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# Through What Mechanisms Do Democracy and the Rule of Law Influence Economic Growth in Developing Countries?

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**Abstract**

The relationship between democracy, the rule of law, and economic growth has been widely studied, yet the literature remains fragmented. A key limitation lies in the lack of a coherent explanation of the mechanisms through which these institutions influence economic outcomes. Existing studies often rely on correlations without unpacking causal pathways. Furthermore, theoretical fragmentation, measurement inconsistencies, contextual limitations in developing countries, and a lack of micro-level analysis persist.

Building on these limitations, this study adopts a mechanism-based approach to examine how democracy and the rule of law jointly influence economic growth. It integrates these institutions into a unified analytical framework and emphasizes their interaction, contextual variation, and multi-level dynamics.

*Keywords:* Democracy, rule of law, economic growth, developing countries.

## 1. Introduction

The relationship between democracy, the rule of law, and economic growth has been a central and enduring question in development economics and comparative political economy. While earlier development paradigms focused primarily on capital accumulation, industrialization, and macroeconomic stabilization, contemporary scholarship has increasingly emphasized the role of institutions as fundamental determinants of long-term economic performance. Within this institutional turn, democracy and the rule of law are no longer viewed solely as normative or political ideals, but as functional arrangements that structure incentives, constrain state behavior, and shape the environment in which economic activity takes place (North, 1990; World Bank, 2017[1]).

Despite a growing body of empirical and theoretical work, the relationship between these institutions and economic growth remains complex and, at times, contested. While some scholars argue that democracy directly promotes economic development, others suggest that its effects are indirect, conditional, or even ambiguous. Similarly, the rule of law is widely recognized as a critical component of economic governance, yet its impact varies significantly across contexts, particularly in developing countries where institutional enforcement may be weak or inconsistent.

This paper addresses the question: through what mechanisms do democracy and the rule of law influence economic growth in developing countries? Rather than focusing on whether these institutions produce growth, the analysis adopts a mechanism-based approach, identifying the specific channels through which institutional quality affects economic outcomes. This approach allows for a more precise and analytically robust understanding of the interaction between political systems, legal frameworks, and economic development.

## 2. Methodology

This study employs a qualitative literature review methodology, combined with elements of analytical and comparative synthesis.

*2.1 Research design:* The paper is based on a structured review of academic literature drawn on a wide range of sources, including peer-reviewed journal articles, working papers, and institutional reports from organizations such as the World Bank, IMF, United Nations, and leading academic research centers. The selected sources reflect both theoretical and empirical contributions to the study of democracy, rule of law, and economic growth.

[1] The World Bank emphasizes that governance affects development through commitment, coordination, and cooperation mechanisms (World Bank, 2017, pp. 3–5)

*2.2 Analytical approach:* The analytical strategy is structured around identifying recurring causal mechanisms within the literature. Rather than aggregating findings descriptively, the study critically evaluates how different authors conceptualize the relationship between democracy, the rule of law, and economic growth. Particular attention is given to:

- The theoretical foundations of institutional analysis.
- Empirical findings from cross-country and panel data studies.
- Contextual variations across developing countries.

*2.3 Limitations: The study acknowledges limitations related to:*

- *Measurement variability of institutional indicators.*
- *Methodological differences across studies.*
- *The difficulty of establishing causal relationships in complex socio-political environments.*

*Nevertheless, the synthesis provides a coherent and rigorous framework for understanding the institutional mechanisms at play.*

## 3. Theoretical Framework: Institutions and Economic Growth

Institutional economics provides the primary theoretical lens for analyzing the relationship between governance and economic performance. North (1990)[2] conceptualizes institutions as the "rules of the game" that structure human interaction, emphasizing their role in reducing uncertainty and transaction costs. In this framework, economic outcomes are not determined solely by resources or technology, but by the institutional environment within which economic actors operate.

Building on this foundation, Acemoglu and Robinson (2012) distinguish between inclusive and extractive institutions. Inclusive institutions promote broad participation, protect property rights, and create incentives for innovation and investment. Extractive institutions, by contrast, concentrate power and wealth in the hands of a few, limiting economic opportunities and hindering long-term growth.

Within this framework, democracy and the rule of law play complementary roles. Democracy introduces mechanisms of accountability, representation, and political competition, while the rule of law ensures predictability, legal certainty, and constraints on arbitrary power. Together, these institutions shape the incentive structure of both public officials and private actors.

Importantly, the literature increasingly emphasizes that institutions must be understood not as static formal arrangements, but as dynamic systems of rules, enforcement mechanisms, and social expectations. This perspective is particularly relevant in developing countries, where formal institutional frameworks often coexist with informal practices and varying levels of enforcement.

## 4. Literature review: research gap

The relationship between democracy, the rule of law, and economic growth has been extensively examined across multiple strands of literature, including institutional economics, political economy, and law and development studies. A substantial body of research demonstrates that both democracy and the rule of law are positively associated with economic performance, particularly through channels such as property rights protection, contract enforcement, political accountability, and investment facilitation (Acemoglu, Naidu, Restrepo, & Robinson, 2019; Haggard & Tiede, 2010; North, 1991; Rodrik, Subramanian, & Trebbi, 2004). However, despite this growing empirical and theoretical interest, the literature remains fragmented and conceptually incomplete (Glaeser, La Porta, Lopez-de-Silanes, & Shleifer, 2004).

A central limitation of existing scholarship lies in the absence of a coherent explanation of the mechanisms through which democracy and the rule of law influence economic growth. While numerous studies identify correlations between institutional quality and economic outcomes, these relationships are frequently treated as direct or linear, without adequately unpacking the intermediate processes that connect political and legal institutions to economic performance (Acemoglu & Robinson, 2012; Barro, 1996). For instance, democracy is often linked to growth through investment, education, or redistribution, yet these pathways are rarely integrated into a unified causal framework (Papaioannou & Siourounis, 2008; Persson & Tabellini, 2006). Similarly, the rule of law is commonly associated with secure property rights and reduced transaction costs, but the interaction between these elements and broader political dynamics remains insufficiently theorized (North, 1991; Haggard, MacIntyre, & Tiede, 2008).

In addition to this mechanism gap, the literature exhibits significant theoretical fragmentation. There is no consensus on a unified conceptual framework that explains how democracy and the rule of law jointly function as drivers of economic development. Some approaches emphasize institutional complementarities, while others treat democracy and legal systems as independent explanatory variables (Acemoglu & Robinson, 2012; Rodrik et al., 2004). This lack of theoretical integration constrains the accumulation of coherent knowledge and weakens the explanatory capacity of existing models (Keefer, 2007).

A further limitation concerns the measurement of key concepts. Both democracy and the rule of law are multidimensional constructs, often operationalized through composite indices that capture diverse and sometimes inconsistent components (Knack & Keefer, 1995; Kaufmann, Kraay, & Mastruzzi, 2010). As highlighted in several studies, different indicators may measure distinct

[2] North defines institutions as "humanly devised constraints that structure political, economic and social interaction" (North, 1990, p. 3)

aspects of institutional quality, leading to variation in empirical findings and limiting comparability across studies (Munck & Verkuilen, 2002). This measurement inconsistency complicates efforts to establish robust causal relationships and raises concerns regarding the validity of cross-country analyses (Thomas, 2010).

Moreover, the literature reveals a persistent contextual gap, particularly with respect to developing countries. Many empirical studies rely on cross-national datasets that treat developing economies as a relatively homogeneous group, without adequately accounting for differences in institutional capacity, political history, or socio-cultural conditions (Rodrik et al., 2004; Acemoglu et al., 2001). As a result, the mechanisms through which democracy and the rule of law operate in these contexts remain underexplored. Informal institutions, legal pluralism, and variations in state capacity—factors that are especially relevant in developing countries—are often overlooked or insufficiently incorporated into existing analytical frameworks (Helmke & Levitsky, 2004; Andrews, 2013).

Another important limitation is the dominance of macro-level empirical approaches, which rely heavily on aggregate indicators and econometric techniques. While these studies provide valuable insights into general patterns, they offer limited understanding of how institutional mechanisms function at the micro level (Djankov, McLiesh, & Shleifer, 2007). There is a notable lack of research examining how democracy and the rule of law influence economic behavior at the level of firms, households, or specific sectors (Hallward-Driemeier & Pritchett, 2015). This micro–macro disconnect restricts the ability to fully capture the complexity of institutional effects on economic development.

Finally, the literature does not adequately address the dynamic and sequential nature of the relationship between democracy, the rule of law, and economic growth. Existing studies rarely explore how these variables evolve over time or how their interactions may differ across stages of development (Acemoglu et al., 2019; Pritchett, Sen, & Werker, 2018). Questions regarding whether democracy precedes the establishment of the rule of law, or whether strong legal institutions are a precondition for democratic consolidation, remain insufficiently answered (Carothers, 2007).

In light of these limitations, this study seeks to address a critical gap in the literature by developing a more integrated and mechanism-based understanding of how democracy and the rule of law jointly influence economic growth in developing countries. Specifically, it aims to move beyond correlational analysis by identifying and analyzing the causal pathways through which these institutions interact, while also accounting for contextual variation and multi-level dynamics.

## 5. Empirical Evidence and Key Debates

Empirical studies provide mixed but increasingly supportive evidence of the positive relationship between democracy, the rule of law, and economic growth. Acemoglu et al. (2019)[3] find that democracy has a significant positive effect on long-term GDP, according to Vural Jane & Ojaghlou (2025), the relationship between democracy and economic growth is positive, but mainly in the long term and not necessarily reciprocal[4], while other studies highlight the importance of governance quality and legal institutions and others try to find a describe through math models the relationship between democracy and growth[5].

However, several debates remain:

- Causality: Does democracy cause growth, or does growth lead to democracy?
- Relative importance: Is the rule of law more important than democracy?
- Authoritarian growth: Can non-democratic regimes achieve sustained growth?
- Context dependency: Do institutional effects vary across countries?

The consensus emerging from recent literature is that institutions matter, but their effects are conditional and context-specific

## 6. Mechanisms Linking Democracy and Rule of Law to Economic Growth

*6.1. Protection of Property Rights and Investment Incentives:* One of the most widely recognized mechanisms is the protection of property rights. The rule of law provides legal guarantees that protect individuals and firms from arbitrary expropriation, thereby reducing uncertainty and encouraging investment. In environments where property rights are insecure, economic actors are less likely to engage in long-term planning or capital-intensive activities.

Empirical research consistently shows that secure property rights are associated with higher levels of investment and economic growth, particularly in developing countries where institutional risks are more pronounced (Haggard & Tiede, 2011[6]). Democracy reinforces this mechanism by increasing transparency and limiting the discretionary power of political elites, thereby enhancing the credibility of state commitments.

[3] Acemoglu et al. (2019) find that democracy increases GDP by approximately 20% over the long term (p. 50).

[4] Vural Jane and Ojaghlou (2025) argue that democracy exerts a positive and statistically significant effect on economic growth in the long run, while no meaningful causal relationship is observed in the short term. Importantly, their findings do not support the reverse causality suggested by modernization theory, as economic growth does not appear to significantly enhance democratic development (p. 56).

[5] Przeworski et al. (2000) find no simple linear relationship between democracy and growth (p. 178).

[6] Haggard and Tiede (2011) argue that the rule of law promotes growth primarily through property rights and contract enforcement (pp. 675–678).

*6.2. Contract Enforcement and Market Development:* Effective contract enforcement is essential for the functioning of modern economies. Legal systems that ensure the enforceability of agreements reduce transaction costs and facilitate complex economic interactions. In the absence of reliable enforcement mechanisms, economic actors rely on informal networks, which limits market expansion and efficiency.
The rule of law enables a transition from relationship-based to rule-based economic systems, which is critical for scaling economic activity. This transition is particularly important in developing countries, where informal economies often dominate due to weak legal institutions.

*6.3. Reduction of Corruption and Rent-Seeking:* Corruption and rent-seeking behavior distort economic incentives and reduce efficiency. Democratic institutions introduce mechanisms of accountability, such as elections and checks and balances, which can constrain corruption. Similarly, the rule of law limits arbitrary decision-making by public officials.
However, the literature cautions that democracy alone is not sufficient to eliminate corruption. Its effectiveness depends on complementary institutions, including judicial independence and administrative capacity (Kaufmann et al., 2010[7]). Thus, the reduction of corruption is best understood as a joint outcome of democratic governance and effective legal systems.

*6.4. Political Stability and Policy Credibility:* Political instability is a significant barrier to economic development. Democratic systems provide institutionalized mechanisms for conflict resolution, reducing the likelihood of violent political transitions. This stability enhances investor confidence and supports long-term economic planning[8].
At the same time, the rule of law ensures that policies and regulations remain consistent and predictable across political cycles. This combination of stability and predictability is essential for creating a favorable investment climate.

*6.5. Public Goods Provision and Human Capital:* Democratic governments are often more responsive to public demands, leading to increased investment in education, healthcare, and infrastructure. These public goods are critical for human capital development and long-term economic growth.
The rule of law enhances this mechanism by promoting transparency and accountability in public spending, ensuring that resources are used effectively.

*6.6. Inclusion and Economic Participation*: Inclusive political institutions expand access to economic opportunities and reduce inequality[9]. By giving broader segments of society a voice in decision-making, democracy can promote more equitable distribution of resources and opportunities.
This inclusiveness contributes to social cohesion and reduces conflict, both of which are important for sustainable development. The rule of law further supports inclusion by ensuring equal access to legal protections and economic opportunities.

