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2 **The impact of organizational learning behavior on digital transformation in SMEs: The**
3 **mediating role of managerial support—Evidence from Spanish wineries**
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Abstract

While existing research identifies managerial support as a critical antecedent of digital transformation, the origins of this supportive intent remain under-explored. Integrating Upper Echelons Theory and Absorptive Capacity Theory, this paper uses technology-agnostic organizational learning—general learning routines not specific to digital technologies—as an entry point to uncover the sources of managerial support for digitalization, and examines the mediating role of this support between such learning and digital transformation. This study empirically tests the proposed theoretical model by applying Partial Least Squares Structural Equation Modeling (PLS-SEM) to survey data from 321 wineries in the Spanish wine industry. The results indicate that both external communication and internal training are significantly and positively associated with managerial support, uncovering the organizational learning sources of such support. Managerial support partially mediates the relationships between organizational learning behavior and digital adoption, confirming its theoretical positioning as both an outcome and an explanatory variable. External communication and internal training thus play complementary roles in the digitalization process, corresponding respectively to knowledge acquisition and knowledge assimilation. This paper extends beyond the common treatment of managerial support as a purely independent variable, revealing its mediating role as both an outcome and an explanatory variable. It provides a theoretical explanation from the perspective of organizational learning behavior for the persistent lag in transformation intent among traditional SMEs. In practice, the findings emphasize that wineries must not only identify opportunities through external scanning but also transform fragmented knowledge into organizational capability through institutionalized internal training, with managerial support serving as the strategic hub linking learning to digital change.

Keywords: Digital Transformation; Wine Industry; Managerial Support; Technology-agnostic Learning Behavior; External Communication; Internal Training

1. Introduction

Digital transformation, involving the shift toward malleable organizational designs and digital business ecosystems, is profoundly reshaping the global landscape of industrial competition [1,2]. However, this process exhibits significant imbalances across sectors: while high-tech firms and large organizations accelerate their lead, traditional SMEs, characterized by resource scarcity, structural rigidity, and path dependency, frequently fall into a transformation lag [3–6]. The wine industry precisely represents a typical microcosm of this dilemma and is widely regarded as a field with insufficient technological momentum. Dominated by small and medium-sized family enterprises, the industry's production logic is deeply embedded in traditional brewing culture and

70 artisanal experience, with relatively closed technological trajectories, thereby generating strong
71 inertial resistance against the digital wave [7,8]. Although digital technologies have demonstrated
72 efficiency-improving potential throughout the entire process from vineyard management to
73 brewing and bottling, their actual adoption remains lagging [9]. Empirical evidence from wineries
74 in Spain and Italy indicates that their digitalization practices are mainly concentrated in marketing,
75 while the digitalization level of production and vineyard management remains considerably low
76 [10,11]. If such traditional industries cannot effectively bridge the digital divide, digital technology,
77 rather than serving as a tool to close the gap, will instead exacerbate and solidify existing industrial
78 disparities [12]. Consequently, how to activate the digital momentum of traditional SMEs has
79 become a core issue of both theoretical urgency and practical significance.

80 Digital transformation in SMEs faces a core paradox: while external conditions for transformation
81 are increasingly mature, the actual effectiveness of these efforts shows significant divergence [13].
82 Some enterprises can swiftly convert external opportunities into competitive advantages, while
83 many more remain at the superficial level of equipment procurement and technical deployment,
84 struggling to achieve substantive process optimization or performance improvement [14]. This
85 divergence is particularly prominent among Spanish SMEs: inertia becomes a core barrier when
86 managers pursue agile innovation while being reluctant to relinquish control rights [15], and
87 enterprises where digital responsibilities are concentrated solely on entrepreneurs exhibit
88 significantly lower levels of IT-driven organizational change [16]. The key explanatory variable
89 for this divergence often lies not at the technical supply end, but at the decision-making hub. SMEs
90 feature flat organizational structures with decision-making power highly concentrated in the hands
91 of founders or a few core members. Formalized strategic planning and evaluation processes are
92 relatively weak, making the initiation and advancement of digitalization highly dependent on the
93 digital literacy, technical cognition, and innovative attitude of these key decision-makers [3,17,18].
94 In such decision-making contexts, management's cognitive interpretation, prioritization, and
95 resource commitment toward strategic issues constitute the core gateway for translating external
96 conditions into organizational action [19–21]. Upper Echelons Theory conceptualizes this
97 phenomenon by stating that an organization's strategic decisions are a reflection of the cognitive
98 base and values of its managers [22]. Regarding digital transformation, this reflection mechanism
99 holds dual significance: management serves as both the receiver of external signals and the
100 mobilizer of internal resources; they are both the interpreters of technical visions and the drivers
101 of organizational change. A study on Spanish wineries by Martínez Falcó et al. [9] indicates that
102 managers significantly shape organizational priority setting and resource allocation by virtue of
103 their strategic status, and senior management awareness plays a vital mediating role between
104 knowledge sharing and innovation output. Therefore, this paper selects “managerial support”,
105 which refers to the sustained resource commitment, risk-taking willingness and strategic advocacy

of core decision-makers within enterprises toward digital transformation, as the object of study to investigate its pivotal role in corporate digital decision-making and implementation.

Does managerial support emerge out of thin air? If not, where does it come from? This is the next question this study addresses. The Upper Echelons Theory suggests that managers' strategic confidence in change stems from their efficacy assessment of the organization's ability to navigate change [23], and research suggests that this ability stems substantially from the organization's absorptive capacity—its capacity to acquire, assimilate, and apply external knowledge [24,25]. Organizational learning is therefore central to how firms build the knowledge base underlying strategic change: organizational learning scholarship conceptualizes it as the processes of knowledge acquisition, distribution, interpretation, and retention [26].

In digital transformation research, however, organizational learning has typically been examined through the lens of technology-specific training, whose importance is widely acknowledged [27]. This study, by contrast, focuses on the general, technology-agnostic side of organizational learning—the recurrent routines through which firms acquire and internalize knowledge irrespective of its content. Academically, this technology-agnostic side of organizational learning has received little attention in the context of SME digital transformation [28]. Based on this logic, this paper examines how organizational learning behavior relates to digital transformation through its association with managerial support. We propose that these learning behaviors may strengthen managerial support for digitalization by enriching the knowledge base that managers draw on when assessing digital change—a mechanism consistent with Absorptive Capacity Theory and Upper Echelons Theory but treated here as a hypothesis to be tested rather than an observed process. Drawing on Absorptive Capacity Theory, this study operationalizes organizational learning through two specific, observable learning behaviors: external communication and internal training. Within this framework, external communication is interpreted as corresponding to knowledge acquisition and internal training to knowledge assimilation [29]; notably, the present measures capture the occurrence of these behaviors rather than absorptive capacity itself. Consequently, this paper proposes the following core research questions:

1. The Source of Momentum: Are wineries' observable learning behaviors—external communication and internal training—associated with managerial support for digital transformation?
2. The Transmission Mechanism: Is organizational learning behavior associated with digital adoption through the mediating role of managerial support?

To answer these questions, this paper analyzes the drivers of digital transformation in wineries using a first-hand dataset collected from 321 Spanish wine companies, employing the PLS-SEM technique. Based on the aforementioned research framework, the potential contributions of this study are reflected as follows:

First, this study shifts the analytical focus on managerial support from its outcomes to its formative origins. Instead of treating managerial support as an exogenously given antecedent variable alongside firm-level attributes, it empirically unpacks the mechanisms through which managerial support for digitalization emerges. Second, it repositions managerial support as a pivotal strategic mediator connecting organizational learning behaviors and digital adoption. This study bridges Upper Echelons Theory and Absorptive Capacity Theory within a unified, testable analytical framework. Third, it identifies technology-agnostic learning routines as important antecedents of digital transformation. Applying this theoretical lens to the wine industry, it accounts for the sector's digital lag stemming from inadequate managerial commitment fostered by organizational learning, yielding direct theoretical and policy implications for wine economics and industrial governance.

