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Leveraging artificial intelligence for innovation in wineries: a global study

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Abstract

Purpose – This study explores the adoption of artificial intelligence (AI) in wineries, with a specific focus on its application to drive innovation and on the organisational and contextual factors that influence its exploration and adoption.

Design/methodology/approach – The research project is based on an exploratory approach employing a questionnaire developed through a literature review and refined using the Delphi method via a survey with over 500 participants.

Findings – Wineries employ many AI solutions, from generative AI tools that facilitate creative and agile processes to more embedded, enterprise-level AI systems that require significant investment and IT integration. They adopt a dual approach to exhibit the highest innovation orientation by integrating AI solutions to promote many dimensions of innovation. In contrast, wineries that rely exclusively on generative AI leverage it to innovate marketing processes. However, most wineries surveyed have not implemented AI solutions for process innovation, suggesting that AI development and adoption are in their infancy.

Research limitations/implications – The study did not examine whether the adoption of AI solutions actually generated innovation, nor was the extent of AI adoption at the micro or meso level assessed. However, the investigations may provide valuable insights and contribute to the development of more targeted strategies for the digital transformation of the wine sector. By exploring organisational and contextual dimensions, it provides a deeper understanding of the variables that may encourage or hinder the implementation of AI technologies.

Originality/value – This study can be leveraged by wineries as a pioneering analysis of innovation-oriented AI adoption in the wine sector in several countries. The findings offer practical value for the wine industry in promoting digital transformation and harnessing the innovative potential of AI in the wine sector.

Keywords Artificial intelligence, Innovation, Wineries, Explorative analysis, Survey, Organisational factors, Contextual factors

Paper type Research article

1. Introduction

The food sector is undergoing a profound transformation due to increasingly pressing consumer demands for sustainability, food safety, nutritional values and business ethics (McDermott *et al.*, 2024; Bigliardi and Filippelli, 2020). In addition to changing consumer needs, the challenges of climate change are transforming the competitive environment from "fast developing" to "turbulent". Therefore, innovation is no longer just a choice but an imperative for food companies (Bigliardi and Filippelli, 2022; Capitanio *et al.*, 2009). Wine consumers are increasingly demanding, and their choices are no longer only a function of superior quality but also of the affinity between their values and those of producers (Fiore *et al.*, 2017). Today, guaranteed transparency in production, sustainability certifications and health-conscious products such as low-alcohol, organic and additive-free wines are becoming

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key factors influencing purchasing decisions (Aiello and Tosi, 2024). These changing preferences require producers to simultaneously rethink their winemaking approaches, marketing strategies and supply chain management (Bresciani *et al.*, 2016). New consumer choices need to be paid more and more attention as the market is experiencing increased global competition (Ohana-Levi and Netzer, 2023; Sacchelli *et al.*, 2016). Countries that were traditionally minor players in wine production, such as China, India, and parts of Northern Europe, are now entering the market, enabled by advancements in agricultural technologies and evolving climate conditions that make viticulture viable in previously unsuitable regions (Ohana-Levi and Netzer, 2023). Climate change, which has allowed many countries to enter the wine market, negatively impacts many territories with a wine-growing tradition and vocation that are therefore forced to adapt to changing environmental conditions. Viticulture is dramatically affected by rising temperatures, unstable weather cycles, and the pests and diseases that dampen many traditionally wine-producing countries (Sacchelli *et al.*, 2016). All of these challenges underscore the critical need for wine industries to innovate on multiple dimensions.

Numerous innovation models, strategies and tools aimed at promoting innovation in the wine sector are in the literature. Focusing on tools, technological advances such as IoT, precision agriculture, and blockchain are revolutionising vineyard management and ensuring greater sustainability and traceability of production (Della Corte *et al.*, 2018; Adamashvili *et al.*, 2024). Similarly, multiple digital marketing platforms enable wineries to engage consumers more effectively (Finotto and Mauracher, 2020; Fiore *et al.*, 2017). In addition, wineries can leverage numerous data analytics and process management IT solutions to optimise operations and decision-making models (Barth *et al.*, 2017; Khan *et al.*, 2021).

Nowadays, Artificial Intelligence (AI) has emerged as an innovative force in the wine sector (Adamashvili *et al.*, 2024). AI tools encompass a broad spectrum, with some being broadly accessible to a wide audience, while others demand considerable investments and significant effort for effective adoption (Corvello, 2025; Rane, 2024). This dichotomy fosters divergent innovation trajectories (Holmström and Carroll, 2024; Roberts and Candi, 2024). Moreover, since the adoption of any new pervasive technology requires tailored organisational efforts, specific organisational challenges are generated by each form of AI solution (Awa *et al.*, 2017; Baker, 2012). These include, on the one hand, an in-depth analysis of the characteristics of the technology and its impact on the organisation and, on the other hand – depending on the level of integration required with existing business processes – the development or activation of a set of dynamic capabilities geared toward exploiting the technology. In this light, the wide heterogeneity of AI tools greatly amplifies these challenges (Zahra and George, 2002). Although many studies have highlighted the challenges associated with implementing AI solutions, few studies have analysed the relationship between organisational/contextual factors and AI adoption choices by innovation-oriented companies in the wine industry. This paper aims to analyse how wine companies in the five major producing countries have adopted AI to support innovation processes. It also highlights the impact that external organisational and contextual factors have on AI implementation processes.

To achieve these objectives, the research is structured into three main sections. The first provides a theoretical background on innovation in the wine sector and the potential use of IA to foster innovation. The second outlines the research methodology. The final sections discuss the findings and their implications for the industry.

