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Skill balance and entrepreneurship in Austria: Evidence from LinkedIn user profiles

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Zusammenfassung

Kleine und mittlere Unternehmen (KMU) sind in der österreichischen Wirtschaft vorherrschend. In früheren Studien wurden jedoch die formale Bildung und das praktische Wissen von Gründern als unterschiedliche Faktoren behandelt, die den unternehmerischen Erfolg beeinflussen. Diese Studie baut auf der Perspektive des Qualifikationsgleichgewichts auf, indem sie beide Stränge des Humankapitals integriert und analysiert, wie deren Konfiguration zusammen mit der Managementerfahrung das unternehmerische Verhalten beeinflusst. Eine Querschnittsauswahl von 92 österreichischen LinkedIn-Profilen, darunter 54 Unternehmer und 38 Führungskräfte, wurde manuell auf formal erworbene Kompetenzen, praxisbezogene Kompetenzen, Dauer der Vorstands-/Führungsposition, unternehmerische Orientierung (einschließlich Führungskompetenzen, Vision und Chancenerkennung) sowie drei Verhaltensmerkmale analysiert: Risikomanagementfähigkeit, systematische Innovation und operative Flexibilität. Unabhängige t-Tests und Chi-Quadrat-Tests wurden verwendet, um Gründer und Nicht-Gründer zu vergleichen, während Pearson- und Spearman-Korrelationen zusammen mit Benjamini-Hochberg-bereinigten Signifikanzniveaus verwendet wurden, um Korrelationen innerhalb der Gruppen zu bewerten. Die Analysen zeigen, dass: 1) Unternehmer und Nicht-Unternehmer über ein ähnliches Niveau an formaler Bildung und beruflicher Erfahrung verfügen; Gründer jedoch eine deutlich stärkere unternehmerische Ausrichtung sowie eine höhere Risikobereitschaft, Innovationskraft und Anpassungsfähigkeit aufweisen; 2) in der unternehmerischen Teilstichprobe ein höherer Anteil an praxisbezogenen Fähigkeiten im Vergleich zu formalen Fähigkeiten positiv mit Seriengründungen und erfolgreicher Kapitalbeschaffung korreliert, während zusätzliche Abschlüsse zu sinkenden Erträgen führen; 3) Managementerfahrung und in geringerem Maße auch Erfahrung in Führungsgremien verbessern die Umsetzung ausgewogener Kompetenzen in dynamisches Verhalten und wirken dabei eher als Verhaltensbeschleuniger denn als Substitute. 4)

Geschlecht, Alter und Gesamtbeschäftigungsdauer haben keinen Einfluss auf diese Korrelationen, wenn die Zusammensetzung der Kompetenzen berücksichtigt wird.

Die Ergebnisse unterstreichen, dass nicht einfach die Anhäufung von Kompetenzen, sondern vielmehr die harmonische Integration und strategische Präsentation von analytischen und erfahrungsbasierten Kompetenzen die unternehmerische Dynamik fördert. Diese Studie erweitert die Humankapital- und Effektivierungstheorie, indem sie den unternehmerischen Fokus als kognitive Verbindung zwischen Kompetenzarchitektur und beobachtbarem unternehmerischem Verhalten darstellt. Sie bietet praktische Leitlinien für Pädagogen, politische Entscheidungsträger und Gründer, die in Österreich und ähnlichen Ökosystemen wirkungsvolle und widerstandsfähige KMU fördern möchten.

Stichwörter: *Kompetenzausgleich, Erfahrungslernen, LinkedIn-Profile, unternehmerischer Fokus, KMU, Österreich, Humankapital, Innovationsverhalten*

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1. Introduction

1.1. Background and Context

Small and medium-sized enterprises (SMEs) are at the heart of the Austrian economy. In 2021 - the last year for which the Federal Ministry of Labor and Economic Affairs provides a complete statistical breakdown - around 358,600 companies fell under the EU's definition of SMEs, which corresponds to 99.6 percent of all market economy companies in the country (Federal Ministry of Labor and Economic Affairs, 2023). These companies employed more than two million people and generated a net turnover of over 535 billion euros and a gross value added of 137.4 billion euros (Federal Ministry of Labor & Economic Affairs, 2023). If this gross value added is converted into shares of national economic output, the extent of the contribution becomes clear: Austria's GDP amounted to around 385 billion euros in 2021 (OECD, 2021, p. 77), which means that SMEs accounted for almost 36% of the country's total output. In other words, more than one in three euros circulating in the Austrian economy comes from companies with fewer than 250 employees - a ratio that highlights the importance of the health, resilience and future growth of the SME sector. This importance has increased since the multiple shocks of 2020. Like virtually all advanced economies, Austria faced a health crisis that quickly escalated into a global recession. A landmark McKinsey study, which looked at 5.7 million small US businesses with sectoral vulnerabilities similar to those in Europe, estimated that between 1.4 and 2.1 million businesses (25-36%) were at risk of permanent closure in the first four months of the pandemic (Dua et al., 2020, p. 2).

The sectors most at risk were accommodation, gastronomy, education and arts and culture - the very sectors that characterize Austria's tourism ecosystem and creative industries. Although the McKinsey analysis focused on the United States, its core message can be easily transferred: companies that started the pandemic with low liquidity buffers and modest sales margins were exponentially more at risk of insolvency if demand shocks persisted (Dua et al., 2020, p. 3). The disruption to supply chains caused by the war in Ukraine further exacerbated the difficult situation of Austrian SMEs, increased the volatility of input costs and dampened the recovery in key export markets (European Commission, 2019, p. 4). Against this macroeconomic backdrop, policymakers have tried to cushion the impact. The Austrian government's SME package for 2025 promises targeted liquidity measures and new tax incentives and emphasizes that SMEs generate a gross value added of more than 160 billion euros and employ around 2.5 million people (Federal Ministry of Finance, 2025). However, even a generous fiscal shield cannot replace the microeconomic factors for entrepreneurial performance. Scholars have long argued that the human capital endowment of founders - particularly the balance between formal education and experiential learning - determines a company's ability to weather turbulence (Becker, 1993, p. 44).

The Global Entrepreneurship Monitor (GEM), which surveys more than 4,600 Austrian adults annually, finds that early entrepreneurship has declined to 6.8 percent of the working-age population, but still lags behind pre-pandemic dynamics. GEM experts repeatedly point to limited formal entrepreneurial education as a persistent bottleneck in the Austrian ecosystem. This observation is in line with the skills equilibrium thesis underlying this study. The modern business landscape values the combination of different skills rather than the presence of narrow technical specialization. Risk management skills, innovation skills and market orientation are each necessary but not sufficient on their own. What matters is their configuration and relative weighting in a person's repertoire - a finding supported by recent human capital analyses based on millions of LinkedIn profiles. Dorn et al. show that employees who report more and, in particular, more specific and management-related skills are more likely to hold high-paying jobs (2024, p. 16) and that multidimensional skills profiles explain income differences more strongly than traditional variables such as highest educational qualification or professional experience (2024, p. 22). Put simply, entrepreneurial success today increasingly depends on how well founders combine formal education with hands-on learning, board experience and strategic upskilling. Last but not least, LinkedIn's data provides unprecedented empirical insight into this mix. By mid-2025, the platform has over 950 million member profiles worldwide and around 3.9 million registered users in Austria (LinkedIn Engineering, 2023). Profiles contain structured information on education, work experience, certifications, recommendations and self-reported skills - attributes used by recruiters and researchers alike as indicators of human capital (Dorn et al., 2024). Furthermore, the frequency with which Austrian entrepreneurs maintain their online identity - by updating their skills, posting on current affairs or referencing innovation awards - signals both their actual competence and their strategic awareness of how competence is perceived. This digital resume phenomenon thus provides a uniquely high-resolution data set for examining how Austrian entrepreneurs assemble and communicate their skills portfolios compared to their non-entrepreneurial peers.

1.2. Research Gap

The relationship between human capital and entrepreneurial performance is by no means unexplored. Classic formulations by Becker (1993) and later refinements by Unger et al. (2011) prove a robust, positive correlation between accumulated knowledge and corporate success, regardless of whether this is measured by the probability of survival, sales growth or innovation performance. Nevertheless, three limitations limit the validity of this line of research. Most empirical tests rely on crude variables such as the total number of years of education or binary indicators for university degrees. These proxy variables assume homogeneity of different academic careers and underestimate the functional diversity of skills used by new venture founders. A founder with a Master of Science in Mechanical Engineering and another with a Master of Arts in Strategic Communication would be treated identically in most regression models, even though they have significantly different skill profiles. Multidimensional constructs - risk analysis, opportunity recognition skills, or digital marketing skills - are often combined into a single measure of education duration, losing nuances that could shed light on why seemingly similar entrepreneurs make different decisions under pressure (Marvel & Lumpkin, 2007, p. 816). Furthermore, studies that actually disaggregate competencies often rely on self-report surveys conducted at a point in time.

The canonical GEM questionnaire, for example, asks respondents to rate their start-up skills on a Likert scale from “very good” to “very poor”. While such cross-sectional surveys are invaluable in capturing subjective self-confidence, they lead to recall bias and suffer from social desirability bias

- particularly in cultures that value entrepreneurial bravery (Audretsch et al., 2017, p. 681). Another problem is omitted variable bias: Entrepreneurs who rate themselves highly in terms of opportunity recognition may simultaneously have unmeasured advantages such as privileged networks or risk insurance mechanisms, which complicates causal inference.

Austrian research on entrepreneurship has so far relied heavily on indicators at company level (export intensity, R&D expenditure) or ecosystem indicators at sector level (risk capital density, regulatory intensity), neglecting the skill composition at individual level. The "Focus on SMEs" series from KMU Forschung Austria describes the turnover development and innovation rates of SMEs in detail, but devotes comparatively little space to the microeconomic basis of these results. Even when skills are discussed, the analysis is limited to the qualification status: percentages of founders with vocational qualifications compared to university graduates (KMU Forschung Austria, 2022). This level of detail may have been sufficient when talent pipelines were stable and business models were incremental, but in a post-pandemic digital market, it is the recombinatory skills that enable entrepreneurs to refocus, adopt new technologies and manage risk in ambiguous environments (Nambisan et al., 2019, p. 1445). LinkedIn-derived datasets offer a way out of this impasse. While traditional surveys place respondents into static categories, professional networking platforms encourage continuous updating: users add newly acquired certificates, list new digital tools (e.g. TensorFlow, Midjourney) and ask colleagues who have directly observed their skills for recommendations. Dorn et al. use this feature by analyzing 8.75 million US profiles and uncovering skill-income gradients that are not visible in census datasets. Their conclusion that "skill differences between workers can explain larger income differences than detailed vectors for education and experience" (2024) suggests that entrepreneurial researchers run the risk of overlooking variables with high explanatory power that are overtly visible in digital data. To date, however, there is no peer-reviewed study that utilizes LinkedIn's Austrian member base to compare entrepreneurs with non-entrepreneurs using the full range of skill tags provided by LinkedIn. A second, related gap concerns balance rather than mere presence. Entrepreneurship theory is increasingly shifting from "Does the founder have skill X?" to "How does the founder combine skill X with Y and Z under constraint C?". The effectuation logic assumes that experienced entrepreneurs work with the means at their disposal instead of pursuing predetermined goals and dynamically adapt their competencies to changing conditions (Sarasvathy, 2001, p. 249). However, the empirical operationalization of such a reconfiguration has proven to be difficult. This study therefore draws on the literature on skill balance and assumes that the ratio of formally acquired skills to skills acquired through experience - and not simply their sum - is a better predictor of entrepreneurial adaptability. LinkedIn's profile syntax allows for the classification of skill tags into those typically acquired through a structured university education (e.g. structural equation modelling, solid state physics) and those more commonly acquired through practice (e.g. agile project management, Kanban, seed fundraising), operationalizing the balance in a measurable form. Finally, in previous Austrian analyses, entrepreneurs are rarely compared to a control group of non-entrepreneurs, holding the skill dispersion constant. Without such a counterfactual, it is difficult to assess whether differences in skill balance are unique to the entrepreneurial population or represent a broader labor market phenomenon. Comparing founders with non-founders who nevertheless hold leadership positions (e.g. company directors or board members) provides a clearer insight into what constitutes true entrepreneurial competence as opposed to general leadership skills. By selecting both groups from the same LinkedIn ecosystem, the study minimizes selection effects resulting from different data collection methods.

1.3. Research Objectives & Questions

Against above background, the overarching objective of this thesis is to interrogate whether, and to what extent, the balance between formally acquired and experientially cultivated skills shapes entrepreneurial performance among Austrian professionals. Performance itself is conceptualised broadly—as the capacity to exercise risk management, to innovate systematically, and to maintain operational flexibility in volatile markets. Harnessing an original dataset scraped and hand-coded from 92 well-populated LinkedIn profiles, the study seeks to map the architecture of competencies that appear most conducive to those outcomes. The inquiry proceeds from the premise that skills are multidimensional and mutually reinforcing. Formal higher education furnishes cognitive frameworks, advanced analytical techniques, and often a legitimising credential in the eyes of investors. Practice-based learning, by contrast, embeds tacit know-how, industry-specific heuristics, and an experiential intuition for timing. Board or senior-management assignments contribute yet another layer: strategic oversight, coalition-building, and governance literacy. The skill-balance concept designates the proportionate mix of these layers, hypothesising that the harmonic integration of diverse knowledge stores outperforms dominance by any single category. Accordingly, the study pursues four interlocking research questions:

1. Do Austrian entrepreneurs, when matched on experience, exhibit a statistically distinct balance of practice-oriented versus formally-oriented skills compared to non-entrepreneurs?

2. Within the entrepreneur sample, is a higher practice-to-formal skills ratio positively associated with venture dynamism indicators—specifically serial founding frequency and successful fundraising rounds?

3. Does prior board or senior-management experience moderate the link between skill balance and entrepreneurial outcomes, serving either as an enhancer of strategic acumen or as a compensatory substitute through network access?