The remainder of this paper is structured as follows: first, the theoretical framework and hypotheses are developed; next, the methodology and results are described; and finally, the theoretical and managerial implications of the findings are discussed.

2. Theoretical framework and hypotheses

2.1 Theoretical framework

2.1.1 Review and extension of Upper Echelons Theory

Upper Echelons Theory (UET) provides a foundational analytical framework for understanding the generative mechanisms of corporate strategic decision-making [30]. The core proposition of this theory is that an organization's strategic choices are not the result of a comprehensive scan and rational calculation of the objective environment, but rather a reflection of the cognitive base and values of its managers [22]. Following this theoretical vein, a substantial body of empirical research has confirmed that observable characteristics of top managers, such as gender, age, tenure, educational background, and nationality, possess significant explanatory power regarding key choices such as diversification strategies, internationalization decisions, and innovation investment [31–33]. Further research has extended its analytical reach into the cognitive and psychological dimensions of managers, finding that the value orientations of top management significantly influence corporate social responsibility practices, environmental strategies, and innovative behavior [19,34,35].

In the field of digital transformation research, UET has similarly demonstrated robust explanatory power. Existing studies indicate that the individual characteristics of managers have a stable and significant impact on their digital decision-making. For instance, Khattak et al. [36] found that an executive's tendency toward overconfidence is significantly and positively correlated with their willingness to invest resources in digital transformation. Merín-Rodríguez et al. [15] pointed out that executives' dynamic managerial capabilities drive digital transformation in a non-uniform

manner, with CEO tenure and age playing moderating roles in this process. Furthermore, research by K. Zhang and Bu [37] found that executives with information technology backgrounds are more proactive in advancing the corporate digitalization process, an effect that remains independent of the firm's existing IT infrastructure level.

Consequently, UET provides the foundational theoretical lens for this study. Among the various individual managerial characteristics related to digitalization, this paper focuses on “managerial support”, a more behavior-oriented variable. Managerial support is generally defined as the explicit commitment, resource allocation, and sustained advocacy exhibited by top managers toward a specific strategy [38]. Notably, managerial support is treated here as the observable, decision-level manifestation of managerial cognition—a behavioral proxy rather than a direct measure of the underlying cognitive processes. This approach aligns with UET's core premise that observable managerial characteristics reflect underlying cognitive processes. Accordingly, UET serves as an interpretative framework in this study, and the cognitive mechanisms it implies are not empirically verified here. In digital transformation research, this variable has been widely integrated into empirical analysis frameworks. Within the Technology-Organization-Environment (TOE) framework, a classic analytical tool in technology adoption research, managerial support is typically categorized under the “Organizational” dimension. In this context, it is often treated as a parallel independent variable alongside other factors and has been found to have a significant positive impact on corporate digital transformation [17,39,40]. Furthermore, the study by M. Zhang et al. [41] moves beyond this parallel logic by considering managerial support as a moderating variable, finding that the promotional effect of organizational digital capabilities on digital transformation is highly dependent on the intensity and consistency of top management support.

However, these studies primarily position managerial support as an explanatory independent variable, that is, a factor used to explain variances in the intensity of digital adoption across firms. This positioning serves a research paradigm focused on identifying adoption conditions, which carries an implicit assumption: that managerial supportive intent is exogenous and self-evident, requiring only a measurement of its strength. This very assumption obscures the most theoretically intriguing link in SME digital transformation: Where does managerial support come from? How are favorable technical and organizational conditions identified, accepted, and converted into sustained behavioral commitments by managers? UET itself suggests that managerial cognition and decision-making do not emerge in a vacuum; rather, they are the outputs of internal and external organizational information after being filtered and interpreted. This implies that managerial support should not only be understood as an antecedent explaining digital transformation but should itself be explained by more fundamental organizational processes. Research by Chen et al. [42] addressed this early on by examining how managerial capabilities

influence a range of TOE factors, including managerial support, thereby indirectly affecting the adoption of digital technologies. Additionally, Nicolás-Agustín et al. [27] studied how corporate ICT training for employees impacts organizational commitment. These studies suggest that managerial support may be shaped by more foundational organizational antecedent processes. Taking this question as an entry point, this paper treats managerial support as a core mediating mechanism, focusing not only on its influence on digital transformation but also probing its own origins, in an effort to provide an integrated analytical path for the application of UET in SME digital transformation research.

2.1.2 Review and extension of Absorptive Capacity Theory

External knowledge sources are often crucial to the innovation process, and the ability to exploit such knowledge is a key component of innovative capability. Consequently, the organizational capacity to absorb external knowledge has been emphasized in the fields of strategic and technology management [24]. Absorptive Capacity Theory (ACT) is frequently employed to analyze diverse, salient, and complex organizational phenomena. It describes how an organization acquires, assimilates, transforms, and exploits knowledge to generate dynamic organizational capabilities [29,43]. Absorptive capacity is central to whether an organization can effectively utilize external knowledge sources, such as partners, academia, and technology markets, to mitigate knowledge silos and enhance innovation efficiency and adaptability. This allows firms to build sustainable competitive advantages within dynamic environments [44]. Research indicates that absorptive capacity has a significant impact on a company's innovative ability, and its importance has become increasingly prominent in contexts such as digital transformation and open innovation [44–46].

In the context of digital transformation, technological iteration is accelerating, data-driven decision-making is becoming ubiquitous, and the complexity of cross-system integration is rising [47]. Organizations face a massive influx of heterogeneous external digital knowledge, making absorptive capacity the critical capability for filtering, decoding, and internalizing digital technical knowledge to achieve business model restructuring [48]. A lack of sufficient absorptive capacity may lead to the paradox of “high digital investment but low transformation rates”. Specifically, absorptive capacity plays an important role in promoting digital innovation, alleviating the digital transformation anxiety of traditional organizations to facilitate their digitalization, and empowering supply chain transformation [49–51].

Absorptive capacity, as a latent organizational attribute, must be activated and institutionalized through specific organizational practices—namely, external communication and internal training. Within Absorptive Capacity Theory, external communication can be interpreted as corresponding to knowledge acquisition, and internal training to knowledge assimilation [29]—an interpretive correspondence that does not entail the direct measurement of absorptive capacity. External

communication refers to the process through which firms interact and collaborate with external entities such as suppliers, customers, and research institutions. This enables them to continuously scan the technological environment, identify market signals, and acquire new technologies, market trends, and best practices [52,53]. Open strategy research demonstrates that sharing knowledge through collaboration creates co-created value [54]. Furthermore, digital collaboration capability—the ability of a company to share and coordinate information with partners via digital channels—is considered a key factor in helping firms achieve differentiated advantages [55]. Internal training refers to the firm’s regular provision of staff skills training, which facilitates the internal diffusion of knowledge and helps the organization assimilate and apply external information [56,57]. Employees play a central role in the development of absorptive capacity [58]. Studies show that through internal training, organizations can strengthen the prior knowledge base of their staff, thereby enhancing their ability to recognize and comprehend complex external information [59].

ACT further emphasizes that an organization’s prior knowledge is a prerequisite for the effective absorption of external knowledge, characterizing absorptive capacity as path-dependent and cumulative [24]. Because this capacity is general and transferable across knowledge domains [29,60], it grows through learning behaviors embedded in daily operations [61,62]. This study therefore focuses on organizational learning behavior—the routine acquisition and internalization of knowledge—as the behavioral foundation on which absorptive capacity is built; the general learning capability it produces is expected to extend to the recognition and assimilation of digital knowledge. Firms’ prior knowledge accumulation has likewise been shown to facilitate digital technology adoption [63]. These learning behaviors are also expected to underpin managers’ confidence that the organization can keep up with change [64], providing the cognitive ground on which managerial support rests.

