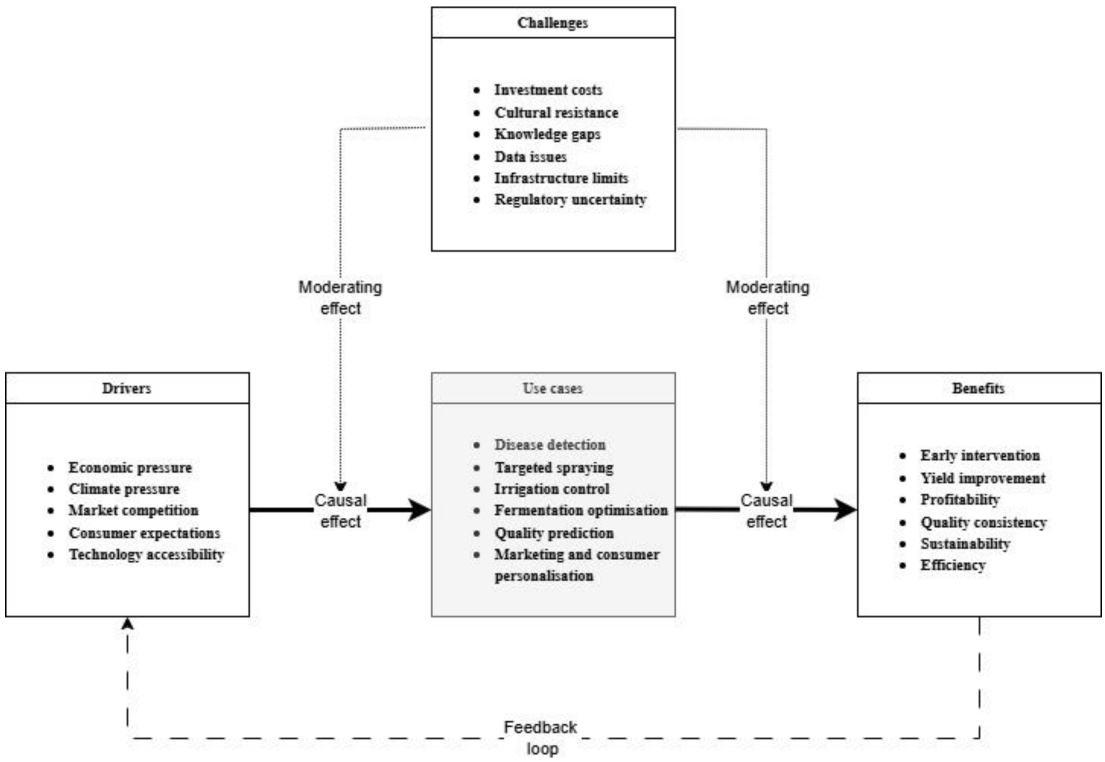
The fourth scientific contribution of this dissertation is the identification and systematisation of the barriers that moderate AI adoption in winemaking, highlighting how technological, organisational, and socio-regulatory constraints shape implementation outcomes. **Cultural resistance** (rooted in heritage, craftsmanship, and concerns about preserving authenticity) was widely recognised as a central barrier. Many winemakers favour long-established practices and exhibit scepticism about the perceived intrusiveness or relevance of AI. **Risk aversion** further strengthens this reluctance, particularly among smaller wineries with limited resources to experiment with new technologies.

Knowledge gaps around AI capabilities, data requirements, and potential benefits constitute an additional barrier, often reinforced by limited digital literacy and fragmented information ecosystems. On the technological and **infrastructural level**, challenges include outdated equipment, insufficient data quality, and high investment costs. Finally, **governance and regulatory constraints**, including policy uncertainty, lack of standardised data frameworks, and limited institutional support, emerged as persistent impediments. Together, these multi-level barriers act as moderating factors that weaken the link between drivers, use cases, and benefits, demonstrating that successful AI adoption in winemaking depends as much on socio-cultural and institutional readiness as on technological feasibility.

