MASTER

MANAGEMENT IN INFORMATION SYSTEMS

MASTER´S FINAL WORK

DISSERTATION

HOW ECOSYSTEM CONDITIONS SHAPE DIGITAL TECHNOLOGY INTEGRATION IN START-UPS: EVIDENCE FROM GERMANY AND PORTUGAL

ALICE HACHENBURG

Lisbon School of Economics & Management
Universidade de Lisboa

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SUPERVISION:
WINNIE NG PICOTO

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*This thesis is dedicated to the
experiences, friendships, and
unexpected adventures
across Portugal, Brazil,
Germany, and the
Netherlands that made the
last two years unforgettable
(and occasionally delayed
the writing process).*

GLOSSARY

AI	– Artificial Intelligence
AVE	– Average Variance Extracted
DC	– Digital Culture (construct)
DEE	– Digital Entrepreneurship Ecosystem
DS	– Digital Skills (construct)
DV	– Dependent Variable (Digital Technology Integration Intensity)
EE	– Entrepreneurship Ecosystem
EU	– European Union
FA	– Funding Access (construct)
GDP	– Gross Domestic Product
GDPR	– General Data Protection Regulation
HTMT	– Heterotrait–Monotrait Ratio
ICT	– Information and Communication Technology
IoT	– Internet of Things
IS	– Institutional Support (construct)
IT	– Information Technology
MGA	– Multi-Group Analysis
NS	– Network Support (construct)
PLS-SEM	– Partial Least Squares Structural Equation Modeling
SEM	– Structural Equation Modeling
SME	– Small and Medium-sized Enterprise
TI	– Technological Infrastructure (construct)
TOE	– Technology–Organization–Environment (framework)
VC	– Venture Capital

ABSTRACT, KEYWORDS AND JEL CODES

Digital technologies are broadly available, yet the depth to which start-ups integrate them varies considerably across national contexts. This thesis examines how Digital Entrepreneurship Ecosystem (DEE) conditions shape the intensity of digital technology integration in start-ups, and whether these influences differ between Germany and Portugal. Drawing on the Technology-Organization-Environment (TOE) framework and DEE literature, six constructs (Digital Culture, Digital Skills, Technological Infrastructure, Funding Access, Network Support, and Institutional Support) are derived and tested against a newly operationalised dependent variable, Digital Technology Integration Intensity. Data from 28 founders and co-founders (Germany = 18, Portugal = 10) were analysed using PLS-SEM in SmartPLS 4. Given the small sample, all results are framed as exploratory and hypothesis-generating. The structural model explains a substantial share of variance in integration intensity (adjusted $R^2 = 0.65$). Although no path reaches conventional significance, Digital Culture emerges as the strongest predictor ($\beta = 0.375$, $p < .10$), followed by Network Support, while Funding Access and Institutional Support show negligible direct effects. Descriptively, Portugal reports higher Institutional Support than Germany yet achieves lower integration depth, pointing to a decoupling between institutional enablement and integration capacity. The comparatively small difference in integration intensity across countries, despite sizable differences in several predictors, supports the view that digital technologies partially dissolve geographic constraints on innovation. The study contributes a continuous measure of technology integration depth, a systematic bridge between TOE and DEE, and a first quantitative Germany - Portugal comparison, together with a replicable instrument for larger follow-up studies.

KEYWORDS: Digital Entrepreneurship Ecosystem; Digital Technology Integration; Start-ups; TOE Framework; PLS-SEM; Germany-Portugal Comparison

JEL CODES: L26; M13; O33; O32; L86; O57

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ACKNOWLEDGMENTS

First, I would like to express my sincere gratitude to my supervisor, Professor Winnie Ng Picoto, for her guidance, insightful feedback, and continuous support throughout the development of this thesis. Your encouragement and advice were invaluable at every stage of this process and the endless times I changed my mind.

I would also like to thank my friends for their constant support, motivating words (often accompanied by a generous supply of coffee), and for always reminding me that there is life beyond writing a thesis.

My heartfelt thanks go to my family, who supported me unconditionally throughout this journey even when the language of this thesis remained mostly beyond translation, their support never was.

Finally, a simple thank-you to myself for seeing this through to the end, there were moments I did not think I would.

1. INTRODUCTION

Start-ups are widely known for being central drivers of innovation, economic development, and structural renewal (Elia et al., 2020). As young, growth-oriented companies with innovative technologies or business models they generate employment growth that is often above average and create particularly highly skilled jobs in niche areas, even when established companies are cutting positions during recessions (Elabidine Madi & Madi, 2024). They act as dynamic catalysts that not only open up new markets but transform entire industries and force established players to adapt (Rong, 2024). Their potential to break existing norms isn't just coming from anywhere but led by the fact of their organizational characteristic: start-ups are less constrained by existing structures than established firms and are therefore frequently the originators of radical and disruptive innovations (Ludwig et al., 2022). Despite economic weakness or stagnating development in major economies such as Germany (European Commission, 2025), the start-up sector continues to grow significantly, especially in the area of digital technologies (Start-up Verband, 2025).

A market trend that is showing this dynamic clearly is the increasing penetration of all economic sectors by information technology (IT). IT is no longer merely a technical tool but the primary driver of a digital transformation that disrupts markets and fundamentally changes how companies create value (Verhoef et al., 2021). Consumer expectations and behavior have been fundamentally changed as a result (Verhoef et al., 2021). The economic significance of digital technologies is shown impressively by the following: whereas a decade ago only one of the five most valuable companies in the S&P 500 was a pure digital company, by 2018 all five were. We all know their name: Apple, Alphabet, Microsoft, Amazon, and Facebook (Verhoef et al., 2021). This development is driven by the increasing capabilities of key technologies: artificial intelligence, the Internet of Things, cloud computing, big data analytics, blockchain, and virtual and augmented reality are collectively transforming existing information systems and enabling real-time efficiency, a seamless convergence of the physical and digital world, and data-driven decision-making (Hamed Taherdoost, 2022).

Seeing these developments often comes with one central question: if these digital technologies are today broadly available globally and equally accessible to start-ups, what is the reason the patterns of usage vary so fundamentally? The answer is simple yet complex. The decisive differences lie not in the availability of the technology itself, but in the institutional framework conditions, cultural influences, and the available base infrastructure of the respective context. It is the so-called Entrepreneurship Ecosystems that serve as the explanatory framework here: a network of interdependent actors including start-ups, established companies, universities, investors, and public institutions (Ludwig et al., 2022). The characteristics of these ecosystems strongly shape how well they can adapt and respond to external shocks and changes (Buratti & Menter, 2025). The fact that especially the impact of technologies is shaped by the specific conditions of the respective ecosystem underlines the importance of start-ups within these ecosystems. They are particularly sensitive and responsive to changes, owing to their low structural path dependency while simultaneously acting as pioneers in the implementation of new digital solutions (Audretsch et al., 2020; Elia et al., 2020; Frank et al., 2019).

These developments are part of the reason that ecosystem structures are evolving into what are known as Digital Entrepreneurship Ecosystems (DEEs): sociotechnical systems in which digital technologies, actors, and institutional framework conditions are closely connected (Elia et al., 2020). Digital technologies there take on a dual role: they are both the subject of entrepreneurial innovation and the infrastructural foundation that enables interaction and value creation in the first place (Elia et al., 2020). The question is therefore no longer whether technology plays a role in start-ups, but how deeply it is integrated, and which digital ecosystem conditions explain this depth of integration.

In this context, certain gaps in the existing literature become apparent. For explaining technology adoption at the organizational level, the TOE Framework by Tornatzky and Fleischer (1990) has established itself as the central theoretical reference framework. Developed not as a fixed model but as a response to the complexity and non-linearity of the innovation process, it is grounded in the insight that innovation occurs simultaneously on many levels: among individuals, teams, organizations, and in the economic environment (Tornatzky & Fleischer, 1990). The framework integrates three systematically distinguished dimensions: the technological context (characteristics of the technology itself), the organizational context (internal company structure and resources), and the environmental context (external framework conditions such as competition, regulation, and infrastructure) (Tornatzky & Fleischer, 1990). It has proven record on studies across different technologies, industries, and national contexts (Baker, 2012). Nevertheless, the existing TOE literature shows two gaps that are central to the present work.

First, TOE studies typically focus on the adoption of a single specific technology, such as cloud computing, ERP systems, blockchain, CRM, or e-business (Baker, 2012; Religia et al., 2024; Satyro et al., 2024). As constructs are chosen context-specifically, the framework lacks systematic comparability across studies (Prakash, 2024). The question of the breadth and depth of digital technology integration as a comprehensive construct, how intensively the entire digital technology portfolio of a company is integrated, thus remains largely unexamined in existing research.

Second, the start-up context is underrepresented in the TOE literature. Existing applications frequently draw on small and medium-sized enterprises (SMEs) as a proxy, as direct start-up studies are rare (Faiz et al., 2024; Lina & Suwarni, 2022). Existing adaptations for the start-up context suggest that the classical TOE model requires adjustment (Amini & Javid, 2024; Marican et al., 2023) since decisions are often made by a single individual, organizational factors operate considerably more strongly than in established companies, which methodologically legitimizes capturing them through individual perceptions (Faiz et al., 2024; Li, 2020). The TOE dimensions are therefore lacking a tailored approach on treating technology integration depth as a target construct.

A further, more fundamental gap concerns the absence of an ecosystem context in TOE research. The framework treats the environmental context as one of three equal dimensions, yet the overarching question of how the national ecosystem as a whole shapes the effect of all three TOE dimensions remains unaddressed. Institutional quality, cultural values, and technological infrastructures differ considerably between countries and thus influence which innovation logics emerge and how technologies are actually used (Elia et al., 2020). TOE research, however, consistently focuses on a specific national environment and thereby omits how different national DEE configurations differentially alter the effect of TOE factors in cross-country comparisons.