Taken together, the two theoretical lenses are integrated through the focal construct of managerial support. Absorptive Capacity Theory illuminates the knowledge side of the mechanism: it explains how learning behaviors—external communication and internal training—build the knowledge base that managers draw upon when assessing digital change. Upper Echelons Theory illuminates the decision side: it explains how this knowledge base is translated, through managerial cognition, into strategic choices—namely the sustained commitment that managers devote to digital transformation. Managerial support thus sits at the intersection of the two theories, serving simultaneously as the outcome of knowledge absorption and the explanatory variable of strategic adoption. This integrated framework anchors managerial support in the organization’s learning routines rather than treating it as an exogenous, self-evident condition.

2.2 Hypothesis development

Based on the theoretical perspectives discussed above, this paper focuses on the following questions and proposes corresponding hypotheses, as illustrated in the theoretical model in Figure 1.

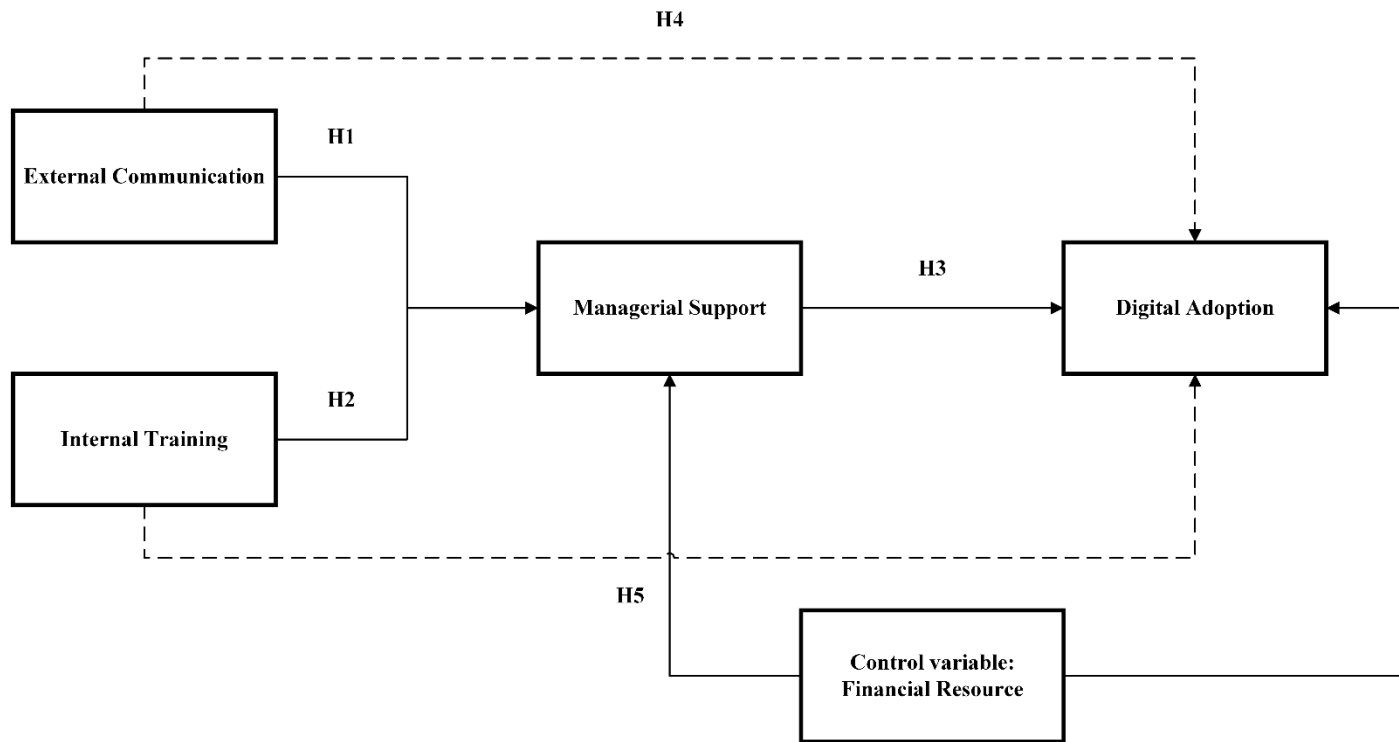


Figure 1 Conceptual research model

To further clarify the constructs, we specify their definitions as follows. External communication refers to firms' frequent communication and collaboration with external partners, with discussion topics not limited to digitalization. Internal training refers to firms' regular provision of staff skills training, which facilitates internal knowledge diffusion and helps organizations understand, assimilate and apply external knowledge; likewise, training contents are not confined to digital-related issues. Managerial support is defined as core decision-makers' persistent resource commitment, risk-taking inclination and strategic advocacy concerning digital transformation. Digital adoption describes the overall depth to which wineries deploy digital technologies across customer interaction, production management, process optimization, analytical decision-making and business model innovation.

The two theoretical lenses map onto distinct segments of the model. Absorptive Capacity Theory underlies the first segment—how learning behaviors shape managerial support—because external communication and internal training correspond respectively to the acquisition and assimilation of knowledge (H1 and H2). Upper Echelons Theory underlies the second segment—how managerial support translates into digital adoption—because strategic commitment is the decision-level manifestation of managerial cognition (H3). The integration of the two theories yields the

mediating hypotheses: organizational learning builds the knowledge base, which is then expected to be translated, through managerial support, into digital adoption (H4 and H5).

2.2.1 External Communication and Managerial Support for Digitalization

External communication serves as a vital channel through which firms acquire external knowledge. Studies have shown that firms increasingly rely on external knowledge sources to enrich their internal knowledge base during digital transformation [65]. Enterprises that continuously obtain, share and internalize knowledge are more likely to foster managers' sense of control and willingness to act amid uncertainties [25]. Specifically, frequent collaboration with external parties is essential for building organizational openness. Frequent interactions with suppliers, customers, research institutions and other external partners broaden managers' scope of knowledge search and keep them updated on the latest technological trends, market demands and competitive landscape [66]. Such frequent acquisition of external knowledge not only provides multi-dimensional references for decision-making, but also remarkably reduces the perceived environmental uncertainty caused by information asymmetry. It strengthens managers' sense of control and further translates into stronger commitment and support [67–69]. This sense of control is particularly critical in digital transformation, which is inherently accompanied by high uncertainty and organizational change risks [70]. The environmental perception capabilities built through external communication equip managers with sufficient information to assess digital transformation risks, making them more inclined to offer supportive commitments [71,72]. Notably, this mechanism does not presuppose that the communication itself concerns digitalization: because the sense of control is cultivated through general, technology-agnostic communication, it readily extends to managers' assessment of digital transformation. Accordingly, we propose the following hypothesis:

H1: The winery's technology-agnostic external communication is positively associated with managerial support for digital transformation.

2.2.2 Internal Training and Managerial Support for Digitalization

As a key approach to knowledge sharing and internalization, corporate internal training is closely related to managerial support for digital transformation. Corporate training not only facilitates skill transmission, but also fosters in-depth organizational learning capabilities [28,73]. Regular investment in training enriches employees' prior knowledge base and strengthens the organization's knowledge internalization mechanism [65]. For managers, such mechanisms of knowledge internalization help develop highly adaptable human capital, while sending a clear signal that the organization is capable of learning and adaptation. One major barrier to digital transformation lies in managers' concerns over the organization's adaptive capacity. While technologies can be acquired, the real risk resides in whether the organization is able to digest and apply them [74]. Internal training effectively alleviates such concerns. It builds up organizational

absorptive capacity, significantly boosting managers' confidence in mobilizing internal resources and their sense of control over transformation pathways, which in turn translates into stronger strategic support [65,74]. Even training that never touches on digital technologies still builds the learning capability and managerial confidence that prepare the firm for digital change. Accordingly, we propose the following hypothesis:

H2: The winery's technology-agnostic internal training is positively associated with managerial support for digital transformation.