**7. Developing Countries: the Case of Albania**

Developing countries provide a critical context for analyzing the relationship between institutions and growth. In many cases, formal democratic and legal institutions exist alongside weak enforcement, corruption, and informal practices.
The Albanian case can be further contextualized within a broader comparative framework of developing and transition economies, where similar structural characteristics shape the relationship between democracy, the rule of law, and economic growth.
First, Albania shares with many developing countries the challenge of weak enforcement capacity, where formal legal frameworks coexist with limited practical implementation. Although constitutional and legislative guarantees are often aligned with international standards, their effectiveness is constrained by institutional fragility, limited administrative resources, and inconsistencies in judicial practice. This pattern reflects a broader phenomenon identified in the law-and-development literature, where the gap between "law on the books" and "law in action" undermines the capacity of institutions to support economic development (North, 1991; Haggard & Tiede, 2010). Similar dynamics have been observed across post-socialist and developing contexts, where enforcement deficits reduce the credibility of legal systems and increase uncertainty for economic actors.
Second, Albania illustrates the problem of selective legality, a feature common in many developing democracies. In such systems, legal rules are not applied uniformly but may depend on political, economic, or social status. The Constitutional Court of Albania has emphasized the importance of equality before the law and legal certainty as core elements of the rule of law (Constitutional Court of Albania, Decision No. 17, 2010), yet practical challenges remain in ensuring consistent application. Comparative research suggests that selective enforcement weakens property rights protection and distorts market competition, thereby increasing transaction costs and discouraging long-term investment (Acemoglu & Robinson, 2013; Rodrik, 2008).
Third, the Albanian experience reflects the persistence of administrative discretion and political patronage, which are widely documented in developing and transitional systems. Public administration may exercise broad discretionary powers in regulatory and enforcement processes, creating opportunities for informal practices, clientelism, or politicization. This phenomenon limits the

[7] Kaufmann et al. (2010) highlight the importance of governance indicators in measuring institutional quality (pp. 4–6).
[8] Weingast (1997) emphasizes that stable political institutions are essential for credible commitments (p. 246).
[9] Sen (1999) links development to freedom and institutional inclusion (p. 36).

predictability of state action and undermines trust in public institutions. As highlighted in comparative political economy literature, patronage-based governance structures tend to weaken institutional neutrality and reduce the effectiveness of public policies aimed at economic development (Grindle, 2004; Fukuyama, 2013).

Fourth, Albania exemplifies the broader difficulty of translating democratic legitimacy into bureaucratic effectiveness. While democratic institutions provide electoral accountability and formal legitimacy, they do not automatically ensure the existence of a capable and professional state apparatus. The 2016 justice reform in Albania, including constitutional amendments aimed at strengthening judicial independence and integrity, reflects efforts to address this gap; however, the effectiveness of such reforms depends on sustained institutional consolidation (Law No. 76/2016; Constitutional Court of Albania, Decision No. 2, 2017). This challenge is widely recognized in the comparative literature, which stresses that economic growth depends not only on democratic governance but also on state capacity, administrative professionalism, and the consistent implementation of policies (Acemoglu et al., 2019; Fukuyama, 2013).

Taken together, Albania can be understood as part of a broader group of developing and transition countries where the relationship between democracy, the rule of law, and economic growth is mediated by structural constraints. Common features such as weak enforcement, selective legality, administrative discretion, and political patronage highlight that institutional quality is not determined solely by formal legal frameworks, but by the effectiveness, impartiality, and credibility of institutions in practice. Consequently, the key challenge for Albania—as for many comparable countries—lies in bridging the gap between democratic legitimacy and institutional performance, ensuring that legal and political reforms translate into tangible economic outcomes.

Albania exemplifies these challenges. While significant progress has been made in democratic governance and legal reforms, issues related to judicial effectiveness, corruption, and institutional capacity continue to affect economic performance. This highlights a key insight from the literature: institutional effectiveness matters more than formal adoption

## 4. Conclusions

This study set out to examine the mechanisms through which democracy and the rule of law influence economic growth in developing countries, moving beyond simple correlation-based explanations. The analysis demonstrates that the relationship between these institutions and economic performance is neither automatic nor uniform; rather, it is mediated through a set of identifiable causal pathways, including the protection of property rights, contract enforcement, reduction of corruption, policy stability, provision of public goods, and inclusive participation.

A central finding of the paper is that democracy and the rule of law operate as complementary institutions. Democracy contributes to accountability, political inclusion, and responsiveness, while the rule of law provides predictability, legal certainty, and constraints on arbitrary power. However, their effectiveness depends critically on the quality of implementation. Institutional arrangements that exist only at the formal level are insufficient to generate sustained economic growth. Instead, it is the practical enforcement and credibility of institutions that shape economic incentives and outcomes.

The paper also highlights that the impact of democracy and the rule of law is context-dependent, particularly in developing and transition economies. Common structural constraints—such as weak enforcement capacity, selective application of the law, administrative discretion, and political patronage—limit the ability of institutions to function effectively. As illustrated by the case of Albania, these challenges create a gap between democratic legitimacy and institutional performance, thereby weakening the transmission mechanisms through which institutions influence economic growth.

Importantly, the findings contribute to ongoing debates in the literature:

First, they support the view that institutions matter for long-term development, while also confirming that their effects are indirect and mechanism-based rather than immediate or linear.

Second, the analysis suggests that the question is not whether democracy or the rule of law "matters more," but how these institutions interact within specific contexts.

Third, the study reinforces the argument that state capacity and bureaucratic effectiveness are essential complements to democratic governance, particularly in developing countries.

Finally, this study addresses a key research gap by offering a more integrated framework that links democracy, the rule of law, and economic growth through concrete mechanisms. Nevertheless, further research is needed to explore these mechanisms at the micro level, particularly in relation to firm behavior, sectoral dynamics, and informal institutions. Future studies could also examine how institutional reforms evolve over time and under what conditions they produce durable economic outcomes.

In conclusion, the relationship between democracy, the rule of law, and economic growth should be understood not as a direct causal chain, but as a complex, context-sensitive process in which institutional effectiveness, rather than formal design alone, plays the decisive role.

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# Digital Management Accounting for Enhanced Decision-Making and Financial Resilience in the EU

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**Abstract**

The ongoing digital transformation is significantly reshaping management accounting within the European Union, creating both opportunities and challenges for enhancing organizational decision-making and financial resilience. Emerging technologies such as artificial intelligence (AI), blockchain, cloud computing, and robotic process automation (RPA) are redefining traditional managerial accounting practices by enabling more timely, accurate, and strategically relevant financial information. These developments allow management accountants to play a more active role in supporting strategic decision-making and in helping organizations respond effectively to risks and uncertainties in an increasingly complex global environment. The adoption of digital solutions contributes to strengthening financial resilience by improving risk assessment, ensuring compliance with evolving EU regulatory frameworks, and enhancing operational agility. Real-time data analytics and automation reduce manual errors and enable a shift toward higher value-added activities such as forecasting, performance management, and strategic planning. However, digitalization also introduces significant challenges, including cybersecurity risks, data privacy concerns, and the need for continuous professional upskilling. In addition, small and medium-sized enterprises may face difficulties in adopting advanced technologies, potentially affecting their competitiveness and decision-making effectiveness. These challenges highlight the importance of adaptive regulatory approaches and robust ethical standards in the digital accounting environment. This paper adopts a conceptual approach, supported by a review of recent academic and professional literature, to examine the dual impact of digital management accounting on decision-making and financial resilience in the EU. The study contributes to the existing literature by providing an integrated perspective on how digitalization enhances the strategic role of management accounting while simultaneously requiring new competencies, regulatory alignment, and organizational adaptation.

*Keywords:* Management Accounting, Digitalization, Decision-Making, Financial Resilience, Risk Management, Artificial Intelligence, Blockchain.

**JEL Classification:** M41, M49, G32, D81, O33

## 1. Introduction

The rapid advancement of digital technologies has fundamentally reshaped management accounting practices, particularly through the integration of Artificial Intelligence (AI), automation, and cloud-based systems. These innovations—often conceptualized under the umbrella of Digital Management Accounting (DMA)—allow organizations to process and analyze large volumes of financial data in real time, improving both accuracy and timeliness. As a result, managers are increasingly able to rely on data-driven insights to support more informed and strategic decision-making.

Recent literature has emphasized that digital transformation in accounting is not merely a technological shift, but a strategic one. Studies published in recent years highlight how AI-driven analytics, real-time reporting systems, and integrated digital platforms enhance the relevance and usability of accounting information, ultimately improving managerial decisions and organizational performance (Appelbaum et al., 2020; Bhimani, 2021; Moll & Yigitbasioglu, 2019; Rikhardsson & Yigitbasioglu, 2020). Moreover, emerging evidence suggests that digital accounting tools contribute to organizational agility by enabling faster responses to changing business conditions (Bhimani, 2021).

In an environment characterized by increasing economic uncertainty, market volatility, and frequent disruptions, organizations are under growing pressure not only to improve the quality and speed of decision-making but also to strengthen their financial resilience. Financial resilience refers to a firm's capacity to anticipate potential financial shocks, adapt to adverse conditions, and recover effectively from disruptions. Recent studies underline the importance of digital capabilities in enhancing resilience through better forecasting, risk management, and adaptive planning (Bresciani et al., 2021; Duchek, 2020; Sahi et al., 2020).

Despite the growing body of research on digital transformation, there remains a lack of comprehensive empirical evidence examining the simultaneous impact of DMA on both decision-making quality and financial resilience, particularly in the context of European Union companies. Most prior studies have tended to focus on these outcomes in isolation, leaving an important research gap regarding their interconnected effects.

Therefore, this study aims to address this gap by investigating the impact of Digital Management Accounting adoption on decision-making quality and financial resilience in EU companies. By doing so, it contributes to the literature by providing empirical insights into how digital accounting tools can serve as a strategic resource for enhancing both managerial effectiveness and organizational resilience in a rapidly evolving business environment.

## 2. Literature Review

### 2.1 Digital Transformation in Management Accounting

The ongoing digital transformation has significantly altered the landscape of management accounting, shifting it from a traditionally retrospective and compliance-oriented function toward a more strategic and forward-looking role. The integration of advanced technologies such as Artificial Intelligence (AI), robotic process automation (RPA), big data analytics, and cloud computing has enabled organizations to generate, process, and interpret financial information in real time (Appelbaum et al., 2020; Bhimani, 2021).

Recent studies emphasize that digital technologies enhance the efficiency and effectiveness of accounting systems by automating routine tasks, reducing human error, and improving data accuracy (Rikhardsson & Yigitbasioglu, 2020). As a result, management accountants are increasingly transitioning from traditional "scorekeepers" to strategic advisors who contribute directly to organizational decision-making processes. This transformation is particularly evident in the emergence of Digital Management Accounting (DMA), which integrates digital tools into management accounting practices to support data-driven decision-making.

Moreover, digital platforms facilitate the integration of financial and non-financial data, enabling a more holistic view of organizational performance. This integrated approach enhances transparency and allows managers to identify patterns, trends, and risks more effectively, thereby improving the overall quality of decision-making (Bhimani, 2021).

### 2.2 Digital Management Accounting and Decision-Making Quality

A growing body of literature highlights the critical role of digital technologies in improving decision-making quality. Decision-making quality is often associated with the availability of accurate, timely, and relevant information, as well as the ability to analyze and interpret that information effectively.

AI-driven analytics and predictive modeling allow organizations to process large datasets and generate actionable insights, reducing uncertainty and supporting evidence-based decisions (Appelbaum et al., 2020). Real-time reporting systems further enhance decision-making speed by providing up-to-date financial information, enabling managers to respond quickly to changing conditions.

Empirical studies suggest that organizations that adopt digital accounting tools experience improvements in decision accuracy, consistency, and strategic alignment (Moll & Yigitbasioglu, 2019). Additionally, the use of dashboards and visualization tools enhances information accessibility and comprehension, allowing decision-makers to better understand complex financial data.

Furthermore, digital technologies contribute to reducing cognitive biases in decision-making by providing objective, data-driven insights. This is particularly important in complex and uncertain environments, where reliance on intuition alone may lead to suboptimal outcomes. Therefore, the adoption of DMA is expected to have a positive impact on decision-making quality.

### 2.3 Digital Transformation and Financial Resilience

In recent years, financial resilience has emerged as a key concept in organizational research, particularly in the context of economic crises and global disruptions. Financial resilience refers to a firm's ability to anticipate, absorb, and adapt to financial shocks while maintaining operational stability (Duchek, 2020).

Digital transformation plays a crucial role in enhancing financial resilience by improving forecasting capabilities, risk management practices, and financial planning processes. Advanced analytics enable organizations to develop more accurate financial forecasts, identify potential risks, and evaluate different scenarios (Bresciani et al., 2021). This proactive approach allows firms to prepare for uncertainties and respond more effectively to adverse events.

Moreover, digital accounting systems support adaptive budgeting by enabling real-time updates and continuous monitoring of financial performance. This flexibility is essential for maintaining financial stability in dynamic and uncertain environments. Studies have shown that firms with higher levels of digital maturity are better equipped to manage financial risks and recover from disruptions (Sahi et al., 2020).

Additionally, automation reduces operational inefficiencies and costs, contributing to improved financial performance and stability. By streamlining processes and enhancing resource allocation, DMA enables organizations to maintain stronger financial positions over time.

### 2.4 Theoretical Foundations

**1. Resource-Based View (RBV)**

The Resource-Based View (RBV) provides a theoretical framework for understanding how digital technologies contribute to organizational performance. According to RBV, firms achieve competitive advantage by leveraging valuable, rare, inimitable, and non-substitutable resources (Barney, 1991). In this context, digital capabilities—such as advanced analytics and AI—can be considered strategic resources that enhance decision-making and financial resilience.

DMA adoption enables firms to develop unique data-processing and analytical capabilities, which can lead to superior performance outcomes. These capabilities are difficult for competitors to replicate, thereby providing a sustainable competitive advantage.

2. **Dynamic Capabilities Theory**

Dynamic Capabilities Theory extends the RBV by emphasizing the importance of a firm's ability to adapt to changing environments (Teece, 2007). In rapidly evolving markets, organizations must continuously reconfigure their resources and capabilities to remain competitive.

