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Smartphone and web apps for pest and disease management in viticulture: A mapping of functionality, AI integration, and accessibility

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ABSTRACT

Smartphone and web-based apps represent a growing interface between agronomic knowledge and digital decision support, offering practitioners accessible tools for preventive and evidence-based integrated pest management (IPM). Viticulture provides an especially relevant system for evaluating such tools, given its economic importance in many countries, the complexity of its pest and disease assemblages, and the multiple intervention decisions required across the growing season. As the landscape of publicly and commercially available apps continues to expand, a systematic understanding of what exists, what it offers, and where gaps remain is vital to guide innovation in meaningful directions. This study mapped 49 publicly available smartphone and web-based apps supporting pest and disease management in viticulture, evaluating them across four layers: IPM support, AI and computational intelligence integration, interoperability, and pricing accessibility. Apps were evaluated against a set of nine IPM components, covering the full spectrum from diagnosis and monitoring to intervention support and regulatory reporting. Results reveal a landscape of growing technological sophistication: AI-enabled apps covered a wider range of IPM functions, but AI functionality was disproportionately associated with subscription-based pricing. Advisory decision support, surveillance and regulatory reporting, and conversational AI integration emerged as the least represented components, pointing to priority areas for the next generation of digital IPM tools. These findings provide a basis to inform future development in digital viticulture, offering actionable insights for app developers, extension services, policymakers, and other stakeholders seeking to support multifaceted, accessible, and scientifically validated digital solutions for sustainable management of grapevine pests and diseases.

1. Introduction

Despite extensive advances in crop protection, pests and diseases remain a major threat to agricultural productivity, causing approximately 20–40% of global annual crop yield losses, translating to over USD 290 billion per year [1]. Since World War II, crop protection has heavily relied on prophylactic and broad-spectrum pesticide applications [2]. While effective in the short term, these approaches have also led to pesticide resistance [3], non-target effects on beneficial organisms [4], environmental pollution [2], and increasingly restrictive regulatory pressure on pesticide use. For instance, the EU Farm to Fork Strategy set a political target of reducing pesticide use by 50% by 2030 [5], reflecting a broader shift toward more sustainable agrifood systems. In response, Integrated Pest Management (IPM) has emerged as a structured and preventive framework combining monitoring, risk assessment, economic thresholds, and targeted interventions to reduce reliance on chemical control while maintaining effective crop protection [6,7].

Within this broader context, viticulture represents a particularly relevant and demanding system for pest and disease management. Grapevines are highly susceptible to fungal diseases and insect pests, requiring frequent monitoring and repeated interventions throughout the growing season [8,9]. Furthermore, climate change is exacerbating these challenges. Global temperatures have risen by approximately 1.1 °C above pre-industrial levels, influencing pest dynamics and disease development [10,11]. This has already imposed measurable impacts on

Abbreviations: AI, Artificial intelligence; API, Application programming interface; CNN, Convolutional neural networks; CV, Computer vision; DSS, Decision support system; GDPR, General data protection regulation; IoT, Internet of things; IPM, Integrated pest management; LLM, Large language model; ML, Machine learning; SWOT, Strengths, Weaknesses, Opportunities, Threats.

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production: in 2023, the International Organisation of Vine and Wine reported one of the lowest global wine outputs in decades, largely due to extreme weather events and associated disease pressure [12].

The effective implementation of IPM in vineyards relies on timely, site-specific information to support monitoring, forecasting, and targeted interventions. In recent years, advances in digital and precision viticulture technologies have expanded the capacity to generate and use such information [13,14]. Tools such as sensors, remote sensing platforms, and decision support systems (DSS), often supported by technologies such as automated weather stations, smart traps, proximal sensing devices, and drone-based imaging and spraying systems, enable disease detection, pest surveillance, and predictive modelling of infection risk, supporting more efficient and sustainable management practices [15,16].

Among these technologies, smartphones and web-based applications (hereafter apps) have emerged as widely adopted digital tools in practical farm settings. Survey evidence from the European Commission's Joint Research Centre indicates that 66% of EU farms used mobile apps for agricultural management, compared to only 11–15% using connected insect traps and 3% using drones for monitoring [17]. Their uptake reflects practical advantages over hardware-intensive alternatives, including lower deployment costs, no dedicated hardware requirements, and direct integration into daily vineyard and farm operations [18–20]. This underscores that software-based tools represent the primary interface between growers and digital decision support in current practice. Notably, the functional scope of these apps has expanded considerably with the integration of Artificial Intelligence (AI), enabling capabilities such as image-based disease and pest identification [21], real-time risk alerts [22], predictive modelling, and increasingly, precision intervention support [23], placing apps at the intersection of accessibility and analytical complexity in modern agriculture.

However, despite their growing availability, these apps often address specific tasks rather than providing comprehensive solutions, resulting in a fragmented digital ecosystem. Growers may need to rely on multiple apps to cover different aspects of pest and disease management, raising challenges related to usability, interoperability, and data management [24]. This fragmentation also carries implications for data governance. Apps collecting farm-level data, such as location, spray records, and pest observations, may handle information subject to the General Data Protection Regulation (GDPR), and the use of multiple tools from different developers compounds the complexity of ensuring compliance and maintaining data sovereignty [25].

This study aims to map and analyse the existing publicly available smartphone and web-based apps supporting pest and disease management in viticulture, identified through a systematic search of commercial app stores and publicly available sources. Specifically, it seeks to:

(i) classify apps according to their IPM-relevant functionalities, including monitoring, forecasting, diagnostic, and other decision support features;
(ii) examine the integration of AI and computational intelligence, including the types of technologies employed and their functional roles;
(iii) evaluate the technical and economic accessibility of identified tools, including interoperability features, pricing models, and transparency of access;
(iv) synthesise findings into an evaluation of the strengths, weaknesses, opportunities, and external pressures shaping the current app landscape, with the aim of identifying priority directions for development, policy support, and improved grower accessibility.

Together, these objectives aim to provide a comprehensive landscape of the current digital support for vineyard pest and disease management and to deliver actionable recommendations for developers, extension services, and policymakers seeking to improve coherence, accessibility, and sustainability of available tools.

2. Methodology

2.1. App search and identification

A preliminary search was conducted in Scopus and Web of Science using relevant keyword combinations to assess the availability of peer-reviewed literature on commercially available viticulture apps. Results predominantly returned academic studies examining disease and pest management strategies and proof of concepts rather than functional tools accessible to practitioners. This confirmed that such apps are distributed via market channels rather than academic publishing platforms. Consequently, the systematic search was designed around sources that more accurately reflect the distribution landscape for publicly available digital tools.