2.2.3 Managerial Support and Digitalization Adoption

As a critical antecedent of digital transformation, the positive effect of managerial support has been validated in numerous empirical studies [17,39,40]. Digital transformation is essentially a strategic initiative involving resource allocation, organizational restructuring and business model adjustment [70], and the decision-making power for these activities rests with managers. Research indicates that the commitment and support of senior management are essential for driving organizational change during digital transformation [72]. Without explicit commitment and continuous promotion from management, digitalization can hardly be translated into practical actions even if the organization owns a solid knowledge foundation and sound technical conditions [75]. A study by M. Zhang et al. [41] further reveals that the facilitating effect of organizational digital capabilities on digital transformation is highly contingent on the strength and consistency of managerial support. Accordingly, we propose the following hypothesis:

H3: Managerial support for digital transformation is positively associated with the digital adoption of the winery.

2.2.4 The Mediating Effect of Managerial Support between External Communication and Digitalization Adoption

External communication keeps managers frequently exposed to external information and broadens the breadth and depth of their environmental perception. Through interactions with suppliers, customers, peer companies and research institutions, enterprises can timely identify the application scenarios, implementation routes and expected benefits of emerging digital technologies, and reduce uncertainties associated with technology adoption [76]. Nevertheless, information acquisition does not equate to strategic action. Market signals and technological trends obtained from external exchanges can only be incorporated into the organizational decision-making agenda after interpretation and evaluation by managers. Managers' cognitive frameworks regarding digital technologies shape their assessment and selection of digitalization pathways [77]. In the study on dynamic capabilities for digital transformation, Warner and Wäger [78] also found that there is a crucial transitional process from sensing to seizing. Managers need to translate their perceptions of external trends into concrete resource commitments and action plans. Gong and Ribiere [79] likewise emphasized that digital transformation hinges on the strategic leverage of key resources

and capabilities, an activity that can only be initiated and driven by managerial teams with decision-making power. Therefore, external communication is expected to influence digital adoption through two routes—directly, as firms absorb the information and digital practices it brings, and indirectly, via managerial support, as managers convert information perception into strategic commitments and resource investment. This mediating logic integrates the two theories: Absorptive Capacity Theory explains the formation of managerial support, while Upper Echelons Theory explains its translation into digital adoption. Accordingly, we propose the following hypothesis:

H4: The winery's technology-agnostic external communication is positively associated with its digital adoption through the mediating role of managerial support.

2.2.5 The Mediating Effect of Managerial Support between Internal Training and Digitalization Adoption

Internal training builds the organization's in-depth learning capacity and lays a solid human capital foundation for digital transformation. Through regular staff skills training, enterprises can gradually improve employees' digital literacy, reduce resistance to technology adoption, foster an innovation-oriented organizational culture [70], and further influence the adoption depth and application performance of digital technologies [80]. Nevertheless, knowledge accumulation cannot automatically lead to organization-wide digital initiatives. Weritz et al. [81] suggest that various dimensions of organizational capabilities generate complementary synergies. Improvement in a single capability is insufficient to deliver successful digital transformation, which also requires activation and integration via specific organizational mechanisms. Organizational inertia stands as one of the major barriers to digital transformation, and overcoming it demands clear strategic orientation and sustained resource commitments from decision-making managers [78]. Hence, internal training shapes digital adoption both directly—by raising employees' digital literacy and lowering their resistance to new technologies—and indirectly, through the managerial support it cultivates, as managers translate confidence in organizational capabilities into strategic priorities and resource commitments. Together with H4, this hypothesis integrates the absorptive-capacity account of managerial support formation with the upper-echelons account of strategic action. Accordingly, we propose the following hypothesis:

H5: The winery's technology-agnostic internal training is positively associated with its digital adoption through the mediating role of managerial support.

3. Methodology

This study adopts a quantitative research paradigm to examine the correlation mechanisms between variables based on cross-sectional survey data. The rationale for selecting the quantitative approach is as follows. First, this research aims to systematically test the theoretical relationships

among multiple constructs, which requires large-sample data for statistical inference. Second, the model combines multi-item latent constructs (managerial support, digital adoption), which require reliability and validity assessment through measurement models, with single-item observed variables (external communication, internal training, financial resources); the quantitative approach accommodates both. Third, quantitative analysis can produce replicable empirical evidence for the research hypotheses. Compared with case studies, qualitative interviews and other methods, the quantitative approach can control for firm-level heterogeneity while verifying the generalizability of the theoretical model across a broader sample. It is highly consistent with the research objective of this paper, which is to explore the general rules governing digital transformation among traditional small and medium-sized enterprises. Therefore, the adoption of a quantitative research design is appropriate.

3.1 Sample and data collection

This study takes the Spanish wine industry, a traditional sector under transformation pressure, as the empirical research context. Selecting this industry as the research setting is appropriate for both theoretical and practical purposes. Spain boasts the world's largest vineyard area and ranks among the world's top three wine-producing countries [82]. The industry is overwhelmingly composed of small and medium-sized family wineries. Among the 321 sampled wineries in this study, over 98% are micro-enterprises with fewer than 50 employees, all complying with the European Union's definition of SMEs. The typical SME characteristics of Spanish wineries serve as key boundary conditions for testing the theoretical framework of this research. First, their organizational structure with highly centralized decision-making power held by founders or core managers creates an ideal context for applying Upper Echelons Theory, where managers' cognition and preferences can be directly translated into organizational actions. Second, path dependence amid resource constraints means that knowledge acquisition and internalization highlighted by Absorptive Capacity Theory constitute a more critical bottleneck for transformation than technology procurement. Furthermore, digital transformation in the Spanish wine industry is marked by mature external conditions yet divergent internal adoption [9], which closely aligns with the core research focus of this paper. In addition, abundant existing empirical studies in this field [7,9,11] provide solid references for variable operationalization and academic discussion of the research findings.

This study adopted a quota-based non-probability sampling approach. Structured questionnaires were distributed to wineries drawn from the database of a national industry association. Data collection continued until two pre-specified conditions were met simultaneously: the sample covered all 68 Spanish Denominación de Origen (DO) wine regions, and the number of valid questionnaires reached no fewer than 300. Because this non-probability design does not rest on a precisely enumerated sampling frame, a formal response rate cannot be reliably computed and

non-response bias cannot be formally assessed; these limitations should be borne in mind when generalizing the findings. Questionnaires were directed to senior managers at each winery, including general managers, owners, or head winemakers, who possess sound knowledge of their firm's strategic, operational, and technological status. Consistent with this targeting, the respondents were predominantly winery owners (62%), and substantial shares also held production (49%), operational (34%), marketing and sales (33%), or viticulture (21%) roles—reflecting the multi-role nature of decision-makers in small family wineries. In terms of winery characteristics, the sample is dominated by limited liability companies (50%) and sole proprietorships (21%), consistent with the family-owned structure of the sector; most wineries are small, with 21% employing a single permanent employee and 46% between two and five, and nearly half (47.4%) are between 11 and 30 years old, confirming the long-established, tradition-bound character of the industry. The research was conducted between May and August 2023. Of the 340 questionnaires returned, 321 valid responses were retained for analysis after rigorous screening. Each sample reflects the actual governance status and digitalization process of the surveyed winery.

3.2 Measures

The measurement instruments in this study were adapted from validated, established scales in relevant fields and were specifically modified and pre-tested for the context of the wine industry. To ensure consistency, all latent variables were measured using a five-point Likert scale (where 1 represents “Strongly Disagree” and 5 represents “Strongly Agree”). The dimensional definitions and specific items for each variable are detailed in Table 1.