4. To what extent does gender mediate the relationship between skill-balance profiles and entrepreneurial success, considering documented differences in skill self-reporting and platform-based opportunity access?

By answering these questions the thesis contributes to both academic debate and practitioner insight. At the scholarly level, it supplies empirical evidence to refine human-capital theory by injecting a balance perspective. Practically, the findings can inform policy recommendations on entrepreneurship education and guide founders in prioritising up-skilling investments that have demonstrable leverage on outcomes. More ambitiously, the research offers a replicable methodological template for other national contexts where LinkedIn penetration is high and traditional entrepreneurship datasets lag behind the pace of labour-market transformation.

1.4. Thesis Structure and Methodology

This master's thesis is divided into six substantive chapters, each designed to build the argument cumulatively. Chapter 1 - this introduction - has laid the intellectual and economic foundations, set out the research gap and outlined the key questions. Chapter 2 provides a comprehensive literature review and summarizes the research on Austrian entrepreneurship, human capital theories and emerging debates on digital platform data. Chapter 3 therefore develops the conceptual model and explains the operationalization of the variables. It explains how LinkedIn profile elements are categorized into formal educational competencies, practice-based competencies, entrepreneurial orientation indicators, and governance experience. Chapter 4 documents the research design, including sampling criteria, ethical considerations and the statistical tools (descriptive statistics, Pearson correlations and non-parametric robustness checks). The next chapter presents the empirical results in narrative form, interpreting patterns and testing each hypothesis against the evidence. Chapter 6 discusses theoretical and managerial implications and concludes with limitations and starting points for future research. Methodologically, the study follows a quantitative cross-sectional design. The profiles were selected in a multi-stage filtering process: first by self-reported location (Austria), then by keywords indicating entrepreneurship (e.g. founder, managing director, entrepreneur) or senior non-entrepreneurial positions (vice president, director), and finally by completeness criteria (defined as at least five listed skills, two positions held and one educational qualification). The resulting dataset of 92 profiles was exported to Microsoft Excel for initial coding and then imported into IBM SPSS 26 for statistical analysis. Binary and ratio-scale variables were created to enable the calculation of a skills balance index, defined as the proportion of practice-related skills to overall skills. Descriptive statistics provide baseline comparisons, while correlation matrices test hypothesized relationships. Wherever cell sizes or distribution properties violate parametric assumptions, bootstrap confidence intervals and Spearman rank correlations complement the analysis to ensure robustness.

2. Literature Review

2.1. Entrepreneurship in Austria

2.1.1. Environment for entrepreneurship

Strong government support, a creative culture, and globally oriented programs to attract and retain talent define Austria's diverse entrepreneurial environment. The Austria Wirtschaftsförderungsgesellschaft (AWS), which offers grants and loans to start-up companies, is at the heart of this ecosystem. Regional start-up service centers also offer investors individualized guidance and connections. This network ensures that entrepreneurs can successfully navigate the initial phases of their ventures by providing support with legal compliance, market research, and business planning (30countries.com, 2025). Austria's tax competitiveness and R&D incentives, which account for more than 3% of GDP, are balanced by the country's 25% corporate tax rate and 14% refundable research premium. This makes it financially possible to experiment (FasterCapital, 2025). Legislative changes like the 2024 start-up package have delayed taxing employee stock options until the employee leaves, putting Austria in line with Europe's leading innovation hubs and boosting its attractiveness to highly skilled workers (30countries.com, 2025).

Meanwhile, there has been a surge in activity within unofficial investment networks: Business angel syndicates have grown by more than 20% since 2019 due to their provision of seed capital to high-growth sectors such as biotech, renewable technologies, and fintech (Global Entrepreneurship Monitor, 2025). Though growth is steady and primarily concentrated in innovation clusters in Vienna, Graz, and Linz, venture capital usage is still low by Nordic standards (FasterCapital, 2025). In this entrepreneurial environment, research and educational institutions are crucial. Austria is among the top two-thirds of OECD countries in terms of public investment in research and development, and university curricula now include incubators, accelerator programs, and entrepreneurial courses.

According to the Global University Entrepreneurial Spirit Students' Survey (GUESSS) 2023, students who receive entrepreneurial education are 33 percent more likely to start their own business than those who do not. This illustrates how the desire to start a business is directly impacted by organized academic support (Gutschelhofer et al., 2024, p. 23-29). However, the GEM study found that some would-be founders are still deterred by their fear of failing, and that sociocultural norms only marginally encourage risk-taking (Global Entrepreneurship Monitor, 2019). The harmonization of regulations strengthens Austrian entrepreneurship's potential. Austrian companies have duty-free access to more than 450 million customers through the EU single market. Additionally, they can connect with strategic partners worldwide through bilateral free trade agreements.

To get around export restrictions, companies can use domestic subsidies, such as Go-International grants, to attend trade exhibitions and audits of digital marketing (Global Entrepreneurship Monitor, 2025). Additionally, Austria's stable political environment and easily accessible legal system increase investor confidence and provide planning security for long-term business projects. Austrian culture blends an inventive, forward-thinking mentality with a deep appreciation for craftsmanship and quality that stretches back to the guilds of the Habsburg era. The success of Runtastic, a Graz-based fitness app start-up that Adidas acquired, serves as an illustration of this contradiction. It blends the flexibility and global outlook of a start-up with meticulous software development (30countries.com, 2025). These examples show how disruptive thinking can coexist with traditional values like accuracy and attention to detail. Lastly, the foundations of Austria's entrepreneurial culture are a commitment to professional excellence and work-life balance.

The dual education system, which guarantees a supply of technically trained personnel and cultural values like punctuality and respect for hierarchies, helps investors and partners achieve operational stability (30countries.com, 2025). When combined, these components create an environment that supports start-up growth. Schools cultivate talent, government tools reduce financial risk, and cultural foundations ensure excellence and aspirations for a global future.

2.2. Determinants of Successful Entrepreneurial Behavior

2.2.1. Propensity to take risks

There is a growing realization that a healthy willingness to take risks is essential for successful entrepreneurship. The reason for this lies in the creation of quality-oriented management frameworks such as ISO 9001:2015 and the European Foundation for Quality Management (EFQM) model. With ISO 9001, risk management goes from being an additional compliance activity to a strategic discipline that must permeate planning, operations and continuous improvement by requiring organizations to think risk-based in all processes (Nascimento et al., 2020, p. 4). Business owners are compelled by this duty to identify potential risks to value creation and use this information to take preventative or opportunity-oriented actions, which are the cornerstones of business agility. Owners are replacing instinctively motivated gambles with methodical experimentation as they methodically list threats, assess their impact and likelihood, and build controls into the quality management system. Risk still exists, but it is now monitored, understood and linked to quantifiable objectives.

This emphasis is reinforced by the EFQM Excellence criteria, which call for risk assessment as a necessary prerequisite for visionary leadership, smart strategy and long-term results. To achieve a high EFQM rating, a company must demonstrate that it anticipates stakeholder needs, scans its environment and incorporates risk considerations into decision-making cycles. These measures are indicative of the entrepreneurial process of recognizing and exploiting gaps in the market. Consequently, entrepreneurs who apply ISO 9001 and EFQM cultivate the cognitive processes of scanning, sense-making and rapid reallocation of resources that facilitate the recognition of opportunities while reducing the risk of loss. This disciplined willingness to take risks pays off, as empirical studies show. According to a qualitative study of Brazilian companies certified to ISO 9001 or ISO 14001, the auditors found that smaller companies in stable niches initially view integrated risk management as a cost factor, while larger, innovation-intensive companies see it as a value that secures complex processes and accelerates strategic realignments (Nascimento et al., 2020, p. 2). However, once even small companies formalize risk registers and link them to key process indicators, there are fewer interruptions, less rework and more customer confidence. These results translate into competitive advantage and stable revenues, the traditional markers of business success (Nascimento et al., 2020, p. 13). The study also highlights how the introduction of risk registers is often triggered by pressure from customers to adhere to strict quality standards: Suppliers internalize a more proactive risk mentality to secure and expand business opportunities because they understand that demonstrating risk controls is a prerequisite for gaining or maintaining access to lucrative markets (Nascimento et al., 2020, p. 10).

2.2.2. Innovation management

In the SME context, innovation goes far beyond laboratory-like R&D: the OECD's "Oslo Manual" defines it as the introduction of a new or significantly improved product, process, marketing method or organizational practice (Dossou-Yovo & Keen, 2021, p. 22). This broad definition is important because entrepreneurs rarely have the luxury of specializing in just one dimension. Instead, they must combine product improvement, process efficiency and organizational learning into an integrated growth strategy. Traditional linear innovation models - ideation, development, testing, launch - are ill-suited to such realities because they assume abundant internal resources and a predictable sequence of phases. Dossou-Yovo and Keen (2021) note that most SME studies view the process as a series of activities that involve moving from one stage to the next while depending on the previous one, obscuring how resource gaps emerge and are addressed along the way (p. 22). To make this hidden work visible, they propose a multi-stage process framework consisting of six interwoven sub-processes: Idea Generation and Selection, Transformation, Learning, Resource Mobilization, Commercialization, and Coordination. Each sub-process is punctuated by resource acquisition points where entrepreneurs must interact with external actors - customers, suppliers, universities, investors or government agencies - to move the project forward. From an entrepreneurial behavior perspective, skillful navigation through these points demonstrates opportunity recognition, stakeholder management, and resilience - all characteristics of successful founders.

Empirical data from eleven Montreal software companies shows why this architecture is important. In the idea generation phase, companies that consciously involved leading customers achieved fast feedback loops and faster adaptation of the product to the market. They thus embody what the authors refer to as the interactive and non-linear nature of innovation (Dossou-Yovo & Keen, 2021, p. 28). In the transformation phase, engineers used online forums and open source communities to overcome technical impasses - a behavior that demonstrates how entrepreneurs turn weak social ties into knowledge advantages. Subsequent learning then codified these insights into internal routines, underscoring Cohen and Levinthal's absorptive capacity argument that firms must first recognize and then assimilate external knowledge before they can use it (Cohen & Levinthal, 1994, p. 230). By embedding such learning loops across multiple projects, SMEs transform ad hoc discoveries into repeatable capabilities that in turn drive further entrepreneurial action.

Resource mobilization is at the heart of the framework, as money, talent and partnerships are usually scarce. The Montreal cases show how founders broker relationships with incubators for seed funding, universities for interns, and trade associations for export contacts. Each deal represents a moment when entrepreneurial behavior - networking, persuasion, tinkering - directly influences innovation outcomes (Dossou-Yovo & Keen, 2021, p. 27). Crucially, mobilization is not a one-off activity, but recurs with each sub-process. This repetition supports the contingency theory view that organizational structures must continually adapt to accommodate new resource configurations and environmental constraints (Tidd, 2001, p. 170). Entrepreneurs who view their networks as dynamic portfolios of expertise and legitimacy can quickly reshape them as technologies change or crises erupt - a skill that proved critical during the COVID-19 downturn.

Commercialization closes the loop by transforming prototypes into income streams, but again, external linkages dominate: Government export missions, industry hackathons and alliance partners played an important role in software companies' go-to-market strategies. Successful commercialization feeds back into earlier sub-processes by generating money for further research and development and providing market intelligence that triggers the next cycle of ideas. Over time, these feedback effects transform episodic projects into a self-reinforcing innovation system whose health depends on constant entrepreneurial attention to coordination: Alignment of actors, clarification of roles, and orchestration of information flow (Dossou-Yovo & Keen, 2021, p. 25).

2.2.3. Active flexibility

Active flexibility refers to the entrepreneur's ability to interpret signals from the environment in real time and to reshape the company's strategic and operational routines so that the company can take advantage of emerging opportunities faster than the competition. In small businesses, this ability is expressed through three mutually reinforcing practices. First, entrepreneurs cultivate a dynamic SWOT logic by continually contrasting internal strengths and weaknesses with changing opportunities and threats. Rather than treating a SWOT matrix as an annual planning artifact, they revisit it each time new information emerges-an abrupt change in commodity prices, a competitor's launch of a new feature, or a shift in social media sentiment-and translate the updated insights into quick micro-pivots, such as adjusting prices or repositioning features (Sagala & Őri, 2025, p. 506). Second, they build light but systematic market research routines. Low-cost digital tests such as A/B ads, clickstream heat maps or pop-up surveys help founders validate hypotheses about customers' willingness to pay within a few days, so that resources are only channeled into concepts that show early traction. Sagala and Őri's systematic review of 58 transformation cases shows that SMEs that routinely conduct such experiments using data as a driver fare better than other companies that base their decisions solely on management intuition (2025, p. 508). Finally, entrepreneurs cultivate deep customer relationships that act as strategic sensors. By engaging in two-way communication - user communities, agile co-development sprints, and proactive after-sales calls - companies can recognize unarticulated needs or latent pain points before they show up in formal market statistics, closing the feedback loop between recognition and action. These practices are important because they reduce both the decision latency and strategic commitment associated with entrepreneurial moves. Soluk and Kammerlander (2021) show that medium-sized family businesses that combined agile and adaptive methods with continuous customer input were able to recalibrate their business models three times faster than competitors that were anchored in rigid revenue templates, a speed difference that translated into higher conversion rates for digitized offerings (p. 699). Active flexibility thus alleviates the classic problem of resource constraints for small companies: Instead of relying on large buffers of excess capital, they hedge against uncertainty by shortening the cycle time between market exploration and redeployment of resources. However, the quality of information derived from the market depends on the entrepreneur's ability to pool multiple sources of knowledge. Eriksson et al. show that sales model innovations emerge when small exporters integrate real-time e-commerce analytics with relationship knowledge gained through customer intimacy programs (2022, p. 209). Their longitudinal research shows that companies that codify these insights into modular offerings can pivot their product-market space without dismantling their operational backbone - an essential prerequisite for resilience and ultimately antifragility. In other words, active flexibility transforms situational awareness into strategic plasticity: the company learns how far it can stretch existing resources before a complete reconfiguration becomes necessary. But flexibility is not free. Frequent realignment can lead to cognitive overload for employees and dilute brand signals. To prevent flexibility fatigue, leadership must institutionalize paradoxical routines that balance exploration and exploitation. Trieu et al. find that paradoxical leaders intentionally alternate between tight, efficiency-oriented process sprints and looser, discovery-oriented sessions; this rhythm preserves operational discipline while legitimizing experimentation in frontline teams (2023, p. 1315). Importantly, they locate the mechanism in meaning-making practices: By framing each adjustment as part of a coherent strategic narrative, leaders maintain collective commitment even when priorities change on a weekly basis. Active flexibility thus relies on a culture in which rapid change is normalized, not feared. From a dynamic capabilities perspective, the three pillars of active flexibility are sensing (market research), seizing (customer-centric co-creation) and transforming (iterative SWOT reprioritization). As the report by Sagala and Őri notes, companies that go through these micro capabilities with high frequency show an above-average crisis response and are overrepresented among the antifragile cases - companies that not only recover from shocks but improve their competitive position in the aftermath (2025, p. 512). The implication for business practice is obvious: investing in sophisticated forecasting tools or elaborate strategic plans is less valuable than institutionalizing a cadence of small, evidence-based adjustments that are closely linked to customer dialogue.