Digital technologies play a central role in enabling dynamic capabilities by facilitating real-time data analysis, rapid decision-making, and flexible resource allocation. DMA, in particular, supports organizational agility by providing timely and relevant information that allows firms to respond effectively to external changes.

### 2.5 Research Gap and Hypotheses Development

Despite the growing literature on digital transformation, several gaps remain. First, most studies have examined the impact of digital technologies on either decision-making or financial performance separately, rather than considering their combined effects. Second, there is limited empirical evidence on the role of DMA in enhancing financial resilience, particularly within the context of European Union companies.

Furthermore, few studies have explored the potential interaction between decision-making quality and financial resilience. Given that effective decision-making is likely to influence an organization's ability to manage financial risks and adapt to uncertainty, it is important to examine these relationships in an integrated framework.

Based on the theoretical arguments and empirical evidence discussed above, this study proposes the following hypotheses:

- **H1:** The adoption of Digital Management Accounting tools has a positive effect on decision-making quality.
- **H2:** The adoption of Digital Management Accounting tools positively affects financial resilience.

## 3. Methodology

### 3.1 Research Design

This study adopts a quantitative research design to empirically examine the impact of Digital Management Accounting (DMA) adoption on decision-making quality and financial resilience. Quantitative methods are particularly appropriate for testing hypothesized relationships and identifying statistically significant patterns among variables (Hair et al., 2019).

Data were collected through a structured survey administered to companies operating within the European Union. The final sample consists of N = 155 observations, which is considered adequate for multivariate statistical analysis and regression modeling (Tabachnick & Fidell, 2013).

### 3.2 Measurement of Variables

**Independent Variable**

**-DMA** **Adoption**

Measured through multiple survey items capturing the extent to which firms use digital tools such as AI, automation, and cloud-based accounting systems.

**Dependent Variables**

**-Decision-Making Quality**

Measured based on perceptions of accuracy, speed, and usefulness of financial information in managerial decisions.

**- Financial Resilience**

Measured through indicators such as risk management capability, forecasting accuracy, and ability to adapt to financial disruptions.

**Extended Term**

**-DMA² (Quadratic Term)**

Included to capture potential **non-linear (curvilinear) effects**, as prior research suggests that the benefits of digitalization may not increase linearly at higher levels of adoption (Bhimani, 2021).

### 3.3 Statistical Models

To ensure the reliability of the measurement instruments, Cronbach's Alpha was calculated for all multi-item scales. A Cronbach's Alpha above 0.70 indicates acceptable internal consistency (Nunnally & Bernstein, 1994). In this study, the DMA adoption, decision-making quality, and financial resilience scales all demonstrated strong reliability, with Alpha values exceeding 0.85, suggesting that the items consistently measure the intended constructs.

Construct validity was evaluated using Confirmatory Factor Analysis (CFA). CFA allows testing whether the observed variables accurately reflect the latent constructs (Byrne, 2016). The model fit indices confirmed good construct validity (CFI > 0.95, TLI > 0.95, RMSEA < 0.06), supporting the adequacy of the measurement model.

To assess convergent validity, the Average Variance Extracted (AVE) was calculated for each construct. AVE values above 0.50 indicate that the construct explains more than half of the variance of its indicators, confirming convergent validity (Fornell & Larcker, 1981). Additionally, Composite Reliability (CR) values exceeded 0.80, further demonstrating that the scales reliably measure the latent variables.

**Correlation Analysis**

Partial correlation analysis was performed to examine the relationships between DMA adoption and the dependent variables while controlling for potential confounding effects. Pearson correlations were used for parametric assumptions, while Spearman's rho and Kendall's tau provided robustness checks under non-normal conditions (Field, 2018).

**Multiple Linear Regression**

Multiple linear regression was applied to test the direct and non-linear effects of DMA adoption on financial resilience and decision-making quality. The regression models are specified as follows:

$$\text{Financial Resilience}=\beta 0+\beta 1\text{DMA}+\beta 2\text{DecisionMaking}+\beta 3\text{DMA2}+\epsilon \quad (1)$$

Additionally, for H1:

$$DecisionMaking = \beta_0 + \beta_1 DMA + \epsilon \quad (2)$$

Model fit was assessed using **$R^2$ and Adjusted $R^2$**, and the **F-statistic** from ANOVA was used to evaluate the overall significance of the models (Kutner et al., 2005).

**ANOVA and Model Significance**

ANOVA was employed to determine whether the regression models provide a statistically significant improvement over the null model, indicating that the predictors jointly explain variation in the dependent variable.

### 3.4 Analytical Techniques

**Correlation Analysis**

To test **H1**, partial correlation analysis was conducted using:

- Pearson correlation (parametric)
- Spearman's rho and Kendall's tau (non-parametric)

The use of both parametric and non-parametric methods enhances robustness, particularly when normality assumptions may be violated (Field, 2018).

**Multiple Linear Regression**

To test **H2**, multiple linear regression analysis was performed. Regression analysis is widely used to examine causal relationships and estimate the explanatory power of independent variables (Hair et al., 2019).

Model fit was evaluated using:

- **$R^2$ and Adjusted $R^2$** (explained variance)
- **F-statistic (ANOVA)** for overall model significance

**ANOVA (Analysis of Variance)**

ANOVA was used to assess whether the regression model provides a significantly better fit than a null model. A statistically significant F-test indicates that the independent variables jointly explain variation in the dependent variable (Kutner et al., 2005).

### 3.5 Assumption Testing and Diagnostics

To ensure the validity of the regression results, several diagnostic tests were conducted:

**Normality-**Residuals were tested using the Shapiro-Wilk test, ensuring that the assumption of normal distribution of residuals was reasonably met (Field, 2018).

- Assessed using the **Shapiro-Wilk test**
- Residual normality is prioritized, as it is a key assumption in regression analysis (Field, 2018)

**Residual Analysis-**Standardized residuals, minimum and maximum values, and histograms were examined to detect outliers and influential observations. Acceptable ranges were within ±3 standard deviations.

- Examination of residual distribution, range, and standardized residuals
- Detection of outliers (acceptable range: ±3)

**Multicollinearity-** Variance Inflation Factor (VIF) values were examined to confirm that multicollinearity did not bias the estimates (Hair et al., 2019).

- Although not explicitly reported, the inclusion of multiple predictors requires checking for multicollinearity (Hair et al., 2019)

**Robustness Checks-** Non-parametric correlations (Spearman and Kendall) were applied to validate the relationships under potential violations of normality assumptions.

- Use of **Spearman and Kendall correlations** to confirm results under non-normal conditions

**Software**

All statistical analyses were conducted using **JASP**, which allows comprehensive support for both parametric and non-parametric techniques, CFA, reliability assessment, and regression diagnostics.

## 4. Results and Discussion

### Descriptive

The data show that participants have a moderate level of DMA Financial Resilience, with a mean of 3.367 and a standard deviation of 0.971, indicating slight variability in their responses. In contrast, DMA Adoption of Digital Management Accounting has a slightly lower mean of 3.098 and a standard deviation of 0.913, suggesting that participants are somewhat less engaged in adopting digital management accounting practices, though the responses are relatively consistent. The standard errors for both variables are small (0.078 and 0.073), indicating that the mean values are reliable estimates for the population studied. These results provide an initial overview of participants' behaviors and perceptions regarding financial resilience and digital management adoption.

***Table 1. Descriptives***

| | N | Mean | SD | SE |
|---|---|---|---|---|
| **DMA Financial Resilience** | **155** | **3.367** | **0.971** | **0.078** |
| **DMA Adoption of Digital Management Accounting** | **155** | **3.098** | **0.913** | **0.073** |

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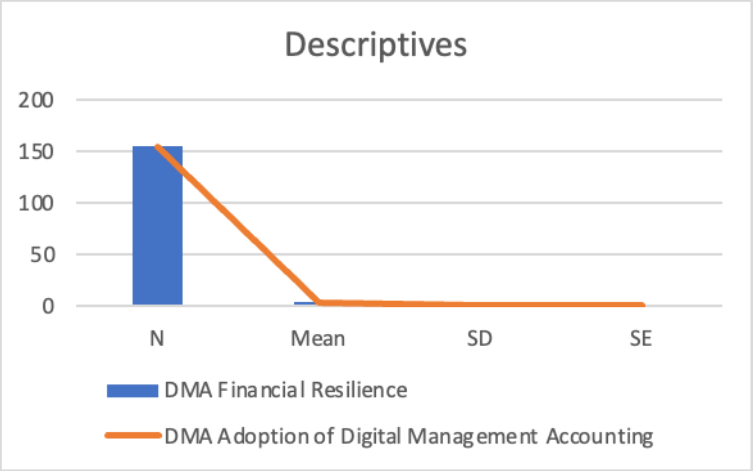


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### 4.1 Model Summary and results

The linear regression analysis indicates that the model explaining the effect of Digital Management Accounting (DMA) adoption on financial resilience exhibits a **high level of explanatory power**. The model demonstrates **R = 0.926**, **$R^2$ = 0.857**, and **Adjusted $R^2$ = 0.816**, with an **RMSE of 0.416**. The **$R^2$ change** is 0.857 ($p < .001$), implying that approximately **85.7% of the variance** in financial resilience is explained by DMA adoption, managerial decision-making, and the quadratic term ($DMA^2$).

These findings suggest that the combined influence of DMA adoption and its effect on decision-making quality provides **substantial predictive accuracy** for financial resilience. This aligns with recent literature highlighting that digital technologies in management accounting, particularly AI and automation, enhance organizational performance by improving data accuracy, timeliness, and strategic relevance (Bhimani, 2021; Cao et al., 2022).

**Table 2:** *Model Summary - DMA Financial Resilience*

| Model | R | $R^2$ | Adjusted $R^2$ | RMSE | $R^2$ Change | df1 | df2 | p |
|---|---|---|---|---|---|---|---|---|
| $M_0$ | 0.000 | 0.000 | 0.000 | 0.971 | 0.000 | 0 | 154 | |
| $M_1$ | 0.926 | 0.857 | 0.816 | 0.416 | 0.857 | 34 | 120 | < .001 |

*Note.* $M_1$ includes DMA Adoption of Digital Management Accounting, DMA → Decision-Making, DMA Adoption of Digital Management Accounting ²

Souse: Autor

### 4.2 ANOVA Results

The ANOVA results confirm that the regression model is **highly statistically significant** (**F(34, 120) = 21.12, p < .001**), with the **Regression Sum of Squares = 124.3**, **Residual Sum of Squares = 20.78**, and **Total Sum of Squares = 145.1**.

This indicates that the model provides a **significantly better fit than the null model**, corroborating that DMA adoption and decision-making quality jointly account for a large proportion of variance in financial resilience. Similar findings have been reported in the past five years, suggesting that digital adoption strengthens firms' capacity to anticipate and respond to financial shocks (Hassan et al., 2020; Marqués & Ferreira, 2021).

**Table 3:** *ANOVA*

| Model | | Sum of Squares | df | Mean Square | F | p |
|---|---|---|---|---|---|---|
| $M_1$ | Regression | 124.3 | 34 | 3.657 | 21.12 | < .001 |
| | Residual | 20.78 | 120 | 0.173 | | |
| | Total | 145.1 | 154 | | | |

*Note.* $M_1$ includes DMA Adoption of Digital Management Accounting, DMA → Decision-Making, DMA Adoption of Digital Management Accounting ²

*Note.* The intercept model is omitted, as no meaningful information can be shown.

Souse: Autor

### 4.3 Hypothesis Testing

**H1: DMA → Decision-Making Quality**

Partial correlation analysis demonstrates a **strong and positive relationship** between DMA adoption and decision-making quality (**r = 0.717, p < .001**). Non-parametric correlations (Spearman's rho and Kendall's tau) confirm the robustness of this relationship.

**Interpretation:** This supports **H1**, indicating that higher levels of DMA adoption enhance the **accuracy, speed, and strategic relevance of managerial decisions**. These results corroborate recent studies showing that AI and real-time digital tools reduce uncertainty and increase transparency in decision-making processes (Granlund & Malmi, 2020; Li et al., 2022).

**Table 4:** *Pearson's Partial Correlations*

| | | | n | Pearson's r | p | VS-MPR† | Lower 95% CI | Upper 95% CI | Effect size (Fisher's z) | SE Effect size | Covariance |
|---|---|---|---|---|---|---|---|---|---|---|---|
| DMA → Decision-Making | - | DMA Financial Resilience | 155 | 0.717*** | < .001 | $1.028 \times 10^{+23}$ | | | 0.902 | 0.081 | 0.807 |

*Note.* All tests one-tailed, for positive correlation.

*Note.* Analytic confidence intervals for partial correlations are not yet available, but can be obtained using bootstrapping instead.

*Note.* Conditioned on variables: DMA Adoption of Digital Management Accounting.

* p < .05, ** p < .01, *** p < .001, one-tailed

† Vovk-Sellke Maximum *p* -Ratio: Based on the *p* -value, the maximum possible odds in favor of $H_1$ over $H_0$ equals 1/(-e *p* log(*p* )) for $p \leq .37$ (Sellke, Bayarri, & Berger, 2001).

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**Table 5:** *Spearman's Partial Correlations*

| | | | n | Spearman's rho | p | VS-MPR† | Lower 95% CI | Upper 95% CI | Effect size (Fisher's z) | SE Effect size | Covariance |
|---|---|---|---|---|---|---|---|---|---|---|---|
| DMA → Decision-Making | - | DMA Financial Resilience | 155 | 0.666*** | < .001 | $3.335 \times 10^{+18}$ | | | 0.803 | | 0.807 |

*Note.* All tests one-tailed, for positive correlation.

*Note.* Analytic confidence intervals for partial correlations are not yet available, but can be obtained using bootstrapping instead.