Table 1 Measurement constructs and questionnaire items

Variable	Indicator Code	Measurement Item
External Communication	EC	Do you think: (1 strongly disagree to 5 strongly agree)
		Your winery frequently communicates or collaborates with other wineries, R & D companies, supply chain partners, non-governmental organizations such as universities or research institutes (not limited to digital skills)
Internal Training	IT	Your winery regularly conducts staff skills training (not limited to digital skills)
Managerial Support	MS 1	Your winery managers have clearly expressed support for the adoption of digital technology
	MS 2	Your winery has a clear roadmap for digitalization, regardless of whether it has been implemented.
	MS 3	Your winery managers are willing to take risks involved in the adoption of digital technology.
Digital Adoption		

Financial Resource	DA 1	Your winery is using digital technologies to understand your customers better.
	DA 2	Your winery is using digital technologies to understand your production process.
	DA 3	Digital technologies are allowing your winery to link customer-facing and production process in new ways.
	DA 4	The core processes of your winery are automated.
	DA 5	Your winery has an integrated view of key operational and customer information.
	DA 6	Your winery uses analytics to make better operational decisions.
	DA 7	Your winery uses digital technologies to increase the performance or added-value of your existing products and services.
	DA 8	Your winery has launched new business model based on digital technologies.
	FR	Your winery has the financial resources to adopt the digital technology.

The designs for the two observable learning behaviors (external communication and internal training), control variable, and the managerial support scale originate from the traditional TOE theoretical framework and have been widely adopted in extensive subsequent literature [39,40,42]. It should be noted that the two independent variables and the control variable were constructed using single items. This choice follows the criterion proposed by Bergkvist and Rossiter [83]: when a construct refers to a concrete, singular object rather than an abstract or multidimensional psychological attribute, a single-item measure does not materially sacrifice predictive validity. The three constructs in question—whether the winery frequently engages in external communication, whether it regularly conducts internal training, and whether it possesses the financial resources for digital adoption—all capture specific, observable organizational behaviors or resource states rather than subjective attitudes, and therefore satisfy this condition. In addition, single-item measures reduce questionnaire redundancy and respondent fatigue, a meaningful consideration given that the survey targeted core decision-makers whose time is limited. Furthermore, to capture learning behaviors that are not confined to digital technologies, this study specifically adapted the original items, shifting expressions that previously targeted digital-specific learning toward general, technology-agnostic learning behaviors.

Regarding the measurement of digital transformation adoption, to characterize the integration quality of digital strategy and organizational processes rather than the mere presence of technology, this study drew upon the eight-item scale developed by Abou-foul et al. [84] and Hu et al. [85]. This construct measures the embedding level of digital technologies within core business processes of wine enterprises. Its measurement items cover multiple practical dimensions including understanding customer demands, coordination between production and commercial operations, process automation, and the advancement of innovative business models, which collectively

reflect the overall depth of firms' digital transformation. In addition, both Managerial Support and Digital Adoption in this study are measured via unidimensional reflective measurement models. The reason is that these two constructs are regarded as latent psychological or organizational states. Each measurement item serves as an external reflection of the corresponding latent variable, rather than an independent component that jointly forms the variable.

Furthermore, this study introduces financial resources as a control variable. The impact of financial resources on digital transformation has been substantiated by extensive literature [39,40,42]. Financial resources are regarded as the foundational safeguard for an organization to implement strategic changes. Digital transformation involves substantial costs for hardware and software procurement, system maintenance, and talent acquisition; sufficient financial resources provide the necessary funding leverage for technology adoption and mitigate financial risks during the transformation process [4,86]. Consequently, financial slack can influence organizational decision-making by modulating management's risk appetite and strengthening their willingness to support high-risk projects. Therefore, this paper controls for financial resources to eliminate their potential effects on both the mediating variable (Managerial Support) and the dependent variable (Digital Adoption).

3.3 Analysis strategy

To test the proposed theoretical model of this study, we employed Partial Least Squares Structural Equation Modeling (PLS-SEM) and conducted the estimation via SmartPLS 4. The rationales for adopting this method are presented as follows. First, although PLS-SEM is commonly used for exploratory research, recent authoritative methodological studies have confirmed its applicability to confirmatory theoretical testing [87]. Second, the proposed model is a mediation model—external communication and internal training relate to managerial support, which in turn relates to digital adoption—requiring the simultaneous estimation of multiple paths, a task to which SEM is well suited. Third, the research goal is largely predictive, in that the model seeks to explain the variance in managerial support and digital adoption, and PLS-SEM maximizes the explained variance of endogenous constructs [88]. Finally, the Shapiro-Wilk test for all items yielded significant results ($p < 0.001$), indicating that the data deviate substantially from a normal distribution, which a non-parametric approach such as PLS-SEM can handle effectively [89].

The valid sample size of 321 in this study exceeds the requirements of G*Power for a statistical power of 0.8 and the general sample size rules for PLS, which fully meets the estimation criteria for confirmatory models [90]. Therefore, PLS-SEM is appropriate for data analysis and model testing in this paper. The Kaiser-Meyer-Olkin (KMO) value was 0.935 and Bartlett's test of sphericity was significant at $p < 0.001$, verifying that the data were suitable for factor analysis. Following standard PLS-SEM procedures, we performed model analysis in two stages: assessment of the outer (measurement) model and the inner (structural) model.

Given that all data were collected from a single questionnaire, the full collinearity VIF approach was adopted to diagnose potential common method bias [91]. The results showed that the VIF values of latent variables were FR = 1.168, EC = 1.641, IT = 1.757, MS = 1.809 and DA = 1.967 respectively, all below the threshold of 3.3. This suggests that severe common method bias is unlikely in this study, although it cannot be entirely ruled out.

Given the cross-sectional, single-respondent design, this study examines associations and path relationships among variables rather than establishing strict causal relationships. Accordingly, all findings are interpreted in associational rather than causal terms throughout the manuscript.

4. Results

4.1 Measurement model

To evaluate the quality of the outer model, we examined internal consistency, reliability, and convergent validity. First, as shown in Table 2, the Cronbach's alpha and composite reliability (CR) values for the two multi-item latent constructs—managerial support and digital adoption—are well above the recommended threshold of 0.70, indicating high internal consistency [92]. The three single-item observed variables—external communication, internal training, and financial resources—have factor loadings fixed at 1.000 by definition and therefore no internal-consistency reliability or AVE is reported for them. For the multi-item constructs, convergent validity was established, as all item factor loadings exceeded 0.70 and the average variance extracted (AVE) was greater than the minimum threshold of 0.50, suggesting strong convergent validity.

Table 2 Descriptive statistics and reliability of measurement items

	<i>M</i> <i>e</i> <i>a</i> <i>n</i>	<i>S</i> <i>D</i>	<i>Indicator</i> <i>Loadings</i>	<i>C</i> <i>R</i>	<i>Cronbac</i> <i>h's alpha</i>	<i>A</i> <i>V</i> <i>E</i>
<i>E</i> <i>C</i>	2 6 9 1 2	1 1 2 4 1	1.000			
<i>I</i> <i>T</i>	8 2 5 2	1 4 3 1	1.000			
<i>F</i> <i>R</i>	7 7 2 3	2 2 8 1	1.000			
<i>M</i> <i>S</i> <i>I</i>	5 9 4	0 4 5	0.873	0 9 1 3	0.858	0 7 7 8

	2	1				
<i>M</i>	.	.				
<i>S</i>	9	1	0.889			
2	4	9				
	4	8				
	3	1				
<i>M</i>	.	.				
<i>S</i>	2	1	0.885			
3	0	0				
	6	5				
	2	1		0		0
<i>D</i>	.	.		.		.
<i>A</i>	2	1	0.828	9	0.927	6
1	7	1		4		6
	5	8		0		3
	2	1				
<i>D</i>	.	.				
<i>A</i>	4	1	0.850			
2	7	8				
	8	0				
	2	1				
<i>D</i>	.	.				
<i>A</i>	4	1	0.838			
3	8	6				
	1	4				
	2	1				
<i>D</i>	.	.				
<i>A</i>	3	2	0.761			
4	8	2				
	1	7				
	2	1				
<i>D</i>	.	.				
<i>A</i>	5	0	0.830			
5	8	9				
	7	5				
	2	1				
<i>D</i>	.	.				
<i>A</i>	6	2	0.779			
6	6	5				
	6	7				
	2	1				
<i>D</i>	.	.				
<i>A</i>	4	1	0.866			
7	5	5				
	3	0				
	1	0				
<i>D</i>	.	.				
<i>A</i>	8	9	0.753			
8	2	8				
	2	9				

Next, we assessed discriminant validity to ensure that each construct is empirically distinct. Two methods were employed. The HTMT results shown in Table 3 indicate that all values are below the conservative threshold of 0.85 [89]. Furthermore, the Fornell-Larcker criterion was satisfied, as the square root of the AVE for each construct is greater than its correlation with any other construct, as illustrated in Table 4; for the single-item variables, this criterion holds automatically because their AVE equals 1.000. Taken together, these results confirm that our measurement model is robust, reliable, and valid, allowing us to proceed with the structural model analysis.