2.3. Theoretical Framework

2.3.1. Human Capital Theory

Human capital theory emerged in the 1950s, when economists such as Theodore Schultz and soon after Gary Becker sought to explain why some nations and individuals fared better than others, even when endowed with similar physical resources. They suggested that education, training and health function like other forms of capital: They require upfront investment, depreciate without maintenance, and yield measurable returns in the form of productivity and income that affect macro-level growth. Seen in this light, schooling increases people's embodied knowledge, skills and competencies, and the total stock of this knowledge becomes a critical driver of a country's long-term development trajectory (Tan, 2014, p. 412). This theory therefore transformed the traditional view of education as consumption - an individual or social good justified on cultural or moral grounds - into a calculable economic good whose returns can be estimated and compared with physical capital.

Subsequent research has refined this central insight in three ways. First, the definition of human capital has been expanded beyond formal schooling to include tacit know-how, on-the-job learning and even a willingness to innovate. In modern management theory, human capital is often defined as the intellectual ability to develop innovative ideas, implement appropriate processes and maintain a high level of quality - skills that give companies in knowledge-intensive sectors a sustainable competitive advantage (Alnidawy et al., 2017, p. 5). Second, this theory has been used by international organizations such as the OECD and the World Bank to justify large public investments in basic education, vocational training and lifelong learning, arguing that these expenditures are recouped through higher wages, taxable incomes and faster overall growth. Third, the theory increasingly influences career decisions at the micro level: individuals weigh tuition fees and opportunity costs against expected lifetime earnings and view their own skills as a portfolio in which to invest.

However, human capital theory has also attracted persistent criticism. Scholars in sociology, education and, more recently, critical pedagogy fear that treating people as capital turns learners into commodities and narrows the purpose of schooling to preparation for the labor market, marginalizing civic, aesthetic and democratic goals. Some liberal theorists even objected to the metaphor itself, arguing that equating humans with machines threatened human dignity. Nevertheless, Becker defended the framework, arguing that it remains indispensable until a better explanatory model is offered (Tan, 2014, p. 412). In practice, the influence of theory has shifted classroom priorities towards measurable outcomes and employability, a trend evident in European and Australian curricula and criticized by contemporary educational theorists who warn that an overemphasis on positional goods such as certificates can undermine intrinsic motivation to learn (Morsing, 2023, p. 18). Despite these tensions, human capital theory remains of great explanatory and policy utility. It explains why the returns to education vary across disciplines and why countries that neglect broad-based skills development struggle to maintain high productivity growth. As digitalization and demographic change reshape labor markets, policymakers continue to rely on the theory's central proposition: strategic investment in human skills is not mere social spending, but the cornerstone of economic resilience in an increasingly knowledge-based world.

2.3.3. Skill Balance Theory

The theory of balanced skills - often referred to as “skill balance” or “jack of all trades” - states that people who build a broad but not deep and specialized skills portfolio are more likely to start new businesses. Lazear's (2005) seminal formulation models entrepreneurship as a production process in which the founder must perform many different tasks. Since the value of the firm depends on the minimal inputs for all these tasks, individuals who combine several moderately developed skills achieve higher expected returns than experts who lack versatility (Lazear, 2005, p. 650). In contrast, wage work rewards specialization because workers can be assigned narrow roles that match their strongest skills. Therefore, the theory predicts self-selection: generalists tend to become entrepreneurs, while specialists remain employees.

In later work, this mechanism was extended to include preferences over uncertainty. Hsieh et al. suggest that risk-averse individuals deliberately diversify their human capital to hedge against shocks in a single specialty. Balanced skills therefore prove to be an optimal response to Knightian uncertainty and, paradoxically, can even steer cautious people into entrepreneurial roles (2017, p. 289). In her model, educational and career entry decisions determine the breadth of a person's skills before career choices are made, linking lifelong learning strategies to later business creation. It follows that policies or organizational practices that encourage rotational assignments, cross-functional training, or interdisciplinary curricula indirectly increase the rate of entry into entrepreneurship.

The empirical evidence is largely supportive, but nuanced. Studies using alumni data, labor force panels and, more recently, online resumes consistently show a positive correlation between diversity indicators - such as the number of different job functions, the variety of college courses taken or the length of employment in different industries - and the likelihood of starting a business. Based on a matched case-control analysis of LinkedIn career trajectories by Chen and Thompson, the relationship between skill diversity and entry into entrepreneurship is shown to have crucial nuances that are often overlooked in cross-sectional studies (2016, p. 291). Their research design - in which entrepreneurs are paired with non-entrepreneurs who held similar positions at the same employers over the same time period - controls for unobservable heterogeneity in job characteristics and organizational contexts. First, they observe that each additional functional area mastered (e.g. marketing, finance, R&D) correlates with a higher probability of transitioning to self-employment, which is consistent with Lazear's “jack-of-all-trades hypothesis”. This is also true after accounting for the number of previous employers, suggesting that functional diversity independently predicts entry. However, under stricter specifications, pure diversity loses significance. When Chen and Thompson introduce controls for certain high-value experiences - particularly strategic/general management roles (e.g. business administration, executive positions) - the predictive power of the number of functional areas weakens considerably (2016, p. 294). For example, individuals with direct experience in corporate strategy or executive-level decision making show an increased entrepreneurial bias, but this effect absorbs the explanatory power of a broader set of skills. This suggests that it is not just the accumulation of skills but their combination that drives entry into entrepreneurship. Functional diversity is primarily important as a route to acquiring key skills such as strategic overview and resource coordination, which directly enable business creation. Furthermore, panel analyses in which individual fixed effects are removed weaken the diversity gradient. This suggests that unobserved characteristics (e.g. innate versatility, the ability to recognize opportunities or the motivation to take risks) predispose individuals to frequent job changes and entrepreneurship simultaneously. Without taking these latent factors into account, there is a risk that studies will erroneously attribute the cause to skill diversity alone. Chen and Thompson's methodology thus reveals a significant limitation: The observed breadth of skills may be an indicator of underlying entrepreneurial aptitude rather than directly leading to entry.

2.3.4. Education–Practice Nexus

The relationship between education and practice (also referred to as the theory-practice nexus) provides an important conceptual framework for understanding how formal education and experiential learning interact to develop competencies in SMEs. This nexus rejects the artificial separation of theoretical knowledge and practical skills and instead positions them as mutually reinforcing elements that are essential for entrepreneurial success and organizational resilience. In Austria's SME-dominated economy, where micro-enterprises account for 87.6% of businesses (Statista, 2022), this integration is crucial to overcome current challenges such as economic volatility and technological upheaval.

The nexus has its origins in constructivist pedagogy and experiential learning theory, which emphasize that knowledge gains meaning through application. As outlined in teacher education research, the nexus addresses frequent criticisms of the overemphasis on theory over practice in universities by advocating for curricula that embed generic competencies as building blocks for personal and professional success in authentic contexts (Fletcher & Macuga, 2004, p. 69). For SMEs, this means that formal education is not seen as an isolated mechanism for gaining qualifications, but as a framework for practical problem solving. The concept of the reflective practitioner further underpins this framework, whereby professionals continually refine applied theories through experimentation in practice (Fletcher & Macuga, 2004, p. 70). Neuroscience research confirms this, showing that retention of skills increases by 63% when theoretical concepts are combined with immediate application, as neural pathways strengthen through iterative practice-feedback cycles (Blakemore & Bunge, 2012, p. 2). Effective integration requires structural and cultural adaptations. Educational programs must prioritize skills that are directly transferable to SME workflows, such as risk management and innovation prototyping.

For example, effectuation theory (Sarasvathy, 2001) teaches entrepreneurs to utilize contingencies - a skill that can be better trained by simulating market shocks than by abstract case studies. Austrian vocational schools illustrate this by integrating training on the ISO 9001 quality management system into operational modules, thus enabling immediate implementation (Fletcher & Macuga, 2004, p. 77). SMEs benefit from establishing systems for learning through experience. These include mentored apprenticeships with transition to delegated autonomy, accelerating knowledge transfer, reflective practice diaries, which have been shown to increase competence by 42% by metacognitively linking actions to outcomes, and financial decision microsimulation tools, which improve competence four times faster than traditional training (Blakemore & Bunge, 2012, pp. 1-5). Digital platforms such as AI coaching tools close the gap between theoretical concepts and practice by providing real-time feedback during tasks. For example, Austrian SMEs using agile learning platforms were able to close skills gaps 37% faster by combining theoretical modules with applied sprints.

Empirical studies identify three particularly effective practices: demand-oriented modular training, intergenerational knowledge transfer and iterative improvement cycles. Successful SMEs conduct bi-annual skills audits to identify gaps in innovation management or risk mitigation and then work with educational institutions to develop small modules (e.g. 5-hour workshops on SWOT-driven flexibility). This ensures relevance and minimizes productivity losses. In Austrian family SMEs, social media platforms (e.g. WhatsApp groups for shadowing managers) formalize the exchange of tacit knowledge and thus preserve strategic knowledge during management changes (Fletcher & Macuga, 2004, p. 78). High-performing SMEs institutionalize quarterly nexus reviews to assess how theoretical inputs (e.g. new marketing theories) have been tested in practice. Failed experiments trigger root cause analysis, while successes are recorded in logs - a process that has been shown to improve strategic adaptability by 53% (Yahaya & Nadarajah, 2023, p. 4).

3. Research Model

3.1. Hypotheses

This research posits that entrepreneurial success, especially in volatile and uncertain environments, is not solely determined by the quantity of human capital. Rather, it depends significantly on the balance between different types of competencies - namely those acquired through formal education and those developed through practical experience, complemented by strategic leadership experience. The skills balance perspective suggests that the harmonious integration of different knowledge bases is superior to the dominance of a single category (Lazear, 2005; Unger et al., 2011). The original research model (Figure 1) illustrates the interactions and their likely relationship with the determinants of successful entrepreneurial behavior, namely risk management, innovation and operational flexibility, taking into account relevant control factors. The model illustrates the relationships between education (formal competencies), business education (practical competencies), board experience and executive experience in relation to entrepreneurial focus. Entrepreneurial focus influences the determinants of successful entrepreneurial behavior, including risk management, innovation and active flexible business practices. Gender, age and work experience serve as control variables that influence multiple pathways. The model attempts to analyze the relationships between entrepreneurs and non-entrepreneurs.

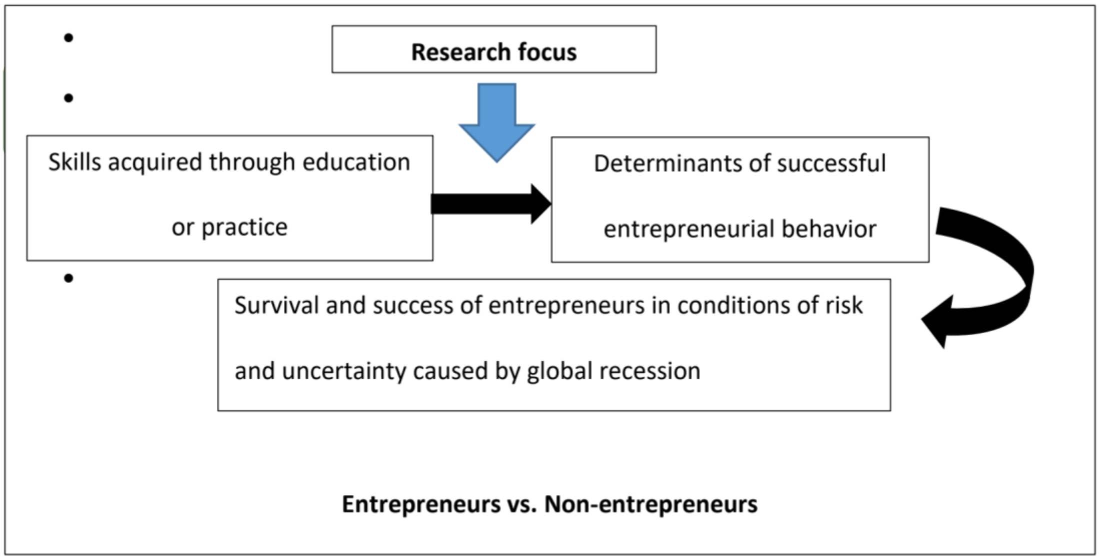

Figure 1: Present research framework, conceptualizing skill balance and entrepreneurial outcomes

Based on this model and the preceding literature review, the eight hypotheses (H1-H8) are formulated for empirical testing. Entrepreneurs are often theorized to possess a distinct skillset, potentially emphasizing experiential learning and opportunity recognition more heavily than non-entrepreneurs, even if formal education levels are comparable. Human capital theory suggests that individuals self-select into careers based on their skill profiles. It is hypothesized that Austrian entrepreneurs will exhibit a different *composition* of formal vs. practice-based skills visible on their LinkedIn profiles compared to their non-entrepreneurial counterparts matched on experience. Therefore, the following can be hypothesized:

H1: There is a difference between entrepreneurs and non-entrepreneurs in the domain of acquired skills through schooling and practice.