Building on these grounds, a systematic search was conducted in English between March and May 2026 to identify smartphone and web-based apps supporting pest and disease management in viticulture. An initial search was performed in March 2026 across two source types: commercial app stores (Google Play and Apple App Store) and Google Search: the latter capturing web-based apps, official developer and project websites, institutional and organisational pages, and other grey literature. A supplementary verification pass was conducted in May 2026, comprising: (i) re-verification of the categorisation and coded variables of all apps identified during the initial search round, and (ii) a supplementary search using a subset of the terms in Table S1 to identify any late-emerging apps. The final dataset reflects all the apps identified until 31 May 2026, with app features and pricing coded at the point of identification and re-verified during the May 2026 pass, such that all app-level information is current as of this date.

App store searches were conducted using newly created accounts with no prior search or download history, registered to Italian addresses. Due to the absence of structured Boolean search functionality within app store platforms, a rotating keyword strategy was adopted, applying a predefined set of terms to maximise retrieval coverage (Table S1). Search terms were combined across the three keyword categories in Table S1. Each keyword row generated three plain search strings: the full three-term combination (vineyard-related, pest/disease-related, and digital/commercial-related terms, e.g. "vineyard pest management app"), and two-term combinations pairing the vineyard-related term individually with the pest/disease keyword (e.g. "vineyard pest management") and with the digital/commercial keyword (e.g. "vineyard app"). This structure was applied systematically across all rows in Table S1. Unlike structured bibliographic database searches, app store platforms return results governed by undisclosed, platform-specific ranking logic. Consequently, a substantially larger number of search strings was required to achieve comparable retrieval coverage. For the May 2026 supplementary pass, only the two-term combinations pairing vineyard-related and digital/commercial-related terms were used, as these had consistently yielded more grapevine-specific apps in the original search than combinations including pest/disease-related terms.

Recognising that app store results are influenced by the geographic region of the registered account, identical keyword searches were subsequently conducted via Google Search to identify any apps unavailable through app stores, including web-based decision support tools disseminated through institutional, developer or project websites, which represent a substantial proportion of publicly available viticulture tools. Google Search queries were conducted in a non-personalised browser environment to minimise algorithmic bias. All searches were conducted from Italy, which may have influenced the visibility and ranking of results.

Platform-specific output volume varied substantially: Google Play searches typically returned up to approximately 30 results per query, Apple App Store searches typically returned 3–10 results (with a substantial number of queries returning no results), and Google Search returned an effectively unbounded number of results per query. As such, a 50-result screening threshold was applied uniformly across all platforms. Within this threshold, app store searches were generally screened exhaustively, as output volumes rarely approached this threshold, whereas Google Search's effectively unbounded output made the threshold the binding constraint for that source. Candidate apps identified during keyword rotation were logged to a running record (app name and source link) where results appeared plausibly relevant to agricultural or viticultural pest and disease management, excluding results clearly unrelated to this domain (e.g., social media or gaming apps). Logged candidates were then formally assessed against the inclusion and exclusion criteria detailed in Section 2.2. Where the same app was subsequently retrieved via an additional source or platform, the corresponding link was appended to its existing entry rather than creating a duplicate record. This process is summarised in Supplementary Figure S1. Although a formal search-saturation analysis was not conducted, observed saturation was reached during keyword rotation, with an increasing proportion of retrieved results corresponding to apps already identified as the search progressed.

2.2. Inclusion and exclusion criteria

Apps were included if they met the following criteria: explicit role in grapevine pest or disease management; commercially or publicly available to use and/or download; support for at least one IPM-relevant functional component (defined in Section 2.3); and delivery through a smartphone app, web-based interface, or integrated digital platform connecting software to external sensing hardware. Standalone hardware tools such as drone systems or sensor networks without an associated user-facing app interface were excluded, as the focus of this review is on software-accessible tools rather than infrastructure-dependent systems. Regional databases and institutional monitoring portals were included where they took the form of an accessible app and explicitly addressed a pest or disease management functionality in viticulture.

The app search protocol and coding framework (Sections 2.1 – 2.3) were developed jointly by both authors. App identification, inclusion/exclusion decisions, and coding of all variables were performed by the primary author, with classifications and scores (Section 2.3) reviewed by the second author to confirm and reach a consensus by both authors on the final coding.

For each app retained, several additional descriptive variables were recorded. Release year, developer country, and continent were determined from publicly available records, including app store metadata, developer pages, company websites, and archived web history, supplemented by other publicly accessible documentation if primary sources were unavailable or incomplete. Where developer country could not be confirmed with certainty, it was recorded as 'Unknown,' with continent retained only if reasonably inferable from other contextual information. Platform availability (e.g., iOS, Android, and/or web) was also recorded for each app, as was whether the app targeted grapevine exclusively or supported multiple crops. Pest and disease coverage figures should be interpreted with caution, as disclosure practices varied substantially across developers, ranging from explicit species-level lists to aggregate counts only. Whether an app disclosed named species, as distinct from an aggregate count, was recorded separately. Full variable definitions and coding are provided in the accompanying supplementary coding dataset.

2.3. IPM scoring and feature classification

Apps were classified into four functional categories based on their primary user-facing function and marketing positioning. Classifications reflected the dominant primary function as determined through a review of developer documentation, app store descriptions, and official app websites, rather than the full range of features offered. The four categories were:

(i) Disease diagnosis and pest identification apps.
(ii) Disease and pest forecasting and monitoring apps.
(iii) Integrated management and sensor platforms.
(iv) Regional, regulatory and advisory apps.

Category assignment followed a hierarchical rule (Supplementary Figure S2). Apps incorporating a dependent hardware component (e.g., connected sensors or monitoring equipment) were classified under category (iii) irrespective of any additional software functionality offered. Among the remaining apps, those with an explicit regulatory or institutional affiliation were classified under category (iv). All other apps were classified according to their dominant marketed function: apps offering a full forecasting or decision-support pipeline were classified under category (ii) even where a secondary, narrower diagnostic feature was also present (e.g., identification limited to one or two diseases); apps whose sole or primary function was diagnostic identification were classified under category (i). These four categories reflect a practitioner-facing classification, capturing how a prospective user would likely first interpret the purpose of an app, rather than a formally validated taxonomic framework.

To assess the full functionality and alignment with IPM principles, beyond their primary function, each app was additionally evaluated against a set of nine IPM functional components (Table 1). While core IPM principles are well-established in the literature [6,7,40], no single framework addresses the full spectrum of functionality offered by digital

Table 1
Classification framework of nine IPM functional components used to derive the IPM coverage score across evaluated viticulture apps.