3.5. Development of a hybrid causal conceptual framework

The results of this dissertation are summarized in a **hybrid causal conceptual framework** that systematically explains the impact of AI adoption on winemaking. This framework synthesises insights derived from the various research stages, resulting in an empirically grounded model that captures the dynamic interactions among core constructs. The model is presented visually in Figure 2.

Figure 2. Theoretical conceptual framework for AI impact on winemaking (source: author)



The framework is structured around a **causal sequence in** which drivers (including economic pressures, climate variability, labour shortages, market competition, and increasing technological accessibility) initiate interest in AI. These **drivers** lead to the identification of use cases across the wine value chain, particularly in domains such as precision agriculture, process optimisation, climate forecasting, quality prediction, and consumer personalisation. The **benefits** generated by these use cases (efficiency improvements, cost reduction, product consistency, sustainability gains, and enhanced market insights) represent the next stage of the causal chain. Importantly, the model incorporates the **moderating role of challenges**, including cultural conservatism, infrastructural limitations, financial constraints, and governance gaps, which influence the feasibility and effectiveness of AI implementation. A final component of the framework is the **feedback loop**, whereby realised benefits strengthen or reshape initial drivers, reinforcing organisational confidence and enabling further adoption. This integrated, multi-method framework offers a coherent explanation of AI-enabled transformation in winemaking.

Table 1. A summary model for AI implementation in winemaking (source: author)

<table>
<tr><th colspan="5">Pre-requisites</th></tr>
<tr><td colspan="2">Data availability</td><td colspan="3">Data preparation</td></tr>
<tr><th colspan="5">Value-driven AI implementation strategy</th></tr>
<tr><td>Opportunity sizing</td><td colspan="2">Capability assessment</td><td colspan="2">Prioritized action list</td></tr>
<tr><td>• Linking potential AI applications to economic value drivers
• Estimate the potential economic impact of applying AI in various parts of the wine value chain</td><td colspan="2">• Assess the availability and quality of data
• Evaluate how the existing data can be analysed
• Identify how the data and insights can be used in practical business scenarios
• Assess the organizational and operational model and skills available</td><td colspan="2">• Create a prioritized list of actions
• Focus on initiatives with the highest impact and the least efforts required
• Develop a three to five years roadmap outlining the areas and use cases to start with
• Focus the start on smaller pilots</td></tr>
<tr><th colspan="5">Potential areas of first-time implementation of AI</th></tr>
<tr><td>Monitoring and spraying</td><td>Automated fermentation processes</td><td>Weather- and disease prediction</td><td>Understanding consumer profiles</td><td>Marketing</td></tr>
<tr><th colspan="5">Success factors</th></tr>
<tr><td colspan="2">Team-based approach</td><td colspan="3">Focus on incremental progress</td></tr>
</table>

3.6. Practitioner-oriented AI adoption model in the wine sector

Finally, this dissertation provides a **practitioner-oriented AI adoption process model** tailored to the specific operational, cultural, and resource conditions of wineries. While the conceptual framework offers a theoretical explanation of AI adoption, the process model transforms these insights into actionable steps that support real-world implementation. The model is presented in Table 1.

The model begins by emphasising the importance of **opportunity assessment**, where wineries estimate the potential impact of AI across the entire value chain. This ensures that both operational needs and strategic pressures (such as climate adaptation, labour shortages, and cost inflation) are considered when prioritising use cases. The next phase, **capability evaluation**, focuses on assessing data quality, digital readiness, staff expertise, and existing organisational processes. Following this assessment, wineries are encouraged to pursue **small-scale pilot projects** that deliver quick, measurable value. These can help reduce cultural resistance, strengthen stakeholder confidence, and build momentum for broader adoption. Finally, the model supports the development of a **three- to five-year roadmap** that scales validated use cases and embeds AI into everyday practice. This stepwise progression ensures that implementation is incremental, collaborative, and aligned with the traditions and operational realities of winemaking, linking academic insights with practical applicability.

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