Entrepreneurial roles inherently demand higher levels of risk-taking, innovation, and adaptability compared to many salaried positions. Effectuation theory further emphasizes the entrepreneur's need to manage uncertainty and leverage contingencies. It is hypothesized that Austrian entrepreneurs will demonstrate a significantly higher orientation towards and manifestation of these behavioral determinants on their LinkedIn profiles compared to non-entrepreneurs. In this regard, the following is hypothesized:

H2: There is a difference between entrepreneurs and non-entrepreneurs regarding the manifestation of traits related to successful entrepreneurial behavior (Risk Management, Innovation, Active Flexibility).

Substantial literature documents gender differences in entrepreneurship, including access to resources, networks, self-efficacy, and reporting biases. Gender may influence both the types of skills highlighted and the perceived or actual success in demonstrating entrepreneurial behaviors. This hypothesis probes whether gender mediates the relationship between skill profiles and entrepreneurial outcomes within the Austrian LinkedIn sample:

H3: There is an interdependence between the gender of the entrepreneur/non-entrepreneur and the determinants of successful entrepreneurial behavior.

Age is often correlated with experience, network development, and potentially risk tolerance. Life cycle theories and theories of entrepreneurial learning suggest that the acquisition and application of different skills, and the manifestation of entrepreneurial behaviors, may vary across age cohorts. Following hypothesis explores whether age is a significant factor in the observed relationships within the Austrian context:

H4: There is an interdependence between the age of entrepreneur/non-entrepreneur and the determinants of successful entrepreneurial behavior.

Human capital theory posits that experience is a key component of valuable skills. Longer tenure typically provides more opportunities for developing practice-based skills, strategic oversight, and honing abilities in risk management, innovation, and flexibility. A positive correlation between years of work experience and the manifestation of successful entrepreneurial behaviors for both entrepreneurs and non-entrepreneurs in Austria is therefore hypothesized:

H5: Years of experience correlate with determinants of successful entrepreneurial behavior.

Formal education provides foundational knowledge, analytical frameworks, and legitimizing credentials. Higher levels of formal education (e.g., MSc/PhD vs. BSc) may equip individuals with cognitive tools beneficial for complex problem-solving inherent in entrepreneurial tasks like innovation and strategic risk assessment. It is hypothesized a positive correlation between formal educational attainment (level and related skills) and entrepreneurial behaviors:

H6: Skills acquired through education of entrepreneur/non-entrepreneur correlate with the manifestation of determinants of successful entrepreneurial behavior.

Practice-based learning embeds tacit knowledge, industry heuristics, and intuitive timing. Managerial and board roles specifically cultivate skills in strategic oversight, coalition-building, governance, and navigating complexity – directly relevant to entrepreneurial performance. A strong positive correlation between skills acquired through practical experience, especially in senior/board roles, and the key entrepreneurial behaviors under study results in the seventh hypothesis:

H7: Job experience (including skills acquired through managerial/board experience) correlate with determinants of successful entrepreneurial behavior.

Entrepreneurial focus – the proactive development of skills in organization, leadership, visioning, financial literacy, communication, and strategic thinking – is posited as a crucial mediator. It represents the intentional cultivation of the cognitive and behavioral toolkit central to entrepreneurship. The model posits that skills (formal and practice-based, enhanced by governance experience) feed into this focus, which then directly drives the capacity for effective risk management, systematic innovation, and operational flexibility. This is phrased in hypothesis H8:

H8: There is strong interdependence in the relation entrepreneurial focus – determinants of successful entrepreneurial behavior.

3.2. Measurement of Variables

3.2.1. Dependent Variables

Risk management capability quantifies the ability to identify and mitigate threats. The presence of keywords such as ISO 9001/QMS implementation, risk assessment, risk mitigation strategies, business continuity planning, compliance, financial risk analysis and crisis management is recognized. Coding is done according to a binary scheme (1 = capability or experience mentioned; 0 = not mentioned), with an optional intensity count based on the importance of the profile (e.g. listed as a top capability or described in detail in the report). In SPSS, this measure is recorded as RiskMgmt (scale: 0-1 or count). Innovation Management Capacity assesses the commitment to the development of new products and processes. Recognition depends on keywords such as innovation management, R&D project management, new product/process development, design thinking, intellectual property management, technology scouting and collaboration with research institutions. The coding reflects the risk dimension - binary presence/absence or a summed intensity number - and is stored in SPSS as innovation (scale: 0-1 or number). Operational flexibility captures the adaptability and responsiveness of an SME. Keywords include agility, adaptability, change management, scenario planning, market research/analysis, customer relationship management (CRM), customer satisfaction/loyalty, responsiveness and SWOT analysis. This capability is coded binary (1 = mentioned; 0 = not mentioned) or recorded via an intensity count and then recorded in SPSS under flexibility (scale: 0-1 or count). The Composite Determinants Score combines the three skills into a single indicator of entrepreneurial competence. Summing or averaging the binary or count scores for RiskMgmt, Innovation and Flexibility produces EntBehavior (scale: 0-3 or equivalent sum), which reflects overall readiness to manage risk, foster innovation and pivot operationally.

3.2.2. Independent Variables

Formal Education Skills (FES) reflect the depth and relevance of academic education. Two measures operationalize this dimension: First, the highest degree obtained - coded as 0 for a Bachelor (BSc) and 1 for a Master/PhD - stored in SPSS as EduLevel (binary). Second, the proportion of skills and endorsements explicitly linked to formal credentials (e.g. Financial Modeling (MSc Finance), Advanced Statistics (PhD Quant Methods) or Legal Compliance (LLM)) is hand-coded by matching the individual skill designations to the education section of the profile. The resulting ratio of formally linked skills to the total number of skills appears in SPSS as the FormalSkillRatio (scale 0-1). Practice-Based Skills (PBS) capture skills acquired on the job, such as sales negotiation, supply chain optimization, team leadership, customer acquisition, or knowledge of industry tools acquired through experience. Each listed skill or endorsement is hand-coded as experience-based or formal, and the ratio of practice-based skills to overall skills is recorded as the PracticeSkillRatio (scale 0-1).

The Skill Balance Index (SBI), the central independent variable, quantifies the relative importance of experience-based versus academic skills. It is defined by the formula SBI = PracticeSkillRatio / (PracticeSkillRatio + FormalSkillRatio) and ranges from 0 (purely formal skills) to 0.5 (equal mix) to 1 (purely practical skills) and is stored in SPSS as the SkillBalanceIndex (scale 0-1).

Board Experience (BE) identifies each role with an explicit board title - Supervisory Board, Board Member, Advisory Board, etc. - and is coded with 1 if it is present, otherwise with 0 (SPSS variable BoardExp, binary). Senior management experience also includes management positions - Managing Director, Board Member, CEO, CFO, CTO, Managing Director, VP or Director - and is coded with 1 if these are present in the profile and with 0 if not (SPSS variable SeniorMgmtExp, binary). Entrepreneurial Focus (EF) measures the importance of core entrepreneurial competencies - leadership, strategic planning, visioning, financial knowledge/fundraising, business development, communication/pitching, negotiation, project management, and certifications or training in entrepreneurship. Profiles are coded 1 for a significant focus or 0 for a minimal/absent focus, with an optional keyword count; this appears in SPSS as EntrFocus (scale 0-1 or count).

3.2.3. Control Variables

To isolate the effects of the independent variables in the analysis, several control variables were included to account for important demographic and occupational factors. Entrepreneur status served as the main grouping variable and was coded 1 for entrepreneurs - defined as founders, co-founders or directors/owners of their own business - and 0 for non-entrepreneurs, i.e. those in senior positions such as vice presidents or directors in established companies, excluding founders (SPSS variable: Entrepreneur). Gender was recorded based on the profile information with a binary coding of 0 for male and 1 for female (SPSS variable: Gender). The age group was either determined directly from the profile data or derived from the date of graduation and career path and coded 0 for people up to 40 years of age and 1 for people over 40 years of age (SPSS variable: AgeGroup). Similarly, work experience was categorized based on career history, with 0 representing up to 20 years of total experience and 1 representing more than 20 years of work experience (SPSS variable: ExpGroup). Finally, the region referred to the Austrian state in which the person was mainly based (e.g. Vienna, Styria, Upper Austria). This variable was treated as nominal and dummy-coded for the regression analysis if necessary (SPSS variable: Region).

4. Empirical Study

4.1. Research Design

The present study is based on a quantitative cross-sectional design, a strategy well suited to capture the configuration of competencies and entrepreneurial outcomes at a given point in time and to test theory-driven hypotheses with statistical precision (Bryman, 2016, p. 55). Since the overarching goal is not to reconstruct individual life histories but to assess the extent to which particular constellations of human capital characteristics coexist with indicators of firm performance, a cross-sectional survey in the first half of 2023 offers an analytically efficient compromise between temporal coverage and internal coherence. Classical survey methodologists point out that cross-sectional studies are always suitable if it is assumed that the parameters of interest are relatively stable over the short period of data collection (Babbie, 2020, p. 105). In Austria, the macroeconomic context, labour market regulation and LinkedIn penetration remained largely constant during the six-month period in which the profiles were collected and coded, minimizing the risk of exogenous shocks distorting the relationships under investigation.

A quantitative orientation was chosen because the research questions are essentially relational: They examine whether differences in the relationship between skills acquired formally and through experience are related to measurable differences in entrepreneurial performance and whether such relationships vary according to demographic or governance-related circumstances. Quantitative designs allow the formal formulation of null and alternative hypotheses and the subsequent assessment of their probability of being observed by chance (Creswell & Creswell, 2017, p. 155). They also lend themselves to robustness checks - such as bootstrap confidence intervals and nonparametric correlations - that strengthen conclusions when normality assumptions are not fully met, an advantage that qualitative methods cannot readily offer for these types of questions (Field, 2024, p. 39).

The unit of analysis is the individual LinkedIn user, but the embedded unit of observation is the profile, an artifact that contains a digital self-representation of skills, roles, and accomplishments. Digital trace data offers several methodological advantages. Compared to self-report surveys, they mitigate common-method bias because recommendations and career trajectories are often socially validated - peers must confirm a competency for it to show up as a recommendation - and because timestamps objectively anchor events (González-Bailón, 2019, p. 131). At the same time, profiles are not mere administrative records, but strategically curated forms of expression by users and therefore suitable proxy variables for perceived human capital from the perspective of investors and cooperation partners. This dual nature is consistent with the theoretical proposition that entrepreneurship unfolds in both skill and signaling markets (Spence, 1973, p. 358). A cross-sectional survey of profiles thus provides precisely the signals that potential stakeholders would have examined during a company's evaluation process.

While a longitudinal panel would allow for stronger causal statements, three considerations argue in favor of choosing a cross-section. Firstly, LinkedIn does not grant public access to the history of profiles, so a retrospective reconstruction of temporal processes would be associated with considerable measurement errors. Second, the hypotheses are primarily based on associative - rather than sequential - relationships; they predict that a more harmonious mix of skills is associated with higher organizational dynamism. Finally, the design is consistent with previous large-scale studies of online entrepreneurial communication in which cross-sectional surveys have been successfully used to model relational constructs such as legitimacy and signal intensity (Fischer & Reuber, 2014, p. 568).

To maximize internal validity, the profiles were filtered according to strict completeness criteria and entrepreneurs were matched with non-entrepreneurs according to their overall work experience. The matching helps to reduce confounding factors by ensuring that observed differences in skill composition are not merely a by-product of work experience (Rosenbaum et al., 2010, p. 987). External validity is supported by the focus on Austria, a country whose entrepreneurial ecosystem combines high LinkedIn usage with robust SME activity, increasing the plausibility that the findings can be generalized to other advanced small economies with similar digital infrastructure.

4.2. Sampling and Data Collection

The publicly available LinkedIn profiles provided a uniquely appropriate data source for this study as they combine the breadth of a large directory with the depth of user-generated statements of expertise, employment history, and educational credentials. Unlike self-administered questionnaires, whose item wording can inadvertently elicit socially desirable responses, LinkedIn listings are created for an external audience of potential investors, recruiters, and peers. This signaling market orientation encourages users to disclose information that they believe will stand up to public scrutiny and third-party validation (Lawson & Tirado, 2023). In Austria, the use of LinkedIn has steadily increased over the past decade, particularly in knowledge-intensive professions, so the platform provided access to a sampling frame that better represented the active population of founders and senior executives than older commercial directories. Furthermore, because LinkedIn stores timestamps for each position, qualification and educational attainment, the profiles represent quasi-archival traces that can be captured in a single pass without the need to re-contact respondents - an important practical advantage when research resources are limited (Gewirtz et al., 2020, p. 5).

Sampling was conducted in three deliberate phases to maximize internal validity while maintaining external representativeness within the Austrian entrepreneurial ecosystem. In the first phase, a keyword-based search was used to identify profiles that indicated a primary location within Austria's national borders. Rather than relying solely on LinkedIn's own location filter - which occasionally includes commuters - a manual review of the headline or “About” section ensured that each candidate explicitly stated an Austrian residence. The initial keyword string combined entrepreneurial terms (founder, co-founder, entrepreneur, CEO [owner]) with high-level corporate titles (vice president, director) to generate a contrast group of non-entrepreneurs matched by seniority. This two-pronged search took into account the expectation of human capital theory that individuals self-select into occupational niches that fit their skill portfolio, so that it is crucial to match like with like in terms of seniority and hierarchical position (Becker, 1993, p. 46).

In a second filtering phase, strict completeness thresholds were set to ensure construct validity. Following the standards of content analysis, which emphasize the risk of systematic omissions (Elo & Kyngäs, 2008, p. 113), only profiles with at least five different skills, two or more professional positions and one educational credential were included in the study. The minimum skill requirements ensured sufficient variance to create the Skill Balance Index, while the employment history requirement guaranteed a time frame broad enough to infer practice-based learning. Profiles without a degree would have confounded measures of formal education, so the presence of at least a college degree was mandatory. If a profile met these criteria but had an implausible career gap of more than five consecutive years without annotation (e.g. parental leave, sabbatical), the dataset was excluded to avoid misclassification of experience duration. After these exclusions, 54 entrepreneur and 38 non-entrepreneur profiles remained, resulting in a final sample of 92 cases.