From this emerges the core gap of the present work: there is no study that analyzes how the configuration of a DEE influences the depth of technology integration in start-ups within the TOE Framework and in particular, which factors exhibit the strongest influences when comparing different national contexts. Despite extensive research on digital entrepreneurship, an integrated understanding is lacking of how national differences in DEE configurations lead to technologies being integrated at different depths and use cases (Elia et al., 2020).

The comparison between Germany and Portugal offers a particularly suitable, controlled contrast for this research question. Both countries operate under the same regulatory EU framework including the GDPR and the EU AI Act, yet differ fundamentally in their ecosystem maturity. Germany, as the world's third-largest economy, possesses a mature but bureaucratically constrained start-up ecosystem (KPMG, 2026; Ludwig et al., 2022), while Portugal represents a dynamically growing, strongly ICT-dominated ecosystem with significant gaps in digital competencies and access to capital (Marujo et al., 2025; Start-up Portugal, 2025). This controlled contrast through a similar legal framework but different ecosystem maturity makes the comparison particularly well-suited to examining whether and how DEE conditions differentially influence the depth of technology integration in start-ups. To the best of current knowledge, no comparable cross-country study between Germany and Portugal with this specific focus exists.

These gaps motivate the objective of this thesis: to examine how national ecosystem conditions influence the depth of digital technology integration in start-ups, and whether these influences differ between Germany and Portugal through a first-of-its-kind quantitative cross-country comparison, which leads to the overarching research question:

"To what extent do Digital Entrepreneurship Ecosystem conditions shape the intensity of digital technology integration in start-ups, and do these influences differ between Germany and Portugal?"

This overarching question is elaborated through three subordinate research questions:

SQ1	How do the start-up ecosystems in Germany and Portugal differ structurally?
SQ2	Which TOE factors are significant drivers of digital technology integration depth in start-ups?
SQ3	Are there country-specific differences within the identified TOE factors outlining different strengths in Germany and Portugal?

The remainder of this thesis is structured as follows. Following this introduction, Chapter 2 establishes the theoretical foundations: it defines and conceptualizes Digital Entrepreneurship Ecosystems, introduces the TOE Framework and defines the factors considered relevant through a systematic literature review. On this basis, the research model of the thesis is presented and the central hypotheses are formulated. Chapter 3 is devoted to methodology: it justifies the quantitative research design, introduces the PLS-SEM approach, and describes the survey instrument as well as the data collection procedure in Germany and Portugal. Chapter 4 presents the results beginning with descriptive findings on the sample, followed by the measurement model assessment, a correlation analysis and the results of the structural model. Chapter 5 discusses the outcomes and compares it to findings of the theoretical foundations and answers the formulated research questions. Chapter 6 reflects on the limitations of the study and derives implications for future research. The thesis concludes with Chapter 7, the Conclusion, in which the central findings are summarized and the scientific and practical contribution of the work is contextualized.

2. THEORETICAL FOUNDATION & LITERATURE REVIEW

2.1. Definition of Digital Start-ups

The concept of a start-up lacks a universally accepted academic definition and is interpreted differently depending on context. Ahn et al. (2022) define start-ups as companies that are less than seven years old, have a clear focus on innovation, and either conduct research and development or pursue the acquisition of new knowledge or new markets with the goal of rapid growth opportunities. Ziakis et al. (2022) and Griva et al. (2023) expand this perspective and underline that start-ups develop new products or services under conditions of extreme uncertainty, with high speed and flexibility regarded as constitutive characteristics. In the context of digital start-ups, Griva et al. (2023), add an important specification, saying that digital technology must be a significant component of the value proposition, not merely a tool for executing traditional business processes.

For the purposes of this thesis, digital start-ups are therefore defined as young (<10 years), innovation-driven companies that develop new products or services under high uncertainty, are oriented toward scalable growth models, and whose value creation is substantially grounded in digital technologies.

2.2. The Technology-Organization-Environment Framework

2.2.1 Origins and Three Dimensions

The TOE Framework was developed in 1990 by Tornatzky and Fleischer as a holistic theoretical approach to explaining the adoption of information technologies at the organizational level (Prakash, 2024; Tornatzky & Fleischer, 1990). Going from fixed models to the non-linearity view, the authors considered that innovations occur simultaneously on many levels, among individuals, social groups, organizations, and in the economic environment and that none of these levels alone is sufficient to fully capture the innovation process (Tornatzky & Fleischer, 1990).

From this foundational idea, the framework distinguishes three systematically integrated dimensions. The technological context encompasses all technologies relevant to the company and differentiates between incremental, synthetic, and discontinuous innovations (Baker, 2012). Relevant factors within this dimension include historically relative advantage, compatibility, complexity, security, and perceived usefulness (Prakash, 2024). The organizational context focuses on internal company characteristics such as firm size, resources, management structure, IT expertise, and top management support, with organic and decentralized structures typically associated with the adoption phase (Baker, 2012; Prakash, 2024). The final dimension is the environmental context and examines the external environment like industry structure, competitive pressure, regulatory framework conditions, and the availability of technology service providers and skilled workers. It also acknowledges that government regulation can both compel and hinder innovation (Baker, 2012; Prakash, 2024).

The framework has shown its relevance in several occasions. It has proven record in a wide range of technologies including ERP, cloud computing, e-business, blockchain, and IoT as well as across industries (Baker, 2012). It takes into account both internal and external dynamics of a company, which is particularly critical for the adoption of (complex) technologies (Satyro et al., 2024). Furthermore, the flexibility of the framework allows constructs within the three contexts to be freely chosen and adapted to specific circumstances, which has generated diverse extensions in the literature: Satyro et al. (2024) add a sustainability dimension and name governance and financial potential as neglected organizational factors; Religia et al. (2024) add Digital Leadership; and Marican et al. (2023) translate TOE into a 4P1C model (Process, Product, Platform, Compliance) for the start-up context.

2.2.2 Transferability to the Start-up Context

Marican et al. (2023) show that applying the TOE Framework to start-ups requires a well-reasoned adaptation. In the existing literature, small and medium-sized enterprises (SMEs) are frequently used as a proxy for start-ups, as both are characterized by agility and resource constraints (Faiz et al., 2024; Lina & Suwarni, 2022). An important finding from these studies is that organizational factors play a considerably stronger role in the SME and start-up context than technological or environmental factors (Faiz et al., 2024). Start-ups are more agile but more resource-constrained than established companies, which necessitates a specific weighting of the TOE constructs (Amini & Javid, 2024). Methodologically, the focus on the decision-maker is particularly well-justified in the start-up context: since top management support in start-ups corresponds directly to the founder's vision and decisions are made through flat hierarchies (Faiz et al., 2024; Li, 2020).

Through a systematic literature review, the factors influencing technology adoption in start-up-relevant contexts were identified across TOE-based studies and consolidated into a structured overview (see Appendix A). While the TOE framework explains technology adoption at the firm level along its three constituent dimensions, it does not systematically account for how national ecosystem conditions shape the effect of these factors. Addressing precisely this connection is the purpose of the Digital Entrepreneurship Ecosystem framework, introduced in the following section.

2.3. Digital Entrepreneurship Ecosystems

2.3.1 From Entrepreneurship Ecosystem to DEE

An Entrepreneurship Ecosystem (EE) is understood as a network of interdependent actors and factors coordinated to enable productive entrepreneurship within a given territory (Stam, 2015). This understanding shifts entrepreneurship from the isolated firm level to the level of a structural environment, in which various actors, resources, and framework conditions jointly shape entrepreneurial activity (Stam, 2015). With the growing importance of digital technologies, this concept has been further developed into the Digital Entrepreneurship Ecosystem (DEE): digital technologies no longer appear merely as an external context but change the very nature of entrepreneurship itself (Bejjani et al., 2023; Nambisan et al., 2019). Elia et al. (2020) describe in this context an "unstoppable convergence" of entrepreneurship and digital technologies. A DEE is accordingly not a purely geographically bounded construct, but a complex digital environment in which actors and organizational structures are connected through digital technologies and leverage collective intelligence to create new value (Elia et al., 2020).

2.3.2 DEE Dimensions as Analytical Framework

For the cross-country comparison in this thesis, categories aligned with Stam's (2015) Entrepreneurial Ecosystem Framework are used, adapted to the digital environment. The original model distinguishes Framework Conditions, Systemic Conditions, Entrepreneurial Activity, and Aggregate Value Creation. For the present thesis the first two levels are particularly relevant, as they determine the structural prerequisites for the strategic orientation of digital start-ups (Stam, 2015).

Framework Conditions include as a first category formal institutions, consisting of the quality of regulatory framework conditions, government effectiveness, transparency, and the rule of law (Stam, 2015). Pulling that into the digital context, it becomes technology-related regulations, data protection requirements, AI legislation, and digital funding programs that are particularly relevant. A second category includes informal institutions and culture, basically the societal attitudes toward entrepreneurship, risk tolerance, attitudes toward failure, and long-term orientation. The literature indicates that national cultural dimensions such as uncertainty avoidance significantly influence the perception of technological risks and adoption barriers (Stam, 2015; Viberg et al., 2025; Zöll et al., 2024). The third category of physical infrastructure is extended in the digital context to include digital infrastructure, covering the state of base technologies as well as internet and broadband access for digital start-ups a necessary precondition (Stam, 2015, adapted; Bergholz et al., 2024).