2. Literature review

Scientific literature provides numerous classifications of innovations in the food industry (Purba *et al.*, 2018; Bigliardi and Filippelli, 2022). Traditionally, innovation in the food industry has been classified into two main categories: product innovation, which focuses on the development of new food products or significant improvements to existing ones, and process innovation, which involves the optimisation of production techniques for improving the efficiency, quality, and cost (Capitanio *et al.*, 2010; Earle, 1997). The focus on these two dimensions was due to the perception that companies, which were strongly tied to traditions or limited by standardised products and processes, could gain competitive advantage primarily through cost minimisation efforts and with new products (Della Corte *et al.*, 2018; Bigliardi and Filippelli, 2022). Subsequently, more recent competitive challenges have prompted scholars to recognise two other critical dimensions of innovation, namely marketing and organisation (Castillo-Valero and García-Cortijo, 2021). The first, focusing on new branding, packaging and communication strategies, is geared toward customer needs; the second, related to changes in business structures, management systems and collaboration models, enhances knowledge acquisition and exploitation of external opportunity (Bigliardi and Filippelli, 2020). More recently, several authors have proposed classifications of innovation that emphasise innovation status and orientation (Tell *et al.*, 2016). For instance, Bigliardi and Filippelli (2022) proposed an advanced classification that includes radical innovation (entirely new technological breakthroughs), market breakthrough innovation (disruptions in consumer preferences and market trends), incremental innovation (gradual improvements of products and processes), technological breakthrough innovation (integration of advanced technologies in food production), and sustainability-driven innovation (developments aimed at reducing environmental impact and ensuring food security). The differences between the classifications reveal the increasing complexity of innovation in the food industry, the emergence of innovation models based on open and collaborative systems and their integration with traditional and linear innovation models, and, finally, the impact of emerging innovation-oriented technologies (Tell *et al.*, 2016). Research focused on the wine sector employed both traditional and modern models to understand the trajectories of firms' innovations. For instance, Dogru and Peyrefitte (2022), through a review of the literature, show that the traditional innovation classification system can be applied to the wine industry. They propose a list of radical and incremental innovations for each of the four dimensions of innovation, i.e. products, processes, marketing, and organisation. Ndou *et al.* (2012), discussing the complexity of key sector trends and dynamics, show how the perception of the wine industry as not very innovative is inaccurate.

Regardless of the classification adopted, research has recognised the organisational and contextual determinants that influence innovative choices and behaviours in food firms (Castillo-Valero and García-Cortijo, 2021). Organisational factors include competitive strategies, innovation culture, leadership vision, decision-making systems, organisational structure, and human resources (Bigliardi *et al.*, 2020; Della Corte *et al.*, 2018). Firm-specific factors, such as size and membership in a business group, also play a pivotal role (Della Corte *et al.*, 2018; Bigliardi *et al.*, 2020; Baregheh *et al.*, 2012). Large firms generally allocate greater financial and human resources to innovation, while small and medium enterprises (SMEs) often leverage flexibility and networking to compensate for limited R&D capabilities (Della Corte *et al.*, 2018; Castillo-Valero and García-Cortijo, 2021). In addition to the external environment factors discussed before, regulatory requirements and dedicated funding for innovation (regional, national or international) are among the main forces driving innovation (Tell *et al.*, 2016; Singh *et al.*, 2024). Finally, territorial vocation plays a crucial role, as firms operating in food clusters or regional agribusiness districts benefit from knowledge spillovers, supply chain integration, and regional branding (Bigliardi and Filippelli, 2022).

Over the last decade, research has increasingly focused on emerging technologies that drive both radical and incremental innovations in the wine sector (Adamashvili *et al.*, 2024). Among them is AI, which has great potential to support organisations toward innovative processes (Adamashvili *et al.*, 2024; Aiello and Tosi, 2024). AI technologies differ significantly in terms of accessibility and integration, particularly between generative AI tools (G-AI) and customised enterprise AI systems (E-AI) (Singh *et al.*, 2024; Rane, 2024). The adoption of AI tools is influenced by various organisational factors, with differences between G-AI and E-AI. The former, require high investment, structured decision-making processes, cross-departmental collaboration, and specialised human capital to manage data integration and scalability (Adamashvili *et al.*, 2024). Conversely, G-AI tools thrive in creative and agile environments, where low-cost experimentation, flexible innovation culture, and employee autonomy are encouraged (Roberts and Candi, 2024; Rane, 2024). Despite these differences, both systems benefit from common enabling factors, including strong leadership with a clear vision for AI, training programs to improve technology literacy and change management strategies to overcome change resistance (Roberts and Candi, 2024; Rane, 2024). In the wine sector, AI technologies have the potential to influence several types of innovation strongly. For instance, with regard to product development, AI enables new wine blends and personalised offerings through advanced data analysis and prototyping tools (Aiello and Tosi, 2024). Process innovations leverage AI for precision viticulture, optimising irrigation, disease management, and harvest timing (Adamashvili *et al.*, 2024; Izquierdo-Bueno *et al.*, 2024). AI also enhances quality control by monitoring fermentation parameters such as temperature and acidity to ensure consistency (Aiello and Tosi, 2024). In marketing, AI supports personalised recommendations, brand storytelling through augmented reality (AR), and consumer engagement analytics (Bhardwaj *et al.*, 2024). Finally, in the organisational dimension, AI-driven decision-support systems and blockchain-based traceability improve supply chain transparency, efficiency, and compliance (Adamashvili *et al.*, 2024). Beyond this evidence, the potential of AI in generating innovations in the wine industry is yet to be explored (Adamashvili *et al.*, 2024). As Corvello (2025) points out, the discussion of the innovation potential of AI must go beyond the purely technical view (technology as a critical success factor for innovation) and include aspects of socio-organisational governance. Indeed, the implementation of AI systems is not a given. On the contrary, both the assessment, identification and understanding of technical and social opportunities and threats and the integration of AI into existing business processes require a high level of organisational commitment. In particular, systemic implementation of G-AI solutions and E-AI systems require changes in organisational structure, job descriptions, and role expectations (Corvello, 2025). Thus on the base of socio-technical systems theory (Trist and Bamforth, 1951; Sony and Naik, 2020), AI implementation processes should be viewed not as a purely technological intervention, but as a transformation that reconfigures organisational workflows, responsibilities, and dynamics of decision-making and governance. Consequently, the development of internal capabilities, such as absorptive capacity, digital skills, and change management practices, are essential to govern its adoption (McDermott *et al.*, 2024). In this perspective, analysing the potential of technology by including theories such as the Technological-Organisational-Environmental (TOE) framework (Awa *et al.*, 2017) and absorptive capacity theory (Zahra and George, 2002; Flatten *et al.*, 2011) can prove particularly useful. These theoretical frameworks provide a view to highlight the impact of organisational factors on new technology adoption processes. Since wine firms differ in their vocations for innovation, and considering the multiple factors driving AI adoption (technical and organisational), looking to understand how they leverage AI systems to achieve their innovation goals can greatly contribute to a better understanding of the potential uses of AI in the industry.