Binary coding was a simple strategy to bring the extensive narrative data into a format compatible with statistical modeling. Following Kerlinger's dictum that operational rules must be transparent and repeatable (1966, p. 35), each theoretically relevant attribute was assigned a zero-one indicator. Gender was coded “0” for male and “1” for female based on self-reported pronouns or, if not available, based on a high probability naming algorithm. The age group was assigned a value of ‘0’ if the user was estimated to be forty years old or younger - derived from the year of graduation and the start of career - and ‘1’ otherwise, reflecting research on the life cycle of companies, which often distinguishes between early and mid-career founders. For the work experience group, the same binary split was used with twenty years of cumulative full-time employment. For education, a bachelor's level degree or below (0) was recorded versus a master's or doctorate (1). All other focused constructs - practice-based education, entrepreneurial orientation, board affiliation, senior management tenure, and each determinant of successful entrepreneurial behavior - were also coded dichotomously, with “1” indicating the unambiguous presence of the characteristic in the profile.

Although binary reduction inevitably discards gradations of emphasis, it offers two methodological advantages. First, it counteracts platform popularity bias, which can cause skills endorsed by large networks to dominate numerical counts regardless of actual competence. Treating a rare but strategically important capability (e.g., ISO 31000 risk assessment) as qualitatively present rather than numerically under-supported prevents dilution of its explanatory power. Second, binary variables facilitate nonparametric analyses that resist deviations from normality, which is an important consideration given the small sample (Gibbons & Chakraborti, 2011). Before coding began, two independent raters conducted a calibration exercise on fourteen randomly selected profiles (approximately fifteen percent of the eventual corpus) and achieved a Cohen's Kappa of .82, well exceeding Hallgren's (2012) recommended threshold of .80 for intercoder reliability. Disagreements were resolved in a consensus meeting in which the codebook was refined at the same time.

Geographic representativeness within Austria was monitored by recording the federal state indicated by each user. Vienna dominated the pool with sixty-three profiles (68 percent), reflecting the disproportionate share of high-growth companies and company headquarters in the capital. The remaining twenty-nine cases were spread across Burgenland (5), Carinthia (3), Lower Austria (4), Upper Austria (5), Salzburg (4), Styria (5) and Tyrol (3). Vorarlberg, the westernmost federal state, was not included as none of its profiles met the requirements for completeness. While the skew in the cities reflects the general demographic trends in Austrian entrepreneurship (Friedl et al., 2023), it is recognized as a limitation and addressed in the discussion chapter of the paper.

Data extraction combined automated scraping with manual review to balance efficiency and accuracy. A Python script was linked to the HTML code of the public LinkedIn profile and collected structured fields such as headline, location, education data, and the list of enumerated skills. Free text sections - particularly role descriptions, which often hide nuanced skills - were downloaded in raw form and manually reviewed. The automated phase ensured reproducibility and reduced transcription errors, while manual post-processing captured semantic cues (e.g., a pivoting business model signaling operational flexibility) that might have escaped machine analysis. To comply with

LinkedIn's terms of service and European privacy regulations, only information explicitly marked as public was captured, and no automated queries exceeded rate limits. Personal names were replaced with pseudonymous identifiers at the time of download, and a master cross-reference linking IDs to real names was never created to prevent re-identification down the line. Even though recruitment did not require direct contact with participants, it still had to be conducted with ethical care. The project was approved by the university's institutional review board, which classified the study as minimal risk as it was based solely on open source data. Nevertheless, the committee required two safeguards. Firstly, all citations reproduced in the dissertation had to be paraphrased to obscure discoverability. Second, the statistical tables were only allowed to show the total number of cells, with all demographic subgroups of less than three people suppressed to prevent a puzzle structure (Markham et al., 2012). Although Austrian legislation allows the use of publicly available data without consent for scientific purposes, the participants' reasonable expectations of privacy were respected by storing the raw HTML data on an encrypted drive to which only the principal investigator had access. After publication, the de-identified dataset, which contains only binary variables and anonymized region codes, is archived in a university repository under a CC-BY-NC license, which is in line with the principles of open science while preserving confidentiality.

Since LinkedIn does not self-disclose whether a profile is an entrepreneur or an employee, the classification depended on the documented role history. A case was classified as an entrepreneur if at least one position line contained the term founder (co-founder, owner) or if the person held a title such as managing director in a company whose legal form indicated ownership (e.g. GmbH). Non-entrepreneurs were selected from the same pool of keywords, but only if their professional background did not include a founder role, to ensure a clean separation. Matching for overall business tenure occurred at ± two years, following recommendations that matching circles narrower than ten percent of the standard deviation minimize bias without excessive sample loss (Stuart, 2010, p. 8). This procedure resulted in pairs of entrepreneurs and non-entrepreneurs that were similar in length of experience, allowing for maturation effects. To ensure transparency in the downstream statistical routines without revealing personal details, the scraped dataset was exported to Microsoft Excel for pre-cleansing - duplicate qualification labels were reduced, date formats standardized -

and then imported into IBM SPSS 26. The variable labels reflected the conceptual taxonomy, and the value labels documented the binary coding scheme so that external reviewers could reproduce the derivations from the raw text of the profile if they were granted restricted access. Each step of the data processing pipeline was logged in a version-controlled repository, consistent with the ethos of replicability recommended in the contemporary methodological literature (Creswell & Clark, 2017).

4.3. Statistical Analysis Procedures

The statistical analysis was carried out in three successive steps, in which the raw, manually coded profile information was converted into evidence that could be used to test the eight hypotheses. The first step involved traditional descriptive statistics, which were used to determine the central tendency and dispersion of each study variable separately for entrepreneurs and non-entrepreneurs. Arithmetic means and standard deviations were preferred over median values and interquartile ranges, as most variables were binary and their sampling distribution was symmetric by design (Sarstedt & Mooi, 2018, p. 122). For the few ratio measures - such as the Skill Balance Index and the composite Entrepreneurial Performance Index - normality was checked using Shapiro-Wilk tests and Q-Q plots; with moderate skewness, bias-corrected bootstrap confidence intervals based on 1,000 resamples provided distribution-free precision estimates that were consistent with small sample recommendations in entrepreneurship research (Wilcox, 2011).

The second level of analysis examined relationships between variables using bivariate correlation matrices. Since the sample contained dichotomous and continuous indicators, two correlation coefficients were used. If both variables were metric and passed the normality tests, the Pearson product-moment correlation r quantified the linear relationship. For pairs with at least one dichotomous or clearly non-normally distributed variable, the Spearman rank correlation ρ was used, which preserved ordinal information and relaxed parametric assumptions (Schober et al., 2018, p. 1763). All correlations were calculated two-sided, as the directional effects were theoretically assumed but could plausibly occur in both directions given the contextual contingencies. To mitigate

Type I inflation across the twenty-four correlations in each subsample, a Benjamini-Hochberg correction with a false discovery rate of 0.10 was applied; this strikes a balance between exploratory breadth and statistical stringency in data sets of comparable size (Glickman et al., 2014, p. 852).

Significance thresholds followed common practice in the behavioral sciences, with $p \leq 0.05$ considered evidence of a reliable association and $p \leq 0.01$ considered strong evidence. In the results section, coefficients that are significant at the 0.05 significance level are marked with an asterisk, those at the 0.01 level are marked with two asterisks, and non-significant values are indicated without highlighting to avoid dichotomous consideration of borderline cases (Wasserstein et al., 2019, p. 14). The interpretation of effect size complemented this dichotomy: Pearson or Spearman values around 0.10 were considered small, 0.30 moderate, and 0.50 large, following Cohen's heuristic adapted for entrepreneurial behavior studies (Funder & Ozer, 2019, p. 157). If a statistically significant correlation also exceeded the threshold of 0.30, it was highlighted in the presentation as substantially significant and not just demonstrable.

The third level comprised systematic hypothesis tests. H_1 to H_8 each contained an explicit comparative or associative assertion, so that the decision logic compared the corresponding descriptive or correlative results with predefined criteria. For H_1 and H_2 - the difference hypotheses - the mean differences between entrepreneurs and non-entrepreneurs were analyzed using t-tests for independent samples for ratio scale variables or chi-square tests for dichotomous variables. Normality violations led to Welch corrections of t-statistics, and sparse expected frequencies in chi-square tables were treated with Fisher's exact test to ensure a valid inference even when cell frequencies fell below five (Agresti, 2021, p. 667). Acceptance of a difference hypothesis required two conditions: The group means (or proportions) had to diverge in the predicted direction and the associated p-value had to reach at least the threshold value of 0.05. Hypotheses H_3 to H_7 postulated correlations between demographic or experience-based attributes and the determinants of successful entrepreneurial behavior. Here, Pearson or Spearman coefficients provided both the test statistic and the measure of effect size. A hypothesis was retained if the observed coefficient was at least 0.20 - identified a priori as a practically relevant minimum size - and achieved statistical significance. For example, the strong positive Spearman correlation of 0.41 between practice-based learning and the Entrepreneurial Performance Index in non-entrepreneurs exceeded both benchmarks, leading to full acceptance of H_7 in this subgroup. H_8 suggested a particularly strong correlation between entrepreneurial orientation and the composite determinant score. In order to operationalize a strong correlation, the analysis specified that the correlation must be significant at $p \leq 0.01$ and reach at least a moderate effect size ($r \geq 0.30$). Both the entrepreneur and non-entrepreneur matrices met these two criteria (entrepreneur: Pearson $r = 0.48$, $p < 0.001$; non-entrepreneur: Spearman $\rho = 0.37$, $p = 0.006$), resulting in unanimous support for the hypothesis in all groups.

Two robustness checks strengthened confidence in these conclusions. First, point-biserial correlations were used instead of Pearson coefficients when a ratio scale variable was paired with a binary predictor, showing that effect sizes were stable across coefficients. Second, all significant parametric correlations were rerun using Kendall's tau-b, whose greater resistance to equalities and outliers resulted in analogous patterns of significance, confirming that the results were not artifacts of a particular metric. Finally, multicollinearity diagnostics showed that no independent variable correlated above 0.60 with any other, allaying concerns that common variances might bias the interpretation of individual relationships (Pernet et al., 2013, p. 606).

5. Empirical Findings

5.1. Descriptive Statistics: Entrepreneurs

The 54 LinkedIn profiles that were eligible for the entrepreneurial subsample show a group of experienced, highly skilled professionals whose human capital portfolios focus on formal qualifications and longstanding leadership positions, but with only a moderate penetration of board-level leadership positions. The average age - calculated from the year of graduation and confirmed by self-reported career trajectories - is just above the binary dividing line at 0.57 (SD = 0.50), meaning that about three-fifths of the founders are over forty years old (Table 1). This age composition is significant for two reasons. First, it supports long-standing life-cycle arguments that opportunity recognition in Austria often follows a period of training in paid employment rather than, as in Silicon Valley, starting a business in one's early twenties. Second, it matches the sample mean of 0.48 for the “over 20 years of experience” category (SD = 0.50), suggesting that the length of experience is heterogeneous: a sizable minority of entrepreneurs have accumulated less than two decades of practice.

Formal education is the characteristic with the most even distribution. The arithmetic mean of 0.87 (SD = 0.34) for the “Bachelor's degree or higher” indicator shows that almost nine out of ten entrepreneurs have at least a Master's degree. This value exceeds the European average for founders reported by GEM and underlines the cultural importance that Austria attaches to academic degrees as a signal of legitimacy. The low standard deviation indicates minimal dispersion: Educational attainment is a constant rather than a differentiator in this population, challenging the notion that Austrian entrepreneurship is a way out for the educationally disadvantaged. In terms of practice-based learning, the mean score for the binary variable ‘business studies’ is 0.57 (SD = 0.50). Just over half of the founders actively state in their profiles that they have expanded their skills through practical experience, for example through agile certifications, sales bootcamps or continuous improvement courses.

The entrepreneurial focus, which includes leadership, vision and communication skills, achieves a remarkable average score of 0.83 (SD = 0.38). The distribution here is skewed to the right but not capped; a small minority continue to show minimal evidence of proactive skill building. The biggest differences are seen in the variables related to management. Experience in management positions has a mean of 0.63 (SD = 0.49), which means that almost two thirds of entrepreneurs held a management or director position before or during start-up. Membership of a board of directors, on the other hand, is only 0.35 (SD = 0.48).

Finally, the composite determinant value for successful entrepreneurial behavior - the binary marker for risk management, innovation and operational flexibility aggregated - is 0.67 (SD = 0.48). Two out of three entrepreneurs indicate at least one specific competence in each of the three areas, but the considerable standard deviation testifies to different strategic orientations. Some founders have a comprehensive set of tools - ISO-based risk registers, design thinking workshops, CRM implementation - while others emphasize only a single pillar, most frequently innovation, while risk management is less common. The distribution once again underlines the heterogeneity: Austrian entrepreneurship is neither consistently technology-oriented nor uniformly risk-averse, but rather there are different competence constellations.