Systemic Conditions on the other hand focus on funding, talent, and networks. Venture capital, business angels, and crowdfunding influence the strategic orientation of young companies, as capital-intensive innovation models have different prerequisites than product-oriented developments (Lado et al., 2024; Stam, 2015). The talent and knowledge base, for example digitally skilled workers, research institutions, and application-relevant knowledge, determines the extent to which complex data-driven business models are achievable (Stam, 2015; Torres & Godinho, 2022). Networks and support structures show the relationships between start-ups, investors, universities, and incubators. They structure knowledge and resource flows and influence the collective coordination capacity of the ecosystem (Fernandes et al., 2022; Stam, 2015).

2.3.3 Mapping TOE Findings in the DEE Dimensions

The TOE findings identified in Section 2.2.2 are now mapped onto the DEE dimensions and consolidated into the research constructs that guide the subsequent analysis. The mapping logic is two-tiered: TOE provides the factor categories that explain technology adoption at the firm level, while DEE provides the structural dimensions of national ecosystems that contextually shape these factors. Findings that appear consistently across multiple TOE studies and simultaneously correspond to a DEE dimension are retained as independent constructs. The resulting mapping is presented in Appendix B.

2.4 Country Characterization: Germany and Portugal

Building on the six constructs derived in Section 2.3.3, this section provides a consolidated overview of the German and Portuguese ecosystems along these dimensions. The aim is to demonstrate that the six DEE dimensions (Digital Culture, Digital Skills, Technological Infrastructure, Funding Access, Network Support, and Institutional Support) manifest meaningfully, yet differently, across the two countries, thereby justifying their inclusion as explanatory constructs in the research model.

2.4.1 Germany

Germany, as the world's third-largest economy with a GDP of €4,470 billion in 2024 hosts a mature start-up ecosystem of approximately 23,000 active start-ups and 31 unicorns (KPMG, 2026; Start-up Verband & ifo Center for Macroeconomics and Surveys, 2025). Across the six DEE dimensions, the ecosystem presents a consistent pattern: structurally strong, but increasingly constrained by its own complexity.

Culturally, German start-ups operate in a planning-oriented, risk-averse environment, reflected in a high Uncertainty Avoidance score (65) and strong long-term orientation (83) where technology adoption is driven by Return On Invest logic and competitive necessity rather than experimentation (Hofstede Insights, 2023; Weiss et al., 2025). Digital Skills are academically strong, with 87% of founders holding university degrees and a substantial international talent pool. Nevertheless do skills shortages and unfavorable taxation constrain the team-building at scale (McKinsey, 2023; Start-up Verband & ifo Center for Macroeconomics and Surveys, 2025). Technological Infrastructure is high on the surface with ICT usage reaching 91–93% of companies and cloud adoption approximately 50–54%. Yet infrastructure quality is internationally rated as "relatively poor," with a significant urban-rural divide and a fragmented federal digital landscape (Bergholz et al., 2024; OECD, 2025). Regarding funding, Germany has a well-developed early-stage culture through programs like the High-Tech Gründerfonds and EXIST, but VC investment at 0.18% of GDP lags well behind comparable economies, and a structural later-stage gap persists (Deutsche Bank Research, 2025). The support network is broad and institutionally mature, encompassing more than 60 public institutions and 64 incubators, with specialized hubs for fintech, AI, and logistics (Federal Office for Migration and Refugees, 2020; Ludwig et al., 2022). Theoretically, Germany scores highly on governance quality with a ranking in Rule of Law ~85 and Regulatory Quality ~78, but bureaucracy, GDPR compliance burdens, and slow administrative processes are consistently cited as the primary barriers to digital start-up growth. More than 87% of start-ups naming bureaucracy as the main reason for considering founding abroad (Start-up Verband & ifo Center for Macroeconomics and Surveys, 2025; World Bank Group, 2025b).

2.4.2 Portugal

Portugal, with a GDP of USD 318 billion (2024) and a growth forecast of +2.2% for 2026, represents a dynamically expanding ecosystem of over 5,000 active start-ups and seven unicorns (Marujo et al., 2025; Start-up Portugal, 2025; World Bank Group, 2025a).

Culturally, Portugal presents a starkly different profile: with one of the world's highest Uncertainty Avoidance scores (104) and a short-term orientation (28). The decision-making tends to follow a Principles-First logic, favoring proven approaches over experimentation (Hofstede Insights, 2023; Miguel Vital Maia, 2025). At the same time, there is a mentality for improvisational problem-solving under uncertainty, which functions as an adaptive advantage in resource-constrained start-up environments (Miguel Vital Maia, 2025). Digital Skills is growing rapidly, with over 100,000 graduates annually and a strong English proficiency ranking (6th globally), but the potential remains structurally underutilized (Cardoso et al., 2022; Start-up Portugal, 2025). Technological Infrastructure is considerably lower than in Germany with ICT adoption laying at around 62–63% and cloud usage at 35–39%. Portugal ranks among the EU-27's weakest performers on digital competencies, with Industry 4.0 remaining largely aspirational for most SMEs (OECD, 2025; Sofrankova et al., 2025). Funding access represents the ecosystem's most critical structural weakness: With a VC volume at 0.01–0.03% of the GDP it is negligible by international standards, early-stage capital is limited, and founders frequently serve as their own primary financing source (Gaio et al., 2022; OECD, 2024). The support network is agile and internationally focused, built around business angels, accelerators, and incubators, though university-industry knowledge transfer remains limited (Coelho, 2025; Coutinho & Au-Yong-Oliveira, 2023). Institutionally, Portugal's governance scores are weaker than Germany's showing a Regulatory Quality of ~67 and a Rule of Law ~75.

2.5 *Hypotheses and Research Model*

Based on the TOE literature review and the DEE framework, as well as the validation of their relevance within the German and Portuguese ecosystems, six constructs are defined and hypotheses derived. Each construct is theoretically anchored in both frameworks and directly linked to its hypothesized effect on Digital Technology Integration Intensity. The operationalization of all constructs is summarized in the Appendix D.

Digital Culture: Digital Culture describes the extent to which a start-up exhibits a cultural orientation toward digital technologies, shaped by founder vision, strategic resource allocation, and an open innovation mindset (Amini & Javid, 2024; Faiz et al., 2024). In the TOE literature it is consistently identified as the strongest organizational driver of adoption, encompassing top management support and entrepreneurial orientation as core sub-dimensions (Amini & Javid, 2024; Faiz et al., 2024). Within the DEE framework it corresponds to the dimension of informal institutions and culture: national cultural dimensions such as uncertainty avoidance shape risk perception and adoption willingness at the ecosystem level (Stam, 2015; Viberg et al., 2025).

***H1:** Digital Culture has a positive influence on Digital Technology Integration Intensity.*

Digital Skills: Digital Skills describes the extent of digital competency and technical expertise within the start-up team, the capacity to implement, maintain, and develop digital technologies (Amini & Javid, 2024; Faiz et al., 2024). In the start-up context this is particularly critical, as no specialized IT department exists and the skill level of a small team determines the entire technological capability of the firm (Amini & Javid, 2024; Marican et al., 2023). Within the DEE framework it corresponds to the talent and knowledge dimension: the ecosystem's talent base directly determines which skill resources start-ups can access (Stam, 2015). Without sufficient digital competency, available technologies cannot be deeply integrated.

H2: *Digital Skills has a positive influence on Digital Technology Integration Intensity.*

Technological Infrastructure: Technological Infrastructure describes the extent of existing technological infrastructure and the capacity to integrate new digital technologies including scalability, interoperability, and technical foundation (Amini & Javid, 2024; Religia et al., 2024). Within the DEE framework it corresponds to the digital infrastructure dimension: broadband availability, ICT penetration, and cloud adoption at the ecosystem level form the foundation for readiness at the firm level (Stam, 2015, adapted; Bergholz et al., 2024). Without adequate infrastructure, deep integration is not possible.

H3: *Technological Infrastructure has a positive influence on Digital Technology Integration Intensity.*

Funding Access: Funding Access describes the extent of access to external capital for digital technology investments (Chakraborty et al., 2023; Frimanslund & Nath, 2024). Within the DEE framework it corresponds to the financing dimension: VC availability and public instruments at the ecosystem level directly determine which funding sources start-ups can draw on (Lado et al., 2024; Stam, 2015). Capital access enables investments in AI development, cloud migration, and infrastructure.

H4: *Funding Access has a positive influence on Digital Technology Integration Intensity.*

Network Support: Network Support describes the extent of external networking and ecosystem integration collaboration, knowledge exchange, and partner and competitive pressure as drivers of digital development (Frimanslund & Nath, 2024; Theodoraki et al., 2022). Competitive pressure and partner demands are consistently identified as strong environmental drivers of adoption across the TOE literature (Amini & Javid, 2024; Faiz et al., 2024; Religia et al., 2024). Within the DEE framework it corresponds to the networks and support structures dimension: ecosystem networks structure resource and knowledge flows and shape the collective coordination capacity that enables deeper integration (Fernandes et al., 2022; Stam, 2015).

H5: *Network Support has a positive influence on Digital Technology Integration Intensity.*

Institutional Support: Institutional Support describes the extent of government and regulatory enablement for digital technology adoption (El-Shihy & Hassan Mohamed, 2023; Jeilani & Hussein, 2025). Clear regulatory frameworks act as enablers; uncertainty and compliance burdens act as barriers (Chakraborty et al., 2023; Staley, 2026). Within the DEE framework it corresponds to the formal institutions dimension: regulatory quality and public instruments at the ecosystem level directly shape the institutional environment for digital start-ups (Stam, 2015; Zhang et al., 2023).