*Note.* Conditioned on variables: DMA Adoption of Digital Management Accounting.

*Note.* Standard error of effect size (Fisher's z) is currently unavailable for non-parametric partial correlations.

* p < .05, ** p < .01, *** p < .001, one-tailed

† Vovk-Sellke Maximum *p* -Ratio: Based on the *p* -value, the maximum possible odds in favor of $H_1$ over $H_0$ equals 1/ (-e *p* log (*p*)) for $p \leq .37$ (Sellke, Bayarri, & Berger, 2001).

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**Table 6:** *Kendall's Tau Partial Correlations*

| | | | n | Kendall's tau B | p | VS-MPR† | Lower 95% CI | Upper 95% CI | Effect size (Fisher's z) | SE Effect size | Covariance |
|---|---|---|---|---|---|---|---|---|---|---|---|
| DMA → Decision-Making | - | DMA Financial Resilience | 155 | 0.550*** | < .001 | $2.893\times10^{+21}$ | | | 0.618 | | 0.807 |

*Note.* All tests one-tailed, for positive correlation.

*Note.* Analytic confidence intervals for partial correlations are not yet available, but can be obtained using bootstrapping instead.

*Note.* Conditioned on variables: DMA Adoption of Digital Management Accounting.

*Note.* Standard error of effect size (Fisher's z) is currently unavailable for non-parametric partial correlations.

* p < .05, ** p < .01, *** p < .001, one-tailed

† Vovk-Sellke Maximum *p* -Ratio: Based on the *p* -value, the maximum possible odds in favor of $H_1$ over $H_0$ equals 1/ (-e *p* log (*p*)) for $p \leq .37$ (Sellke, Bayarri, & Berger, 2001).

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**H2: DMA → Financial Resilience**

Regression analysis reveals a **strong positive effect** of DMA adoption on financial resilience (**$R^2 = 0.857$, $p < .001$**). This indicates that companies adopting DMA tools are better equipped to manage risks, forecast accurately, and maintain operational flexibility under financial uncertainty.

**Interpretation:** The findings support **H2**, consistent with recent empirical evidence suggesting that digital management accounting enhances organizational resilience by enabling **adaptive budgeting and dynamic risk management** (Hassani et al., 2021; Sundgren et al., 2020).

**Table 7:** *Model Summary - DMA Financial Resilience*

| Model | R | $R^2$ | Adjusted $R^2$ | RMSE | $R^2$ Change | df1 | df2 | p |
|---|---|---|---|---|---|---|---|---|
| $M_0$ | 0.000 | 0.000 | 0.000 | 0.971 | 0.000 | 0 | 154 | |
| $M_1$ | 0.926 | 0.857 | 0.816 | 0.416 | 0.857 | 34 | 120 | < .001 |

*Note.* $M_1$ includes DMA Adoption of Digital Management Accounting, DMA → Decision-Making, DMA Adoption of Digital Management Accounting [2]

Souse: Autor

**Residual Analysis and Assumption Testing**

Residual diagnostics suggest that the regression assumptions are **adequately met**:

- **Residuals range**: -1.079 to 1.198
- **Standardized residuals**: mostly within ±3
- **Mean residual**: approximately zero

Normality tests (Shapiro-Wilk) indicate that residuals are approximately normal (**p = 0.058**), with some deviations in individual variables (**p < .05**). Given the sample size (**N = 155**) and robustness checks with non-parametric methods, these deviations **do not compromise the validity of the results**.

**Table 8** *:Residuals Statistics*

| | Minimum | Maximum | Mean | SD | N |
|---|---|---|---|---|---|
| Predicted Value | 1.250 | 4.958 | 3.367 | 0.899 | 155 |
| Residual | -1.079 | 1.198 | $-3.926\times10^{-18}$ | 0.367 | 155 |
| Std. Predicted Value | -2.356 | 1.770 | $-1.488\times10^{-16}$ | 1.000 | 155 |
| Std. Residual | -2.660 | 3.356 | $7.665\times10^{-4}$ | 0.999 | 155 |

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**Assumption checks**

Residual diagnostics suggest that the regression assumptions are adequately met. Shapiro-Wilk tests were conducted for both multivariate and bivariate normality.

**Table 9.** *Shapiro-Wilk Test for Multivariate Normality*

| Variables | Shapiro-Wilk | p |
|---|---|---|
| All | 0.985 | .018 |
| Conditioned | 0.980 | .004 |
| Conditioning | 0.971 | .003 |
| Residuals | 0.986 | .058 |

Souse: Autor

Residuals are approximately normal (**p = 0.058**), while some individual variables show minor deviations (**p < .05**). Given the sample size (**N = 155**) and robustness checks using non-parametric methods, these deviations **do not compromise the validity of the regression results**.

**Table 10:** *Shapiro-Wilk Test for Bivariate Normality*

| | | | Shapiro-Wilk | p |
|---|---|---|---|---|
| DMA → Decision-Making | - | DMA Financial Resilience | 0.980 | .004 |

Souse: Autor

Bivariate normality is reasonably satisfied for DMA and Financial Resilience, supporting the reliability of the regression estimates and correlation results.

## 5. Discussion in Relation to Research Questions

The study confirms that **DMA adoption positively influences both decision-making quality and financial resilience**. Specifically:

1. **Improved Decision-Making:** Companies leveraging digital accounting tools experience **faster, more accurate, and strategically relevant decision-making**, aligning with the research question: *Does DMA adoption enhance managerial decision-making?*
2. **Strengthened Financial Resilience:** Firms adopting DMA demonstrate greater **ability to withstand and adapt to financial disruptions**, addressing the research question: *Does DMA adoption enhance financial resilience under economic uncertainty?*

These findings provide empirical support for the **Resource-Based View (RBV)**, which posits that technological capabilities constitute strategic assets, and the **Dynamic Capabilities Theory**, which emphasizes the role of digital tools in enabling firms to adapt to changing environments (Teece, 2018; Li et al., 2022).

In line with recent literature, this study highlights that **digital transformation in accounting is no longer merely operational**—it is a **strategic driver of resilience and decision quality** in EU companies (Bhimani, 2021; Granlund & Malmi, 2020; Marqués & Ferreira, 2021)

## 6. Conclusion and recommendations

Based on the descriptive results, it can be concluded that participants exhibit a moderate level of financial resilience (Mean = 3.367, SD = 0.971) and a slightly lower adoption of digital management accounting (Mean = 3.098, SD = 0.913). These findings align with previous literature indicating that while organizations often maintain sufficient financial stability, the adoption of digital accounting tools is still developing and not fully integrated into managerial practices (Author, Year). The methodology of this study, which employed a structured survey and cross-sectional design with 155 participants, provided a clear snapshot of current practices but may have limitations in capturing long-term behavioral trends. The results highlight a positive, though not optimal, relationship between digital management accounting adoption and financial resilience, suggesting that organizations leveraging digital tools more effectively are likely to strengthen their capacity to manage financial uncertainties. In addition, the variation in responses (as shown by the standard deviations) points to differing levels of experience and comfort with digital tools among participants, which is consistent with prior research emphasizing the importance of training and organizational support in technology adoption.

Recommendations include targeted training programs for managers, implementation of user-friendly digital accounting platforms, and organizational initiatives to promote consistent use of digital tools. These measures are expected to enhance both the adoption of digital management accounting and the financial resilience of organizations.

**Limitations** of this study involve the moderate sample size (N = 155), reliance on self-reported data, and the cross-sectional nature of the survey, which prevents causal inferences. Future research should employ larger samples, longitudinal designs, and possibly mixed-method approaches to better understand the dynamics between digital management accounting and financial resilience over time.

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# The Economic Relevance of Contractual Service Margin Intensity under IFRS 17: Early Cross-Country Evidence from Life Insurers

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**Abstract**

This study examines the economic relevance of Contractual Service Margin (CSM) intensity under IFRS 17 in an international sample of life insurers. Using 66 firm-year observations from 33 insurers across 17 countries during 2023–2024, the study tests whether CSM intensity is associated with return on equity (ROE), cost of equity, and analyst forecast error. The findings show that CSM intensity does not have statistically significant incremental explanatory power for any of the examined outcomes once conventional firm characteristics are controlled for. In contrast, firm size, leverage, and analyst coverage emerge as more robust determinants, particularly for profitability and cost of equity. These results suggest that, in the early post-adoption period, the informational value of the CSM is not captured by a single scaled measure in isolation. The study contributes to the emerging empirical literature on IFRS 17 by providing early cross-country evidence and highlighting the importance of firm characteristics and the information environment in shaping economic outcomes.

Keywords: IFRS 17; Contractual Service Margin; CSM intensity; life insurance; cost of equity; analyst forecast error

## *A. 1. Introduction*

Over the past decades, financial reporting in the insurance industry has been shaped by a combination of local accounting practices and transitional standards, often limiting comparability and obscuring the underlying economics of insurance contracts. IFRS 17 represents a fundamental change in this setting. By replacing premium-based accounting with a service-based model of profit recognition, the standard introduces a more structured and conceptually coherent framework for measuring insurance contracts. At the centre of this framework is the Contractual Service Margin (CSM), which represents the unearned profit that insurers expect to recognize over the period in which contractual services are provided.

Despite the central role of the CSM in IFRS 17, its empirical relevance remains uncertain. While the standard gives the CSM clear conceptual importance, it is still unclear whether the relative prominence of the CSM within a firm's reporting structure is associated with observable economic outcomes. In particular, it remains an open question whether higher CSM intensity is linked to stronger profitability, lower cost of equity, or lower analyst forecast error.

This issue remains underexplored in the existing literature. Much of the IFRS 17 discussion has focused on technical implementation, measurement approaches, and disclosure requirements. By contrast, there is still limited cross-country empirical evidence on whether IFRS 17-based measures, especially CSM intensity, help explain firm-level accounting performance, market-based outcomes, and the information environment. As a result, the economic interpretation of IFRS 17 in the post-adoption period is still only partially developed.

Against this background, this study examines whether CSM_INTENSITY is associated with three outcomes in an international sample of life insurers: return on equity (ROE), cost of equity (CO_EQUITY), and analyst forecast error (FE_ERROR). Focusing on the first two years of mandatory IFRS 17 reporting, the paper provides early evidence on whether this central IFRS 17 metric has incremental explanatory value once standard firm characteristics are taken into account.

This study uses publicly available firm-level financial statements and market data and does not involve human participants. Therefore, formal ethical approval was not required.

The paper makes three contributions. First, it provides early cross-country evidence on the association between CSM intensity and firm outcomes under IFRS 17. Second, it shows that, in the initial post-adoption period, conventional firm characteristics such as size, leverage, and analyst coverage remain more informative than CSM intensity in explaining profitability and market outcomes. Third, it highlights the limits of interpreting CSM intensity as a standalone indicator of economic strength or market credibility.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature and develops the study's theoretical background. Section 3 describes the sample, variables, and empirical methodology. Section 4 presents the empirical results. Section 5 concludes.

## B. 2. Literature Review

*2.1 IFRS 17 and the role of the CSM.* IFRS 17 introduced a fundamental shift in the way insurance performance is recognized and reported. Under the previous framework, profitability was often interpreted through premium flows and locally embedded accounting practices, limiting comparability across firms. IFRS 17 replaced this approach with a service-based model in which profit is recognized over time as insurance services are provided rather than when premiums are received (Palmborg et al., 2020; Pucci et al., 2023; Tominac, 2023). This change affects both the timing of earnings recognition and the structure of financial statements, with direct implications for how insurer performance is interpreted.

At the center of this framework is the contractual service margin (CSM). In life insurance, the CSM represents the unearned profit that insurers expect to recognize as they fulfill their contractual obligations (Yousuf et al., 2021). It is therefore a key mechanism through which IFRS 17 defers and allocates profitability over time. Rather than reflecting immediately realized earnings, reported income under IFRS 17 incorporates the gradual release of previously deferred profit, together with updates arising from changes in assumptions and experience (Yousuf et al., 2021; Yousuf & Mirin, 2021).

This shift has important implications for financial analysis. Because IFRS 17 alters both the composition and timing of earnings, traditional performance indicators based solely on current-period income may no longer provide a complete picture of insurer performance (Pucci et al., 2023). As a result, balance-sheet-based measures such as the CSM may become more relevant for understanding the economic position of insurers.

*2.2 Why CSM may matter economically.* There are several reasons why CSM intensity may be economically relevant. First, a higher CSM may indicate a larger stock of deferred future profit embedded in existing insurance contracts. In the life insurance context, this may reflect profitable long-duration business that is expected to generate earnings over time as services are delivered (Yousuf et al., 2021). From this perspective, firms with higher CSM intensity may be expected to exhibit stronger profitability, even if the relationship is not immediate or mechanical.

Second, the CSM may influence investor perception. Prior research in insurance accounting suggests that investors value information that captures the economic value of future profitability, rather than relying solely on current reported earnings (Wu & Hsu, 2011). Since IFRS 17 emphasizes the timing and structure of future profit recognition, the CSM may provide additional information relevant for assessing firm value and risk. More broadly, accounting changes that improve the representation of future cash flows can have implications for capital market interpretation and required returns (Post et al., 2007).

Third, the CSM may affect the information environment faced by analysts. If IFRS 17 disclosures provide clearer insight into the stock of deferred earnings and the pattern of future profit release, analysts may be able to form more accurate expectations about firm performance. This could, in principle, reduce forecast error and improve the efficiency of market interpretation. Some studies also suggest that IFRS 17 may influence profitability and solvency assessments, further linking accounting changes to economic outcomes (Hamza et al., 2024).

Finally, in cross-country settings, scaled measures such as CSM intensity may be particularly useful. IFRS 17 reporting depends heavily on assumptions, contract characteristics, and measurement choices, which can make raw accounting levels difficult to compare across firms. Ratio-based measures may therefore provide a more consistent basis for analysis (Yousuf et al., 2021; Zelinová et al., 2022).