3. Research methodology

3.1 Main purpose

The objective of this study is to understand which AI tools or systems are implemented by wineries to generate innovations and to understand the organisational and contextual factors that influence their implementation. It should be emphasised that the study does not explore in detail the level of implementation (exploration, dissemination, systemic use), but seeks to uncover trends in the implementation of innovation-oriented AI. The article does not analyse the relationship between the type/size and/or country of the winery and the type of innovation. It investigates whether a winery's cluster of use/non-use of AI solutions can be discriminated by internal/external organisational and contextual factors.

3.2 The units of analysis

The study focuses on wineries in the five major wine-producing countries. This choice is based on three fundamental reasons; the importance of these countries in the wine sector having the highest wine production (OIV, 2024). These countries are technologically advanced and innovative therefore their wineries can more readily exploit and leverage technological externalities and opportunities (Bigliardi and Filippelli, 2020). Therefore, this recruitment could reveal potential uses of AI that have not yet been explored. Finally, the inclusion of companies from both countries with strong ties to tradition (Italy, France, and Spain) and emerging countries with high production potential (the United States and Australia) may capture differences in the adoption of innovation-oriented AI (Della Corte *et al.*, 2018) (see Table 1).

3.3 Research framework

Drawing on Ndou *et al.* (2012) and Dogru and Peyrefitte (2022), a list of innovations in the wine sector was crafted. Next, through a literature review, potential applications of AI to achieve innovation in each of the items on the list were evaluated. The potential applications that emerged and were listed were evaluated through the Delphi Method (Gordon, 1994). For this purpose, three experienced artificial intelligence consultants, two CEOs of world-class, highly innovative wine companies and three university professors with expertise in food innovation were involved. Panel members were asked to provide their assessment and

Table 1. The four-phased research methodology adopted

Phase	Description	Key outputs/indicators
Phase 1 – Framework definition	Identification of AI-driven innovation types and influencing factors through a structured literature review Development of the conceptual model and dimensions for empirical analysis	(1) Conceptual framework established (2) Classification of AI-related innovations (3) List of organisational and contextual factors impacting AI adoption
Phase 2 – Questionnaire design	Initial items were evaluated via a two-round Delphi method involving 8 experts (3 AI consultants, 2 winery CEOs, 3 food innovation academics) The preliminary questionnaire was tested for clarity and appropriateness with a subsample of 80 wineries Revisions were made based on face validity	(1) Delphi consensus after 2 rounds - Item-level CVI > 0.78 for each item (2) S-CVI/AVE > 0.85 for each construct (3) Revised questionnaire
Phase 3 – Data collection and validation	Final questionnaire distributed to 4,115 wineries in IT, FR, ES, US and AU. After data cleaning, 535 valid responses retained Non-response bias was tested across countries	(1) Valid responses: 535 (2) Non-response bias: $\chi^2 = 6.60$; df $= 4$; $p = 0.159$
Phase 4 – Data analysis	Descriptive statistics and adoption rates of G-AI and E-AI analysed Confirmatory factor analysis performed for construct validation Multinomial logistic regression assessed the influence of internal and external variables on AI implementation clusters	(1) KMO $= 0.88$; Bartlett's test $p < 0.01$; For each construct: AVE > 0.50 and Cronbach's $\alpha > 0.85$ (2) Multinomial regression model: $\chi^2 = 447.15$; $p < 0.01$ and classification accuracy: 85.6%

Source(s): Authors' own work

categorise each potential application of the AI tools with respect to innovation as well as the organisational and contextual factors that influence wineries' AI implementation choices and patterns were submitted for evaluation. Two Delphi cycles were needed to reach convergence on both the classification of potential AI-derived innovations and the organisational and contextual factors impacting AI implementation.

Tables 2 and 3 show the results of the Delphi analysis. The Item-Level Content Validity Index (I-CVI) was used to assess the perceived appropriateness of the items discussed (Koller *et al.*, 2017). Each item resulting from the Delphi analysis has an I-CVI greater than 0.78.

Going beyond the research evidence, the panel emphasised that G-AI adoption depends on additional contextual factors, many of which are in common with E-AI solutions (Table 2).