H6: *Institutional Support has a positive influence on Digital Technology Integration Intensity.*

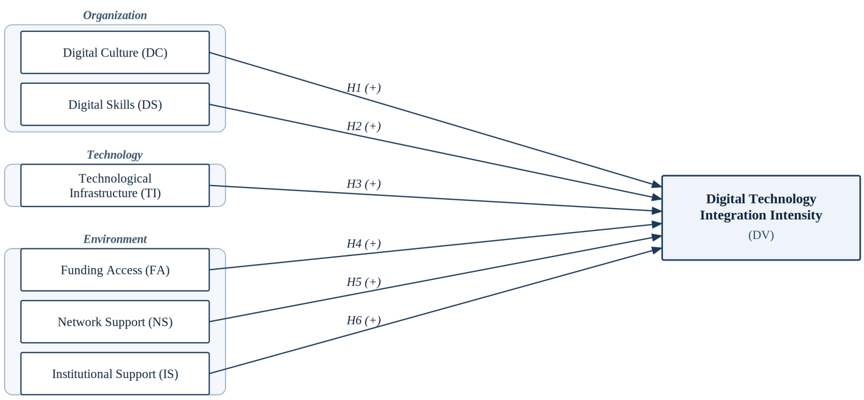

FIGURE 1 – *Research model with hypotheses. Source: own elaboration*

3. METHODOLOGY

3.1. Research Design

This thesis follows a deductive approach: hypotheses are derived from existing theory and subsequently tested empirically (Bryman, 2016). The TOE Framework (Tornatzky & Fleischer, 1990) and DEE literature (Elia et al., 2020; Stam, 2015) provide the theoretical foundation from which six hypotheses are derived. A quantitative design is the only methodologically appropriate choice given the research objectives: hypothesis testing requires numerical data and significance testing, the cross-country comparison requires standardized, comparable data across groups, and inferences about start-up populations in two countries require inferential statistics. The survey design follows Hair et al. (2022): all constructs are measured through multiple observable indicators using a five-point Likert scale, as latent concepts such as digital culture or institutional support cannot be directly observed. The design is cross-sectional, as the research question concerns current ecosystem influences rather than change over time.

3.2. Survey Instrument

All items were adapted from validated scales in the existing TOE literature. Adaptations were limited to linguistic adjustments for the start-up context without altering the broad substantive content, preserving the construct validity of the original scales (see Appendix D). No items were newly developed. A formal pre-test was not conducted, as all scales had been previously validated in comparable research contexts. As a quality assurance measure, all items were reviewed by the supervising academic for clarity, unambiguity, and construct fit prior to data collection. The survey was administered exclusively in English, which is the dominant working language of digital start-ups in both countries. A single language version also eliminates the risk of translation-induced measurement non-equivalence in the cross-country comparison.

Items were collected using a five-point Likert scale in the direction 1 = "Fully Agree" to 5 = "Fully Disagree." Prior to analysis, all items were reverse-coded using the formula recoded value = 6 - raw value, so that throughout the analysis 5 = high agreement and 1 = low agreement. As all items are positively worded, the recoding was applied uniformly.

3.3. Sample & Data Collection

The target population comprises founders and co-founders of digital start-ups in Germany and Portugal. Five inclusion criteria were applied: company age of maximum ten years, consistent with the start-up definition in Section 2, digital orientation, operationalized through the keyword "Digital" on LinkedIn; company size of 1–200 employees to exclude established firms, private company type; and a minimum role of co-founder, ensuring that technology adoption decision-makers are surveyed.

Sampling followed a purposive strategy, as the target population is clearly defined but not reachable through random sampling. The primary data collection channel was LinkedIn Sales Navigator, through which founders and co-founders were contacted directly based on the defined filters, exclusively via direct message. Data collection took place from May 29 to June 8, 2026.

3.4. Data Cleaning

In order to assure coherent analysis strict listwise deletion was applied. Therefore any case with at least one missing Likert item was fully excluded from the analysis. This decision is methodologically justified, as PLS-SEM construct scores are based on the mean of all associated items. A missing value would distort the construct score and compromise comparability across respondents. Missing items showed no systematic pattern across constructs or countries, providing no indication of systematic non-response bias. The final analytical sample comprises n = 28 (Germany: 18, Portugal: 10).

3.5. Analytical Approach

Partial Least Squares Structural Equation Modeling (PLS-SEM) is used for statistical analysis, implemented in SmartPLS 4 (Version 4.1.1.8). PLS-SEM was chosen for two reasons: it performs better with smaller samples, and the familiarity with the tool. It is explicitly acknowledged that n = 28 falls below the recommended minimum even for PLS-SEM; all results are therefore interpreted as exploratory.

The analysis follows the two-step procedure, with the first step assessing the measurement model before interpreting the structural model (Anderson & Gerbing, 1988). Measurement model assessment covers outer loadings (threshold ≥ 0.70), internal consistency via Cronbach's Alpha and Composite Reliability (rho_c ≥ 0.70), convergent validity via Average Variance Extracted (AVE ≥ 0.50), and discriminant validity via the HTMT ratio (threshold < 0.85). Structural model assessment covers standardized path coefficients (β), the coefficient of determination (R^2), and effect sizes (f^2) (Cohen, 1988).

The planned Multi-Group Analysis (MGA) cannot be conducted, as both subgroups Germany (n = 18) and Portugal (n = 10) fall substantially below the recommended minimum of approximately 30 observations per group required for stable MGA estimates. Conducting MGA under these conditions would produce numerically unstable bootstrapping results with very wide confidence intervals and negligible statistical power, rendering any group comparison methodologically indefensible.

4. RESULTS

4.1. Sample Description

The final analytical sample comprises 28 complete responses after listwise deletion. Of these, 18 respondents (64.3%) are from Germany and 10 (35.7%) from Portugal. This distribution is unequal and falls short of the minimum group sizes typically required for Multi-Group Analysis in PLS-SEM. For this reason the MGA is not conducted, and the country comparison is limited to descriptive statistics reported later in this section. The implications of this sampling limitation are addressed in Section 6.

The respondents represent predominantly small, technology-centred start-ups: roughly three quarters employ ten people or fewer (1–5 employees: 28.6%; 6–10: 46.4%), and most are in early to intermediate growth stages, with market-ready (35.7%) and MVP/prototype (32.1%) ventures dominating, followed by scaling firms (25.0%). The most frequent sectors are HealthTech/MedTech (28.6%), followed by E-commerce/Retail and FinTech (17.9% each), and business models are mainly B2B (42.9%), a pattern that is particularly pronounced among the German firms (55.6%). Across both countries, digital technology is central to the venture rather than merely supportive: 64.3% of respondents describe technology as the core of their product or service, and the most widely used technologies are cloud computing (46.4%), data analytics/BI tools (35.7%), and artificial intelligence/machine learning (32.1%). The funding profile is dominated by bootstrapping and own funds (78.6%, reported by all Portuguese firms), while institutional venture capital remains rare (7.1%) and a majority of firms are not yet profitable (53.6%). A full breakdown of all sample characteristics, including the country-level distribution, is provided in Appendix C.

Taken together, the sample describes a set of small, technology-oriented start-ups in early to intermediate growth stages, distributed unevenly between Germany and Portugal. While the sample size represents a significant methodological constraint, the data is treated as a pilot-level dataset suitable for exploratory analysis. All findings reported in the following sections must be interpreted with this constraint explicitly in mind.

4.2. Descriptive Statistics & Country Comparison

Prior to the measurement model assessment, descriptive statistics at the construct level are reported and mean differences between Germany and Portugal are examined. All construct means are calculated as the average across the recoded items of each construct, where higher values reflect stronger agreement (5 = Fully Agree, 1 = Fully Disagree). Given the small group sizes (n_DE = 18, n_PT = 10), formal significance testing via Welch t-tests is conducted for descriptive purposes only; results should not be interpreted as statistically robust, and Cohen's d is reported as the primary indicator of effect magnitude, with thresholds of 0.20 (small), 0.50 (medium), and 0.80 (large) following Cohen (1988). Table 1 summarizes the results.

	Germany		Portugal		Δ				
Construct	M	SD	M	SD	DE−PT)	t	p	Cohen 's d	Effect size
Digital Culture (DC)	3.72	0.79	3.27	0.94	+0.46	1.301	.212	0.53	medium
Digital Skills (DS)	3.57	0.86	3.05	0.65	+0.52	1.793	.086 †	0.68	medium
Institutional Support (IS)	2.68	0.62	3.43	0.46	−0.74	−3.612	.001 **	−1.36	large
Network Support (NS)	3.38	0.75	3.25	0.72	+0.13	0.435	.668	0.17	negligible
Funding Access (FA)	2.73	0.73	2.74	0.89	−0.01	−0.020	.984	−0.01	negligible
Tech Infrastructure (TI)	3.69	0.77	3.40	0.70	+0.29	1.030	.315	0.39	small
DT Integration Intensity (DV)	4.01	0.83	3.83	0.58	+0.19	0.706	.487	0.26	small

Table 1: Descriptive Statistics

The results reveal a broadly consistent directional pattern: Germany scores higher than Portugal on Digital Culture, Digital Skills, Tech Infrastructure and the dependent variable Integration Intensity. Network Support shows a marginal difference in the same direction, while Funding Access is virtually identical across both groups, suggesting that perceived access to external capital does not differ meaningfully between German and Portuguese start-ups in this sample. Institutional Support is the only construct where Portugal scores noticeably higher than Germany.