IPM Component	Description	Reference
Disease or pest diagnosis and identification	Identification of pests, diseases, or disorders based on symptoms, images, or reference information.	[26–28]
Field monitoring and scouting	Regular, field-level observation and recording of pest or disease presence and density/intensity within individual vineyards.	[6,29,30]
Disease or pest risk forecasting	Prediction of pest/disease development based on weather, phenology, or epidemiological models and/or risk or infection and infestation pressure delivered to the user.	[31,32]
Management options and control measures	Provision of available IPM tactics, chemical and non-chemical control options, and product information relevant to identified pests or diseases.	[33,34]
Intervention timing optimisation	Dynamic guidance on when to act, based on models, weather, or phenology, beyond static product information; optimal timing recommendations.	[14,34]
Precision and site-specific management	Support for spatially targeted management decisions within individual vineyards, including hotspot mapping, treatment zone delineation, location-tagged field observations, or integration of sensor and spatial data for variable-rate intervention support.	[34,35]
Recordkeeping and documentation	Digital logging and storage of observations, treatments, and management actions for traceability and compliance.	[36,37]
Surveillance or regulatory reporting	Systematic collection and transmission of pest/disease occurrence data for regional monitoring, biosecurity, or regulatory purposes.	[38]
Communication of alerts, warnings or information	Delivery of pest or disease alerts and warnings, whether issued by external authorities (e.g. by extension services or regional authorities) or generated internally by the app based on model outputs and thresholds.	[30,38, 39]

tools in viticultural pest and disease management. Therefore, the classification framework presented here was developed by drawing from the literature to identify and define the distinct functions and services that such tools can offer to practitioners. This secondary classification was conducted to account for cases in which apps offer a broader suite of features than their primary marketing positioning suggests – scored independently of an app's primary category assignment – and to enable structured comparison of functional IPM coverage across all identified tools regardless of category. The presence or absence of each component was recorded as a binary variable (1 = present; 0 = absent). An aggregate IPM score was calculated for each app as the sum of present components ranging from 0 to a maximum of 9. Components were weighted equally to capture the breadth of functional coverage offered by each app – that is, the extent to which one tool consolidates functions a user might otherwise need to source across multiple apps – rather than to differentially weight functions according to their relative agronomic importance.

This two-stage classification approach enabled the assessment of two complementary analytical questions: which type of tool dominates the current landscape, and whether individual apps provide sufficiently integrated IPM support or contribute to a fragmented digital ecosystem in which growers may rely on multiple tools to cover the full spectrum of pest and disease management needs.

AI usage was recorded where explicitly stated and technically corroborated in developer documentation or publicly available app materials. Non-AI computational methods, including rule-based logic, mechanistic epidemiological models, and weather-driven forecasting, were recorded using the same evidentiary standard, reflecting that the coding process was designed to classify the full range of computational approaches employed. Where AI integration was claimed but not described in sufficient technical detail to confirm the underlying method, classification was inferred from the specific terminology and functional descriptions used in developer websites, app store listings, and associated communications (e.g. product newsletters), which frequently provided clear indications of the underlying technique even without formal technical disclosure. Mechanistic epidemiological models and weather-driven forecasting tools were not classified as AI-enabled unless an app separately incorporated a distinct machine-learning-based function. AI technologies were categorised into four functional types: (1) image-based diagnosis and pest identification, typically implemented through convolutional neural networks (CNNs) and computer vision (CV) approaches [41]; (2) risk forecasting and predictive analytics, commonly employing machine learning (ML) algorithms [42]; (3) advisory and conversational AI systems, increasingly enabled by large language models (LLMs) [43]; and (4) sensor analytics, integrating AI-driven interpretation of IoT and trap monitoring data, as distinct from rule-based threshold alerts [16]. These four AI functional types are not mutually exclusive, and an app may be coded positively for more than one type.

Interoperability and accessibility were assessed across three binary variables: presence of an open or third-party Application Programming Interface (API) enabling data exchange with external systems; integration of external weather data sources (i.e. weather APIs); and availability of data export functionality in a standard, readable format (such as JSON or CSV). For export capability specifically, status was additionally recorded as 'unknown/not disclosed' where this could not be determined from publicly available materials, distinct from a confirmed absence of the feature.

Pricing accessibility was recorded as a categorical variable with four models: (1) fully free tools, available at no cost; (2) freemium models where a free tier was available alongside one or more paid subscription tiers; (3) subscription-based tools with publicly disclosed pricing; and (4) subscription-based tools for which pricing was not publicly available and required direct vendor contact. The fourth category was treated as an indicator of limited pricing transparency for the analysis. Open-source status was recorded where an app's source code was publicly available via a code repository (e.g., GitHub) under an explicit open-source license.

2.4. Data analysis

All statistical analyses were conducted using IBM SPSS Statistics (Version 30). The relationship between the total number of pests and diseases covered by each app and its corresponding level of IPM coverage was assessed using Spearman's rank-order correlation. Apps missing organism coverage data were excluded from this analysis only.

A Mann-Whitney U test was applied to examine whether IPM scores differed between AI-enabled and non-AI apps, with the asymptotic significance calculation accounting for tied observations. Visual inspection of the distribution histograms and boxplots did not indicate substantial differences in shape, spread, or skewness of IPM scores between the two groups. Therefore, the assumption of similarly shaped distributions can be considered satisfied, supporting the interpretation of the Mann–Whitney U test as a comparison of medians between groups.

A chi-square test of independence (χ^2) was conducted to examine the association between AI implementation and app pricing models, using a binary comparison (free vs subscription). For this comparison, freemium apps were classified as "subscription," reflecting that full functionality required payment; a separate variable recorded whether any free-tier access existed regardless of overall pricing classification. Assumptions regarding minimum expected cell frequencies were checked before interpretation. Pearson's asymptotic χ^2 significance is reported as the primary result. Fisher's exact test (two-sided) was additionally examined given the moderate sample size and supported the same conclusion. Effect sizes were estimated using the rank-biserial correlation (r_{rb}) for the Mann-Whitney U test and Cramér's V for the χ^2 test.

As a mapping rather than hypothesis-driven study, the inferential statistical tests characterise patterns observed in the data rather than confirm pre-specified predictions. Statistical significance was set at $\alpha = 0.05$ for all tests. Graphical presentations were created using *ggplot2* in R (version 4.5.1 [44]) within RStudio (version 2024.4.2 [45]).

3. Results

3.1. General trends

In total, 49 smartphone and web-based apps supporting pest and disease management in viticulture were identified through the systematic search and met the inclusion criteria (Table S2). App counts reflect applications identified through this research, not a complete historical census. Commercial vineyard pest and disease management apps emerged gradually between 2000 and 2011, followed by a sustained expansion phase after 2012 (Fig. 1). The cumulative number of commercially available apps increased most steeply in 2018 (+6 apps). AI-enabled apps became increasingly common after 2017, with rapid growth continuing through the most recent years of app development, culminating in the highest annual increase in AI-enabled apps in 2025 (+5 apps).