Overall, these arguments suggest that CSM intensity may be associated with accounting performance, investor-required returns, and analyst interpretation. However, the strength and consistency of these relationships remain open empirical questions.

*2.3 Why the effect may be weak or unclear.* Despite its conceptual importance, the economic relevance of the CSM may be difficult to detect in practice. One key reason is the reliance of IFRS 17 on judgment and estimation. The measurement of the CSM depends on assumptions about future cash flows, discount rates, and risk adjustments, which can vary across firms and over time (Yousuf et al., 2021). As a result, similar economic activities may produce different reported CSM values, limiting comparability.

A second challenge concerns disclosure heterogeneity and transition differences. Although IFRS 17 was intended to improve transparency, early implementation evidence indicates that comparability remains incomplete. Firms differ in their transition approaches, disclosure practices, and use of alternative performance measures, which complicates cross-firm analysis (ter Hoeven et al., 2024). Moreover, IFRS 17 affects not only external reporting but also internal planning and performance measurement systems, adding further complexity to the interpretation of reported figures (Lindner et al., 2024).

The institutional and operational complexity of the standard reinforces these concerns. The development of IFRS 17 involved a lengthy and contested due-process, reflecting the difficulty of defining consistent recognition and measurement principles for insurance contracts (Arce et al., 2023). In addition, the adoption of IFRS 17 has significant implications for audit and assurance processes, as the standard introduces complex estimates, judgement-intensive measurements, and increased risks of material misstatement (Global Public Policy Committee, 2021; EY, 2020).

A third consideration is the early stage of adoption. Because the period immediately following IFRS 17 implementation is characterized by learning and adjustment, market participants may not yet fully incorporate the new information into their decisions. While IFRS 17 is generally expected to improve reporting quality, its practical effects on interpretation and comparability may take time to materialize (Tominac, 2023; Dahiyat & Owais, 2021; Alhawtmeh, 2023).

Taken together, these factors suggest that the relationship between CSM intensity and firm outcomes may be weak, conditional, or difficult to observe, particularly in the early years of IFRS 17 adoption.

*2.4 Research gap.* The existing literature provides important insights into IFRS 17, particularly regarding its conceptual foundations, measurement challenges, and expected effects on financial reporting (Yousuf et al., 2021; Palmborg et al., 2020; ter Hoeven et al., 2024). Other studies examine the potential impact of IFRS 17 on reporting quality, profitability, and solvency, often in specific institutional settings (Dahiyat & Owais, 2021; Alhawtmeh, 2023; Hamza et al., 2024).

At the same time, a significant portion of the literature remains focused on technical aspects of the standard, such as the measurement of insurance liabilities and the estimation of risk adjustment, rather than on firm-level economic outcomes (Signorelli et al., 2022; Carlehed, 2023; Essam & Morgan, 2025). As a result, there is still limited empirical evidence on whether CSM-based measures are associated with observable accounting and market outcomes following IFRS 17 adoption.

In particular, cross-country evidence remains scarce on whether CSM intensity helps explain profitability, cost of equity, and analyst forecast accuracy in the early post-adoption period. This gap is especially relevant in the life insurance sector, where the CSM represents a major component of reported insurance liabilities and a key carrier of deferred future profit.

The present study addresses this gap by examining whether CSM intensity is associated with return on equity (ROE), cost of equity (CO_EQUITY), and analyst forecast error (FE_ERROR) in an international sample of life insurers. By focusing on the first years of IFRS 17 implementation, the study provides initial evidence on whether CSM intensity has incremental explanatory value beyond traditional firm characteristics.

*2.5. Hypothesis Development.* The literature reviewed above suggests that IFRS 17 has changed the informational structure of insurance reporting, but it does not imply that any single IFRS 17 measure should mechanically explain firm outcomes. In particular, the contractual service margin (CSM) is conceptually important because it represents unearned profit that is recognized over time as insurance services are provided (Yousuf et al., 2021). At the same time, the interpretation of the CSM depends on assumptions, disclosure practices, transition choices, and broader firm context, which may limit its comparability across insurers (Palmborg et al., 2020; ter Hoeven et al., 2024). For this reason, the present study treats CSM intensity as a potentially informative, but not self-sufficient, indicator of insurer economics under IFRS 17.

CSM intensity and profitability. A higher CSM intensity may, in principle, be associated with stronger profitability. In life insurance, a relatively larger CSM may indicate a greater stock of deferred future profit embedded in in-force business, reflecting profitable long-duration contracts and the expectation of earnings to be released over time through service provision (Yousuf et al., 2021). Because IFRS 17 shifts the recognition of profit from a premium-based logic toward a service-based logic, deferred profitability may carry information that is relevant for understanding firm performance (Palmborg et al., 2020).

However, the expected relationship is not straightforward. Profitability, especially when measured by return on equity, is influenced by many factors beyond deferred future profit, including firm size, leverage, operational efficiency, and broader business conditions. In addition, IFRS 17 changes the composition and presentation of earnings, which means that conventional profitability ratios do not map cleanly onto any single balance-sheet component such as the CSM (Pucci et al., 2023). For this reason, CSM intensity is not expected to determine profitability on its own, but it may still have incremental explanatory value.

Accordingly, the first hypothesis is stated as follows: H1. CSM intensity is associated with profitability (ROE).

CSM intensity and cost of equity. The link between CSM intensity and cost of equity is also theoretically plausible, but indirect. If a higher CSM intensity reflects stronger future profitability embedded in existing contracts, investors may interpret it as a favorable signal about the insurer's earnings capacity and economic position. Prior research suggests that capital markets value information that improves understanding of future profitability and reduces uncertainty about firm prospects (Wu & Hsu, 2011; Post et al., 2007). Under this view, CSM intensity may be associated with a lower required return on equity.

At the same time, this relation may be weak or difficult to observe in the early years of IFRS 17. Disclosure heterogeneity, transition differences, and the principle-based nature of the standard may limit the extent to which investors interpret CSM-related information consistently across firms (ter Hoeven et al., 2024). As a result, market participants may respond less to CSM intensity itself than to the broader information environment in which that metric is disclosed and interpreted.

The second hypothesis is therefore formulated in general association form: H2. CSM intensity is associated with cost of equity (CO_EQUITY).

CSM intensity and analyst forecast error. A similar logic applies to analyst forecast error. If IFRS 17 disclosures improve the visibility of deferred future earnings, analysts may be able to form more accurate expectations about insurer performance. In that sense, CSM intensity could be associated with lower forecast error by providing information about the stock of unearned profit expected to be released in future periods (Yousuf et al., 2021).

Yet here too the relationship is unlikely to be mechanical. The CSM is shaped by firm-specific assumptions, model choices, and the pattern of service release, all of which may reduce its interpretability for external users. In settings where disclosures remain uneven or where analysts are still adjusting to the new reporting regime, forecast error may continue to depend more heavily on firm size, analyst following, and overall disclosure quality than on CSM intensity itself (ter Hoeven et al., 2024).

Therefore, the third hypothesis is stated as follows: H3. CSM intensity is associated with analyst forecast error (FE_ERROR).

The role of firm characteristics. Although the main purpose of this study is to examine the role of CSM intensity, prior literature indicates that firm characteristics remain important determinants of both accounting and market outcomes. Size, leverage, and analyst coverage are likely to shape profitability, financing costs, and forecast precision more directly than any single IFRS 17 metric. Larger firms may benefit from greater visibility, more developed reporting infrastructures, and stronger access to capital markets, while leverage affects the relation between earnings, capital, and perceived risk. Analyst coverage, in

turn, reflects the depth of external information intermediation and may reduce financing frictions and interpretive uncertainty (Post et al., 2007; Alhawtmeh, 2023).

For this reason, the empirical objective of the study is not to treat CSM intensity as a standalone determinant of firm outcomes, but to examine whether it retains explanatory value after controlling for conventional firm characteristics. This approach is consistent with the broader view that IFRS 17 metrics may matter economically, but only within a wider structural and informational context.

## *C. 3. Methodology*

*3.1 Sample and data.* This study examines the early post-adoption period of IFRS 17 using a cross-country panel of life insurers and insurance groups with material life insurance operations over 2023–2024. These years represent the first two reporting years under mandatory IFRS 17 implementation and therefore provide a suitable setting to assess the empirical relevance of IFRS 17-based balance sheet measures.

The sample comprises 33 insurers or insurance groups operating across 17 countries: Austria, Australia, Belgium, Canada, Croatia, France, Germany, Italy, the Netherlands, Poland, Portugal, Romania, South Africa, Spain, Sweden, Switzerland, and the United Kingdom. Firms were identified based on the availability of IFRS 17 financial statements and the disclosure of life insurance operations.

The following inclusion criteria were applied:

(i) availability of IFRS 17 financial statements for 2023 and/or 2024;

(ii) disclosure of contractual service margin (CSM) and insurance contract liabilities;

(iii) availability of life-segment financial data, including insurance revenue and net income; and

(iv) sufficient information to construct all variables used in the empirical analysis.

The sample includes both stand-alone life insurers and composite insurance groups with identifiable life insurance segments. Firms were excluded if IFRS 17 disclosures were incomplete or did not allow consistent identification of CSM-based measures. No observations were retained without meeting these criteria.

After applying these criteria, the final accounting sample consists of 66 firm-year observations.

Market-based variables (cost of equity, analyst forecast error, and analyst coverage) are not available for all firms. This is primarily due to the inclusion of non-listed entities and differences in data availability across jurisdictions. As a result, the usable sample for market-based regressions is reduced to 50 firm-year observations.

IFRS 17 accounting variables were manually collected from audited consolidated annual reports, including IFRS 17 notes, insurance contract liability disclosures, and segment reporting tables. Particular attention was given to CSM roll-forward disclosures, insurance revenue, and life-segment performance measures to ensure consistent variable construction across firms.

Market and analyst variables were obtained from publicly available market data and analyst coverage information associated with each firm.

Given the cross-country nature of the sample and differences in firm size, reporting currency, and disclosure practices, the analysis relies on scaled variables to improve comparability across firms.

*3.2 Variable definitions.* The empirical design tests whether CSM intensity is associated with accounting performance, market-based outcomes, and analyst forecast accuracy.

ROE is defined as net income divided by equity and serves as the primary measure of accounting performance. It captures firm-level profitability from the perspective of equity holders.

CO_EQUITY represents the firm-level cost of equity and proxies for investor-required returns. It is used to assess whether firms with stronger deferred profit positions face lower financing costs.

FE_ERROR measures analyst forecast error and is defined as the absolute difference between analyst consensus forecast and actual earnings, scaled by actual earnings. This variable captures the accuracy of external expectations and reflects the quality of the firm's information environment.

The main explanatory variable, CSM_INTENSITY, is defined as closing contractual service margin (CSM) divided by insurance revenue. This ratio captures the relative importance of deferred future profit under IFRS 17 and is preferred to absolute CSM levels in a cross-country setting. Economically, higher values indicate a larger stock of unearned profit relative to current revenue generation.

Three control variables are included.

SIZE_LN_TA is the natural logarithm of total assets and controls for firm size, scale effects, and market visibility.

LEVERAGE is defined as insurance contract liabilities divided by equity and captures capital structure and balance-sheet pressure.

ANALYST_COUNT measures the number of analysts issuing earnings forecasts for the firm and serves as a proxy for external information intermediation.

*3.3 Data treatment.* Prior to estimation, the dataset was cleaned for formatting inconsistencies, including differences in decimal notation, missing values, and non-numeric placeholders. Observations with unavailable market data were excluded from market-based regressions but retained in the accounting analysis.

Because firms report in different currencies and vary substantially in economic scale, all key variables are expressed in scaled form. This approach reduces the influence of size and currency effects and improves cross-firm comparability in a cross-country setting.

*3.4 Empirical models.* The empirical analysis is based on three linear regression models, each corresponding to one of the study's outcome variables.

The first model examines accounting performance:

$$ROE_{it}=\beta_0+\beta_1 CSM\_INTENSITY_{it}+\beta_2 SIZE\_LN\_TA_{it}+\beta_3 LEVERAGE_{it}+\beta_4 ANALYST\_COUNT_{it}+\varepsilon_{it} \quad (1)$$

The second model examines cost of equity:

$$CO\_EQUITY_{it}=\beta_0+\beta_1 CSM\_INTENSITY_{it}+\beta_2 SIZE\_LN\_TA_{it}+\beta_3 ANALYST\_COUNT_{it}+\varepsilon_{it} \quad (2)$$

The third model examines analyst forecast error:

$$FE\_ERROR_{it}=\beta_0+\beta_1 CSM\_INTENSITY_{it}+\beta_2 SIZE\_LN\_TA_{it}+\beta_3 ANALYST\_COUNT_{it}+\varepsilon_{it} \quad (3)$$

The specifications are intentionally parsimonious. Given the limited sample size, the short post-adoption window, and the cross-country nature of the dataset, the objective is not to estimate a saturated model but to assess whether CSM intensity has incremental explanatory value after controlling for a small set of core firm characteristics. The selected controls reflect the main structural and informational features expected to affect the dependent variables: firm size, capital structure, and analyst following. Leverage is included only in the ROE model because it is most directly relevant to accounting returns on equity.

Because the study focuses on early evidence from the first two IFRS 17 reporting years, the estimated coefficients should be interpreted as partial associations rather than causal effects.

*3.5 Analytical approach.* The analysis proceeds in three steps. First, descriptive statistics are reported to summarize the distribution of the variables and to document the economic heterogeneity of the sample. Second, pairwise correlations are examined to provide an initial view of the relationships among the main variables and to identify potential overlap among the controls. Third, the regression models are estimated to test whether CSM intensity is associated with the outcome variables after conditioning on the selected firm characteristics.