The preliminary questionnaire, constructed as a result of the Delphi analysis, consists of 3 sections. In Section 1 firms are asked for basic demographic information: turnover in the last 3 years, membership in a group or consortium, target market (domestic and foreign), and type of winery (traditional, innovative, commercial). The organisational factors section consists of 15 questions. Access to Industry 4.0 and 5.0 funds and incentives and collaboration oriented to innovation are assessed with one question each and involve yes/no answers. The information technology system to support the AI solution and Information technology skills are analysed with two questions on a 1–5 Likert scale. Absorptive capacity is assessed using a customised unidimensional scale based on Flatten *et al.* (2011). It consists of ten questions on a 1–5 Likert scale. Finally, in Section 3 companies were asked to indicate the use of G-AI and E-AI technologies to drive innovations in each of the identified innovations opportunities (yes/no).

The questionnaire was assessed by means Scale's Content Validity Index Value (S-CVI/AVE). Based on the panel assessment, no changes to the questionnaire were necessary at this stage (S-CVI/AVE>0.85) (Koller *et al.*, 2017). The preliminary questionnaire was tested through face validity (Repke and Dorer, 2021) by involving 80 companies. At the end of the test, two questions inherent to absorptive capabilities and the description of the scale to assess the readiness of IT firms' systems were modified and resubmitted.

3.3.1 Questionnaire distribution. The questionnaire was sent to 4,115 wineries where a total of 535 responses were included in the data analysis (after elimination of 43 responses with missing values). The websites of major winery associations and observatories in Italy, France, Spain, the U.S. and Australia were queried for the random selection of wineries. It is crucial to note that since the regulations inherent in the classification of companies by size vary among countries and sectors, the study uses the current EU classification for productive firms. On account of such a low response rate and the number of re-submissions (three times in five months), non-response bias was assessed through a χ^2 test aiming to compare the percentage of responding wineries with the percentage of total questionnaires sent out in each country (Petroni *et al.*, 2017). The results of the test did not show any significant difference between the response rates of the countries, and thus, the data were accepted ($\chi^2 = 6.60$; d.f. $= 4$; $p = 0.159$).

4. Results

4.1 Descriptions of the survey sample and AI solutions

The survey sample includes 535 wineries across five countries, with a predominance of small firms (Table 4). Traditional wineries are particularly common in Italy and France, while the US and Australia show a greater concentration of commercial-type firms. Innovative wineries represent about 17% of the total sample. Despite some possible overestimation due to limited public data on innovation-oriented wineries, the sample reflects the structure of the global wine sector.

Table 5 completes and deepens the description of the sample. Large wine companies show the highest integration in innovation ecosystems, with full participation in both business groups and global markets in all countries with the exception of the United States, where global market presence drops to 66.67%. Large firms also report the highest access to public funding

Table 2. IA potential impact on innovation

Final list: potential AI impact on innovation	Preliminary list	References
Product innovation		
Improving product (I_IP)	New or significantly improved product Increased quality	Xue *et al.* (2023), Aiello and Tosi (2024)
Product differentiation (I_PD)	Product differentiation	Xue *et al.* (2023), Newlands (2021)
New wine container (I_WC)		
Process innovation		
Production processes (I_PP)	New or improved raw materials; Production techniques; Equipment and Technology; Transformation techniques; Use of organic, chemical, and innovative substances	Aiello and Tosi (2024), Newlands (2021)
Internal logistics processes (I_IL)	Internal logistics processes	Xue *et al.* (2023), Izquierdo-Bueno *et al.* (2024)
Sustainable production practices (I_SP)	Reduction of material and water; alternative energy use, packaging, and waste disposal; reduction of refrigeration loads; energy management	Newlands (2021), Namkhah *et al.* (2023), Xue *et al.* (2023)
Vineyard management (I_VM)	Vineyard management; Harvest process optimisation	Izquierdo-Bueno *et al.* (2024), Talaviya *et al.* (2020)
Warehousing management (I_WM)	Warehousing and breeding management	Lam *et al.* (2013), Ben Ayed and Hanana (2021)
Production process control and quality (I_PC)	Monitoring wine quality; Heated and refrigerated maceration	Cranefield *et al.* (2023), Aiello and Tosi (2024), Ben Ayed and Hanana (2021)
Automation/ Autonomation (I_AA)	Automation of production processes	Cranefield *et al.* (2023), Rane (2024)
Marketing innovation		
Digital marketing (I_DM)	Digital marketing tools	Ben Ayed and Hanana (2021), Rabby *et al.* (2021)
New packaging/labels (I_NP)		
Strategic marketing analysis (I_SM)	Market analysis; Data analysis	Shen *et al.* (2021), Rabby *et al.* (2021), Haenlein and Kaplan (2019)
Brand identity and positioning (I_BI)	New or significantly improved marketing methods; Strengthen brand	Shen *et al.* (2021), Haenlein and Kaplan (2019), Namkhah *et al.* (2023)
Organisational innovation		
Workplace organisation (I_WO)	Human resources policies; New or significant communication management; Change management	Cranefield *et al.* (2023), Roberts and Candi (2024), Corvello (2025)
Decision-making Systems (I_DS)	Simplification of the decision-making process; New business or management strategy	Roberts and Candi (2024), Rane (2024)
Knowledge management (I_KM)	Training; Coaching; Mentoring; Knowledge acquisition	Roberts and Candi (2024), Rane (2024)
Supply chain integration (I_SC)	Supply chain management; Partnerships; Supply chain traceability	Adamashvili *et al.* (2024), Newlands (2021)