Commercial vineyard pest and disease management apps were geographically concentrated in Europe, which accounted for 67.3% of all identified apps, followed by North America (14.3%) and Oceania (10.2%; Fig. 2); the remaining 8.2% (4 apps) were distributed across Africa and Asia. These findings describe the geographic distribution of app developers represented in the retrieved dataset, rather than the global distribution of available viticulture technology more broadly. Among apps with a confirmed developer country (n = 48), Italy was the leading developer country (25.0%), followed by Germany (14.6%), the United States (10.4%) and Australia (8.3%). The concentration of development activity in Europe and North America may reflect both the global distribution of commercial viticulture and the concentration of high-value wine-producing regions, as well as inherent discoverability bias of searches conducted via international commercial platforms and

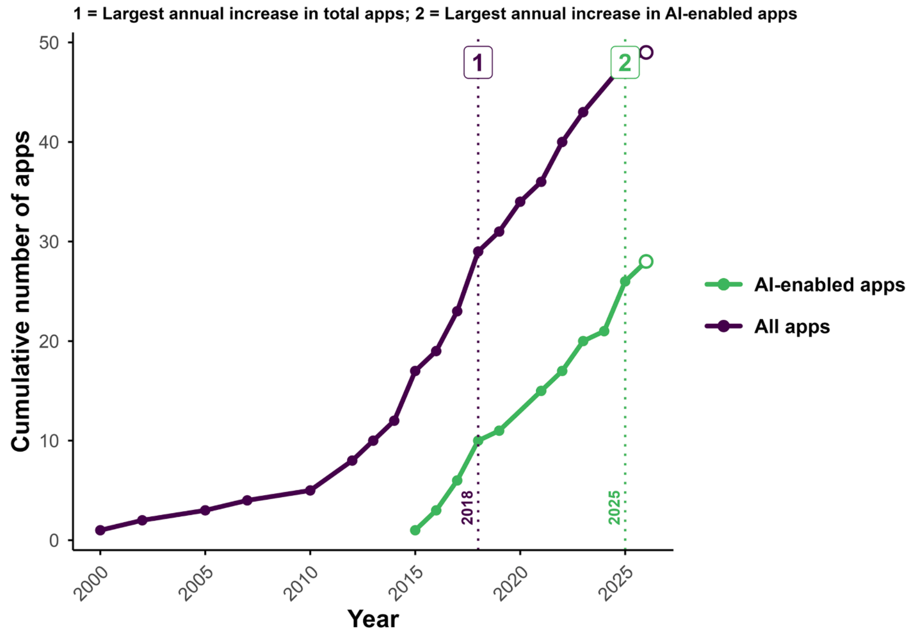

Fig. 1. Cumulative growth of smartphone and web-based viticulture apps for pest and disease management (2000–2026). The purple line represents all identified apps; the green line represents the subset integrating AI. Vertical dashed lines indicate two notable transitions: the largest annual increase in total apps (2018) and the largest annual increase of AI-enabled apps (2025). Open circles indicate the partial data collection of 2026 (through 31 May 2026), which may understate the true annual increase of this year in comparison with the earlier full-year bins.

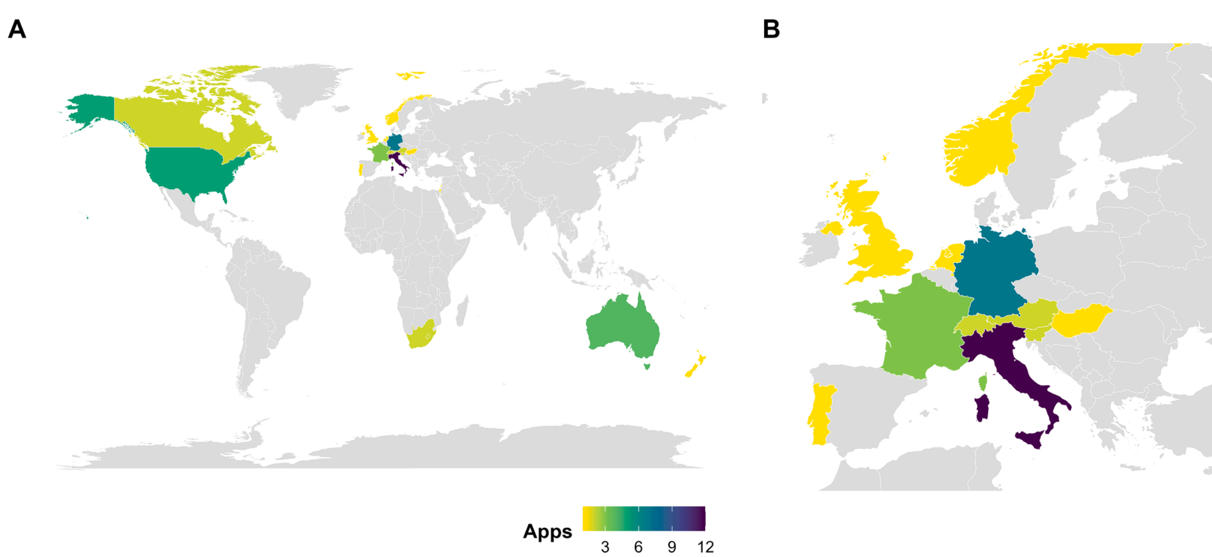

Fig. 2. Geographic distribution of app developer locations for the identified apps for pest and disease management in viticulture . Panel A shows the global distribution; panel B provides a zoomed view of Europe. Colour intensity reflects the number of apps per developer country. Grey countries indicate no apps were identified through the search protocol; this should not be interpreted as confirming the absence of relevant tools. The same legend applies to both panels.

English-language sources, as discussed in Section 4.1.

3.2. IPM coverage

Disease and pest forecasting and monitoring apps represented the largest category (Fig. 3), accounting for 29 apps (59.2%), followed by integrated management and sensor platforms with 10 apps (20.4%). Disease diagnostic and pest identification apps comprised 7 apps (14.3%), while regional, regulatory and advisory tools were the least represented category, with 3 apps (6.1%), consistent with their specialised and often publicly driven objectives.

IPM scores ranged from 2 to 9 (mean = 5.24; SD = 1.87; median = 5). The distribution of total scores (Fig. 4) shows two local peaks, at scores 4 (20.4% of apps) and 7 (24.5%), rather than a single concentration around the median. Only one app achieved complete coverage of all nine components – this app belonged to the integrated management and sensor platform category.

The most common components were precision and site-specific management (77.6%), monitoring and scouting (75.5%), and record-keeping and documentation (75.5%; Table 2). Forecasting functionalities were also common, being implemented in 63.3% of apps, followed by intervention timing optimisation (57.1%) and alerts and communication systems (55.1%). In contrast, diagnosis and identification functionalities were present in approximately half of the reviewed apps (49.0%), while management options and control measures were identified in 44.9% of apps. Surveillance and regulatory reporting

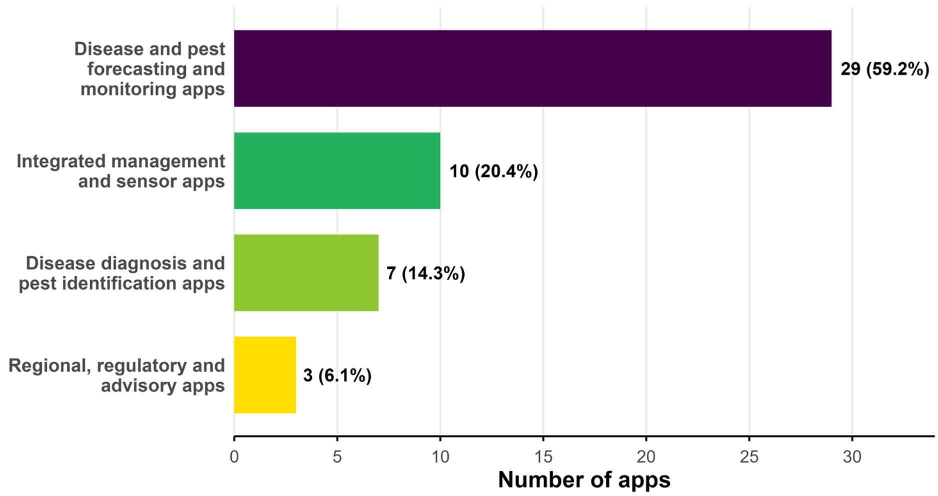

Fig. 3. Distribution of the identified apps for pest and disease management in viticulture by primary functional category.