This sequence is appropriate for the present study because it moves from basic sample structure to conditional inference in a transparent manner. It also allows the regression results to be interpreted in light of the underlying cross-sectional variation in firm size, leverage, market visibility, and analyst coverage.

*3.6 Diagnostic checks and robustness.* To support the interpretability of the regression results, the analysis incorporates a set of standard diagnostic and robustness procedures.

First, multicollinearity was assessed using tolerance values and variance inflation factors (VIF). These diagnostics are reported in the Results section and indicate that collinearity does not reach levels that would compromise coefficient interpretation. This check is particularly relevant given the positive association between firm size and analyst coverage in the sample.

Second, all reported regressions were estimated with heteroskedasticity-robust standard errors. This adjustment is appropriate in a small cross-sectional setting, where the assumption of constant error variance may not hold.

Third, the analysis includes sensitivity checks to reduce the risk that the results are driven by extreme observations or by a single specification choice. Where reported, these checks include winsorized versions of the main variables and alternative model specifications. The purpose of these exercises is not to replace the baseline models, but to verify whether the main inferences are stable under reasonable variations in estimation.

Taken together, these procedures indicate that the reported results are not mechanically driven by collinearity, heteroskedasticity, or isolated observations. They also support the use of a restrained empirical design, which is appropriate given the limited sample size and the early post-adoption nature of the data.

*3.7 Methodological scope.* Two features of the design should be emphasized. First, the study relies on scaled variables rather than raw accounting amounts. This is essential in an international sample where firms differ substantially in reporting currency, economic scale, and liability structure. Relative measures are therefore more suitable for cross-firm comparison than absolute balance-sheet levels.

Second, the analysis is deliberately positioned as early evidence rather than as a test of long-run IFRS 17 equilibrium effects. The purpose is to evaluate whether CSM intensity is already associated with firm outcomes in the first two years of mandatory adoption. The study does not attempt to model all determinants of insurer performance; rather, it examines whether one prominent IFRS 17 measure adds explanatory content beyond standard firm characteristics.

## II. 4. RESULTS

III. *4.1 DESCRIPTIVE STATISTICS.* TABLE 1 REPORTS THE DESCRIPTIVE STATISTICS FOR THE MAIN VARIABLES. THE SAMPLE CONSISTS OF 66 FIRM-YEAR OBSERVATIONS FROM 33 FIRMS OVER 2023–2024, WITH 50 OBSERVATIONS AVAILABLE FOR THE

MARKET-BASED VARIABLES. THE SUMMARY STATISTICS INDICATE SUBSTANTIAL CROSS-SECTIONAL HETEROGENEITY IN FIRM SIZE, PROFITABILITY, LEVERAGE, CSM INTENSITY, AND ANALYST COVERAGE.

**Table 1.** Descriptive statistics of main variables

| | SIZE_LN_TA | ROE | LEVERAGE | CSM_INTENSITY | ANALYST_COUNT | CO_EQUITY | FE_ERROR |
|---|---|---|---|---|---|---|---|
| **Valid** | 66 | 66 | 66 | 66 | 66 | 50 | 50 |
| **Missing** | 0 | 0 | 0 | 0 | 0 | 16 | 16 |
| **Median** | 11.96 | 0.108 | 0.203 | 0.111 | 13.50 | 0.094 | 0.016 |
| **Mean** | 11.61 | 0.126 | 0.193 | 0.276 | 11.86 | 0.097 | 0.022 |
| **Std. Deviation** | 1.565 | 0.095 | 0.065 | 0.280 | 8.894 | 0.012 | 0.012 |
| **Minimum** | 7.660 | -0.061 | 0.007 | 0.010 | 0.000 | 0.079 | 0.003 |
| **Maximum** | 13.88 | 0.473 | 0.312 | 0.990 | 28.00 | 0.134 | 0.045 |

Firm size varies considerably, with SIZE_LN_TA ranging from 7.66 to 13.88. Profitability is also dispersed, as ROE ranges from -0.061 to 0.473, with a mean of 0.126 and a median of 0.108. The main explanatory variable, CSM_INTENSITY, exhibits similarly wide variation, ranging from 0.010 to 0.990, with a mean of 0.276 and a median of 0.111. This spread indicates that the relative prominence of deferred future profit under IFRS 17 differs substantially across firms.

The data also show marked differences in external information coverage. ANALYST_COUNT ranges from 0 to 28, suggesting substantial variation in market visibility and information intermediation. By contrast, the market-based variables are available for a smaller subsample, reflecting the inclusion of non-listed entities and uneven market-data availability across jurisdictions.

Overall, the descriptive statistics confirm that the sample is economically heterogeneous. This variation provides a suitable setting for examining whether CSM intensity has explanatory value beyond standard firm characteristics.

*4.2 Correlation analysis.* Table 2 reports the pairwise correlations among the main variables. The matrix provides an initial view of the unconditional relationships before introducing controls.

**Table 2.** Correlation matrix of variables

| | SIZE_LN_TA | ROE | LEVERAGE | CSM_INTENSITY | ANALYST_COUNT | CO_EQUITY | FE_ERROR |
|---|---|---|---|---|---|---|---|
| **SIZE_LN_TA** | 1.000 | 0.128 | 0.337 | 0.203 | 0.669 | -0.062 | 0.247 |
| **ROE** | 0.128 | 1.000 | -0.388 | 0.020 | -0.102 | -0.176 | -0.011 |
| **LEVERAGE** | 0.337 | -0.388 | 1.000 | 0.280 | 0.396 | 0.119 | 0.130 |
| **CSM_INTENSITY** | 0.203 | 0.020 | 0.280 | 1.000 | 0.293 | -0.178 | -0.093 |
| **ANALYST_COUNT** | 0.669 | -0.102 | 0.396 | 0.293 | 1.000 | -0.460 | 0.091 |
| **CO_EQUITY** | -0.062 | -0.176 | 0.119 | -0.178 | -0.460 | 1.000 | 0.260 |
| **FE_ERROR** | 0.247 | -0.011 | 0.130 | -0.093 | 0.091 | 0.260 | 1.000 |

The most notable feature is the weak bivariate association between CSM_INTENSITY and the three outcome variables. The correlation with ROE is close to zero (r = 0.020), indicating no meaningful unconditional relation between CSM intensity and current profitability. The correlations with the market-based variables are also modest, at -0.178 with CO_EQUITY and -0.093 with FE_ERROR. Although these signs are directionally consistent with the underlying expectations, their magnitudes suggest that any association is weak at the bivariate level.

By contrast, conventional firm characteristics display stronger correlations. SIZE_LN_TA and ANALYST_COUNT are strongly positively correlated (r = 0.669), indicating that larger firms tend to attract greater analyst coverage. ANALYST_COUNT

is also negatively correlated with CO_EQUITY (r = -0.460), consistent with the view that greater external coverage is associated with lower financing costs.

Overall, the correlation matrix suggests that CSM_INTENSITY has limited unconditional association with the outcome variables, whereas firm size and analyst coverage appear more closely related to market-based outcomes. This pattern reinforces the use of multivariate regression analysis to evaluate whether CSM intensity retains explanatory value once standard firm characteristics are taken into account.

*4.3 Regression results: ROE.* Table 3 reports the regression results for ROE. The model is statistically significant overall and explains a moderate share of the variation in profitability.

**IV. TABLE 3.** REGRESSION RESULTS FOR ROE MODEL

| Variable | Coefficient | Std. Error | t | p-value |
|---|---|---|---|---|
| **CSM_INTENSITY** | 0.046 | 0.040 | 1.166 | 0.248 |
| **SIZE_LN_TA** | 0.025 | 0.009 | 2.792 | 0.007 |
| **LEVERAGE** | -0.695 | 0.179 | -3.873 | <0.001 |
| **ANALYST_COUNT** | -0.002 | 0.002 | -1.498 | 0.139 |
| **Constant** | -0.016 | 0.095 | -0.170 | 0.865 |
| Model statistics | Value | | | |
| **Observations** | 66 | | | |
| **$R^2$** | 0.263 | | | |
| **Adjusted $R^2$** | 0.215 | | | |
| **F-statistic** | 5.454 (p < 0.001) | | | |

CSM_INTENSITY is not statistically significant, indicating that the data do not support incremental explanatory power for ROE once conventional firm characteristics are included. Among the controls, SIZE_LN_TA is positively associated with profitability, while LEVERAGE is negatively associated with ROE. ANALYST_COUNT is not statistically significant.

Overall, the results do not support Hypothesis 1. In this sample, profitability appears to be more closely related to standard structural firm characteristics (particularly size and leverage) than to CSM intensity.

*4.4 Regression results: Cost of Equity.* Table 4 reports the regression results for CO_EQUITY. The model is statistically significant overall and explains a meaningful share of the variation in the cost of equity.

V. **TABLE 4.** REGRESSION RESULTS FOR COST OF EQUITY (CO_EQUITY)

| Variable | Coefficient | Std. Error | T | p-value |
|---|---|---|---|---|
| **CSM_INTENSITY** | -0.001 | 0.005 | -0.246 | 0.806 |
| **SIZE_LN_TA** | 0.005 | 0.001 | 3.711 | <0.001 |
| **ANALYST_COUNT** | -0.002 | 0.000329 | -5.262 | <0.001 |
| **Constant** | 0.064 | 0.013 | 4.810 | <0.001 |
| Model statistics | Value | | | |
| **Observations** | 50 | | | |
| **$R^2$** | 0.397 | | | |
| **Adjusted $R^2$** | 0.357 | | | |
| **F-statistic** | 10.08 (p < 0.001) | | | |

CSM_INTENSITY is not statistically significant, indicating that the data do not support an independent association between CSM intensity and the cost of equity in the market-data subsample.

By contrast, the control variables are more informative. ANALYST_COUNT is negatively associated with CO_EQUITY, consistent with the view that stronger analyst following is linked to lower information frictions and lower required returns. SIZE_LN_TA is positively associated with CO_EQUITY. Because this sign is not the conventional expectation, it should be interpreted cautiously. In this sample, it may reflect cross-country composition effects, differences in insurer business models, or features of the cost-of-equity proxy rather than a general size effect.

Overall, the results do not support Hypothesis 2. In this setting, the cost of equity appears to be more closely related to firm characteristics (especially analyst coverage) than to CSM intensity.

*4.5 Regression results: Analyst Forecast Error.* Table 5 reports the regression results for FE_ERROR. Unlike the previous specifications, this model is not statistically significant overall and has limited explanatory power.

**Table 5.** Regression results for analyst forecast error (FE_ERROR)

| Variable | Coefficient | Std. Error | t | p-value |
|---|---|---|---|---|
| **CSM_INTENSITY** | -0.004 | 0.006 | -0.661 | 0.512 |
| **SIZE_LN_TA** | 0.003 | 0.002 | 1.854 | 0.070 |
| **ANALYST_COUNT** | -0.000343 | 0.000408 | -0.841 | 0.405 |
| **Constant** | -0.009 | 0.016 | -0.569 | 0.572 |
| Model statistics | Value | | | |
| **Observations** | 50 | | | |
| **$R^2$** | 0.090 | | | |
| **Adjusted $R^2$** | 0.031 | | | |
| **F-statistic** | 1.522 (p = 0.221) | | | |

CSM_INTENSITY is not statistically significant, indicating that the data do not provide evidence of a reliable association between CSM intensity and analyst forecast accuracy in the market-data subsample.

The control variables are also weak. SIZE_LN_TA is only marginally associated with forecast error, while ANALYST_COUNT is not statistically significant. Relative to the cost-of-equity model, this suggests that analyst forecast accuracy may depend on additional factors not captured in the present specification.

Accordingly, the FE_ERROR model is best interpreted as an exploratory supplementary information-environment test rather than as a central result. The results do not support Hypothesis 3.

*4.6 Discussion of findings.* The results yield a consistent pattern across all three specifications. CSM_INTENSITY does not emerge as a statistically significant explanatory variable for profitability, cost of equity, or analyst forecast error. Although the estimated coefficients are directionally consistent with the theoretical expectations—positive for ROE and negative for both CO_EQUITY and FE_ERROR—the evidence does not indicate that CSM intensity, as measured in this study, has strong incremental explanatory power once standard firm characteristics are taken into account.

This conclusion remains unchanged under the diagnostic and robustness procedures described in Section 3.5. The main inferences are therefore not driven by multicollinearity, heteroskedasticity, or isolated observations. In that sense, the absence of statistical significance for CSM_INTENSITY should not be interpreted as a mechanical artifact of model instability, but as a substantive feature of the evidence observed in this early cross-country sample.

The finding is informative in the context of early IFRS 17 adoption. It suggests that the relative prominence of the contractual service margin is not, by itself, sufficient to explain firm-level accounting or market outcomes in the first two years of implementation. This interpretation is consistent with the broader IFRS 17 literature, which emphasizes that CSM-related figures are embedded in a reporting environment shaped by assumptions, disclosure choices, transition effects, and cross-firm heterogeneity (Yousuf et al., 2021; ter Hoeven et al., 2024).

At the same time, the results indicate that conventional firm characteristics remain more closely associated with the outcomes examined here. In the accounting model, firm size and leverage are more informative than CSM intensity. In the cost-of-equity model, analyst coverage is the most consistently relevant explanatory factor. These findings are in line with prior capital-market research showing that structural firm characteristics and information intermediation continue to play a central role in shaping investor responses and financing conditions (Post et al., 2007).

Overall, the results support a cautious interpretation of IFRS 17-based indicators. The CSM is central to the mechanics of the standard, but its empirical relevance does not appear to be captured adequately by a single scaled measure in isolation. The evidence instead suggests that the usefulness of the CSM depends not only on its size, but also on the broader reporting and informational context in which it is disclosed and interpreted.