The dependent variable itself shows a comparatively small mean difference between the two countries (Δ = +0.19, DE higher), which is substantially smaller than the differences observed for organizational predictors such as Digital Culture and Digital Skills. This pattern should be noted: despite differences in several constructs, the actual level of digital technology integration achieved by start-ups in both groups is more similar than the construct gap would suggest. This observation could reinforce the central motivation of the structural analysis: ecosystem-level differences in the predicting constructs do not automatically translate into proportional differences in integration depth, and the structural model is required to identify which factors independently drive the remaining variance. The following section assesses the measurement model before turning to those structural relationships.

4.3. Measurement Model Assessment

Following the two-stage approach recommended by Anderson and Gerbing (1988), the measurement model is evaluated before interpreting any structural path relationships. Assessment proceeds along four criteria: indicator reliability (outer loadings), internal consistency (Cronbach's Alpha and Composite Reliability), convergent validity (AVE), and discriminant validity (HTMT ratio).

Table 2 reports the outer loadings for all 28 indicators across seven constructs. A threshold of ≥ 0.70 is applied as recommended by Hair et al. (2021). The majority of indicators meet this criterion comfortably. Digital Culture (DC1 = 0.752, DC2 = 0.862, DC3 = 0.873), Digital Skills (DS1 = 0.815, DS2 = 0.862, DS3 = 0.779, DS4 = 0.779), Tech Infrastructure (TI1 = 0.897, TI2 = 0.817, TI3 = 0.756, TI4 = 0.799), and the dependent variable DT Integration (DV1 = 0.802, DV2 = 0.840, DV3 = 0.825, DV4 = 0.773) all yield loadings well above the threshold.

Four indicators fall below the 0.70 benchmark and require discussion. IS4 yields a loading of 0.430, which is substantially below the threshold and constitutes the most critical item-level concern in the measurement model. NS2 loads at 0.642, and FA4 and FA5 at 0.685 and 0.653 respectively. In each case, the item was retained rather than removed. The decision rests on two considerations: first, removal of individual items at n = 28 would further reduce the informational basis of already sparsely measured constructs, potentially destabilizing rather than improving construct estimation; second, in no case would removal substantially alter the AVE of the affected construct in a direction that would change its convergent validity assessment. IS4 in particular is acknowledged as a clear limitation. Its content validity is defensible but its low loading indicates that it does not share sufficient variance with the remaining IS indicators in this sample. This limitation is revisited in Section 6.

Construct	Item 1	Item 2	Item 3	Item 4	Item 5
DC	0.752	0.862	0.873		
DS	0.815	0.862	0.779	0.779	
DV	0.802	0.840	0.825	0.773	
FA	0.817	0.739	0.736	**0.685 †**	**0.653 †**
IS	0.911	0.735	0.722	**0.430 †**	
NS	0.818	**0.642 †**	0.792	0.806	
TI	0.897	0.817	0.756	0.799	

Table 2: Outer Loadings

Table 3 reports Cronbach's Alpha (α), Composite Reliability (rho_a and rho_c), and Average Variance Extracted (AVE) for all seven constructs. All Cronbach's Alpha values exceed the 0.70 threshold, ranging from 0.750 (IS) to 0.835 (TI), indicating adequate internal consistency across all constructs. All composite reliability values (rho_c) exceed 0.80, further confirming acceptable reliability. AVE values exceed the minimum threshold of 0.50 proposed by Hair et al. (2021) for all constructs, confirming that each construct explains more variance in its indicators than is attributable to measurement error, and thus establishing convergent validity.

Two constructs sit close to the 0.50 boundary: Institutional Support (AVE = 0.519) and Funding Access (AVE = 0.530). This marginal performance is directly traceable to the subthreshold indicator loadings discussed above : IS4 in the case of IS, and FA4/FA5 in the case of FA. While both constructs formally pass the convergent validity criterion, they do so with limited margin, and the robustness of their AVE estimates at $n = 28$ should be treated with appropriate caution.

Construct Reliability and Validity

Construct	Cronbach's α	Composite reliability (ρ_a)	Composite reliability (ρc)	AVE
DC — Digital Culture	0.775	0.788	0.870	0.691
DS — Digital Skills	0.825	0.836	0.884	0.655
DV — DT Integration Intensity	0.827	0.837	0.884	0.657
FA — Funding Access	0.794	0.806	0.849	*0.530 †*
IS — Institutional Support	0.750	0.848	0.803	*0.519 †*
NS — Network Support	0.765	0.782	0.850	0.589
TI — Tech Infrastructure	0.835	0.841	0.890	0.670

Table 3: Construct Reliability

Discriminant validity is assessed using the Heterotrait-Monotrait ratio (HTMT), with a threshold of 0.85 (Hair et al., 2021). Table 4 presents the full HTMT matrix. The majority of construct pairs fall clearly below this threshold, confirming adequate discriminant validity for most construct combinations.

Five construct pairs reach or exceed the 0.85 threshold and require discussion: DC–DV (0.927), NS–DV (0.874), DS–DV (0.857), DS–TI (0.856), and DC–DS (0.852). A consistent pattern emerges: the elevated values cluster among the organizational and technological predictors (Digital Culture, Digital Skills, Technological Infrastructure, Network Support) and, above all, in their relationship with the dependent variable. This is theoretically interpretable: a start-up's cultural orientation toward digital technology, the digital competency of its team, and its technological readiness tend to develop jointly and to move closely with the depth of technology integration, as all reflect facets of organizational digital readiness. These constructs are nonetheless conceptually distinct and are consistently operationalised separately in the relevant literature, which justifies retaining them as separate factors.

A further consideration specific to the present dataset is that HTMT estimates derived from n = 28 carry considerably wider confidence intervals than those from larger samples, and point estimates at this sample size are less stable. It is therefore possible that the precise values observed here overstate the true degree of construct overlap. This limitation is acknowledged and revisited in Section 6. Beside these concerns, the measurement model provides a sufficiently acceptable foundation for the exploratory structural analysis that follows.

HTMT Discriminant Validity Matrix

	DC	DS	DV	FA	IS	NS
DS	**0.852 ***					
DV	**0.927 ***	**0.857 ***				
FA	0.294	0.449	0.327			
IS	0.328	0.325	0.337	0.218		
NS	0.758	0.801	0.874	0.453	0.304	
TI	0.714	0.856	0.784	0.342	0.404	0.812

Table 4: HTMT

4.4. Structural Model Results

The structural model was estimated using SmartPLS 4 with bootstrapping based on 5,000 subsamples, a two-tailed test, and the Percentile Bootstrap method. The model's overall explanatory power is assessed through the coefficient of determination (R^2), and the practical relevance of individual predictors is quantified using effect sizes (f^2) following Cohen (1988). Given the sample size of n = 28, the interpretation of all structural results is explicitly framed as exploratory: with six predictors and 28 observations, the model is likely to produce upwardly biased R^2 estimates due to overfitting, and statistical power is insufficient to reliably detect path coefficients of small to moderate magnitude. These constraints are not a reason to withhold the results, but they are a necessary frame for interpreting them.

The structural model yields $R^2 = 0.724$ and an adjusted $R^2 = 0.645$ for DT Integration Intensity. The adjusted value is the more appropriate indicator here and falls between the benchmarks for moderate (0.50) and substantial (0.75) explanatory power as defined by Hair et al. (2021). The gap between the unadjusted and adjusted values ($\Delta = 0.079$) is consistent with the expected degree of overfitting at this sample size and confirms that the adjusted figure should be treated as the operative measure of model fit.

Structural Model: Path Coefficients, Bootstrapping Results, and Hypothesis Outcomes

Path	β	M	STDEV	t	p	f²	Effect	Decision
TI → DV	0.088	0.118	0.253	0.349	.727	0.011	negligible	Not supported
DC → DV	0.375	0.345	0.222	1.690	*.091 †*	0.244	medium	*Not supported †*
DS → DV	0.198	0.211	0.204	0.972	.331	0.045	small	Not supported
FA → DV	−0.004	−0.019	0.176	0.023	.982	0.000	negligible	Not supported
NS → DV	0.298	0.292	0.230	1.294	.196	0.147	small–medium	Not supported
IS → DV	−0.096	−0.076	0.154	0.624	.533	0.028	small	Not supported

Table 5: Path Coefficients

No path coefficient reaches the conventional 5% significance threshold. This result is interpreted primarily as a consequence of insufficient statistical power: at $n = 28$ with six predictors, the model lacks the power to reliably detect effects of the magnitude typically observed in social science research of this kind. The absence of significance is therefore not treated as evidence against the theoretical relationships hypothesized in this study, but rather as an expected consequence of the sample size constraint.

Within this context, Digital Culture (H1) yields the largest path coefficient ($\beta = 0.375$, $t = 1.690$, $p = .091$) and approaches marginal significance at the 10% level. The effect size of $f^2 = 0.244$ qualifies as medium by Cohen's (1988) benchmarks, indicating that

Digital Culture accounts for a meaningful portion of the explained variance in DT Integration Intensity within the present sample. This constitutes the strongest exploratory signal in the structural model and suggests that an organization's cultural orientation toward digital technology may be a relevant driver of integration depth. A finding that requires validation in subsequent studies.

Network Support (H5) displays the second-largest coefficient ($\beta = 0.298$, $p = .196$) with a small-to-medium effect size ($f^2 = 0.147$), though it does not approach significance. Digital Skills (H2) yields $\beta = 0.198$ ($p = .331$, $f^2 = 0.045$), a result that is notable given the strong bivariate association between DS and DV observed at the descriptive level. This divergence between bivariate and structural results is consistent with the high degree of collinearity between Digital Culture and Digital Skills (HTMT = 0.852): when both constructs are estimated simultaneously in the structural model, the shared explanatory variance is partially absorbed by DC, reducing the independent coefficient of DS. This is a technically expected pattern in the presence of correlated predictors and does not imply that Digital Skills are unimportant. It purely reflects the difficulty of separating two closely related organizational constructs with a small sample.