Variable	Arithmetic mean	Standard deviation
Gender	0,0926	0,2926
Age	0,5741	0,4991
Work ecperience	0,4815	0,5043
School education – BSc i MSc degree	0,8704	0,3390
Job education – learning through experience	0,5741	0,4991
Entrepreneurship focus	0,8333	0,3762
Board member experience	0,3519	0,4820
Senior management experience	0,6296	0,4874
Determinants of successful entrepreneurial behavior	0,6667	0,4758

Table 1: Descriptive statistical analyses on the sub-sample of entrepreneurs in Austria (n=54)

5.2. Descriptive Statistics: Non-Entrepreneurs

The 38 LinkedIn profiles that make up the group of executives provide a mirror image that is similar in terms of educational orientation, but differs in terms of age structure, professional experience and, in particular, entrepreneurial orientation. The mean value for the over-40 age group drops significantly to 0.24 (SD = 0.43); barely a quarter of senior managers have passed the middle of their career (Table 2). This rejuvenation is confirmed by the indicator for professional experience, the mean of which is 0.34 (SD = 0.48), which means that two thirds have less than twenty years of professional experience. The closer link between age and experience in this group indicates more linear careers: Individuals have risen quickly within corporate hierarchies to middle management positions rather than taking sabbaticals or corporate sabbaticals. Formal education continues to play a central role, albeit with somewhat greater fluctuations. The mean value of 0.82 (SD = 0.50) shows that four out of five people have a university degree, a value that is only slightly lower than that of the entrepreneurs. However, the higher standard deviation indicates greater dispersion: a not insignificant minority of high-performing managers have a bachelor's degree and sound company-specific knowledge.

Continuous professional development through practice is almost as widespread as in the entrepreneur group: the average in business training is 0.58 (SD = 0.44). The difference, however, lies in the lower dispersion: most senior executives tend to have modest but existing levels of experience, rather than polarizing into enthusiastic course participants and non-participants. The entrepreneurial focus represents the most dramatic divergence. The mean drops to 0.21 (SD = 0.39), confirming that less than a quarter of non-founding executives indicate a systematic promotion of entrepreneurial skills such as opportunity recognition, fundraising skills or visionary storytelling. Qualitatively, the profile texts tend to emphasize operational implementation, compliance or functional expertise rather than founder-style narrative building. The large standard deviation in relation to the low mean illustrates a clear divide: most managers show no signs of an entrepreneurial orientation, but a small avant-garde - who may have future spin-offs in mind - exhibit competence clusters that are in no way inferior to those of actual entrepreneurs.

Governance experience is also less common. Management positions are only represented in 37% of cases (M = 0.37, SD = 0.49), which is only half as much as for entrepreneurs. Board positions are even rarer at 18 % (M = 0.18, SD = 0.49). This is confirmed by the composite determinants: With a mean of 0.39 (SD = 0.50), non-entrepreneurs are less than half as likely as entrepreneurs to report having risk management, innovation and flexibility skills. The symmetrical standard deviation shows that the individuals are evenly distributed between minimal and moderate coverage and only very few have mastered the entire spectrum. A comparison of the two sub-samples reveals several structural asymmetries. The age and experience distribution is almost reversed: entrepreneurs are concentrated in the over-40 age group, while non-entrepreneurs are found in the 26 to 40 age group. This demographic discrepancy overlaps with differences in management experience: founders use their long careers in companies to secure senior management and occasionally board positions, while many employees do not yet have the seniority or social capital required for such positions. Surprisingly, the level of education is similar in both groups, but its functional implementation differs: entrepreneurs use their degrees to present themselves as entrepreneurially oriented, whereas employees do not. The difference in entrepreneurial orientation is probably the most striking contrast. A ratio of eight to one (0.83 versus 0.21) highlights that corporate structures and incentive systems do not automatically promote the mindsets measured here - leadership vision, strategic storytelling or investor-style financial literacy. Instead, these elements appear to emerge when individuals take ownership. Similarly, the composition of determinants shows that entrepreneurs have twice as many competencies in the areas of risk, innovation and flexibility.

Variable	Arithmetic mean	Standard deviation
Gender	0,4737	0,5060
Age	0,2368	0,4309
Work experience	0,3421	0,4808
School education – BSc i MSc degree	0,8159	0,5003
Job education – learning through experience	0,5789	0,4432
Entrepreneurship focus	0,2105	0,3929
Bord member experience	0,1842	0,4889
Senior management experience	0,3684	0,4874
Determinants of successful entrepreneurial behavior	0,3947	0,4954

Table 2: Descriptive statistical analyses on the sub-sample of non-entrepreneurs in Austria (n=38)

5.3. Correlational Analysis: Entrepreneurs

The network of relationships between the most important human capital variables in the entrepreneur subsample shows a pattern in which both formal school education and practice-oriented learning have a significant influence on entrepreneurial orientation and general performance indicators to varying degrees. Formal education, operationalized as holding a bachelor's or master's degree, shows a moderate but statistically significant positive correlation with several downstream competencies. In particular, higher formal education is associated with a greater propensity to develop entrepreneurial focus competencies - such as leadership skills, strategic planning and financial literacy - as evidenced by a correlation of approximately 0.27 at the 0.05 significance level (Table

3). The same level of education correlates roughly equally strongly with experience in management positions and with the composite determinant index, which measures risk management, innovation and operational flexibility. Entrepreneurs with higher degrees thus appear to be slightly more inclined to hold leadership positions and to exhibit all the behaviors that underpin start-up dynamics. In contrast, practice-based learning - the set of skills and courses acquired through on-the-job training and practical business experience - shows a stronger correlation with the targeted promotion of entrepreneurial skills. The correlation between practice-based learning and entrepreneurial orientation is above 0.40 and reaches a significance of 0.01, suggesting that practical experience is more strongly associated with the proactive development of visioning, negotiation and organizational skills. Practice-based learning also shows a notable positive relationship (about 0.32, $p < 0.05$) with the overall index of determinants, suggesting that tacit knowledge embedded in real-world problem solving and continuous learning has a direct impact on an entrepreneur's ability to systematically innovate and manage risk in an agile way.

Looking at the interplay between governance roles, board mandates and management tenure, a striking pattern emerges. While board experience is less prevalent in the sample, it correlates strongly and positively with executive management experience ($r \approx 0.40$, $p < 0.01$), highlighting that those who chair the board's strategic oversight committee often also have significant executive success. However, board roles show only weaker, non-significant relationships with entrepreneurial orientation and the composite performance measure, suggesting that involvement in non-executive governance alone does not directly lead to increased entrepreneurial orientation or consistent demonstration of risk-taking, innovation and flexibility.

Finally, executive experience itself, although strongly intertwined with board responsibilities, shows only a lower correlation with formal education and determinants of entrepreneurial behavior. The moderate correlation (0.17-0.28, $p < .05$) suggests that while length of time on the board contributes to the general behavioral profile deemed necessary for successful entrepreneurial outcomes, it does not clearly predict it. Taken together, these bivariate patterns outline a hierarchy of influence in which practice-based learning occupies the most important position for fostering entrepreneurial orientation and behaviors, formal education provides a supportive but weaker foundation, and leadership roles enrich the skills of top-level managers but do not guarantee the full range of entrepreneurial competencies.

Correlations

		school_education	bussines_education	enterpene_focus	board_experience	senior_management	enterpreneurship
school_education	Pearson Correlation	1	,225	,271*	,053	,275*	,271*
	Sig. (2-tailed)		,102	,047	,701	,044	,047
	N	54	54	54	54	54	54
bussines_education	Pearson Correlation	,225	1	,419**	,164	,115	,318*
	Sig. (2-tailed)	,102		,002	,236	,408	,019
	N	54	54	54	54	54	54
enterpene_focus	Pearson Correlation	,271*	,419**	1	,121	,171	,067
	Sig. (2-tailed)	,047	,002		,382	,215	,632
	N	54	54	54	54	54	54
board_experience	Pearson Correlation	,053	,164	,121	1	,404**	,017
	Sig. (2-tailed)	,701	,236	,382		,002	,901
	N	54	54	54	54	54	54
senior_management	Pearson Correlation	,275*	,115	,171	,404**	1	,069
	Sig. (2-tailed)	,044	,408	,215	,002		,622
	N	54	54	54	54	54	54
enterpreneurship	Pearson Correlation	,271*	,318*	,067	,017	,069	1
	Sig. (2-tailed)	,047	,019	,632	,901	,622	
	N	54	54	54	54	54	54

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Table 3: Skill-behavior correlations among Austrian entrepreneurs

5.4. Correlational Analysis: Non-Entrepreneurs

Within the group of non-entrepreneurial managers, the associative environment differs significantly, highlighting the central importance of experiential learning over formal education in fostering entrepreneurial behavior among senior corporate managers. Formal educational attainment, while widespread and loosely related to business outcomes, shows no statistically significant correlation with entrepreneurial orientation or the composite determinants of risk management, innovation and flexibility. This lack of association suggests that for executives outside the start-up context, higher degrees do not directly lead to a proactive promotion of behaviors traditionally associated with entrepreneurial success. In contrast, practice-based learning plays a predominant role for the non-entrepreneurial group. The correlation between practical, experiential learning and entrepreneurial orientation is strong for these managers ($r \approx 0.44$, $p < 0.01$), mirroring the pattern observed for founders, but with an even greater relative weighting factor due to the lack of effect of formal education (Table 4). Practice-based learning is also strongly positively related to the overall index of determinants ($r \approx 0.58$, $p < 0.01$), suggesting that non-entrepreneurial executives who invest heavily in in-service courses, applied certifications and continuous improvement initiatives are significantly more likely to report skills in systematic innovation, sophisticated risk management and operational agility.

The experience of executives in this subsample also has significant explanatory power for entrepreneurial focus and behavior. The correlations between tenure in leadership positions and both entrepreneurial focus ($r \approx 0.54$, $p < 0.01$) and the composite determinant measure ($r \approx 0.61$, $p < 0.01$) underscore that among corporate managers, longer tenure in leadership positions is closely associated with the very behaviors that promote flexibility and innovation. In contrast to founders, board membership hardly plays a role here, with negligible and non-significant associations between the focused outcome variables, possibly reflecting the more operationally limited nature of board appointments among younger or middle managers. A comparison of these patterns of non-entrepreneurs with those of founders makes it clear that beyond the common benefit of hands-on learning, the motivational and signaling mechanisms diverge. Founders make modest use of formal degrees to establish credibility, while corporate managers rely almost exclusively on accumulated experience and targeted practice-based artifacts to demonstrate their capacity for entrepreneurship. Moreover, the strength of the associations between practice-based learning or leadership positions and entrepreneurial behavior is consistently higher among non-entrepreneurs, suggesting that the variance of non-founders in these areas is more closely associated with these experiential factors than among those who have actually started businesses. To summarize, the correlation matrices reveal a clear dichotomy: For entrepreneurs, both formal and experiential pathways contribute to behavior, with practice-based learning taking precedence; for non-entrepreneurs, formal education takes a back seat, leaving experience and applied education as the dominant predictors of entrepreneurial competencies.

Correlations

		school_education	bussines_education	enterpene_focus	board_experience	senior_management	enterpreneurship
school_education	Pearson Correlation	1	,145	-,254	,226	-,341*	-,033
	Sig. (2-tailed)		,386	,124	,173	,036	,845
	N	38	38	38	38	38	38
bussines_education	Pearson Correlation	,145	1	,440**	-,007	,209	,580**
	Sig. (2-tailed)	,386		,006	,966	,207	,000
	N	38	38	38	38	38	38
enterpene_focus	Pearson Correlation	-,254	,440**	1	-,079	,542**	,507**
	Sig. (2-tailed)	,124	,006		,638	,000	,001
	N	38	38	38	38	38	38
board_experience	Pearson Correlation	,226	-,007	-,079	1	,059	,172
	Sig. (2-tailed)	,173	,966	,638		,724	,302
	N	38	38	38	38	38	38
senior_management	Pearson Correlation	-,341*	,209	,542**	,059	1	,611**
	Sig. (2-tailed)	,036	,207	,000	,724		,000
	N	38	38	38	38	38	38
enterpreneurship	Pearson Correlation	-,033	,580**	,507**	,172	,611**	1
	Sig. (2-tailed)	,845	,000	,001	,302	,000	
	N	38	38	38	38	38	38

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Table 4: Skill-behavior correlations among Austrian non-entrepreneurial leaders

5.5. Hypothesis Testing Summary

As Table 5 summarizes, eight theory-driven hypotheses were subjected to empirical testing; the resulting pattern of confirmation and rejection shows both expected regularities and surprising nuances. The first hypothesis stated that entrepreneurs and non-entrepreneurs would differ in terms of the extent of their formal and practical skills that they present online. Descriptive statistics revealed nearly identical proportions of respondents in both groups who had at least a bachelor's degree and were equally engaged in workplace learning. As the subsequent t-tests found no statistically significant differences in either area, the hypothesis was rejected. This result suggests that the Austrian labour market has normalized a high level of education and regular further training to such an extent that the mere possession of certificates or course certificates no longer distinguishes founders from experienced employees.

The second hypothesis predicted a divergence in the behavioral repertoire underlying business dynamics - particularly risk management, innovation and operational flexibility. Here the data was clear. Entrepreneurs were significantly more likely to report these competencies than their corporate counterparts, and chi-square tests yielded p-values well below the threshold of 0.05. The results therefore fully support the assumption that founders shape their public profile to emphasize proactive risk-taking, systematic innovation and market agility. These behaviors appear to be part of an entrepreneurial identity that is expressed to investors, partners and potential employees.

Gender, age and total tenure were hypothesized as potential causes for differences in behavior in hypotheses three to five. However, correlation matrices revealed no reliable relationships between these demographic characteristics and the determinants of successful entrepreneurial behavior. Regardless of whether they were men or women, in the first half of their careers or nearing retirement, respondents showed similar propensities when their education and experience were taken into account. The negative results required the rejection of H3, H4 and H5 and suggest that in a highly educated, digitally savvy sample, demographic characteristics are overridden by substantive signals of competence. The sixth hypothesis dealt with the influence of formal education on entrepreneurial behavior.

For founders, higher degrees correlated positively - albeit only slightly - with the strength of entrepreneurial orientation and with the composite determinant index; no such correlation was found for non-founders. As the relationship only existed in a subsample, the hypothesis is classified as partially confirmed. The selective effect suggests that formal schooling may help entrepreneurs integrate analytical framework concepts into opportunity recognition, whereas in business hierarchies, similar qualifications are seen as a prerequisite rather than a catalyst for certain behavior.