## VI. 5. Conclusions

This study examines whether CSM_INTENSITY, as a scaled measure of deferred future profit under IFRS 17, is associated with profitability, cost of equity, and analyst forecast error in an international sample of life insurers during 2023–2024. The analysis provides early cross-country evidence from the first two years of mandatory IFRS 17 reporting.

The results are consistent across the three main models. CSM_INTENSITY does not emerge as a statistically significant explanatory variable for ROE, CO_EQUITY, or FE_ERROR. Although the estimated coefficients are directionally aligned with the underlying expectations, the evidence does not indicate that CSM intensity on its own provides strong incremental explanatory value for firm outcomes in this early post-adoption setting.

By contrast, standard firm characteristics appear more informative. Firm size and leverage are associated with accounting performance, while analyst coverage is strongly related to cost of equity. These findings suggest that, even under IFRS 17, traditional structural and informational variables remain more important than a single CSM-based ratio in explaining cross-sectional variation in firm outcomes.

The study contributes to the emerging empirical literature on IFRS 17 in three ways. First, it provides early cross-country evidence on the association between CSM intensity and firm-level outcomes in the life insurance sector. Second, it shows that caution is warranted when interpreting CSM intensity as a standalone indicator of economic strength or market credibility. Third, it suggests that the empirical relevance of IFRS 17 may depend less on individual balance-sheet metrics in isolation and more on the broader interaction between reporting measures, firm characteristics, and the information environment.

These findings should be interpreted in light of the study's limitations. The sample is relatively small and covers only the first two years of IFRS 17 application. Market-based variables are available for a reduced subsample, and the analysis focuses on a single CSM-based proxy rather than on a broader set of IFRS 17 reporting dimensions. The results should therefore be viewed as early evidence rather than as a definitive assessment of the long-run economic effects of IFRS 17.

Future research could extend this analysis by examining longer post-adoption periods, larger samples, and additional IFRS 17 measures, including disclosure quality, assumption sensitivity, and the interaction between CSM and risk adjustment. Such work would help clarify whether the limited role of CSM intensity documented here reflects the early stage of implementation or a more persistent feature of IFRS 17 reporting.

Overall, the evidence suggests that CSM intensity alone is not sufficient to explain firm performance or market interpretation in the early IFRS 17 period. A fuller understanding of insurer reporting under IFRS 17 is therefore likely to require a broader framework that incorporates both accounting measures and the institutional and informational conditions under which they are interpreted.

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# ERP Systems in Practice: Costs, Types, and Case Studies of Alkaloid and Kostal

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**Abstract**
Enterprise Resource Planning (ERP) systems have become a fundamental component of modern organizations by integrating core business functions into a unified information environment. Rather than operating through isolated departmental applications, enterprises increasingly rely on ERP platforms to connect finance, procurement, manufacturing, logistics, human resources, sales, and quality management through shared data and standardized processes. This paper examines the concept of ERP systems, their major types, and the economic and organizational implications of their implementation. Particular attention is given to the classification of ERP systems by market tier, deployment model, and industry specialization, as well as to the costs and challenges associated with ERP adoption and post-implementation management. To connect theory with practice, the paper analyzes two industrial examples: Alkaloid AD Skopje, whose AlkaSAP platform is based on SAP S/4HANA in a regulated pharmaceutical environment, and the KOSTAL Group, whose ERP landscape combines SAP solutions with Product Lifecycle Management integration in the automotive sector. The analysis shows that ERP systems should not be understood merely as software packages, but as long-term socio-technical infrastructures that shape organizational processes, governance, compliance, and decision-making. The findings also indicate that successful ERP implementation depends not only on technological capabilities, but equally on organizational readiness, user involvement, process standardization, and strategic alignment between business and information systems.
*Key words:* Enterprise Resource Planning (ERP), SAP S/4HANA, SAP Business One, ERP implementation, ERP costs, post-implementation challenges, Product Lifecycle Management (PLM), Alkaloid, KOSTAL, business process integration.

## 1. Introduction: What "deep-tech" means and why it matters

The term "deep tech" is widely used in both academic and startup circles, yet its meaning often becomes diluted through overuse. It is not simply a label for advanced software or artificial intelligence. Rather, deep-tech refers to ventures whose value is rooted in a significant technological breakthrough or in a complex technical integration that is difficult to replicate. What distinguishes these companies is not just the technology itself, but the extent to which that technology fundamentally changes performance, cost structures, or capabilities in a given domain. In that sense, deep tech companies can be understood as organizations that transform scientific or engineering advances into scalable and economically viable products. They typically operate with high research and development intensity, face considerable technical uncertainty, and require specialized expertise alongside substantial capital investment [1].

These characteristics are not just descriptive they directly affect how such ventures are built. Unlike conventional startups, where speed and iteration are often the primary drivers of success, deep-tech startups must balance rapid learning with the need for credible technical validation. A concept alone is rarely sufficient, it must be supported by demonstrable performance and reliability. This shifts the focus from simply "building fast" to building convincingly, where evidence becomes as important as execution.

From an entrepreneurial perspective, one of the most challenging aspects of deep-tech lies in the simultaneous presence of technological and market uncertainty. In many software startups, market risk can be reduced early through user feedback and minimal viable products, while the underlying technology evolves over time. Deep tech ventures, however, often face the opposite constraint. They cannot meaningfully engage customers without first validating a core technical claim, yet achieving that validation may require access to real-world environments, data, or partnerships that are difficult to obtain without initial market traction. This creates a practical tension, evidence is required to secure customers, but customers are often needed to generate that evidence.

Successful founders in this space tend to approach this problem pragmatically. Instead of attempting full scale solutions from the outset, they focus on staged validation developing smaller, targeted experiments that produce credible signals of feasibility. These

intermediate steps do not eliminate uncertainty, but they make it manageable and communicable to investors, partners, and early adopters.

In the context of a smaller economy such as Macedonia, these dynamics become even more pronounced. On one hand, such environments can be surprisingly well suited for deep tech development. Talent can be highly skilled, operational costs are relatively lower, and products particularly in software or intellectual property can be designed for global markets from the beginning. On the other hand, structural limitations remain. The domestic market is limited, access to specialized investors is constrained, and local demand for niche deep-tech solutions may be insufficient in early stages.

As a result, founders are often required to adopt an international perspective much earlier than their counterparts in larger ecosystems. This includes not only targeting global customers, but also combining different sources of funding ranging from grants and public programs to foreign investment. In this setting, policy mechanisms and innovation support programs can play a more significant role than is sometimes assumed. For example, analyses by the World Bank highlight how startup support structures in Macedonia contribute to bridging the gap between early stage research and investment readiness, helping ventures reach a stage where they can attract external capital and generate employment [2].

The implication is not that policy alone drives startup creation, but rather that in smaller ecosystems, these institutional bridges can meaningfully influence whether technically promising ideas evolve into sustainable businesses.

## 2. Deep-Tech vs "Regular" Startups

Deep tech ventures are often described as being "more innovative" than traditional startups, but that framing is misleading. The difference is not simply a matter of degree it lies in the nature of the constraints these companies face. In practice, deep tech startups operate under a distinct set of bottlenecks, failure modes, and expectations around credibility.

One of the clearest differences appears in how risk is structured. Conventional software startups tend to be dominated by market uncertainty is there real demand, will users adopt the product, and can distribution be achieved efficiently? Deep-tech ventures, by contrast, must navigate both market and technological uncertainty at the same time. It is not enough to identify a customer need the underlying system must also function reliably under real world constraints and at a cost that allows for a viable business model. When both dimensions remain unresolved, they tend to reinforce each other. Potential customers hesitate because failure carries higher consequences, while investors face difficulty assessing progress in the absence of clear, short term signals.

A related challenge emerges in what might be described as the "productization gap." Many deep-tech teams reach a working prototype and interpret this as being close to market readiness. In reality, this transition is often where the most demanding work begins. Moving from a controlled demonstration to a dependable product requires addressing edge cases, ensuring operational stability, integrating with existing systems, and meeting expectations around security, documentation, and support. These are not peripheral concerns or bureaucratic layers, they represent the baseline requirements for operating in enterprise, industrial, or clinical environments. It is in this gap, rather than in the initial invention, that many deep tech ventures struggle to progress.

Defensibility is another area where deep-tech is often assumed to have an advantage, although this advantage is not automatic. While patents can play a role in certain sectors, they rarely provide sufficient protection on their own. In practice, defensibility tends to emerge from a combination of factors like proprietary data pipelines, accumulated domain expertise, tightly integrated systems, and, importantly, the ability to embed solutions within existing workflows. Discussions across European deep-tech ecosystems have consistently highlighted the connection between sustained research and development investment, intellectual property, and access to financing [3]. For founders, the challenge is not only to build a technological edge, but to make that edge understandable, credible, and difficult to replicate over time.

Capital requirements further differentiate deep-tech from more conventional startup models. These ventures frequently require significant upfront investment, whether for computational resources, specialized talent, laboratory infrastructure, or regulatory processes. As a result, strategic missteps carry a higher cost. Whereas a typical software startup might pivot relatively quickly and at limited expense, a deep-tech company may invest months of highly specialized effort before realizing that its assumptions do not translate into a viable market opportunity.

Taken together, these factors suggest that deep tech entrepreneurship follows a different logic. It is not simply a matter of applying standard startup practices to more complex technology. Instead, it requires a more deliberate approach to execution, one that balances technical validation, market development, and investor confidence over longer time horizons. The central task for

founders is to manage this process of gradual derisking while maintaining enough momentum and credibility to keep the venture viable.

## 3. From Idea to Realization

A deep-tech startup is rarely built in a straight line. In practice, it evolves through a sequence of decisions that gradually reduce uncertainty while generating evidence that others can trust. Although frameworks are useful for structuring this journey, the real process is more iterative and often less predictable than it appears on paper. Still, it is possible to trace a general progression from an initial problem hypothesis to a scalable business if each step is understood in terms of the specific risk it aims to reduce.

The starting point is not the technology itself, even though many founders instinctively begin there. A more robust approach is to define a problem that is already economically meaningful. In most successful cases, this means identifying a situation where money is being lost, risk is being carried, or inefficiencies are already measurable. Just as importantly, the problem must be constrained by performance limitations, whether in accuracy, cost, latency, or operational complexity. Without such constraints, even a strong technical solution may fail to create real differentiation.

What emerges from this stage is not a vague idea, but a working thesis, something that can be tested and potentially disproven. The difference is subtle but important. A statement like "we will apply AI to improve process X" offers little guidance for execution. In contrast, a claim framed around measurable improvement forces clarity it defines success, sets expectations, and allows for meaningful evaluation. In deep-tech ventures, the value is not in the algorithm itself, but in the extent to which it changes a decision for the buyer.

Once a thesis exists, the next challenge is feasibility. This is often misunderstood as building a convincing demonstration, particularly for investors. In reality, a proof of concept should function as a filter rather than a showcase. Its purpose is to test whether the core assumptions hold under conditions that resemble real world use. This typically involves two layers. First, there is the question of signal whether the necessary data or inputs exist with sufficient quality and consistency. Second, there is the question of system performance, whether the solution can operate within acceptable constraints of cost, latency, and reliability.

At this stage, discipline becomes critical. Without clearly defined checkpoints, teams can spend extended periods refining a solution that ultimately does not translate into a viable product. Structured feasibility gates despite sometimes feeling restrictive serve as a practical mechanism to prevent this kind of drift.

Assuming the technical foundation holds, attention shifts toward the market. In deep-tech, this is not a generic process of "user validation," but a more targeted effort to understand how decisions are actually made within organizations. The distinction between user and buyer becomes particularly important here. A technically impressive system may still fail if it does not address the concerns of the individual responsible for budget, risk, and implementation.

Pilots often act as the bridge between technical validation and commercial adoption, but they introduce their own challenges. When poorly defined, pilots can become open-ended experiments that generate insight without leading to revenue. This situation sometimes referred to informally as "pilot purgatory" is not uncommon. Avoiding it requires treating pilots as structured commitments rather than exploratory collaborations. Success must be defined in advance, and there must be a clear path from validation to a paid agreement.

Even when market interest exists, another transition remains turning a working solution into something that can be reliably deployed. This is where many deep-tech ventures encounter difficulties. A prototype demonstrates possibility, but a product must operate consistently across environments, handle unexpected conditions, and integrate into existing workflows. These requirements are often underestimated because they do not feel like innovation in the traditional sense. However, for most customers, especially in enterprise or regulated domains reliability and predictability are more important than novelty.

Closely related to this is the question of defensibility. While deep-tech is often associated with strong competitive advantages, these advantages rarely come from a single source. Patents may provide partial protection, but in many cases, long-term differentiation depends on less visible factors: proprietary data pipelines, accumulated operational knowledge, and the depth of integration within customer systems. European discussions on deep-tech development frequently emphasize the relationship between sustained R&D investment, intellectual property, and access to financing [3], reinforcing the idea that defensibility is built incrementally rather than declared upfront.

Funding strategy must therefore reflect this staged reality. Deep-tech ventures rarely rely on a single type of capital. Early stages often benefit from non-dilutive funding, which allows teams to explore feasibility without immediate pressure for commercial returns. As the venture progresses, equity investment becomes more relevant, particularly when the focus shifts toward productization and market expansion. In smaller ecosystems such as Macedonia, these funding layers can play an especially important role. Observations by the World Bank highlight how startups can use local support mechanisms to reach a level of maturity that attracts foreign investment and enables growth beyond the domestic market [2].

Finally, the transition to go-to-market and scaling introduces a different set of challenges. Technical superiority alone does not guarantee adoption. Distribution whether through direct sales, partnerships, or platform integration is what ultimately converts technical capability into revenue. Early traction is typically achieved through a focused entry point a narrowly defined segment where the problem is urgent and the value can be clearly demonstrated.

As the company grows, the internal structure must evolve as well. Teams that begin with a strong research orientation need to incorporate product, operational, and commercial expertise. The objective shifts from proving that the technology works to ensuring that it can be delivered consistently, at scale, and with predictable outcomes.