Source(s): Authors' own work

Table 3. Organisational and external factors affecting AI implementation

AI technology	Final list: organisational and external factor affecting AI implementation	Preliminary list	References
	Organisational factor		
(G-AI); (E-AI)	Absorptive capacity	Innovation culture; Transformational leadership; Change management; Managerial support; Knowledge management	Roberts and Candi (2024), Rane (2024), Kurup and Gupta (2022), Tariq *et al.* (2021)
(E-AI)	R&D partnerships and collaboration	Cooperation; Partnerships; Networking; Joint Venture	Heimberger *et al.* (2024), Iyelolu *et al.* (2024)
(E-AI)	Industry 4.0 and 5.0 funds and incentives	Industry 4.0 and 5.0 funds; R&D funds; State and regional incentives for business development	Heimberger *et al.* (2024), Iyelolu *et al.* (2024)
(E-AI)	Information Technology (IT) systems	Information Technology (IT) systems; Data availability	Adamashvili *et al.* (2024), Kurup and Gupta (2022)
(E-AI)	Information Technology skills	Digital skills; Data analysis skills; Data management skills	Heimberger *et al.* (2024), Kinkel *et al.* (2022)
	Firm characteristics		
(G-AI); (E-AI)	Size	Size	Heimberger *et al.* (2024), Iyelolu *et al.* (2024)
(E-AI)	Status	Legal form; Membership in business groups	Heimberger *et al.* (2024), Iyelolu *et al.* (2024)
(G-AI); (E-AI)	Type (product)	Product complexity; Product type	Heimberger *et al.* (2024), Kinkel *et al.* (2022)
(G-AI); (E-AI)	Market orientation	Market orientation	Heimberger *et al.* (2024)
	External context		
(G-AI); (E-AI)	Country	Laws and regulation; Territorial brand	Heimberger *et al.* (2024)

Source(s): Authors' own work

(ranging from 50% to 100%) and substantial engagement in collaborative networks, with the exception of Italy (50%).

Medium-sized wineries exhibit more heterogeneous characteristics. Their affiliation with business groups ranges from 29.41% in Australia to 77.78% in the United States, and their global market presence ranges from 33.33% (US) to 75% (Spain). Access to finance is relatively limited for these types of firms (between 11.76 and 31.25%) and collaboration rates remain modest with the exception of firms in the US (44.44%). Collaboration levels vary greatly within the group. Spanish firms stand out as having the highest level of collaboration among small firms (17.54%). These results highlight the resource and capacity constraints that characterise small manufacturing firms and their peripheral integration into innovation ecosystems.

Data shown in Table 6 answer the research question regarding the type of AI solutions implemented by wineries. They show a higher prevalence of G-AI adoption (17.57%) than E-AI (11.40%). The joint use of G-AI and E-AI remains by far the least common (8.79%). Despite the lower frequency, the integrated adoption of both types of AI seems to allow companies to explore more opportunities for innovation. Wineries using both G-AI and E-AI report an average of 4.74 types of innovation, compared to 3.20 for those using only G-AI and 2.18 for those adopting E-AI. Table 7 deepens the analysis on AI adoption and shows the correlation between innovations driven by AI solutions.

Table 4. Sample description

Country	Size	Commercial	Innovative	Traditional	Total by size
Australia (AU)	Large	2			2
	Medium	14	1	2	17
	Small	42	8	10	60
France (FR)	Large	2		2	4
	Medium	27	2	12	41
	Small	14	14	84	112
Italy (IT)	Large	2			2
	Medium	15		8	23
	Small	10	35	65	110
Spain (SP)	Large	1			1
	Medium	11	2	3	16
	Small	18	5	34	57
US (US)	Large	3			3
	Medium	22	5		27
	Small	28	20	12	60
Total by type		211	92	232	535

Source(s): Authors' own work

Table 5. Characterisation of sample companies through internal and external contextual variables

Country	Size	Business group (Y)	Market (global)	Industry 4.0 and 5.0 funds and incentives (Y)	Collaboration with external innovative agencies (Y)
AU	Large	100.00%	100.00%	50.00%	100.00%
	Medium	29.41%	23.53%	11.76%	17.65%
	Small	23.33%	20.00%	6.67%	13.33%
FR	Large	100.00%	100.00%	75.00%	75.00%
	Medium	51.22%	53.66%	21.95%	29.27%
	Small	9.82%	26.79%	1.79%	1.79%
IT	Large	100.00%	100.00%	100.00%	50.00%
	Medium	60.87%	60.87%	30.43%	13.04%
	Small	14.55%	28.18%	3.64%	10.00%
SP	Large	100.00%	100.00%	100.00%	100.00%
	Medium	62.50%	75.00%	31.25%	25.00%
	Small	12.28%	21.05%	8.77%	17.54%
US	Large	100.00%	66.67%	66.67%	100.00%
	Medium	77.78%	33.33%	22.22%	44.44%
	Small	5.00%	20.00%	5.00%	8.33%

Source(s): Authors' own work

The results reported in Table 7 show that G-AI is more widely implemented across various innovation domains than E-AI. G-AI is implemented to guide innovation in product (81 cases), marketing (138 cases) and processes (84 cases). While it is intuitive and expected to see a high correlation between items inherent in innovations of the same dimension, the result showing a high correlation between innovative items of different dimensions is not at all. The strong correlation between items of different dimensions indicates that companies are leveraging AI to create integrated, cross-functional innovations. For instance, digital marketing innovation

Table 6. Descriptive analysis of AI solution adoption

AI solutions	E-AI	G-AI	E-AI and G-AI
Wineries employing AI solution	11.40%	17.57%	8.79%
Number of AI-driven innovations			
Min	1	1	2
Max	5	7	8
Average	2.48	3.20	4.74

Source(s): Authors' own work

Table 7. Descriptive analysis of the adoption of AI solutions and their correlation