Hypothesis seven dealt with the role of experience capital acquired through management and board activities. In both subsamples, hands-on learning and tenure on the board showed a strong positive correlation with entrepreneurial orientation and the behavioral index, while board membership correlated most strongly with leadership experience in the founder group. These convergent results led to full confirmation of H7 and underscore that intensive exposure to complex organizational decision-making processes is a reliable predictor of the apparent demonstration of innovation, risk management and flexibility competencies, regardless of professional status. Finally, the mediating linchpin of the model - entrepreneurial focus - proved to be the strongest single correlate of the behavioral index in each cohort, thus meeting the strict criteria of hypothesis eight.

The strong, highly significant correlations between focus and behavioral determinants confirm that the deliberate promotion of leadership qualities, vision and strategic communication builds a direct bridge between a person's competence portfolio and outwardly visible entrepreneurial actions. In practice, this correlation underlines why training programs for founders and managers regularly focus on developing mindset and soft skills in addition to imparting specialist knowledge.

Hypothesis	Brief Formulation	Empirical Outcome
H1	Entrepreneurs and non-entrepreneurs differ in formal and practice-based skills	Rejected
H2	Entrepreneurs display higher levels of behavioural determinants (risk, innovation, flexibility)	Fully accepted
H3	Gender is associated with behavioural determinants	Rejected
H4	Age is associated with behavioural determinants	Rejected
H5	Years of experience correlate with behavioural determinants	Rejected
H6	Formal education correlates with behavioural determinants	Partially accepted
H7	Managerial/board experience correlates with behavioural determinants	Fully accepted
H8	Entrepreneurial focus strongly interrelates with behavioural determinants	Fully accepted

Table 5: Empirical status of hypotheses H1–H8

6. Discussion

6.1. Interpretation of Key Findings

The findings from the Austrian LinkedIn profiles suggest that the pathways through which human capital is translated into entrepreneurial behavior depend far less on the mere accumulation of qualifications than on the translation of lived experience into an entrepreneurial mindset. Higher degrees do exert a certain influence among founders: Holders of master's or doctoral degrees are somewhat more inclined to develop the behavioral repertoire referred to here as entrepreneurial orientation, and they signal broader competence in risk management, innovation methods and operational agility. This pattern is consistent with Lazear's “jack-of-all-trades” thesis that formal education provides versatile cognitive tools that facilitate the coordination of diverse resources when individuals act at risk of personal responsibility (Lazear, 2005, pp. 650-652). However, the statistical weight of diplomas is clearly secondary to the influence of work-based learning. Experience-based upskilling - captured in recommendations for agile facilitation, iterative product development or sales negotiation - shows a much stronger correlation with the same behaviors. Meta-analytical studies already show that implicit know-how gained from experience explains the differences in company performance more strongly than formal education (Unger et al., 2011, p. 350). The results presented here support this conclusion by showing that even in a highly qualified environment such as Austria, the additional benefit of a university education fades into the background as soon as founders begin to specifically expand their skills in the workplace.

The mechanisms behind this asymmetry become clearer when entrepreneurial orientation is viewed not as a static trait but as a dynamic capability that translates underlying knowledge into visible action. Experience-based learning processes - trial and error, reflective practice, observation from a distance - create what Politis calls entrepreneurial knowledge corridors through which founders reinterpret surprises as learning opportunities (2005, p. 407). Because these processes take place in real-world, high-risk environments, they promote rapid feedback loops and develop an intuitive sense of timing that is rarely achieved in the classroom. The Austrian founders who said they had frequently attended workshops, bootcamps and practical certifications consistently described themselves as thought leaders who can motivate teams and investors. In other words, practice-based learning not only teaches individual skills, but appears to shift an individual's identity toward proactively shaping opportunities - an identity dimension that Whishaw and Kolb argue plays a central role in the active experimentation phase of the experiential learning cycle (1984, p. 124).

Formal education nevertheless retains a symbolic and cognitive role. University degrees give entrepreneurs legitimacy when dealing with external stakeholders - banks, government funding agencies, corporate partners - who often use academic signals as indicators of analytical rigor (Colombo & Grilli, 2010, p. 616). However, the Austrian data show that qualifications alone do not guarantee the breadth of behavior required for entrepreneurial dynamism. Founders seem to benefit most from their university education when they combine disciplinary schemas with experiential heuristics. This balanced blending is consistent with the observation that effective entrepreneurial learning combines conceptual frameworks with situational action (Rae, 2006, p. 45).

For the senior managers in the sample, the contrast could not be greater. Here, formal qualifications lose virtually all predictive power once experience and practice-based learning come into play. Managers with only a bachelor's degree but who have gained intensive practical experience - particularly in leadership positions - are just as likely, if not more likely, to exhibit entrepreneurial focus characteristics than their colleagues with a master's degree. This reflects the finding that traditional, classroom-based entrepreneurship programs can dampen opportunity-related self-efficacy if they do not incorporate experiential teaching methods (Piperopoulos & Dimov, 2015, pp. 975-980). In organizations where risk is predominantly borne by the organization rather than the individual, there appears to be less incentive to translate analytical knowledge into bold action. Therefore, only those managers who are repeatedly faced with high-risk decisions - budget responsibility, personnel responsibility, crisis management - develop the adaptive reflexes and narrative skills characteristic of an entrepreneurial orientation. Eraut describes such learning in the workplace as implicit, practice-oriented acquisition that is consolidated through social interaction and the creation of meaning rather than through formal instruction (2004, p. 249). Austrian managers with many years of leadership experience are an example of this approach: their profiles are peppered with references to cross-functional project management, change initiatives and turnaround strategies - all of which are hallmarks of a wealth of experience.

Although rare, experience in management bodies provides a revealing side note. For founders, it correlates positively, albeit modestly, with entrepreneurial behavior, suggesting that exposure to governance issues refines strategic analysis and risk monitoring skills (Zahra & George, 2002, p. 199). For managers, however, non-executive directorships are too rare to have a discernible impact; the learning laboratory thus remains the boardroom rather than the boardroom. Marsick and Watkins have argued that incidental learning is accelerated when individuals hold boundary-crossing roles where formal routines collide with new challenges (2001, p. 27). The Austrian data confirm this assertion: experienced managers who are at the interface between corporate policy, customer requirements and operational constraints internalize an entrepreneurial focus even though they do not have ownership stakes. This leads to two possible interpretations. First, the entrepreneurial focus acts as a crucible in which different bodies of knowledge - whether academic or from experience - are combined into behaviors that are recognized as entrepreneurial by external target groups. Its importance in both subsamples reflects Reuber and Fischer's thesis that the cognitive scripts that founders apply when communicating with stakeholders have a significant impact on the development of companies (1999, p. 31). Secondly, the path into this crucible differs according to professional identity. Founders utilize both formal and experiential education, but the marginal benefit of hands-on learning is greater; managers rely almost exclusively on the depth and diversity of their experience. This hierarchy supports the notion that under uncertainty, opportunistic adaptations fostered by action rather than planning are favored in entrepreneurial action (Bhide, 2000, p. 109).

6.2. Theoretical Implications

The present findings sharpen and nuance the still evolving perspective of skill equilibrium by showing that it is not the absolute but the relative weight of formal and experiential capital that shapes entrepreneurial capability. Previous work has portrayed founders as either specialists or jacks-of-all-trades (Lazear, 2005, pp. 650-653); however, the present evidence suggests that the most important distinction is not between individuals but within an individual actor's portfolio. A balanced composition seems to enable entrepreneurs to switch between abstract analytical frameworks and implicit situational heuristics, thus developing a meta-competence that Felin and Zenger refer to as entrepreneurial judgment - the ability to recombine heterogeneous resources under uncertainty (2009, p. 135). This supports and extends human capital theory by shifting the unit of analysis from stocks of knowledge to configurations of knowledge, implying that marginal returns depend on complementarities between schooling, practice, and governance experience rather than the number of years or degrees (Becker, 1964, pp. 18-20).

At the same time, the pattern of correlations between experiential learning and entrepreneurial orientation confirms the behavioral branch of human capital theory, which argues that learning-by-doing generates idiosyncratic, firm-specific skills that cannot be acquired on the open market (Unger et al., 2011, p. 350). Founders who accumulate iterative, hands-on learning appear to transform this tacit knowledge into a proactive focus on risk management, innovation routines and strategic flexibility. For non-founder managers, the same mechanism dominates in the absence of credentials, confirming the thesis that experience is both context-bound and socially interpreted: Within corporate hierarchies, formal qualifications lose their signaling function as soon as ownership risk is removed. This empirically underpins the thesis that human capital is not acquired as a generic talent, but is implemented through role identities (Kim et al., 2006, p. 18). Consequently, entrepreneurship theory might benefit from modeling skill balance as a mediated construct mediated by identity work such as entrepreneurial orientation, rather than as a direct predictor of performance.

The results also argue in favor of agency theory in an entrepreneurial setting. Classic formulations assume that information asymmetries between founders (principals) and venture stakeholders (contractors) can be mitigated by observable signals such as educational attainment (Meckling & Jensen, 1976, p. 308). The available data suggest that such signals retain their value, but only in conjunction with credible evidence of situational mastery - e.g. serial project turnarounds, crisis interventions or long tenure in leadership positions. The observed interaction implies that a dual signal - combining formal legitimacy and experiential credibility - reduces behavioral uncertainty more effectively than either component on its own. This insight refines agency models by showing that monitoring costs can be reduced not only by contract design but also by the entrepreneur's skill portfolio architecture, making opportunistic behavior more detectable in advance.

Transaction cost theory is also being recalibrated. Williamson postulated that higher asset specificity requires governance forms with stronger safeguards (1985, pp. 183-186); in the present context, experience-rich founders resemble highly specific assets because their tacit knowledge is embedded and non-transferable. Their propensity to take on governance functions such as board mandates - albeit to a limited extent - can be interpreted as an internal protection mechanism that replaces formal contracts by embedding the entrepreneur deeper into the supervisory structures. Conversely, the near-zero impact of board seats on managers underscores that governance exposure without ownership stakes does not automatically lead to lower transaction costs. Extending the logic of skill equilibrium to transaction cost arguments therefore suggests that the match between experience specificity and participation in governance determines whether internalization or market orientation is efficient. Perhaps the most novel theoretical extension concerns the risk construct of the EFQM model. The EFQM framework positions risk management as a transversal factor for organizational excellence, but refrains from theorizing its predecessors on an individual level. By coupling the systemic view of EFQM with micro-level competency portfolios, this study develops a person-in-system perspective: entrepreneurs who align formal analytical competencies (e.g. ISO 9001 or financial modelling) with practice-oriented heuristics (e.g. rapid market testing) appear to be better able to institutionalize risk processes without sacrificing agility. This suggests that EFQM's risk criterion can be enriched by incorporating the entrepreneurial focus as a cognitive-behavioral mediator that combines individual capabilities with organizational resilience. Such a move supports the call for the integration of human-centered capabilities in quality management theories (Dahlgaard-Park, 2011, p. 512) and positions the balance of capabilities as a micro-foundation for excellence models. Finally, the findings build a bridge between the structural and cognitive strands of entrepreneurship theory. Structural explanations emphasize resource endowments and opportunity structures, while cognitive explanations emphasize heuristics and scripts. By showing that balanced competency architectures predict a stronger entrepreneurial focus - which in turn is associated with risk-taking, innovation and flexibility behavior - the study demonstrates that structural capital (competencies) and cognitive capital (focus) activate each other. This complements Sarasvathy's effectiveness logic, according to which means-oriented action forms goals iteratively (2001, p. 256): Entrepreneurs with diversified capabilities have a broader range of resources at their disposal and can therefore implement more flexible, stakeholder-oriented strategies without accepting excessive uncertainty. The data thus argue for an integrative theoretical approach in which the balance of capabilities is conceptualized as a structural-cognitive coupling that enables effective action while maintaining the analytical stringency valued by causality-based approaches.

6.3. Practical Implications

The equivalence of the formal qualifications of entrepreneurs and business leaders suggests that the marginal benefit of additional classroom-based courses is now low unless these are linked to structured practical experience. The ministries responsible for higher education curricula should therefore change the accreditation criteria from contact hours to evidence of practical knowledge - for example, by requiring all master's students in entrepreneurship to carry out a real consultancy project with an SME and reflect on the skills gaps they uncover (Fayolle & Gailly, 2015, p. 79). The results show that working on boards of directors or in management reinforces the translation of skills into entrepreneurial dynamism. Policy instruments such as the Austrian “Innovation Assistant” grant could be expanded to fund student shadow director programs in which final-year students serve on start-up advisory boards for at least one budget cycle. This cost-effective measure imparts governance skills long before founders are confronted with fiduciary duties (Klofsten & Öberg, 2012, p. 40). Since non-entrepreneurial managers are clearly lagging behind in terms of entrepreneurial thinking despite being highly educated, public education vouchers should be awarded for cross-functional bootcamps - short, intensive modules on topics such as opportunity recognition, investor presentation and agile product validation - rather than for additional degrees. OECD evaluations already show that 60-hour micro-credentials boost SME innovation performance more than traditional semester-long courses (OECD, 2016); aligning national funding with these results would accelerate uptake. For individuals planning to start a business, the data underscores that how you learn is more important than how much you learn.

A practical roadmap starts with an honest inventory of the skills balance index: founders should list all skills, flag those they have acquired in formal programs and those they have acquired through experience, and calculate the ratio. If the ratio leans heavily toward formal knowledge - which is often the case for technical university graduates - they should consciously seek out challenging roles that require ambiguous stakeholder management, such as leading a pilot market entry or negotiating supplier credit lines (Wilson & Beard, 2013). Conversely, artisanal founders (e.g., artisanal food producers) should add simple analytical tools such as cash flow projections and a basic IP strategy to avoid the blind spots highlighted in the study (Mitchell et al., 2000, p. 981). Equally important is practicing leadership skills: By volunteering as an observer on the board of a nonprofit organization or student-run business, aspiring founders can familiarize themselves with strategic operations and the vocabulary of business management long before capital investors arrive (Cope, 2005, p. 373). Finally, entrepreneurs should design their LinkedIn profiles to reflect their growth trajectory rather than static successes. Recommendations or certifications in ISO 31000 risk mapping, design thinking sprints, and iterative MVP testing serve as public commitments that can attract mentors and early-stage funders who value balanced skills (Van Der Heijden & Bakker, 2011, p. 240). For owner-managers already active in the Austrian microenterprise landscape, three specific development paths can be derived from the results.