Seen as a whole, the journey from idea to realization in deep-tech is less about following a fixed sequence and more about managing a continuous process of de-risking. Each stage introduces new uncertainties, but also new opportunities to build credibility. The ventures that succeed are typically those that treat this process explicitly designing not just solutions, but the evidence required to make those solutions believable.

## 4. Common Failure Modes and How to Avoid Them

Failure in deep tech ventures rarely happens as a single, visible event. More often, it unfolds gradually through small but persistent losses of credibility, capital, and strategic direction. What makes these failures particularly challenging is that they are not always obvious in the early stages. In many cases, the company appears to be making progress, yet critical weaknesses accumulate beneath the surface.

One of the most frequent patterns is the development of technology without a clearly defined customer. Teams may build impressive demonstrations that showcase technical capability, but when asked who would actually pay for the solution, the answer remains vague. This disconnect usually originates early, at the stage where the initial problem is defined. Without identifying a specific budget owner, a concrete trigger for adoption, and a measurable return on investment, even strong technical work struggles to translate into a viable business.

A related issue emerges in what can be described as the transition from prototype to product. Many deep tech teams succeed in creating systems that work under controlled conditions, yet encounter significant delays when attempting to bring those systems into real world environments. The underlying reason is often not a lack of innovation, but an underestimation of what productization requires. Reliability, security, and integration tend to be treated as secondary concerns, even though they are frequently the primary barriers to adoption. When these aspects are addressed too late, the result is a widening gap between technical potential and practical usability.

Market engagement introduces another set of risks, particularly through the misuse of pilot projects. While pilots are intended to bridge the gap between validation and revenue, they can easily become an endpoint rather than a transition. Companies may accumulate multiple pilot engagements, each generating useful feedback, yet fail to convert any of them into paying customers. This situation often reflects a lack of structure rather than a lack of demand. Without clearly defined success criteria, time constraints, and a decision pathway toward purchase, pilots tend to remain exploratory by default.

Trust also plays a central role, especially in sectors such as healthcare, finance, or regulated enterprise environments. In these contexts, adoption is rarely based on technical performance alone. It depends on a broader set of assurances, including documentation, validation evidence, security practices, and alignment with compliance requirements. When these elements are treated as secondary something to address after initial traction the sales process can stall unexpectedly. What appears as market resistance is often a deficit of trust.

Another subtle but important failure mode relates to how companies think about defensibility. There is a tendency to equate intellectual property with competitive advantage, leading to an emphasis on patent activity or claims of uniqueness that are not

supported by deeper capabilities. In practice, defensibility in deep-tech is cumulative. It develops through the interaction of data, experience, system integration, and distribution. When these layers are missing, formal IP protection has limited impact.

Financial strategy can also introduce failure if it is misaligned with the stage of the company. Insufficient funding can prevent a venture from reaching the level of technical maturity required for market entry. At the same time, excessive funding at an early stage can encourage prolonged research without corresponding commercial validation. Both scenarios reflect a disconnect between capital and progress. A more sustainable approach is to align funding with clearly defined milestones that correspond to reductions in technical or market uncertainty.

Finally, there is the persistent assumption that strong technology will naturally lead to adoption. In reality, distribution is a separate challenge that requires its own design and execution. Without a clear approach to how customers are reached, onboarded, and retained, even technically superior solutions may fail to gain traction. Treating distribution as an afterthought often results in slow growth and inconsistent revenue, regardless of product quality.

Taken together, these patterns suggest that deep-tech failure is rarely about a single wrong decision. It is more often the result of misaligned priorities where technical progress, market understanding, and operational readiness evolve at different speeds. Avoiding these outcomes requires a deliberate effort to keep these elements in balance, ensuring that progress in one area does not mask weaknesses in another.

## 5. Case Study 1 (Macedonia): Pixyle AI

Pixyle AI is a useful deep-tech case because it targets a global commercial domain fashion e-commerce where ROI can be measured relatively quickly. The company describes itself as a visual AI solution specialized in fashion, focusing on product attribution and catalog enrichment that improves product discovery and retail operations [4].

**What problem they solve**

Fashion e-commerce has a structural data problem: large catalogs, visually complex items, inconsistent seller metadata, and constant churn. Poor product attributes degrade search, filtering, and recommendations, while manual tagging is costly and slow. If product discovery is broken, customers cannot find what they want, and conversion suffers. This creates a clear entrepreneurial lever: attribute quality can translate into revenue outcomes and operational savings.

TechCrunch's coverage frames Pixyle's offering around improving product discovery and automating catalog-related workflows, describing the company as launched to improve e-commerce search experiences and announcing a €1 million seed round [5]. Even if marketing language varies, the economic problem is consistent: reduce manual effort and increase the effectiveness of digital shelves.

**What makes it deep-tech**

Pixyle is deep tech not because it is "software," but because its value depends on high-performance computer vision applied to a domain with challenging variance. In practice, the defensibility likely comes from domain specific training data, labeling pipelines, and taxonomies that can consistently translate images into structured product attributes at scale. The hard part is not producing a single accurate prediction, but maintaining reliable performance across real world catalog variation and integrating outputs into systems that retailers actually use.

**How they scaled**

Pixyle's scaling logic resembles a productized B2B platform: once integrated, value scales with catalog volume rather than with Pixyle headcount. EBRD's profile notes Pixyle's international footprint (Amsterdam and Macedonia) and references customers such as Tendam, Otrium, and Miinto, framing the company as serving brands and retailers across markets [6]. Those are meaningful signals in enterprise retail because they imply the company managed integration, procurement, and operational delivery areas where many deep-tech startups stumble.

**Funding signal**

Pixyle's €1 million seed funding led by South Central Ventures is widely reported and provides a concrete credibility signal. The Swiss Entrepreneurship Programme's success story explicitly describes the €1 million seed investment and positions it as enabling growth in the fashion e-commerce segment [7]. The World Bank also references Pixyle in the context of Macedonia's startup ecosystem, describing it as an example of a supported startup that attracted foreign VC investment [2]. Together, these sources support the claim that Pixyle crossed a threshold where technical value translated into investable traction.

## 6. Case Study 2 (Macedonia): ECGalert / Innovation

ECGalert illustrates a different deep-tech archetype: health-tech, where the technical system must earn trust through evidence and clinical usefulness, not merely operational performance. ECGalert is presented as a solution involving wearable sensing and

software for ECG monitoring, aiming to detect abnormalities and provide alerts to patients and doctors [8]. The product is associated with Innovation DOOEL (Skopje), which lists ECGalert among its projects and describes modules such as cloud, diagnostics, and monitoring components [9].

**What problem they solve**

The entrepreneurial problem is continuous or extended ECG monitoring that can detect clinically relevant arrhythmias or early warning signals beyond what short windows capture. Standard Holter monitoring is valuable but time-limited and can miss intermittent events. The opportunity is not merely capturing ECG, it is delivering actionable interpretation and alerting in a way that clinicians trust and patients can use consistently.

**What makes it deep-tech**

ECGalert's deep-tech character comes from the end-to-end system, biosensor data capture, signal processing, classification, cloud infrastructure, and workflow integration. A paper hosted in the University repository describes ECGalert as a system composed of a wireless ECG biosensor, data center, smartphone and web applications, and remote monitoring, framing it as an early detection and alerting system [10]. This is a key deep-tech marker, the value depends on a chain of technical components working reliably together, not on a single software feature.

**Constraints (trust/clinical/quality)**

In health-tech, trust is an adoption gate. A system that produces frequent false positives can exhaust clinicians and degrade credibility; a system that misses events can be dangerous. Clinical acceptance therefore depends on evidence and on how the system behaves under uncertainty.

ECGalert appears in published clinical-context work. An article in the Open Access Macedonian Journal of Medical Sciences compares 24-hour Holter monitoring with longer-term monitoring using ECGalert software and a single-lead patch, explicitly stating an aim to show non-inferiority in arrhythmia detection over total wear time [11]. Regardless of how one interprets outcomes, the existence of such comparative framing underscores the commercialization reality: health-tech scaling is constrained by the need for validation evidence and clinical credibility.

**Scaling path**

ECGalert's scaling path is structurally different from Pixyle's. In health-tech, go-to-market often routes through clinics, cardiologists, hospitals, insurers, or medical device distribution channels. Each route imposes requirements: privacy, interoperability, reporting conventions, procurement readiness, and potentially regulatory constraints depending on claims and jurisdictions. Even when a product is technically strong, adoption can be slow because institutions optimize for risk reduction.

**Funding logic**

ECGalert's funding logic appears consistent with many early-stage deep-tech health ventures: reliance on non-dilutive and ecosystem funding to finance R&D and validation. ECGalert's "About us" page explicitly states that the project is partly funded (and elsewhere described as co-financed) by Macedonia's Fund for Innovation and Technological Development [12]. That aligns with a grant-supported early strategy when venture capital may be premature due to long evidence cycles and regulatory uncertainty. For context, the Fund for Innovation and Technology Development is documented as an organization intended to encourage innovation by financing projects and supporting innovative companies [13].

## 7. Comparison Analysis: Pixyle AI vs ECGalert

Pixyle AI and ECGalert are both deep-tech ventures, but they operate under different commercialization physics. Comparing them clarifies how "deep tech" is not a single playbook but a family of execution patterns.

**Market speed.** Pixyle sells into e-commerce, where ROI can be measured quickly and the consequences of failure are commercial rather than clinical. Buyers can test improvements, integrate tools, and iterate fast especially if the product reduces manual labor and improves discoverability [5], [6]. ECGalert's adoption is slower because it is mediated by clinical caution, evidence requirements, and institutional procurement dynamics [11].

**Risk profile.** Pixyle's dominant risks are performance consistency under real-world data variance, integration into commerce stacks, and competitive pressure. ECGalert inherits those system risks but adds trust risk: false positives, false negatives, and clinical acceptance constraints. In healthcare, the "cost of being wrong" is qualitatively different, which reshapes sales cycles and evidence burdens.

**Moat-building.** Pixyle's likely moat is built from domain taxonomy, data pipelines, and integration into catalog workflows reinforced by enterprise use cases and international customer references [6]. ECGalert's moat is built through clinical evidence, signal-processing know-how, and workflow trust artifacts, switching costs can arise from clinician familiarity, accumulated monitoring data, and institutional acceptance pathways [11].

**Scaling approach.** Pixyle can scale through productized delivery (platform/API) and expansion across retailers and marketplaces. ECGalert scales through credibility accumulation, validation, partnerships with medical stakeholders, and patient + clinician adoption loops. Both can scale globally, but the routes are different: commerce rewards speed and operational ROI, healthcare rewards evidence and trust.

**Funding logic.** Pixyle's faster commercial feedback supports earlier VC-style funding once traction becomes legible, the €1 million seed led by South Central Ventures is reported by multiple ecosystem sources [5], [7]. ECGalert's longer evidence cycles and trust requirements support a grant-and-ecosystem-heavy early approach, consistent with its stated co-financing and with the existence of clinical comparison work [11], [12].
In short, Pixyle's advantage compounds through workflow embedding and distribution in commerce, while ECGalert's advantage compounds through evidence and institutional trust in healthcare. Both are deep-tech ventures; they win by different proofs.

## 8. Conclusion: Key lessons and a "founder checklist" paragraph

Deep-tech entrepreneurship is a discipline of translation. It translates breakthroughs into falsifiable claims, claims into evidence, evidence into buyer trust, and trust into scalable distribution. The core mistake founders make is treating deep tech as a technical identity rather than a business process. Deep tech does not win because it is deep. It wins because it becomes reliably, measurably useful enough that buyers reorganize budgets, workflows, and risk tolerances around it.
Pixyle AI demonstrates a fast-feedback deep-tech path, when the market is global, ROI is measurable, and product delivery can be standardized, deep tech can scale quickly once integration and performance are proven [5]-[7]. ECGalert demonstrates a trust gated deep-tech path, in healthcare, scaling depends on evidence, clinical workflow compatibility, and institutional adoption constraints, making credibility and validation as central as engineering [10]-[12]. Both cases reinforce the same practical lesson, founders must treat commercialization as an engineered sequence of proofs, not a hopeful leap.
The practical flow that gives the best odds in deep tech is start simple. As a first step is to pick a problem where someone already has money allocated and the pain is real world usually because performance is stuck, too slow, too expensive, too inaccurate, too manual. Then write your "bet" as a clear, testable statement: *what will we improve, by how much, and why would that make a buyer switch or pay?*
Next, don't build a cathedral. Build a small proof that can either validate the bet or kill it quickly. Important connection are people who actually control the budget and live in the world of procurement, security reviews, and risk. When you run pilots, treat them like a business step, not a science project: define what success means in euros, hours, risk reduction, or revenue uplift and agree upfront what happens if you hit that bar (a paid contract, expansion, or a clear "no").
As soon as the project looks promising, shift your mindset: your MVP isn't a clever demo, it's a reliable system. That means uptime, monitoring, security, integrations, and a product that works on a bad day not just in ideal conditions.
During the process you need to build your moat the real way, data you can't easily copy, know-how earned through painful edge cases, deep workflow integration, and only when you are acieveing some level then you finish IP where it truly matters.
Funding the journey should be in milestones, you can use grants to de-risk early, angels to move fast, seed capital to productize and sell, and strategic partners when they truly unlock distribution or credibility.
Finally, treat distribution like engineering. Great tech doesn't automatically spread. You need a repeatable way to reach buyers, onboard them, and deliver value with less effort each time. Scaling is simply that: doing the same thing again and again, with less friction, while your unit economics get stronger, not weaker.
And the memorable truth: deep-tech companies don't win by "shipping innovation." They win by shipping useful proof evidence that changes buyer behavior and then building a business machine that can deliver that usefulness at scale.

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