AI-driven innovation implementation		E-AI	Corr. E-AI	G-AI	Corr. G-AI
Product innovation	(I_IP)	19	(I_PC), 0.76	29	(I_SP), 0.43; (I_PC), 0.41; (I_BI), 0.47
	(I_PD)	6	(I_AA), 0.50	41	(I_PP), 0.47; (I_DM), 0.46
	(I_WC)	0		11	
Process innovation	(I_PP)	17	(I_AA), 0.53	31	(I_PD), 0.47
	(I_IL)	6	(I_SC), 0.51; (I_WM), 0.47	0	
	(I_SP)	4		20	(I_IP), 0.43; (I_VM), 0.44; (I_PC), 0.40; (I_NP), 0.44; (I_BI), 0.40
	(I_VM)	23		15	(I_SP), 0.44; (I_PC), 0.47
	(I_WM)	3	(I_IL), 0.47	0	
	(I_PC)	20	(I_IP), 0.76	18	(I_IP), 0.41; (I_SP), 0.40; (I_VM), 0.47
	(I_AA)	16	(I_PD), 0.50; (I_PP), 0.53	0	
Marketing innovation	(I_DM)	0		64	(I_PD), 0.46
	(I_NP)	0		23	(I_SP), 0.44; (I_BI), 0.46
	(I_SM)	4	(I_BI), 0.47; (I_SC),0.42	24	
	(I_BI)	1	(I_SM), 0.47; (I_DS), 0.71	27	(I_IP), 0.47; (I_SP), 0.40; (I_NP), 0.46
Organisational innovation	(I_WO)	2		0	
	(I_DS)	2	(I_BI), 0.71	0	
	(I_KM)	0		7	
	(I_SC)	10	(I_IL), 0.51; (I_SM), 0.42	0	

Note(s): Correlation indexes reported: c.i < −0.4; c.i. > 0.4 and $p < 0.05$
Source(s): Authors' own work

and product differentiation correlation (c.i. = 0.46) could indicate ways in which companies use AI for integrate activities oriented to market positioning. Another key aspect that emerges from the analysis is the contribution of G-AI to the practices of introducing sustainable innovations. Sustainable production (20 cases) is one of the most significant areas in which G-AI plays a transformative role. The high correlation with product innovation (c.i. = 0.43) and new packaging development (c.i. = 0.44) seems to indicate the use of G-AI for the development of eco-friendly approaches. Similarly, the correlation between sustainable production and product innovation (c.i. = 0.43) highlights how AI can support the creation of more sustainable winemaking processes, characterised, for example, by less wasted water and energy and the use of more sustainable alternative ingredients. Finally, regarding the implementation of G-AI solutions, it is interesting to note that some firms employ it to innovate knowledge management activities (7).

E-IA solutions are implemented in every dimension discussed. The highest frequency of use is found for process (73 cases) and product innovation (23 cases). In particular, E-AI is implemented to achieve innovations in vineyard management (23 cases), production control (20 cases) and product development (19 cases). As with G-AI, the results of the correlations between items show that the use of E-AI is geared towards developing integrated innovations in several areas. For instance, correlation results indicate a strong connection between automation, production processes (c.i. = 0.53) and product development (c.i. = 0.50). Furthermore, the correlation between production control and product innovation is very strong (c.i. = 0.76). Unlike G-AI, E-AI is also leveraged to innovate inter-organisational processes. The result show that innovation in supply chain process integration has a strong correlation with internal logistics processes (c.i. = 0.51) and strategic marketing (c.i. = 0.47). While this result suggests that E-AI solutions based on marketing data can streamline logistics and improve the synchronisation of production and distribution processes, it may indicate that conversely, it is marketing strategies that are shaped by logistics processes.

4.2 Factors influencing the implementation of AI solutions

Wineries were grouped into four clusters: (C1) wineries that adopt both G-AI and E-AI solutions, (C2) wineries that implement only E-AI, (C3) wineries that use only G-AI, and (C4) wineries that do not use any AI. However, the low number of companies in (C1) and (C2) in comparison to those in (C3) and (C4) would have led to large deviations in representation, so (C1) and (C2) were merged. Multinomial logistic regression was applied to assess the organisational and contextual factors, both internal and external, that discriminate between the different clusters. The choice of this tool is due in part to the type of data available, namely categorical (country; size; type; company group; industry 4.0 and 5.0 funds and incentives; market orientation; partnership and collaboration) and continuous (IT infrastructure; IT skills and absorption capacity), and also to its ability to provide coefficients indicating the effect of each independent variable on each class.

Prior to the data analysis, confirmatory factor analysis was performed to verify that the items related to absorptive capacity and computer skills converged into consistent factors. Next, the level of variance inflation factor (VIF) was tested for collinearity of all factors.

As shown in Table 8, the factor analysis revealed four constructs inherent in absorptive skills (acquisition, assimilation, transformation, and exploitation) and one inherent in IT skills (Hair *et al.*, 2014). The items converge as expected in relation to the questionnaire's demands.

The results of the correlation analysis (Table 9) confirmed that the items of each construct contribute more to the variance explained within their construct than other constructs (Hair *et al.*, 2014). The collinearity analysis showed that the variable IT infrastructure has a VIF of 6.1. To address collinearity issues, in particular the high correlation between IT infrastructure and IT skills (c.i. = 0.71), and to preserve both constructs within the analysis, a composite measure of "IT readiness" was created by averaging the two. This reduced the VIF from 6.1 to 5.3, mitigating multi collinearity and maintaining theoretical consistency in the representation of digital maturity.