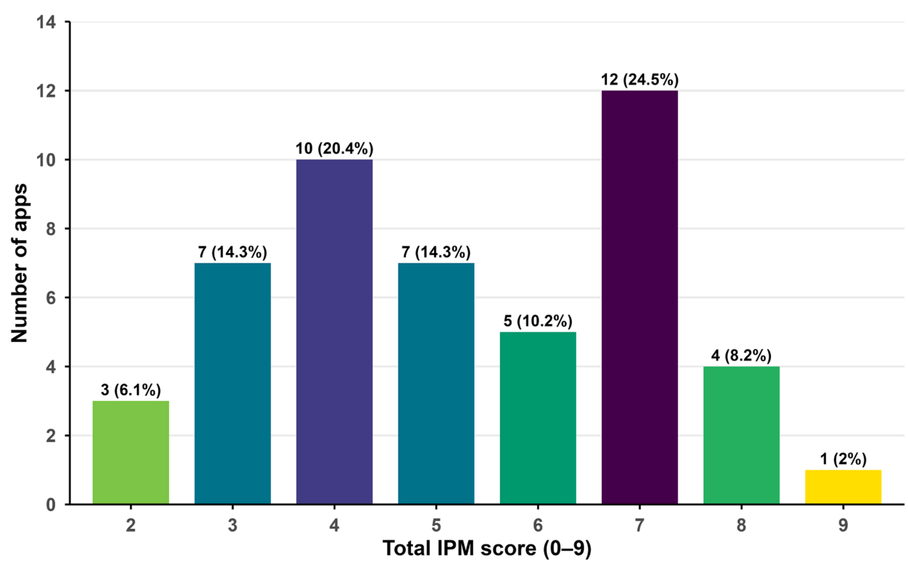

Fig. 4. Distribution of total IPM scores (0–9) across the identified apps. Numbers and percentages of apps achieving each score are reported above each bar.

Table 2
Prevalence of IPM functional components across all identified apps.

IPM Component	n	%
Precision & site-specific management	38	77.6
Monitoring & scouting	37	75.5
Recordkeeping	37	75.5
Risk forecasting	31	63.3
Intervention timing	28	57.1
Alerts & communication	27	55.1
Diagnosis & identification	24	49.0
Management options	22	44.9
Surveillance & regulatory reporting	13	26.5

represented the least common IPM component, implemented in only 26.5% of apps, suggesting that most tools prioritise operational decision support over formal compliance and reporting functions.

Thirty-four out of the 49 identified apps disclosed the specific species names of pest or disease species covered – this reflects what was explicitly stated by developers and not the actual representation of an app's full species coverage. Among these, Powdery mildew [*Erysiphe necator* Schwein. (Erysiphaceae)], downy mildew [*Plasmopara viticola* (Berk. & M.A.Curtis) Berl. & De Toni (Peronosporaceae)], and the European grapevine moth [*Lobesia botrana* (Denis & Schiffermüller) (Lepidoptera: Tortricidae)] were commonly referenced.

An overall count of target organisms covered was disclosed by 39 apps, ranging from 1 to 200 (Supplementary Figure S3). A Spearman correlation between organism coverage and IPM score did not provide sufficient evidence of association ($r_s = -0.28$; 95% CI: -0.556, 0.046; $p = 0.081$, n = 39).

3.3. AI-enabled apps

AI technology was integrated into 28 of the identified apps. AI predictive analytics and risk forecasting represented the most frequently implemented AI functionality, occurring in 22 apps (44.9% of all 49 identified apps), primarily applied to weather and epidemiological data for disease and pest risk estimation. CV-based identification and diagnostic systems were present in 19 apps (38.8%), while sensor analytics, integrating AI-driven interpretation of IoT, trap, or proximal sensing data, were identified in 17 apps (34.7%). In contrast, AI-driven advisory systems capable of generating contextualised management recommendations were comparatively rare and identified in only 3 apps (6.1%). These four AI functional types are not mutually exclusive; an app may be assigned to more than one category. AI-enabled apps (n = 28) incorporated a significantly greater number of IPM components than non-AI apps (n = 21) (U = 430.50, z = 2.80, $p = 0.005$; Fig. 5), representing a moderate-to-large effect (rank-biserial correlation $r_{rb} = 0.46$; 95% CI: 0.15, 0.74). The median IPM score was 6 (IQR: 5–7) for AI-enabled apps compared with 4 (IQR: 3–6) for non-AI apps.

3.4. Interoperability and accessibility

Weather API integration represented the most common interoperability-related feature, identified in 31 apps (63.3%), reflecting the widespread reliance of viticulture pest and disease models on real-time or forecast meteorological data (Fig. 6A). Export capabilities were present in 28 of the 49 identified apps (57.1%), export status was undisclosed for 8 apps (16.3%), and the remaining 13 apps (26.5%) did not offer this feature. Open APIs (defined here as publicly documented interfaces enabling third-party integration and interoperability) were comparatively less frequent, occurring in only 17 apps (34.7%). Notably, only two apps were identified as fully open source, representing a very small fraction of the landscape and highlighting the proprietary nature of the majority of current viticulture digital tools.

Subscription-based models dominated the identified apps landscape (65.3% of apps), with fully free apps representing the remaining 34.7%. However, pricing structures were more nuanced than this binary split suggests: nearly half of all apps (49.0%) offered some form of free-tier or freemium access, indicating that subscription models frequently co-exist with partial access to core features. More notably, 18 subscription-based apps provided no publicly available pricing information, relying instead on enterprise-oriented or quote-based commercial models. This lack of pricing transparency represents a meaningful accessibility barrier, particularly for smaller-scale growers and independent producers who cannot easily evaluate cost-benefit before engaging with a commercial provider, and it complicates independent comparative evaluation of tools within the research context.

Pricing models were significantly associated with AI integration status (χ^2 (1, N = 49) = 8.17, $p = 0.004$; Fig. 6B; Supplementary Table S4). This association was of moderate-to-large magnitude (Cramér's V = 0.41). AI-enabled apps were more likely to adopt a subscription-based pricing model (82.1%), whereas apps without AI implementation were more likely to offer a free pricing model (57.1%).