Tech Infrastructure (H3) yields a small and non-significant coefficient ($\beta = 0.088$, $p = .727$, $f^2 = 0.011$). Institutional Support (H6) produces a negative coefficient ($\beta = -0.096$, $p = .533$, $f^2 = 0.028$), consistent with the descriptive finding that IS is higher in Portugal while DT Integration is higher in Germany. The construct-level relationship in this sample runs counter to the hypothesized direction, though the coefficient is far from significant. Funding Access (H4) is effectively zero ($\beta = -0.004$, $p = .982$, $f^2 = 0.000$), representing a robust null finding in this dataset.

Taken together, all six hypotheses must formally be classified as not supported on the basis of the significance criterion. However, the exploratory framing of this study means that the directional pattern of coefficients retains interpretive value. Digital Culture emerges as the most promising candidate for a meaningful predictor in a larger replication, while Institutional Support and Funding Access show no evidence of a positive direct effect in the present sample.

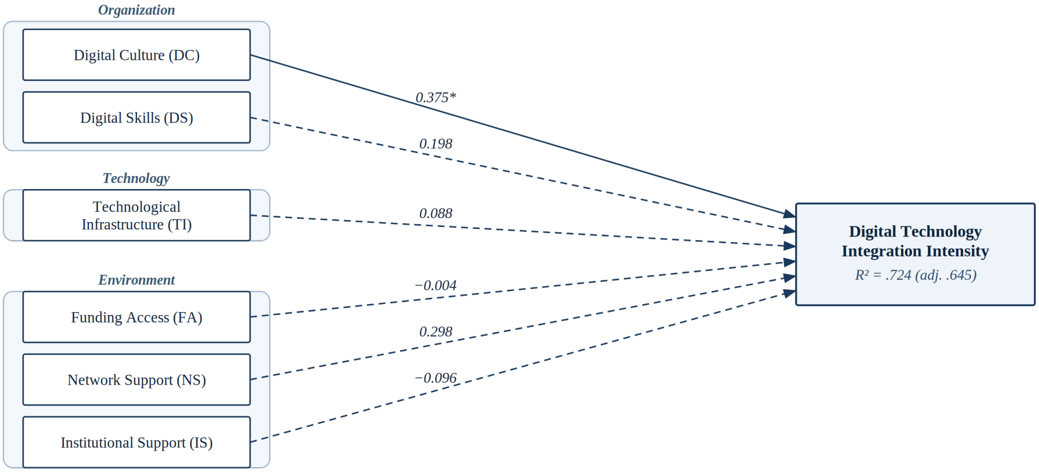

FIGURE 2 – *Structural model results (standardised path coefficients).*

5. DISCUSSION

5.1. Interpretation of Main Findings

The structural model yields an adjusted R^2 of 0.645, indicating that the six TOE-derived predictors collectively explain a substantial portion of the variance in Digital Technology Integration Intensity. All findings are treated as exploratory signals rather than confirmatory results, given $n = 28$ and six predictors.

Addressing which TOE factors drive integration depth (SQ2), no factor reaches conventional significance at $n = 28$; the strongest structural signal is produced by Digital Culture ($\beta = 0.375$, $f^2 = 0.244$, $p = .091$), approaching marginal significance despite the power constraints of the sample. This is theoretically consistent with the TOE literature, in which digital culture is consistently identified as the most robust organizational driver of technology adoption in start-up contexts (Faiz et al., 2024; Amini & Javid, 2024). In a start-up, where organizational culture and founder vision are effectively the same thing, the degree to which technology is understood as a strategic asset directly shapes how deeply it is embedded across the business model and operations, for example determining resource allocation, hiring criteria, and build-versus-buy decisions.

Digital Skills yields a weaker coefficient of $\beta = 0.198$ despite one of the strongest bivariate correlations with the dependent variable. This divergence reflects the high collinearity between Digital Culture and Digital Skills (HTMT = 0.852): shared explanatory variance is partially absorbed by Digital Culture, reducing the independent effect of Digital Skills. This is a common pattern when two correlated predictors compete for explanatory variance and does not imply that digital competencies are irrelevant. Rather, it reflects a possible deeper reality: in early-stage digital start-ups, cultural orientation and technical competency are not independent forces. Founders who build a digitally oriented organization simultaneously tend to attract and retain technically skilled teams. Culture and skills should therefore be understood as a composite organizational capability.

Network Support produces the second-largest path coefficient ($\beta = 0.298$, $f^2 = 0.147$), directionally consistent with H5. In start-ups characterized by severe internal resource constraints, ecosystem embeddedness and external collaboration serve as a partial substitute for internal capabilities, accelerating technology decisions and deepening integration in ways a small founding team alone cannot achieve. This is treated as an exploratory directional signal needing to be explored in further investigation.

Institutional Support produces a small, non-significant, and directionally negative coefficient ($\beta = -0.096$). The negative sign does not constitute evidence of a negative relationship since the confidence interval includes zero. What it does reflect is the structural pattern in the data: Portugal reports substantially higher perceived Institutional Support than Germany (PT = 3.43 vs. DE = 2.68), while Germany achieves higher integration depth. This suggests a decoupling between institutional enablement and integration capacity: state programs can lower financial barriers to technology access, but the depth of integration into strategy and operations is primarily driven by organizational factors that institutional support cannot substitute. A complementary reading concerns Germany specifically: high institutional quality in the governance sense does not automatically produce high perceived institutional support at the start-up level, where GDPR compliance burdens dominate the experience of the regulatory environment.

Funding Access produces an effect of effectively zero ($\beta = -0.004$, $f^2 = 0.000$), representing the most robust null finding in the model. This is partly explained by near-identical mean Funding Access scores across both countries (DE = 2.73, PT = 2.74), meaning the predictor contains almost no between-group variance to explain the outcome. A deeper interpretation that would need further validation: capital access may be a necessary condition for initial technology investments, but beyond a baseline level it is cultural orientation and team competency that drives integration depth.

5.2. Country Comparison and DEE Perspective

The country comparison is limited to descriptive patterns, as the Multi-Group Analysis could not be conducted. Addressing the structural differences between the two ecosystems (SQ1): the predictor landscape diverges most in Institutional Support (higher in Portugal) and in Digital Culture and Digital Skills (higher in Germany), while Funding Access is near-identical, yet the dependent variable remains more similar than this gap would suggest (DE = 4.01 vs. PT = 3.83, $\Delta = +0.19$).

This pronounced gap in Institutional Support (PT = 3.43 vs. DE = 2.68) directly reflects the DEE characterization in Section 2.4: Portugal's ecosystem is organized around active state intervention (Coelho, 2025). German start-ups, by contrast, experience a regulatory environment dominated by compliance friction: GDPR burdens and bureaucratic processes that 87.8% of founders cite as a primary driver of considering relocation (Start-up Verband & ifo Center for Macroeconomics and Surveys, 2025). Portugal's world-leading Uncertainty Avoidance score (UA = 104) adds a further layer: in a culture with an exceptionally strong preference for clear frameworks, the visibility of state programs is experienced as meaningful support that reduces the uncertainty inherent in technology decisions (Hofstede Insights, 2023).

That this elevated institutional support does not translate into higher integration depth is the most theoretically significant finding of the country comparison and shows how the same factors carry different weight across the two ecosystems (SQ3), confirming the decoupling observed in the structural model.

Digital Culture and Digital Skills are both higher in Germany, consistent with its ecosystem characteristics: a high share of academically trained founders (87%), a mature technical university landscape, and a long-term cultural orientation (LTO = 83) that supports sustained investment in digital capabilities (Hofstede Insights, 2023; Start-up Verband & ifo Center for Macroeconomics and Surveys, 2025). Portugal's structural challenges for example emigration of skilled talent, a private sector unable to fully utilize available talent, and a short-term cultural orientation (LTO = 28) constrain organizational digital capability building at the firm level (Cardoso et al., 2022; Coutinho & Au-Yong-Oliveira, 2023).

The near-identical Funding Access scores across countries (DE = 2.73, PT = 2.74) are counterintuitive given the macroeconomic VC gap between the two countries. Two explanations are plausible: the sample consists predominantly of very early-stage start-ups for whom institutional VC is structurally limited in both countries, and the survey measures perceived rather than actual access, a gap that may be narrower at the individual founder level than aggregate figures suggest.

The small gap in integration depth despite substantially different ecosystem conditions suggests that digital technologies partially dissolve geographic constraints on innovation (Elia et al., 2020): Early-stage start-ups using globally available tools may reach similar integration depths regardless of which country they operate in, driven more by their founding team than by their national environment.

5.3. Contributions to the Literature

This study makes three contributions. Conceptually, it introduces Digital Technology Integration Intensity as a continuous dependent variable, departing from the binary adoption logic that dominates the TOE literature. For digitally native start-ups, the relevant variance lies not in whether technology is used but in how deeply it is embedded. Theoretically, the study proposes a systematic integration of the TOE Framework with DEE literature, providing a bridge that makes DEE theory empirically operationalizable and TOE findings ecosystemically interpretable. Empirically, it constitutes the first quantitative cross-country comparison of digital start-up technology integration between Germany and Portugal, providing an initial evidence base and replicable research instrument for larger follow-up studies.