Table 8. Factor analysis for absorptive capacity and information technology skills

Construct items	Factor loading	AVE	Cronbach's α
Information technology skills (IT)		0.81	0.95
IT_1	0.91		
IT_2	0.89		
Acquisition (AC)		0.56	0.87
AC_1	0.75		
AC_2	0.82		
AC_3	0.63		
Assimilation (AS)		0.59	0.85
AS_1	0.75		
AS_2	0.86		
AS_3	0.68		
Transformation (TR)		0.61	0.86
TR_1	0.82		
TR_2	0.73		
TR_3	0.75		
Exploitation (EX)		0.82	
Ex_1	0.90		

Note(s): KMO = 0.88; Bartlett's test: $\chi 2$ = 4801.08; d.f. = 66; p < 0.01
Source(s): Authors' own work

Table 9. Correlation analysis

	IT skills	Acquisition	Assimilation	Transformation	Exploitation
IT skills	1.000				
Acquisition	0.19***	1.000			
Assimilation	0.21***	0.34***	1.000		
Transformation	0.25***	0.414**	0.44***	1.000	
Exploitation	0.14***	0.14***	0.16***	0.22***	1.000

Note(s): *p < 0.10; **p < 0.05; ***p < 0.01
Source(s): Authors' own work

Table 10 shows the results of the multinomial logistic regression, providing an in-depth assessment of the factors influencing cluster membership. The model exhibits robust performance, with an omnibus chi-square of 528.86 (d.f. = 26, p < 0.01), demonstrating that the predictors, taken together, significantly differentiate between clusters. Pseudo R-square values indicate a strong explanatory power, and the overall classification accuracy of 85.61%, alongside weighted precision (84.40%), recall (85.61%), and F1 scores (84.10%), underscores the model's reliability. Within this framework, the individual variables reveal nuanced effects on cluster assignment. Regarding external and internal contextual variables, the country, size, industry 4.0 and 5.0 funds, incentive accounting, and collaborations are useful in discriminating between clusters. Using the US as the reference category, countries such as AU, IT and especially SP show significant negative coefficients, suggesting that US-based firms are more likely to use G-IA. Size also plays a critical role: medium-sized organisations are more likely to be classified in (C3). Access to industry 4.0 and 5.0 funds and incentives and collaboration with innovation partners is linked to a higher likelihood of membership in the cluster (C1). Organisational variables, namely IT readiness and absorptive capacity, emerge as significant predictors of clusters. This confirms their importance in driving differentiation among business behaviours toward AI solutions. The findings indicate that companies in (C1) exhibit notably high levels of IT readiness and robust absorptive capacity, encompassing

Table 10. Multinomial logistic regression results

		Cluster 1	3	4	Model fitting information d.f	p	$\beta_{C1\ vs\ C4}$	$\beta_{C3\ vs\ C4}$
Intercept					0		−16.48***	−6.36***
Country	AU	11	13	55	8	0.00	0.48	−1.93***
	FR	14	24	119			−0.19	−1.48***
	IT	11	11	113			1.18	−1.82***
	SP	7	6	61			0.29	−2.47***
	US	18	40	32				
Size	Large	6	2	4	4	0.00	0.23	−0.66
	Medium	42	10	72			0.77	−1.87***
	Small	13	47	339				
Type	Commercial	48	21	142	4	0.78	–	
	Innovative	4	20	68			–	
	Traditional	9	18	205			–	
Group	N	11	49	341	2	0.32	–	
Business	Y	50	10	74			–	
Market	Local	35	40	291	2	0.82	–	
	Global	26	19	124			–	
Funding	N	15	56	404	2	0.04	−1.75***	−0.51
	Y	46	3	11				
Collaboration	N	20	52	383	3	0.03	−2.30***	−0.94
	Y	41	7	32				
IT readiness		3.64 (0.81)	2.98 (0.90)	2.64 (1.02)	2	0.00	1.30***	0.41**
Absorptive capacity	Acquisition	3.64 (0.58)	3.04 (0.78)	2.45 (0.70)	2	0.02	0.67***	0.35**
	Assimilation	3.92 (0.61)	3.49 (0.73)	2.25 (0.75)	2	0.00	1.10***	0.52**
	Transformation	3.52 (0.99)	3.31 (1.07)	2.28 (0.98)	2	0.00	1.52***	0.64**
	Exploitation	3.78 (0.88)	3.01 (0.90)	2.44 (0.88)	2	0.00	1.25***	1.01***

Note(s): Omnibus Tests of Model Coefficients: $\chi^2 = 447.15$; d.f. = 26; $p < 0.01$
Pseudo R-square values: Cox and Snell = 0.57; Nagelkerke = 0.711; McFadden = 0.52
Percentage correctly classified: 85.61%; Precision (weighted): 84.40%; Recall (weighted): 85.61%; F1 Score (weighted): 84.10%
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$
Source(s): Authors' own work

acquisition, assimilation, transformation, and exploitation. Country, size, and absorptive capacity provide good discrimination between companies belonging to (C3) and (C4). IT readiness, absorptive capacity, collaboration, and access to Industry 4.0 and 5.0 funds and incentives are the variables that best explain the differences between (C1) and (C4).

5. Discussion

Innovations driven by G-AI and E-AI manifest themselves in different dimensions and business processes, highlighting a complementary but interconnected use of these technologies. Interestingly, the use of AI allows the traditional classification of dimensions of innovations in the food industry to be overcome, making the dimensions interconnected. E-AI is used to drive innovations in production processes, supply chain management, and quality control (Singh *et al.*, 2024; Rane, 2024). On the other hand, G-AI fosters innovation in marketing, product differentiation and brand identity. Despite their differences, both forms of

AI show convergences in the areas of sustainability and organisational efficiency: G-AI contributes to the development of sustainable packaging strategies and product value communication, while E-AI optimises production resources and reduces waste. Therefore, the integrated adoption of these technologies emerges as a strategic lever for increasing innovative capacity, fostering synergies between operational improvements and enhancement of market offerings (Roberts and Candi, 2024; Adamashvili *et al.*, 2024).