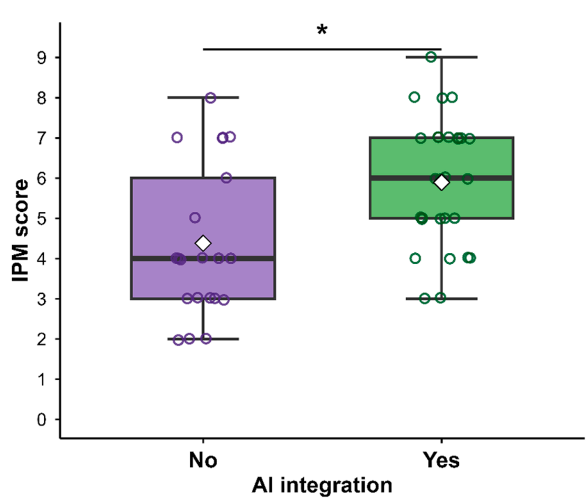

Fig. 5. IPM score by AI integration across identified viticulture apps. Boxes represent the interquartile range, horizontal lines indicate the median, whiskers extend to 1.5 × the interquartile range, and diamonds indicate group means. Open circles show individual apps. The asterisk denotes a statistically significant difference between groups as detected by the Mann-Whitney U test ($p = 0.005$).

4. Discussion

4.1. General overview and defining trends

The viticulture pest and disease management mapping of commercial apps reveals that the landscape has expanded substantially since 2012, with AI integration emerging as a defining trend from approximately 2017 onward. This trend aligns with the broader rise of digitalisation in agriculture, where the convergence of mobile technology, cloud computing, and machine learning has progressively lowered the barrier to developing and deploying decision support tools [46–48]. The concentration of apps in Europe, North America, and Australia broadly corresponds to established viticulture regions [49], though this pattern may not be explained exclusively by the distribution of viticulture. The geographic distribution of agricultural technology investment and innovation capacity may also play a role, and notably, several apps identified in this review offer multi-crop functionality extending beyond viticulture. This suggests that developer origin may reflect broader agricultural technology ecosystems rather than viticulture-specific development activity.

However, the absence of apps from China and South America warrants specific consideration. In the case of China, this likely reflects the structural separation of Chinese digital markets from international platforms, with major domestic app distribution channels operating independently of Google Play and the Apple App Store, and therefore, not detectable with the search protocol employed here [50]. Given China's substantial viticulture sector and documented investment in agricultural AI [51], the absence of Chinese tools from the identified dataset should be interpreted as a discoverability gap rather than a development gap. In contrast, the limited representation of South America likely reflects both lower agri-tech investment relative to European and North American counterparts [52] and the language bias of a search conducted in English. Taken together, these geographic patterns underscore a broader findability challenge. Tools not found from these major international commercial platforms are likely as difficult for practitioners to discover in practice, since growers and agronomists may typically rely on the same search channels used in this study when seeking digital IPM support autonomously.

4.2. Functional coverage, IPM integration, and the specialisation trade-off

The IPM functional coverage analysis reveals a landscape that is operationally capable but structurally incomplete. The dominance of monitoring, recordkeeping and documentation, and precision/site-specific management functions (each present in over three-quarters of apps) reflects the commercial viability of tools supporting routine vineyard operations and data logging. However, the lower prevalence of management options and control measures and near-absence of surveillance and regulatory reporting functions indicate that the current landscape is better equipped to help with observations and recording than to guide growers through the full decision-making cycle that IPM requires [40,53,54]. Moreover, the finding that only one app achieved complete coverage of all nine IPM components, and that the median functional coverage score was 5, suggests that truly integrated digital IPM support remains the exception rather than the standard. This is especially relevant in the context of policies such as the EU Farm to Fork Strategy's political target of a 50% reduction in pesticide use by 2030 [5] and Directive 2009/128/EC [55] on the sustainable use of pesticides, which requires Member States to promote IPM through National Action Plans. Together, these policy commitments underscore a broader push toward more evidence-based, threshold-driven intervention logic that the current app landscape only partially supports.

The negative relationship between taxonomic breadth and IPM functional coverage, though not statistically supported, offers an exploratory hypothesis worthy of further investigation. This would have practical consequences for growers, as a tool that identifies many

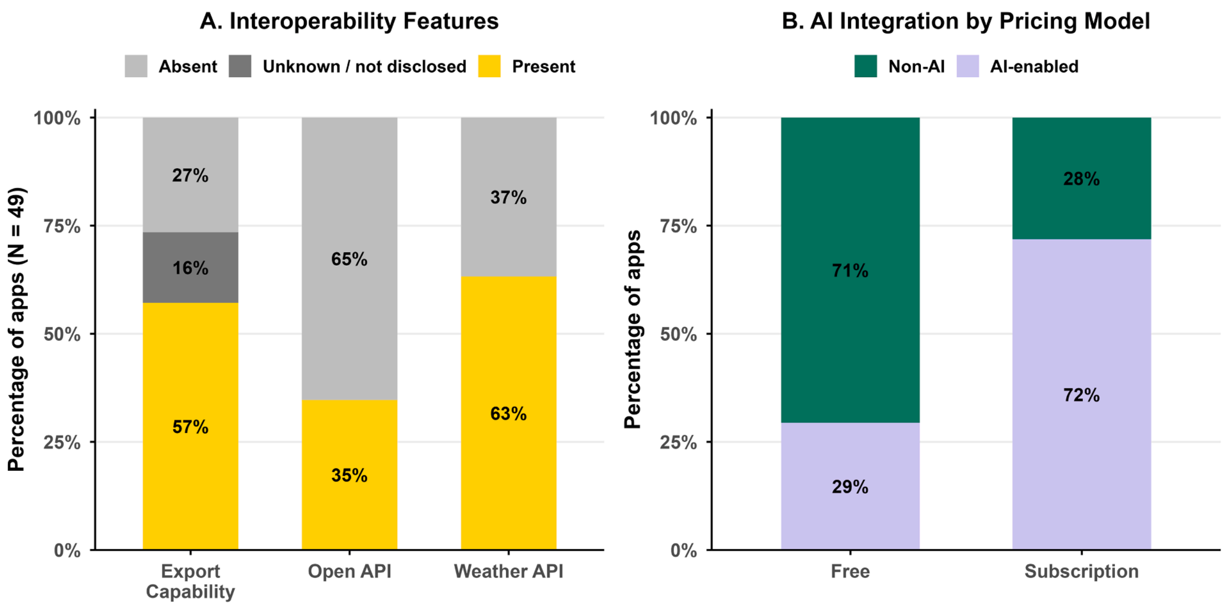

Fig. 6. Interoperability features and pricing model distribution by AI integration status across identified viticulture apps. Panel A shows the presence, absence, and undisclosed status of three interoperability features across all apps (N = 49 for each feature). Panel B shows the proportion of AI-enabled and non-AI apps within each pricing model category. A significant association was identified between AI integration status and pricing model, with subscription-based models disproportionately represented among AI-enabled apps as detected by the χ^2 test ($p = 0.004$).

organisms but provides limited management guidance would contribute less to IPM implementation than a narrow tool with a more complete decision-support workflow. Testing whether tools that combine broad taxonomic coverage with wider IPM integration are achievable may represent an interesting priority for app manufacturers in the near future.