Table 3 Discriminant validity- HTMT

	<i>EC</i>	<i>IT</i>	<i>FR</i>	<i>MS</i>	<i>DA</i>
<i>EC</i>					
<i>IT</i>	0.527				
<i>FR</i>	0.452	0.490			
<i>MS</i>	0.542	0.586	0.495		
<i>DA</i>	0.560	0.593	0.587	0.678	

Table 4 Discriminant validity- Fornell & Larcker

	<i>EC</i>	<i>IT</i>	<i>FR</i>	<i>MS</i>	<i>DA</i>
<i>EC</i>	1.00 0				
<i>IT</i>	0.52 7	1.00 0			
<i>FR</i>	0.45 2	0.49 0	1.00 0		
<i>M</i>	0.50 2	0.54 4	0.46 0	0.88 2	
<i>S</i>					
<i>D</i>	0.54 2	0.57 6	0.56 7	0.611	0.81 4
<i>A</i>					

4.2 Structural model and hypothesis testing

Before testing the structural model, it is necessary to assess its collinearity using the Variance Inflation Factor (VIF), where the ideal result is a VIF value close to and not exceeding 3 [93]. Our results, shown in Table 5, indicate that all VIF values are below this threshold, suggesting that no collinearity exists between the constructs.

Table 5 Variance inflation factor (VIF)

	<i>MS</i>	<i>DA</i>
<i>EC</i>	1.485	1.585
<i>IT</i>	1.557	1.724
<i>FR</i>	1.413	1.472
<i>MS</i>		1.630

Next, we examined the explanatory and predictive power of the model. We analyzed the R^2 values (as shown in Table 6), which demonstrate the model's predictive capability by indicating the variance in endogenous variables explained by the exogenous variables. The R^2 values show that the model explains 38.7% of the variance in MS and 53.4% of the variance in DA, both substantial in magnitude. The f^2 effect sizes (see Table 7) indicate that all paths possess small explanatory power ($0.02 < f^2 < 0.15$). Furthermore, following the recommendations of Hair et al. [93], we assessed the out-of-sample predictive relevance of the model. Table 8 presents the results of the predictive power test. For MS, the Q^2 predict value is 0.371, the Root Mean Square Error (RMSE) is 0.798, and the Mean Absolute Error (MAE) is 0.612. For DA, the Q^2 predict value is 0.466, the

RMSE is 0.735, and the MAE is 0.584. Because MS and DA are the two multi-item latent constructs in the model, predictive relevance is assessed for these two endogenous variables: their Q^2_{predict} values are distinctly above zero, indicating satisfactory predictive validity, and the RMSE and MAE values are consistent with the magnitude of prediction error expected on a five-point Likert scale.

Table 6 Explanatory power (R^2)

	R^2
MS	0.387
DA	0.534

Table 7 Explanatory power (f^2)

	MS	DA
EC	0.067	0.040
IT	0.108	0.048
FR	0.042	0.094
MS		0.119

Table 8 Model's out-of-sample predictive relevance (Q^2_{predict})

	Q^2_{predict}	RMSE	MAE
MS	0.371	0.798	0.612
DA	0.466	0.735	0.584

Next, we tested our hypotheses using a bootstrapping procedure with 5,000 resamples and a 95% confidence level to estimate confidence intervals. The results of the path analysis are presented in Table 9. The results have given support to all hypotheses in varying degrees:

- Relationship between independent variables (EC, IT) and the mediator (MS): Consistent with the prediction of H1, EC is significantly and positively associated with MS ($\beta=0.247, p<0.001$). Consistent with H2, IT is significantly and positively associated with MS ($\beta=0.321, p<0.001$). This indicates that a winery's technology-agnostic external communication and internal training behaviors are positively associated with higher managerial support for digital transformation.
- Relationship between the mediator (MS) and the dependent variable (DA): Consistent with the prediction of H3, MS is significantly and positively associated with DA ($\beta=0.300, p<0.001$). This result confirms the direct positive association of managerial support on a winery's digital transformation and also satisfies the prerequisite for MS to act as a mediating variable.
- Relationship between independent variables (EC, IT) and the dependent variable (DA): Regarding direct effects, EC is significantly and positively associated with DA ($\beta=0.173, p<0.001$). Also, IT is significantly and positively associated with DA ($\beta=0.196, p<0.001$). This demonstrates

the direct positive effect of technology-agnostic external communication and internal training on a winery's digital transformation.

- Mediation effect: First, consistent with H4, EC is significantly and positively associated with DA through MS ($\beta=0.074, p<0.001$), with a Variance Accounted For (VAF) of 30% (as shown in Table 10). Second, Consistent with H5, IT is significantly and positively associated with DA through MS ($\beta=0.096, p<0.001$), with a VAF of 33%. This indicates that MS plays a significant partial mediating role between the two independent variables and the dependent variable DA.

- Although IT exhibited numerically larger path coefficients than EC, a bootstrap test of the coefficient difference did not reach significance (the 95% confidence interval of the difference included zero), indicating that the two learning behaviors are comparable in magnitude.

- Control Variables: Additionally, the results suggest that FR is significantly associated with both MS and DA ($\beta=0.192, p<0.001$) and DA ($\beta=0.254, p<0.001$), indicating that the introduction of financial resources effectively controls the model.

Table 9 Effect of all paths

	β	S D	t - st at is ti cs	p - v a l u e	2 5 % L L C I	9 7 5 % U L C I	Re sul ts
E	0	0	4.	0	0	0	H1
C	.2	.0	1	.0	.1	.3	Su
$>$	4	6	2	0	1	3	pp
M	7	0	6	0	3	6	ort
S				0	4	6	ed
I	0	0		0	0	0	H2
T	.3	.0	5.	.0	.2	.4	Su
$>$	2	5	7	0	0	2	pp
M	1	6	1	0	0	2	ort
S			0	0	7	6	ed
E	0	0		0	0	0	-
C	.1	.0	3.	.0	.0	.2	
$>$	1	0	6	0	0	2	
D	7	4	6	0	8	6	
A	3	7	2	0	2	6	
I	0	0		0	0	0	-
T	.1	.0	3.	.0	.0	.2	
$>$	9	5	8	0	0	2	
$>$	6	1	7	0	9	9	
			1	0	6	5	