5.4. Practical Implications

For founders, the findings suggest that integration depth is primarily a leadership and culture challenge rather than a resource challenge: how technology is positioned in the company's mission and hiring decisions matters more than funding volume. For investors and accelerators, the null finding for Funding Access suggests that due diligence should place greater weight on founding team orientation and competencies, and that network embeddedness may be a higher-return investment than capital provision alone. For policy-makers, the decoupling between institutional support and integration capacity implies that programs targeting organizational capability like mentoring, digital culture development, ecosystem connectivity could be more effective than financial instruments alone in driving deeper technology integration.

6. Limitations and Future Research

6.1. Limitations

Four limitations are material to the interpretation of this study's findings.

The most consequential is the sample size of n = 28, which falls substantially below the recommended minimum of approximately 60 observations for stable PLS-SEM estimation with six predictors. As a direct consequence, no path coefficient reaches conventional significance thresholds, R^2 is upwardly biased, and all measurement model estimates carry wider confidence intervals than in adequately powered studies. The study is explicitly framed as a pilot-level exploration; all findings are hypothesis-generating rather than hypothesis-confirming.

The second limitation is the unbalanced country distribution (DE: n = 18, PT: n = 10). The Portuguese subsample falls far below the minimum required for reliable Multi-Group Analysis. The country comparison is consequently limited to descriptive mean differences, a significant constraint given that the cross-country comparison represents a central part of the original research design.

The third limitation concerns measurement model performance. Four items fall below the recommended outer loading threshold of 0.70, with IS4 (0.430) being the most critical case. The resulting AVE values for Institutional Support (0.519) and Funding Access (0.530) are marginally above the 0.50 threshold, indicating fragile convergent validity for these two constructs. Five HTMT values additionally exceed the 0.85 discriminant validity threshold, though each is theoretically interpretable given the conceptual proximity of the affected constructs.

The fourth limitation concerns sample generalizability. Recruitment via LinkedIn and start-up associations introduces selection bias toward digitally active, professionally networked founders, a profile likely correlated with higher Digital Culture and integration depth than the broader start-up population. The findings therefore reflect the experience of a specific and engaged subpopulation rather than a representative cross-section of digital start-ups in either country.

6.2. Future Research

The most immediate priority is a direct replication with a substantially larger and more balanced sample. For example, a target of $n \geq 150$, distributed evenly between Germany and Portugal, would provide sufficient statistical power, enable the Multi-Group Analysis, and allow measurement model estimates to stabilize. The theoretical model and survey instrument developed in this thesis are immediately deployable, the marginal cost of larger-scale data collection is low relative to the inferential gains it would produce.

Beyond replication, two conceptual extensions are recommended. First, future research should examine whether ecosystem conditions influence integration depth indirectly rather than through direct effects. This would better reflect the DEE literature's view of the ecosystem as a shaping context rather than a direct cause. Second, start-up development stage should be explored as a moderator, as the relative importance of different TOE factors likely shifts over time: Digital Culture may dominate in early stages, while Network Support and Funding Access become more relevant as the start-up grows and external relationships deepen.

Finally, expanding the country comparison beyond the Germany–Portugal ecosystem would allow the moderating role of DEE conditions to be estimated across a wider parameter range. A longitudinal design would additionally establish causal direction and track whether the descriptive patterns observed here are stable structural features or momentary conditions as both ecosystems continue to develop.

7. CONCLUSION

This thesis set out to answer a question at the intersection of two bodies of literature that have rarely been brought into direct empirical contact: to what extent do Digital Entrepreneurship Ecosystem conditions influence the degree of digital technology integration intensity in digital start-ups, and do these influences differ between Germany and Portugal? The answer the present study can offer is constrained by a pilot-level sample of n = 28 that limits the statistical power. But the answer is not empty, and the contributions of the study extend well beyond what the structural results alone can demonstrate. In direct response to the overarching research question, DEE conditions do appear to shape integration intensity, but predominantly through organizational rather than institutional or financial channels, and the cross-country differences are smaller than the ecosystem gap would predict

The point of departure was a gap in the TOE literature: existing studies measure whether a specific technology is adopted, not how deeply the full digital technology portfolio of a firm is integrated into its strategy, business model, and operations. For digital-native start-ups, organizations for which technology is not an add-on but a constitutive element of the value proposition, this binary framing misses the relevant variance. The conceptual core of this thesis is therefore the operationalization of Digital Technology Integration Intensity as a continuous dependent variable, measured through an instrument derived from validated existing scales. This construct and its measurement tool represent the primary scientific contribution, standing independently of the structural results and available as a reusable foundation for future research.

The theoretical contribution is the integration of the TOE Framework with the DEE literature into a coherent research model. TOE provides the firm-level factor structure and DEE provides the national ecosystem context that shapes those factors. The systematic mapping of TOE findings onto DEE dimensions constitutes a theoretical bridge that makes ecosystem conditions empirically testable at the construct level and is therefore addressing a gap that neither framework resolves in isolation.

The empirical results, interpreted within an explicitly exploratory frame, held a consistent and theoretically coherent pattern. Digital Culture emerges as the strongest structural signal reinforcing the argument that integration depth is primarily a leadership and culture challenge rather than a resource challenge. Institutional Support and Funding Access produce negligible structural effects, which is a pattern that the country comparison helps explain. Portugal reports substantially higher perceived Institutional Support than Germany yet achieves lower integration depth: institutional programs lower financial barriers to technology access but do not build the organizational capacity to integrate technology deeply. The small difference in integration depth between the two countries despite larger differences in several predictor constructs supports the DEE literature's claim that digital technologies partially dissolve geographic constraints on innovation, and that organizational factors operate more universally across national contexts than ecosystem-level conditions.

The limitations of this study are clear and have been stated without attenuation. A sample of n = 28 is insufficient for confirmatory PLS-SEM with six predictors, the country distribution precludes the Multi-Group Analysis the design requires, and selection via LinkedIn likely overrepresents digitally active founders, which introduces a ceiling effect that may compress the variance available for structural estimation.

What this study can claim is a theoretically grounded instrument for measuring digital technology integration intensity, a replicable research architecture for future cross-national start-up technology studies, and a clear empirical agenda: a replication with n ≥ 150 distributed evenly across both countries would provide the statistical power to convert the exploratory signals observed here into confirmatory findings. The broader question this thesis addresses: how national ecosystem conditions shape the depth of technology integration in digital start-ups matters for founders, investors, and policymakers alike. The present study cannot answer it definitively. What it does is establish the conceptual foundation and empirical roadmap for the research that will.

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APPENDICES

APPENDIX A – TOE FRAMEWORK LITERATURE REVIEW

Finding	Description	Sources & Contexts
Organization		
Digital Culture	Strongest driver of digital technology adoption; companies with strong digital culture integrate technologies seamlessly; promotes flexible digital mindset	Faiz et al. (2024): SMEs; Amini & Javid (2024): AI start-ups
Resistance to Change	Organizational barriers and reluctance to abandon established practices; counterpoint to digital culture	Staley (2026): fintech start-ups (emerging markets); Bańka et al. (2023): PT companies
Top Management Support	In small firms, management attitude critical for resource allocation; in start-ups = direct founder vision	Faiz et al. (2024); Amini & Javid (2024); El-Shihy & Hassan Mohamed (2023); Lina & Suwarni (2022); Jeilani & Hussein (2025); Religia et al. (2024); Weiss et al. (2025)
Entrepreneurial Orientation	Proactivity, openness to innovation, and risk-taking of founders; international orientation as moderator	Amini & Javid (2024); Faiz et al. (2024)
IT/IS Knowledge of Employees	IT competency fundamental for operation and maintenance; specific expertise in small team especially critical	Faiz et al. (2024); Lina & Suwarni (2022); Amini & Javid (2024); Chakraborty et al. (2023)
Resource Scarcity (personnel)	Lack of qualified workers as structural barrier; limited understanding of technology potential	Marican et al. (2023); Staley (2026); Jeilani & Hussein (2025)
Adoption Costs	High initial setup costs; mitigated by pay-as-you-go but still relevant for resource-constrained start-ups	Faiz et al. (2024); Staley (2026); Amini & Javid (2024); Moharrak et al. (2024)
Firm Size	Influences willingness and capacity for innovation; adoption ability varies by growth stage	Jeilani & Hussein (2025); Amini & Javid (2024); Chang et al. (2020)
Technology		
Technical Readiness / Infrastructure	Existing IT infrastructure as prerequisite for adoption; availability of sufficient facilities and competent personnel	Amini & Javid (2024); Religia et al. (2024); Chang et al. (2020)
Scalability and Interoperability	Difficulty adapting systems to large data volumes; integration with legacy systems	Staley (2026); Amini & Javid (2024)
Relative Advantage	Perception that innovation is better than current solution; ROI focus as decision basis	El-Shihy & Hassan Mohamed (2023); Lina & Suwarni (2022); Amini & Javid (2024); Religia et al. (2024); Weiss et al. (2025)
Compatibility	Degree of alignment with existing values, processes, and IT infrastructure	Chang et al. (2020); Lina & Suwarni (2022); El-Shihy & Hassan Mohamed (2023); Amini & Javid (2024); Religia et al. (2024)
Complexity	Degree of difficulty in operating technology negatively correlated with adoption; ease of use as counterpoint	Baker (2012); Amini & Javid (2024); Chakraborty et al. (2023); Jeilani & Hussein (2025)
Data Security and Privacy	Protection of sensitive data and algorithms; GDPR as critical filter in Germany	Staley (2026); Amini & Javid (2024); Chakraborty et al. (2023); Weiss et al. (2025)
Data Quality and Availability	AI models require high-quality data volumes; data scarcity and lack of standardization as barriers	Amini & Javid (2024); Weiss et al. (2025)
Environment		
Competitive Pressure	Strategic compulsion to remain competitive through new technologies; adoption as defensive necessity	Faiz et al. (2024); Amini & Javid (2024); Lina & Suwarni (2022); Religia et al. (2024); Jeilani & Hussein (2025); Weiss et al. (2025)
Partner and Customer Pressure	Start-ups yield to technological pressure from larger supply chain partners; requirements of ecosystem stakeholders	Faiz et al. (2024); Marican et al. (2023); Amini & Javid (2024); Lina & Suwarni (2022)
External Network Access	Access to advisors, cloud providers, government programs; university cooperation vital for resource-constrained firms	Amini & Javid (2024); Weiss et al. (2025); Fernandes et al. (2022); Hajli et al. (2025)
Funding Access	Access to capital providers as critical success factor; business angels as smart money; subsidies lower entry barrier	Chakraborty et al. (2023); El-Shihy & Hassan Mohamed (2023); Weiss et al. (2025); Lado et al. (2024)
Resource Scarcity (financial)	Limited financial resources as adoption barrier; founder as primary source when external capital access is difficult	Moharrak et al. (2024); Marican et al. (2023); El-Shihy & Hassan Mohamed (2023)
Regulatory Framework	Laws and policies promote or hinder technology adoption; clear guidelines as enabler, uncertainty as barrier	Jeilani & Hussein (2025); El-Shihy & Hassan Mohamed (2023); Amini & Javid (2024); Chakraborty et al. (2023); Staley (2026); Weiss et al. (2025)
Institutional Support	Government programs, tax incentives, funding policies as active enablers; institutional gaps as impediment or innovation opportunity	El-Shihy & Hassan Mohamed (2023); Moharrak et al. (2024); Zhang et al. (2023); Torres & Godinho (2022)
Market Conditions	Ease of market entry; internationalization; consumer behavior as driver of digital adoption	Torres & Godinho (2022); Moharrak et al. (2024); Staley (2026)