4.3. AI integration, the advisory gap, and the research-deployment divide

The significantly greater IPM functional coverage of AI-enabled apps compared with non-AI apps suggests that AI integration is associated with broader functional scope rather than simply the addition of isolated intelligent features. This finding is consistent with the hypothesis that AI development requires and incentivises a more comprehensive data infrastructure, encompassing monitoring inputs, model outputs, and decision support interfaces, that naturally supports a wider range of IPM functions [56–58].

The distribution of AI types across the landscape reveals a clear hierarchy of maturity. CV-based identification and predictive analytics are well established, reflecting the maturation of deep learning frameworks and the availability of large, annotated training datasets for plant disease and pest recognition [21,59–63]. Sensor analytics represent an emerging middle tier, dependent on hardware integration that adds cost and complexity but enables real-time field-level data interpretation [64–66]. Advisory systems, by contrast, remain almost absent from the observed landscape despite representing the functional category with the greatest potential to close the gap between information provision and management actions. Studies demonstrating the application of LLMs to agronomic advisory and IPM planning have emerged in increasing numbers [67–69], yet this research has not translated into commercially deployed viticulture tools at a meaningful scale. The reasons are likely multiple: regulatory caution around AI-generated agrochemical recommendations, liability concerns for developers, and the technical challenge of integrating conversational AI with the real-time data streams that effective advisory support requires [43,69].

A further concern is the absence of standardised data collection protocols and cross-validation frameworks across apps [70]. The epidemiological and ML models underpinning forecasting functions are seldom benchmarked against independent datasets or validated across different viticultural regions and seasons, making critical evaluation of output reliability difficult for end users [71]. As AI-generated recommendations increasingly inform consequential management decisions, including pesticide timing, organism identification, and precision intervention targeting, the development of shared validation standards represents an urgent priority for both the research community and regulatory bodies.

4.4. Accessibility and interoperability

The interoperability findings reveal a landscape in which environmental data integration is broadly supported but true technical openness remains limited. The high prevalence of weather API integration reflects the near-universal dependence of viticulture pest and disease models on meteorological inputs [72,73]. However, the limited prevalence of open APIs and the existence of only two fully open-source apps indicate that, while apps are effective at consuming external data, they offer comparatively limited capability for sharing data externally or enabling third-party integration. It is worth noting that among the apps offering open API access, several operate under enterprise licensing models. This means that while technically open, integration remains conditional on commercial agreements and thus inaccessible to many potential users. This asymmetry between high data ingestion and low data egression is consistent with documented proprietary platform dynamics elsewhere, in which competitive advantage has been linked to data accumulation and structural barriers to user migration or consolidation across tools [24,74].

This technical fragmentation has practical consequences that extend beyond usability. Where data generated across multiple apps cannot be consolidated due to absent standardised data collection protocols and limited interoperability, the cumulative informational value of individual tools is diminished, and the burden of manual data reconciliation falls on the grower or agronomist. This mirrors the broader fragmentation challenge documented in the IPM DSS literature, where access to decision tools has remained scattered across multiple platforms restricted by region, provider, and user group, limiting the collective impact on IPM adoption [70,75]. Addressing this fragmentation would require not only technical standardisation but a shared commitment to open data exchange – an approach exemplified by initiatives such as the

IPM Decisions platform, which established open APIs to enable interoperability between decision tools, weather data sources, and external systems across Europe [75]. Furthermore, managing data across multiple platforms from different developers creates complex governance environments with potential implications under GDPR, particularly where apps collect location-tagged field observations, spray records, or farm-level production data [25].

The pricing landscape further compounds accessibility concerns. The significant association between AI integration and subscription-based pricing indicates that access to apps with broader IPM coverage is disproportionately linked to commercial monetisation, creating a two-tier landscape in which free tools are predominantly non-AI and, therefore, tend to offer more limited coverage. The widespread reliance on undisclosed, quote-based pricing among 18 subscription platforms limits independent evaluation and risks deepening the digital divide in agriculture by placing the most comprehensive tools furthest out of reach for smaller producers and individual growers who lack the negotiating capacity of larger agricultural operations [76–78].

The contrast between the predominantly free regional and regulatory apps and the predominantly subscription-based forecasting and monitoring tools is itself instructive. As a potential direction for future development, a hybrid model, in which publicly funded open infrastructure provides the data backbone (including standardised monitoring protocols, validated epidemiological models, open APIs) upon which commercial tools can build accessible and interoperable user-facing apps, represents a productive direction that has been explored in other agricultural digital infrastructure contexts [79] but seems to remain unrealised in viticulture pest and disease management. The expansion of open-source development beyond the two apps currently identified would improve equitable access and may support greater transparency and peer scrutiny relative to proprietary systems, though this alone would not be sufficient to establish scientific validation.

4.5. Synthesis: A SWOT analysis of the viticulture app landscape

Synthesising the findings presented across Sections 4.1 to 4.4, the current viticulture app landscape emerges as one of growing technological sophistication yet presents structural limitations in functional integration, accessibility, and scientific validation. These characteristics are synthesised in a Strengths, Weaknesses, Opportunities, and Threats (SWOT) analysis of the app ecosystem (Fig. 7).

Strengths. The evaluated landscape demonstrates that digital viticulture tools have matured beyond simple information delivery toward genuinely functional IPM support [16,66]. The broad operational coverage of monitoring, forecasting, and recordkeeping functions, combined with the demonstrated association between AI integration and broader IPM functional scope, suggests that technological advancement and functional integration are moving in the same direction: a promising path that provides a meaningful foundation for future development.