<i>D</i>								
<i>A</i>								
<i>M</i>								<i>H3</i>
<i>S</i>	0	0	6.	0	0	0		<i>Su</i>
<i>-</i>	.3	.0	4	.0	.2	.3		<i>pp</i>
<i>></i>	0	4	3	0	0	9		<i>ort</i>
<i>D</i>	0	7	9	0	6	1		<i>ed</i>
<i>A</i>								
<i>E</i>								<i>H4</i>
<i>C</i>								<i>Su</i>
<i>-</i>	0	0	3.	0	0	0		<i>pp</i>
<i>></i>	.0	.0	6	.0	.0	.1		<i>ort</i>
<i>M</i>	0	0	3	0	0	1		<i>ed</i>
<i>S</i>	7	2	3	0	3	1		
<i>-</i>	4	0		0	8	8		
<i>></i>								
<i>D</i>								<i>H5</i>
<i>A</i>								<i>Su</i>
<i>I</i>								<i>pp</i>
<i>T</i>								<i>ort</i>
<i>-</i>	0	0	3.	0	0	0		<i>ed</i>
<i>></i>	.0	.0	8	.0	.0	.1		
<i>M</i>	0	0	9	0	0	4		
<i>S</i>	9	2	5	0	5	8		
<i>-</i>	6	5		0	2			
<i>></i>								
<i>D</i>								
<i>A</i>								
<i>F</i>	0	0	3.	0	0	0		-
<i>R</i>	.1	.0	3	.0	.0	.3		
<i>-</i>	9	5	2	0	7	0		
<i>></i>	2	8	3	1	9	5		
<i>M</i>								
<i>S</i>	0	0	5.	0	0	0		-
<i>F</i>	.2	.0	1	.0	.1	.3		
<i>R</i>	5	5	2	0	5	5		
<i>-</i>	4	0	3	0	6	2		
<i>></i>								
<i>D</i>								
<i>A</i>								

Table 10 Mediation effect

	<i>Direct effect</i>		<i>Indirect effect</i>		<i>Total effect</i>		
	β	<i>T</i> - s t a t i s t i c a l u e s	β	<i>T</i> - s t a t i s t i c a l u e s	β	<i>T</i> - s t a t i s t i c a l u e s	<i>V</i> <i>A</i> <i>F</i>

	<i>i</i>			<i>i</i>			<i>i</i>			
	<i>c</i>			<i>c</i>			<i>c</i>			
	<i>s</i>			<i>s</i>			<i>s</i>			
<i>E</i>										
<i>C</i>										
-	0	3		0	3		0	4		
>			*			*			*	3
<i>M</i>	.	.		.	.		.	.		
<i>S</i>	1	6	*	0	6	*	2	7	*	0
-	7	6	*	7	3	*	4	9	*	%
>	3	2		4	3		7	5		
<i>D</i>										
<i>A</i>										
<i>I</i>										
<i>T</i>										
-	0	3		0	3		0	5		
>			*			*			*	3
<i>M</i>	.	.		.	.		.	.		
<i>S</i>	1	8	*	0	8	*	2	8	*	3
-	9	7	*	9	9	*	9	6	*	%
>	6	1		6	5		3	2		
<i>D</i>										
<i>A</i>										

*** $p < 0.001$

5. Discussion

5.1 Summary and interpretation of key findings

Integrating Upper Echelons Theory and Absorptive Capacity Theory, this paper intends to answer the core research question in digital transformation literature: Where does managerial digital support originate, and what role does it play in digital adoption within small and medium-sized family firms? This study reveals that managerial support is crystallized at the decision-making level from firms' accumulated learning routines. Serving simultaneously as an outcome of organizational learning and an explanatory variable of digital transformation implementation, managerial support forms the transmission chain of "accumulation of organizational knowledge → strategic managerial support → practical adoption of digital technologies".

5.1.1 The Source of Momentum for the Formation of Managerial Support

As an outcome variable of organizational learning, the formation of managerial support can be interpreted from two complementary dimensions: external perception and internal efficacy. First, the validation of H1 indicates that technology-agnostic external communication builds an "external perception channel" for managers. Frequent inter-organizational information flows enable managers of small and medium-sized wineries to dynamically track shifts in the technological environment and promptly identify strategic opportunities of digital tools in production control, brand marketing and other links, thus lifting the priority of digitalization during

organizational resource allocation. Meanwhile, frequent acquisition of external information mitigates information asymmetry in decision-making, equipping managers with comprehensive risk perception and control competence and strengthening their psychological certainty to advance substantive reforms.

Second, the support for H2 reveals that internal training delivers an “efficacy basis” for managers to assess transformation feasibility. Fragmented digital knowledge acquired externally can only be decomposed and restructured via institutionalized internal training to become absorbable and usable organizational capability reserves. From the perspective of perceived organizational efficacy, frequent knowledge internalization builds abundant organizational competence and human capital, boosting winery managers’ confidence in the organization’s capacity to weather the pains of reform. Such positive evaluation of implementation capacity effectively offsets worries over potential transformation risks and translates into tangible resource commitments and persistent strategic advocacy.

5.1.2 Direct Effect of Managerial Support on Digital Adoption

This study statistically verifies the significant positive association of managerial support with digital adoption (Hypothesis 3), and this finding bears profound theoretical implications and contextual rationality. For small wineries featuring highly integrated ownership and management rights, managerial support represents the most immediate enabling condition for digital adoption without cumbersome hierarchical approval or interdepartmental bargaining. Once managers develop clear supportive attitudes toward digitalization, such attitudes translate into three types of practical actions. First, substantial financial resource input covering procurement of software and hardware as well as engagement of technical service providers. Second, institutional process restructuring such as incorporating digitalization indicators into the production performance appraisal system. Third, behavioral demonstration: managers’ active adoption of digital tools improves employees’ acceptance and participation. Such a “decision equals implementation” governance feature renders the direct facilitating effect of managerial support on digital adoption particularly prominent within the winery context. Meanwhile, this result lays the fundamental prerequisite for the existence of the hypothesized mediating effects.

5.1.3 Transmission Mechanism from Organizational Learning to Digital Transformation: The Mediating Role of Managerial Support

Built upon the verification of H3, the core finding of this study is that managerial support partially mediates the relationships between technology-agnostic organizational learning behaviors and digital adoption (H4, H5), which carries important theoretical implications. This research systematically points to a “cognitive transmission” mechanism underlying digital transformation among SMEs in traditional industries. As disruptive innovation, digital technologies require sufficient knowledge accumulation for firms to fully identify their application value and

implementation routes. Technology-agnostic organizational learning, whether through externally accessing industrial technical information or delivering in-house training, is associated with renewed managerial cognitive frameworks, lower perceived uncertainty toward digital technologies, and more confident judgments on transformation feasibility, which in turn accompany a higher likelihood of resource allocation and strategic backing. Such a transmission logic of “organizational knowledge accumulation → managerial cognitive renewal → practical strategic implementation” is particularly salient in family enterprises with unified ownership and management control, offering a novel theoretical lens to unpack the micro-level mechanisms of SME digital transformation.

Effect decomposition indicates that indirect effects transmitted via managerial support account for 30% of the total effect for external communication and 33% for internal training. This outcome reveals that organizational learning affects digital adoption through two parallel pathways: the cognitive transmission route mediated by managerial support, and a direct practical route where learning behaviors promote digital adoption directly. The coexistence of both routes jointly demonstrates the multi-faceted facilitating mechanism of organizational learning for digital transformation. Specifically, the cognitive route is consistent with the theoretical positioning of managerial support as a “strategic mediator”, which receives strategically valuable cognitive gains from organizational learning and translates them into top-down driving forces for digitalization. In contrast, the direct practical route implies that learning also exerts positive influences from bottom-up channels including improved employee digital literacy, cultivation of organizational digital culture, and natural integration of digitalization into daily business processes. Operating respectively at the strategic and operational levels, these two pathways together form an integrated driving system for corporate digital advancement.