Appendix B – Mapping DEE Dimensions and TOE Findings

DEE Dimension	Construct	TOE Findings (see Appendix A)	TOE Dim.	Key Sources
Culture (informal institutions)	**Digital Culture**	Digital culture + Top mgmt. support + Entrepreneurial orientation + Resistance to change	Organization	Faiz et al. (2024); Amini & Javid (2024); El-Shihy & Hassan Mohamed (2023); Lina & Suwarni (2022); Weiss et al. (2025)
Talent and knowledge	**Digital Skills**	IT/IS knowledge of employees + Resource scarcity (personnel)	Organization	Faiz et al. (2024); Lina & Suwarni (2022); Amini & Javid (2024); Marican et al. (2023); Staley (2026)
Digital infrastructure	**Technological Infrastructure**	Technical readiness + Scalability/interoperability + Relative advantage* + Compatibility* + Complexity*	Technology	Amini & Javid (2024); Religia et al. (2024); Staley (2026); Chang et al. (2020)
Funding	**Funding Access**	Funding access + Resource scarcity (financial) + Adoption costs**	Environment	Chakraborty et al. (2023); El-Shihy & Hassan Mohamed (2023); Lado et al. (2024); Weiss et al. (2025); Moharrak et al. (2024)
Networks and support structures	**Network Support**	External network access + Competitive pressure + Partner/customer pressure	Environment	Faiz et al. (2024); Amini & Javid (2024); Marican et al. (2023); Weiss et al. (2025); Hajli et al. (2025)
Formal institutions	**Institutional Support**	Regulatory framework + Institutional support + Market conditions***	Environment	Jeilani & Hussein (2025); El-Shihy & Hassan Mohamed (2023); Amini & Javid (2024); Zhang et al. (2023); Torres & Godinho (2022)

APPENDIX C – DESCRIPTIVE SURVEY RESULTS

Sample Description (n = 28)

Characteristic	Total	DE	PT
Industry			
HealthTech / MedTech	29%	28%	30%
E-commerce / Retail	18%	17%	20%
FinTech	18%	11%	30%
Mobility / Logistics	11%	11%	10%
IT / Software	11%	17%	–
Other	11%	11%	10%
Energy / Sustainability	4%	6%	–
Company size (employees)			
1–5	29%	33%	20%
6–10	46%	39%	60%
11–25	14%	11%	20%
26–50	7%	11%	–
100+	4%	6%	–
Start-up stage			
Idea stage	7%	6%	10%
MVP / Prototype	32%	39%	20%
Market-ready	36%	33%	40%
Scaling	25%	22%	30%
Business model			
B2B	43%	56%	20%
B2B2C	25%	22%	30%
Platform / Marketplace	14%	6%	30%
B2C	14%	11%	20%
Other	4%	6%	–

Characteristic	Total	DE	PT
Financial status			
Not yet profitable	54%	56%	50%
Break-even	18%	22%	10%
Profitable	29%	22%	40%
Funding sources (multiple)			
Bootstrapping / own funds	79%	67%	100%
Business Angels	14%	22%	–
Public funding / grants	11%	11%	10%
Family & Friends	11%	11%	10%
Venture Capital	7%	11%	–
Bank loans	7%	6%	10%
Role of technology			
Core of product / service	64%	61%	70%
Equally central (ops & product)	29%	28%	30%
Supports internal operations	7%	11%	–
Technologies used (multiple)			
Cloud computing	46%	39%	60%
Data analytics / BI	36%	39%	30%
AI / ML	32%	39%	20%
No-code / low-code	25%	28%	20%
Cybersecurity tools	11%	11%	10%
CRM / ERP systems	11%	11%	10%
Automation / RPA	7%	6%	10%
IoT solutions	7%	6%	10%
Blockchain	4%	6%	–

APPENDIX D – ITEM CONSTRUCTION

Construct	Item	Source
Digital Culture	There is a clear orientation toward digital technology adoption within the company's culture.	Faiz et al. (2024)
	Top management in our firm considers the adoption of digital technologies to be important.	Faiz et al. (2024)
	Top management in our firm has allocated the necessary resources to support the adoption of digital technologies.	Faiz et al. (2024)
Digital Skills	Our employees are proficient in using advanced technology.	Faiz et al. (2024)
	Our firm possesses a high degree of computer-based technical expertise.	Branch et al. (2011)
	Our start-up is capable of attracting and hiring employees with the technological skills it needs.	El-Shihy & Hassan Mohamed (2023)
	Our start-up has sufficient technical staff to adapt and implement new technologies.	El-Shihy & Hassan Mohamed (2023)
Technological Infrastructure	Our start-up has the technological infrastructure needed to support the adoption of digital technologies.	Religia et al. (2024)
	Our existing technological systems enable the integration of new digital technologies.	Religia et al. (2024)
	Our start-up has the technical infrastructure necessary to scale digital operations.	Xia & Johar (2024)
	Our technological setup allows us to efficiently integrate digital technologies into our business processes.	Xia & Johar (2024)
Funding Access	We have (had) sufficient access to external capital.	Frimanslund & Nath (2024)
	We have (had) sufficient access to funding opportunities for digital innovation.	Frimanslund & Nath (2024)
	We have (had) sufficient access to private investors.	Frimanslund & Nath (2024)
	We have (had) sufficient access to venture capital funds or similar.	Frimanslund & Nath (2024)
	We have (had) sufficient access to public grants, loans or investments.	Frimanslund & Nath (2024)
Network Support	Our start-up benefits from digital collaboration with external partners and ecosystem actors.	Frimanslund & Nath (2024)
	Our start-up actively collaborates with external organizations to support digital innovation and technology development.	Frimanslund & Nath (2024)
	Participation in entrepreneurial ecosystems is important for our start-up's development and innovation activities.	Frimanslund & Nath (2024)
	Complementary knowledge and resources within the ecosystem support our start-up's digital development.	Theodoraki et al. (2022)
Institutional Support	The government has established an adequate legal framework for the adoption of digital technologies.	Faiz et al. (2024)
	The government has provided public infrastructure that supports the adoption of digital technologies.	Faiz et al. (2024)
	Government bodies provide sufficient support for the adoption of new technologies.	Smirnova & Travieso-Morales (2025)
	Regulatory requirements facilitate the implementation of new digital technologies.	Smirnova & Travieso-Morales (2025)
Integration Intensity (DV)	Digital technologies are central to the value of our business model.	Almaiah et al. (2022); Ladu et al. (2024); Wang et al. (2008); Xia & Johar (2024)
	Our start-up considers the adoption of digital technologies strategically important to remain competitive.	Faiz et al. (2024)
	Our start-up uses digital technologies across multiple parts of the business to improve and scale operations.	Lin et al. (2009); Wang et al. (2008); Xia & Johar (2024)
	Digital technologies are integrated into most of our core business activities.	Almaiah et al. (2022); Ladu et al. (2024); Wang et al. (2008); Lin et al. (2009); Xia & Johar (2024)

AI DISCLAIMER

Artificial intelligence tools were used during the preparation of this thesis in a supportive capacity. Specifically, AI assistance was employed for language refinement and proofreading, for improving the clarity and structure of written passages, for formatting and laying out tables and figures, and as a sounding board for outlining and organising content. All substantive academic work was carried out independently by the author. This includes the conceptual development and research design, the construction and distribution of the survey, the statistical analysis in SmartPLS, and the interpretation of the findings and conclusions drawn from them. No AI tools were used to create or fabricate sources, or to replace the author's own critical reasoning and academic judgment. All sources have been verified by the author and cited in accordance with academic standards. The author takes full responsibility for the content, accuracy, and originality of this thesis.