Weaknesses. The most significant weakness of the current landscape is not any individual functional gap but the absence of integrating architecture, including standardised data protocols, cross-validation frameworks, and interoperable infrastructure, that would allow individual tools to function as components of a coherent system rather than isolated solutions [24,74,79]. The concentration of AI capability within subscription-based commercial models compounds this by ensuring that the tools most capable of bridging functional gaps are least accessible to

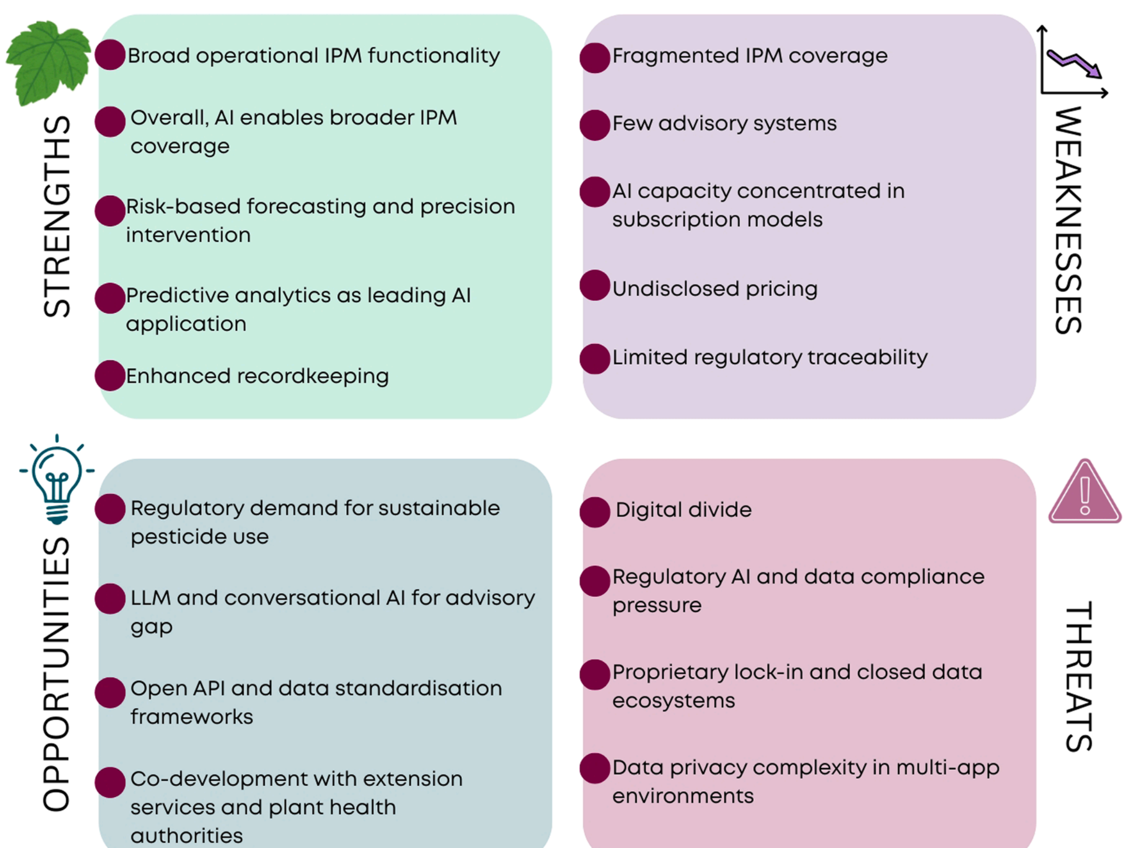

Fig. 7. SWOT analysis of smartphone and web-based apps for pest and disease management in viticulture. Quadrant items were synthesised narratively from the findings and interpretations presented in Sections 4.1–4.4. Strengths and Weaknesses reflect internal characteristics of the current app landscape as identified through a systematic review of the commercially available and publicly accessible tools. Opportunities and Threats reflect external factors (including regulatory, technological, and socio-economic dynamics) shaping the future development and adoption of digital pest management solutions in viticulture.

growers from certain contexts.

Opportunities. The convergence of pesticide reduction policies (e.g. the EU Farm to Fork, Directive 2009/128/EC [55]), EU AI Act [80] transparency requirements, and growing farmer demand for evidence-based decision support [81,82] creates a regulatory environment that could actively incentivise the development of more integrated, validated, and accessible tools. This is possible if developers, public institutions, and policymakers coordinate rather than respond independently. The technical components for a more coherent landscape, such as LLM advisory systems, open APIs, and validated epidemiological models, exist in research contexts and require institutional rather than technological breakthroughs to reach deployment.

Threats. The most systemic threat is the emergence of a two-tier digital landscape in which AI-powered, subscription-based tools serve well-capitalised operations while smaller producers rely on free tools with limited functional scope. This makes for a digital analogue of the broader inequalities in agricultural technology access documented in the literature [77,78]. Without deliberate intervention through open-source development, public funding, and interoperability standards, market forces alone are likely to deepen rather than resolve this divide.

4.6. Limitations

While mapping the publicly available app landscape is valuable for future development and deployment, this type of review carries some limitations. First, no official protocol exists for conducting app-store-based reviews of this kind, a challenge also documented in other scientific fields [83]. We addressed this by reporting our search and screening process as transparently and reproducibly as possible, with classifications guided by explicit, pre-defined criteria (Section 2.3) and jointly confirmed by both authors. Second, the search was conducted from a single country (Italy), a single user profile, and in English only; this may have missed apps marketed primarily in other languages or regions, as well as results that a wider range of search profiles or locations could otherwise have emerged. Third, app stores can vary results by region even with impersonalised accounts, though newly created accounts with no search history were used throughout to minimise this risk. Fourth, app functionality was assessed from developer-published materials rather than hands-on testing, a deliberate choice that avoided introducing bias against subscription-based tools that could not be freely accessed. Finally, to our knowledge, no established framework – comparable to the IPM pyramid for on-farm practices – currently exists for weighting the relative contribution of different digital functionalities to IPM outcomes, leaving no evidence base on which to ground a weighted score. The nine components were therefore weighted equally, offering a transparent, reproducible view of the functional landscape rather than a subjective judgement of relative importance. However, we recognise that some functionalities, such as diagnosis and identification, are likely more impactful than others, such as recordkeeping, and developing a validated weighting framework for digital IPM tools may represent a valuable direction for future research.

5. Conclusions

Based on a mapping of publicly available apps for viticulture pest and disease management, digital apps are increasingly supporting key components of IPM in vineyards, though functional coverage varies substantially across the landscape. Apps addressed a median of 5 of the 9 IPM components assessed, and only one app achieved complete coverage. Apps with broader IPM functional coverage were concentrated within commercial subscription models, an association that may potentially present a specific accessibility barrier for smaller producers. AI integration was significantly associated with broader functional scope, but the nearly absent AI advisory systems represent the most significant frontier for future development, while fragmented data environments and limited interoperability may constrain the collective utility of the current landscape.

As evolving IPM practices and sustainability policies intensify the demand for evidence-based, threshold-driven crop protection, these findings offer a functional baseline and a set of clear priorities for commercial developers, extension services, and researchers seeking to build the next generation of digital IPM support. These include closing the advisory AI gap and developing open, interoperable, and validated platforms that are accessible across scales of operation and viticultural contexts.

Statement for studies in humans/animals

This study did not involve human participants, animal subjects, or any data collected from natural persons. The research consisted solely of the analysis and evaluation of commercially available vineyard management applications. No ethical approval was required.

CRediT authorship contribution statement

Agata Morelli: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Validation, Visualization, Writing – original draft, Writing – review & editing. **Antonio Masetti:** Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.atech.2026.102480.

Data availability

Data will be made available on request.

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