5.2 Theoretical implications

Based on the aforementioned discussion, the theoretical contributions of this paper can be summarized into the following three points:

First, it completes a conceptual shift in the theoretical identity of “managerial support”, repositioning it from a parallel independent variable to a strategic mediating variable that bridges organizational learning behavior and digital transformation. This study finds that managerial support is both the decision-level outcome of organizational antecedent processes and a direct explanatory variable of digital transformation initiatives. This dual identity as both an outcome and an explanatory variable fundamentally distinguishes it from the conventional treatment in existing research—where it is often listed alongside factors like organizational size and IT maturity—providing a new analytical lens for future research to re-examine this classic variable. Second, it reveals the formation mechanism of managerial support, directly addressing the long-unresolved question of where this support originates. This study finds that routine learning

behaviors accumulated by the enterprise—external communication and internal training—are critical antecedents to management’s willingness to support digitalization. This finding illuminates the formation process of managerial support, not only uncovering its cognitive sources but also providing a verifiable analytical path for integrating Upper Echelons Theory with Absorptive Capacity Theory.

Third, it traces the drivers of digital transformation back to an enterprise’s routine learning behaviors that are independent of specific technologies, rather than treating them as specialized responses forced by the digital wave. This suggests that overcoming transformation delays in traditional SMEs depends on recurrent learning orientation rather than impromptu measures taken under environmental pressure. When specific technical capabilities cannot be supplemented in the short term, technology-agnostic accumulated learning habits serve as the final stabilizer of organizational adaptability and the foundation of confidence for management to judge whether the “organization can keep up” in the face of unknown changes.

Also, this study speaks specifically to wine economics by addressing a puzzle distinctive to the wine industry: digitalization lags in a sector that already enjoys mature technology, strong export markets, and protected regional brands. Two features of the wine industry make this lag theoretically meaningful and distinguish it from generic manufacturing. First, product quality is deeply embedded in terroir and artisanal tradition, and the Denominación de Origen system codifies this tradition into binding production standards, so digital transformation confronts an unusually strong inertial pull toward established practices. Second, wineries are typically owner-managed, so the cognition of a single manager translates directly into organizational action without bureaucratic buffering. Our findings show that, under these conditions, the availability of technology and finance is not sufficient for digital adoption; the winery’s technology-agnostic learning routines—external communication and internal training—renew managerial cognition and cultivate the managerial support needed to break this inertia. The study thereby offers a learning-based account of digital transformation tailored to territorially embedded, tradition-bound industries.

5.3 Managerial and practical implications

The empirical results of this study provide clear practical guidance for the digital transformation of SMEs in traditional industries, as exemplified by wineries. First, managers should establish institutionalized external scanning mechanisms. By participating in industry technology alliances or forming cross-industry partnerships, managers can more effectively identify digital opportunities and relevant information, thereby calibrating the priority of digital agendas within the organizational strategy.

Second, wineries should ensure that externally acquired digital knowledge is transformed into internal capability through institutionalized training. Consistent with the distinction between

potential and realized absorptive capacity [29], external communication helps managers recognize digital opportunities, but such knowledge generates strategic value only after it is assimilated and embedded within the organization. Management should therefore move beyond the mere acquisition of external information and continuously internalize it through structured training programs, integrating it with existing routines and competencies to attenuate organizational resistance to technology adoption. This knowledge-internalization mechanism enhances managers' perceived feasibility of change and thereby fosters firmer resource commitments and sustained strategic advocacy.

Third, digital transformation should be viewed as a collaborative evolutionary process between managerial will and organizational capability. Managers need to leverage the cognitive dividends accumulated through learning behaviors to ensure, via explicit resource orchestration, that capital and talent are precisely directed toward key areas that enhance value across the industrial chain. Finally, for wine-sector policy, this implies that equipment subsidies, while helpful, are unlikely to be sufficient on their own. Because managerial support—the decisive gateway in owner-managed wineries—is itself cultivated by technology-agnostic external communication and internal training, DO regulatory councils and industry associations should complement hardware support with investments that build learning capacity, such as inter-winery knowledge-sharing networks and subsidized managerial training. Such a dual approach strengthens the absorptive capacity of small and medium-sized wineries at its source and is especially relevant for traditional wine regions seeking to close the digital divide, a logic that may also be relevant for other protected-origin agri-food industries, such as olive oil, cheese, and cured ham.

6. Conclusion

Digital transformation research has long suffered from a theoretical gap: existing literature is far more informative regarding what resources are required for transformation (technology, capital and talent) than how transformation drivers are formed. Based on Upper Echelons Theory and Absorptive Capacity Theory, this empirical analysis of Spanish wineries identifies managerial digital support as a vital mediating channel and points to an overlooked transmission logic between organizational learning and technology adoption. Managers' willingness to support digitalization derives neither solely from innate strategic vision nor passive compliance driven by technological disruption; to a considerable extent, it crystallizes at the decision-making tier from firms' accumulated learning routines.

This result suggests that the prevalent lag in digital transformation intention among traditional SMEs is related not only to technical or financial constraints but also to insufficient cumulative organizational learning. Where externally acquired information and internally built capabilities fail to translate at the cognitive level, externally imposed policy incentives or technical provision tend

to deliver limited outcomes. Managerial support serves as a critical nexus bridging knowledge accumulation and strategic action, which absorbs partial gains from organizational learning and thereafter supports digital advancement. Nevertheless, consistent with the partial mediation findings of this study, this is not the sole connecting pathway; organizational learning is also directly associated with digital practices via multiple alternative routes.

This constitutes the core value of the present study: it establishes an analytical anchor rooted in organizational learning behaviors for unpacking the micro-level mechanisms behind digital transformation in traditional industries and shedding light on the formation of managerial support. Meanwhile, it offers a fresh theoretical explanation for resolving the predicament of delayed digitalization intention among traditional SMEs. For the wine industry in particular, the findings attribute the sector's persistent digital lag—despite mature technology and protected regional brands—to a deficit in technology-agnostic learning routines rather than in technology or finance, thereby informing both wine-economics theory and sector policy.

Despite its contributions, this study has several limitations that offer directions for future research: First, limitations in causal inference. This study utilizes cross-sectional data. Although a logical path between learning behavior and digital transformation was established through theoretical inference, it is difficult to fully confirm the causal chronology between variables. Moreover, since all constructs were measured from a single respondent per winery at a single point in time, common method variance cannot be entirely ruled out, although the full collinearity VIF test (all values below 3.3) suggested that severe common method bias is unlikely. Future research could employ longitudinal tracking designs or quasi-experimental methods to dynamically observe the deep-seated impact of organizational learning behaviors on managerial decision-making and technology adoption over time.

Second, the measurement of the independent variables relied on single-item scales. Although these items capture concrete, observable organizational behaviors rather than subjective attitudes, single-item measures cannot fully cover the breadth of the underlying constructs and, combined with the five-point scale, cannot entirely rule out respondent bias. This represents a genuine limitation of the present study. Future research should replace these single items with objective behavioral indicators—such as the annual number of external communication activities, the frequency of internal training sessions, or the share of revenue invested in digitalization—to enhance measurement accuracy and the robustness of the findings. Moreover, because managerial cognition was not directly measured but inferred through the behavioral proxy of managerial support, the specific cognitive contents underlying this support could not be directly observed, which warrants caution in interpreting the cognitive mechanisms.

Third, a significant portion of the impact of learning behavior on digital transformation remains unexplained by the mediating mechanism in this study. Future research could explore other

potential mediating paths, such as employee digital capabilities, organizational digital culture, and organizational structural flexibility, to further refine the path model from organizational learning to digital transformation.

Finally, the empirical findings of this study are bounded by certain limitations in external validity, thereby calling for prudence in interpretation and generalization. The empirical sample is confined to Spanish wineries regulated under Spain's distinctive Denominación de Origen (DO) appellation system. Accordingly, the results are most applicable to small and medium-sized branded wineries in traditional European and American wine-producing regions with analogous institutional frameworks and scale attributes. Cross-industry generalization requires full consideration of contextual disparities including industrial institutions and resource endowments. Future research may expand samples across diverse regions and sectors to further verify the generalizability of the proposed theoretical model.

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