The analysis of companies identified three distinct clusters: *strongly AI-oriented wineries*, *AI-explorer wineries*, and *old-fashioned wineries*. Most strongly AI-oriented adopt both E-AI and G-AI and are characterised by high absorptive capacity, evolved IT systems and strong integration with innovation ecosystems. In addition, these companies generally have better access to industry 4.0 and 5.0 funding and incentives. This contributes to further strengthening their innovation capabilities. In particular, s*trongly AI-oriented wineries* cluster includes companies of varying sizes, with a significant subset of small companies located in the United States, Spain, and Australia. These small companies stand out for their high level of collaboration with innovative partners (90%), broad access to industry 4.0 and 5.0 funds (85%), and use of G-AI (100%). This shows that constraints related to scarce financial resources can be overcome through integration strategies with partners or by taking advantage of R&D 4.0 and 5.0 policies (Heimberger *et al.*, 2024; Iyelolu *et al.*, 2024). There are no differences in representation across countries in this group of companies, which suggests that both the countries' innovation ecosystems and policies and the wineries' orientation belonging to different territories toward these technologies are comparable. The combination of high IT readiness and strong absorptive capacity positions these wineries at the forefront of innovation. *AI explorer wineries* have a predominance in the United States. This phenomenon could be attributed to the country's propensity to adopt new technologies, and the positive perception of G-AI as a tool for innovation. Compared to *AI-oriented wineries*, these companies do not fully exploit the synergies between E-AI and G-AI. However, compared to *old-fashioned wineries*, they show a greater capacity for technology assimilation and digital transformation. In countries with a strong winemaking tradition, the use of G-AI could be limited by the fact that it is perceived primarily as a tool for developing creativity and incremental improvements. The *old-fashioned wineries*, mostly small in size, remain on the periphery of digital transformation. Their limited efforts in knowledge management, IT, absorptive skills development, external collaboration, and structural constraints result in significant barriers to AI adoption (Tariq *et al.*, 2021).

From a research perspective, the study invites a shift from a dual distinction (adopter/non-adopter or G-AI/E-AI) to more layered models of AI adoption, recognising both the differentiated roles of G-AI and E-AI in innovation processes and the use of AI technologies to drive cross-functional and, in some cases, cross-organisational innovations. Furthermore, the results of the study provide managers with insights into both the opportunities offered by AI in terms of innovation and the organisational factors to be exploited to effectively implement AI technologies. In particular, the results stress that technological investments alone are insufficient: AI adoption requires strategic alignment, cultural readiness, and capability building. Managers are required to support the creation of synergies between internal and external enabling factors and to overcome structural and organisational barriers that can undermine the implementation of AI solutions. However, these challenges differ according to the adoption strategy and technology. While leveraging culture and absorptive capabilities is critical for the adoption of G-IA solutions, to fully leverage AI, managers need to aid development of strong IT capabilities and invest in training programs that improve digital skills, to ensure their companies have IT readiness to integrate complex AI systems. Also seeking external partnerships and obtaining funding through industry 4.0 and 5.0 initiatives can provide the financial and technical support needed to fill existing digital gaps. Managers should also adapt their strategies according to the type of business and innovation sought. AI-explorer wineries could consider incremental investments in internal IT systems and establish partnerships geared toward the development of AI systems. In contrast, old-fashioned wineries must embark on an internal journey to overcome all barriers and enter the digital arena.

On a societal level, the risk of technological divergence is evident. Without targeted policy support, smaller and traditional wineries may be excluded from the benefits of AI implementation and exploitation. The different models, adoption choices and enabling factors of AI implementation revealed by the study highlight the need for policy makers and industry associations to plan and programme tailored guidance and support mechanisms. The former are called upon to define policies to facilitate access to funding or the creation of specific funds for AI innovation and adoption. The latter, on the other hand, should support the creation of IT skills and innovation ecosystems that foster the adoption and exploitation of these technologies. The findings can offer concrete directions for institutional actors who wish to promote digital transformation. Supporting AI transformation programs could prove to be a strategic lever for both innovation policy and industrial development, strengthening the practical and social relevance of this research. These findings, consequently, offer concrete indications for institutional actors wishing to promote digital transformation. Support for AI transformation programmes could prove to be a strategic lever for both innovation policy and industrial development, reinforcing the practical and societal relevance of this research.

6. Conclusion

The purpose of this study was to understand the patterns of AI adoption by wine companies; to identify AI-driven innovations being implemented in five major wine-producing countries and to examine the organisational and contextual factors influencing the choices and opportunities for implementing AI systems. The exploratory study demonstrates that the success of AI integration in the wine industry depends on a synergistic relationship between organisational capabilities and internal and external contextual factors. The findings both underscore and have implications for the need for wineries to strategically invest in IT readiness and absorptive capacity while engaging in broader innovation ecosystems to secure the financial and collaborative resources essential to advance AI-driven innovation. This synergistic approach is critical for wineries that want to remain competitive in an increasingly digital and global marketplace.

A limitation of the research is that although non-response tests showed no significant differences between countries, the low response rate may limit the generalisability of the results. Also, the study did not examine whether the adoption of AI solutions actually generated innovations, nor did it assess the extent of AI adoption at the micro or meso level. Future research will be geared toward filling these gaps. These investigations may provide valuable insights and contribute to the development of more targeted strategies for the AI transformation of the wine sector. Another promising avenue for future research would be to investigate the factors and antecedents behind the adoption of AI tools and systems, and how in the wine industry AI tools can influence both organisational arrangements and decision-making models. These aspects should be explored in the different forms of wineries ranging from traditional family businesses to large worldwide groups.

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