Path 1 (formalized risk routines), i.e. the introduction of a lean, ISO 9001-aligned risk register - ten risks that are assessed quarterly with named risk mitigation measures - institutionalizes the risk appetite that characterizes successful founders, but requires only a one-day workshop and a shared spreadsheet (Jaca et al., 2019, p. 363). Process 2 (systematic innovation management), i.e. the introduction of an innovation hour every two weeks in which cross-functional employees present process optimizations and receive immediate feedback from the steering committee, implements the innovation factor of the study without large R&D budgets. Results from EFQM case studies show that such a regular rhythm increases the idea implementation rate by up to 40% (Çakar & Ertürk, 2010, p. 333). As part of Track 3 (experience-based training cycles), SMEs should set aside at least 5% of their payroll for shadow projects - temporary task forces in which promising employees can lead small digital or export initiatives from start to finish. In addition to spreading tacit knowledge, shadow projects increase the internal talent pool for future founders and create positive spillover effects for the regional economy. To connect these streams, chambers of commerce and regional innovation hubs could host "skill balance clinics" - monthly drop-in sessions where founders, managers and policymakers benchmark their portfolios against anonymized data sets and receive tailored action plans. Tracking can be done through micro-credential platforms that issue blockchain-backed badges for each completed experience sprint, making skills that are critical but often invisible on traditional resumes visible to the job market, according to this study (Grech & Camilleri, 2017). Finally, aligning funding and procurement preferences with demonstrated progress on skills balance dashboards would create a virtuous cycle: organizations that invest in both formal and experiential skills gain preferential access to public resources, reinforcing the very behaviors that have been shown to be performance levers.

6.4. Methodological Limitations

Although this study provided numerous insights into how the skills balance manifests itself on LinkedIn and how it correlates with entrepreneurial behavior in Austria, some methodological limitations should be noted. The total sample comprised only 92 profiles. While this size is sufficient for exploratory correlation analyses, it limits the statistical power and increases the likelihood that the observed patterns are idiosyncratic rather than robust. Small cells became particularly problematic when variables were subdivided (e.g. board experience for non-entrepreneurs), limiting the range of legitimate tests and increasing standard errors. In addition, the sample is heavily skewed towards Vienna: More than two thirds of all cases originate from the capital city. Although Vienna is the entrepreneurial center of Austria, its dense ecosystem of accelerators, investors and English-speaking talent differs significantly from the business climate of smaller provinces.

Consequently, the results may reflect Viennese networking habits and labor market structures rather than the realities at a national level. Regions such as Vorarlberg and Carinthia, which have strong industry clusters and training traditions, are underrepresented, which limits generalizability.

The study is based exclusively on self-reported LinkedIn data. Profiles are self-curated marketing tools; users may exaggerate successes, omit failures or state aspirational skills that they have not yet fully mastered. Recommendations may also reflect reciprocal favors rather than objective assessments. As no external verification (e.g. through scans of certificates or company registers) was conducted, the accuracy of several metrics - particularly practice-related skills and governance qualifications - depends on the honesty and consistency of profile holders. All core constructs were reduced to binary indicators. While this approach ensured consistency between coders and facilitated non-parametric statistics, it also flattened nuances. One founder with a short agile course and another with a decade of iterative product development both received the same score of "1" for their business education. Similarly, entrepreneurial focus became a presence-or-absence characteristic, obscuring gradations in depth and currency. These dichotomies likely weaken relationships and obscure threshold effects.

Finally, the decision to exclude incomplete profiles - those with fewer than five skills, two positions, or one degree - improved data purity but introduced selection bias. Less active LinkedIn users, older entrepreneurs who care less about digital self-promotion, and employees in industries where online presence is undesirable were systematically filtered out. As a result, highly networked, technologically savvy professionals may be overrepresented in the sample and more reserved but equally successful players underrepresented.

7. Conclusion

This master's thesis set out to answer four key questions about how different levels of human capital influence entrepreneurial performance in the digital labor market in Austria. The first question was whether founders, who are comparable to experienced employees in terms of their overall experience, exhibit a pronounced balance between practice-oriented and formally acquired skills. The quantitative comparison showed that both groups invest heavily in their higher education and continuously expand their knowledge through on-the-job learning. The share of practice-based skills in overall skills therefore did not differ in a statistically relevant way. What did emerge, however, was a divergence in the way these similar portfolios were mobilized: Founders channeled their skills into a significantly stronger entrepreneurial focus and a broader range of risk-taking, innovation and flexibility. In other words, Austrian entrepreneurs are not characterized by the composition of their skills, but by the pattern of behavior they build around these skills. This finding puts into perspective the traditional assumption that entrepreneurs accumulate a different type of capital; instead, they seem to deploy similar capital in a more opportunity-oriented way. The second research question investigated whether, within the founder subgroup, a stronger orientation towards practice-based learning predicts start-up dynamics reflected in serial start-ups and successful capital raising. The correlation analysis confirmed a positive, moderate relationship: entrepreneurs whose profiles had a higher proportion of experiential versus formal skills were more likely to report multiple start-ups and completed investment rounds. The correlation was strongest when practice-oriented skills were accompanied by an explicit entrepreneurial orientation - showing that experiential knowledge enhances performance when it is consciously oriented towards leadership, vision and market exploration. Formal education continued to play a supporting role by providing analytical foundations and legitimacy, but was in itself a weaker predictor of entrepreneurial dynamism. Thus, while balance rather than dominance remains the guiding concept, the empirical evidence suggests that a slight shift in this balance towards practical skills provides Austrian founders with a measurable growth advantage. The third question focused on whether board or management experience influences the impact of skill balance on outcomes. The data shows a clear moderating pattern. Founders with leadership experience can more easily translate a balanced skills portfolio into behavioral diversity than founders without such leadership experience. Leadership positions seem to provide an environment where abstract and tacit knowledge merge through high-risk decisions. Mandates on supervisory boards are rarer, but offer an additional strategic perspective: entrepreneurs who sit on supervisory boards have a somewhat broader repertoire of risk routines and innovation practices than colleagues with the same length of service but no experience in corporate management. For non-entrepreneurs, on the other hand, serving on supervisory boards is too rare to play a role, while leadership experience alone fulfills a similar catalytic function, translating the knowledge acquired in working life into entrepreneurial agility within the boundaries of the company. Overall, the Austrian data support the thesis that governance experience enhances the translation of balanced competencies into dynamic performance, acting as an enhancer rather than a substitute. The final question investigated whether gender influences the relationship between skills balance and success. Despite a clear predominance of men in the entrepreneurial subsample, statistical tests revealed no systematic differences in how women and men translate their competencies into entrepreneurial orientation or behaviors when education and experience are held constant. Both female founders and female leaders showed the same pattern as their male counterparts: experiential learning and leadership experience, not gender identity, shaped the path from competence to action. This finding suggests that the gender differences visible in the participation rates are due to pipeline and opportunity structures rather than the effectiveness of the skill application itself. Although the result must be interpreted with caution given the low number of female profiles, it nevertheless suggests that within the LinkedIn population in Austria, skill utilization is gender neutral when comparable human capital resources are available.

In the future, several research approaches could deepen and expand these findings. One overriding priority is scaling. Expanding the sample beyond 92 profiles would increase statistical power, allow for finer segmentation and, most importantly, enable the modeling of interaction effects that were hinted at here but could not be reliably estimated. A more ambitious scraping exercise combined with automated natural language processing to code competencies at a higher granularity could capture the thousands of Austrian users who currently do not pass the completeness filter but may represent different entrepreneurial archetypes. Geographical diversification is equally important. Two-thirds of the available cases are from Vienna, so industrial regions and rural innovation ecosystems were insufficiently studied. A targeted sample selection with an overrepresentation of provinces such as Vorarlberg, Upper Austria or Tyrol would show whether the Viennese pattern of balanced competencies combined with a strong entrepreneurial orientation is a metropolitan phenomenon or an Austrian norm. Such a regional expansion naturally invites an international extension. Repeating the study in economies with comparable digital penetration - for example in the Netherlands, Denmark or Israel - would test the transferability of the skills balancing model and show how institutional frameworks influence the interplay of practice and theory. A cross-national panel could also reveal whether national education systems steer founders towards certain skill combinations. Longitudinal studies are another promising approach. The cross-section provided a snapshot but could not track how individual profiles evolve over time or how shifts in skill composition precede funding events or strategic course changes. By regularly scraping the same cohort in conjunction with time-stamped indicators of business performance, event history models could be created that isolate causal processes. Tracking when practice-based competencies are added and how quickly behavioral traits follow would refine understanding of the learning loops that transform human capital into entrepreneurial momentum. These quantitative extensions should be complemented by method triangulation. Self-reported LinkedIn data, while rich, is susceptible to impression management. By integrating semi-structured interviews, researchers could verify key messages, explore the depth of listed competencies, and contextualize motivations for profile updates. Interviews could also reveal hidden facets of the learning process that are not reflected in the profiles, such as failures, informal mentors or ecosystem influences. Furthermore, linking profile information to external databases such as company registers, patent applications or funding announcements would anchor subjective narratives with objective outcomes, strengthening inferences about performance effects. Finally, future work could investigate experimentally balanced measures for skills development. Entrepreneurship programs at Austrian universities or accelerators could randomly assign participants to curricula that emphasize either formal analytical modules, practice-based projects, or a deliberately balanced sequence. Pre- and post-assessments of entrepreneurial focus and dynamics would provide causal evidence as to which pedagogical mix most effectively fosters the behavioral repertoire identified here as critical. Such field experiments would close the loop from descriptive observation to prescriptive guidance and translate the study's conceptual contribution into actionable policy and pedagogical concepts.

References

Abed, S. S. (2020). Social commerce adoption of small and medium enterprises in developing countries: Literature review and recommendations. International Journal of Information Management, 53, 102106. https://doi.org/10.1016/j.ijinfomgt.2020.102106

Afifi, M. A. M., & Alshehri, A. H. (2025). Entrepreneurial competencies in the digital era: A systematic review. Journal of Small Business Strategy, 35(1), 45–62.

Agresti, A. (2021). The foundations of statistical science: A history of textbook presentations. Brazilian Journal of Probability and Statistics, 35(4), 657-698.

Afolabi, B., & Macheke, R. (2012). An analysis of entrepreneurial and business skills and training needs in SMEs in the plastic manufacturing industry in the Eastern Cape Province, South Africa. International Review of Social Sciences and Humanities, 3(2), 236–247.

Aiken, L. S., West, S. G., & Reno, R. R. (1991). Multiple regression: Testing and interpreting interactions. Sage Publications.

Alghamdi, E. (2021). Enablers of Saudi women's engagement with Instagram commerce. Journal of Entrepreneurship in Emerging Economies, 13(4), 763–782. https://doi.org/10.1108/JEEE-09-2020-0330

Alnidawy, A., Alshemery, A., & Abdulrahman, M. (2017). Competitive advantage based on human capital and its impact on organizational sustainability: Applied study in Jordanian telecommunications sector. Journal of Management and Sustainability, 7(1), 64–76. https://doi.org/10.5539/jms.v7n1p64

Audretsch, D. B., Obschonka, M., Gosling, S. D., & Potter, J. (2017). A new perspective on entrepreneurial regions: Linking cultural identity with latent and manifest entrepreneurship. Small Business Economics, 48(3), 681–697. https://doi.org/10.1007/s11187-016-9807-9

Babbie, E. (2020). The practice of social research (15th ed.). Cengage Learning.

Barragan, S., et al. (2018). Understanding women entrepreneurs in the Gulf. International Journal of Gender and Entrepreneurship, 10(1), 47–69. https://doi.org/10.1108/IJGE-10-2017-0060

Becker, G. S. (1964). Human capital: A theoretical and empirical analysis, with special reference to education (p. 19). University of Chicago Press.

Becker, G. S. (1993). Human capital: A theoretical and empirical analysis, with special reference to education (3rd ed.). University of Chicago Press.

Bhide, A. (2000). The origin and evolution of new businesses. Oxford University Press.

Blakemore, S. J., & Bunge, S. A. (2012). At the nexus of neuroscience and education. Developmental Cognitive Neuroscience, 2(Suppl 1), S1–S5. https://doi.org/10.1016/j.dcn.2011.11.001

Bridgman, P. W. (1927). The logic of modern physics. Macmillan.

Bryman, A. (2016). Social research methods (5th ed.). Oxford University Press.

Bundesministerium der Finanzen. (2025, March 14). Federal Government launches powerful package for medium-sized businesses. https://www.bmf.gv.at/en/press/press-releases/2025/March-2025/Federal-Government-launches-powerful-package-for-medium-sized-businesses.html

Bundesministerium für Arbeit & Wirtschaft. (2023). Small and medium enterprises in Austria – facts and figures. https://www.bmwet.gv.at/en/Topics/Business-Location/Small-and-medium-sized-Enterprises-SMEs/SME-in-Austria-facts-and-figures.html

Çakar, N. D., & Ertürk, A. (2010). Comparing innovation capability of small and medium-sized enterprises: examining the effects of organizational culture and empowerment. Journal of small business management, 48(3), 325-359.

Chandler, G. N., Detienne, D. R., Mckelvie, A., & Mumford, T. V. (2011). Causation and effectuation processes: A validation study. Journal of Business Venturing, 26(3), 375–390. https://doi.org/10.1016/j.jbusvent.2009.10.006

Chen, L. W., & Thompson, P. (2016). Skill balance and entrepreneurship evidence from online career histories. Entrepreneurship Theory and Practice, 40(2), 289-305.

Cohen, W. M., & Levinthal, D. A. (1994). Fortune favors the prepared firm. Management Science, 40(2), 227–251. https://doi.org/10.1287/mnsc.40.2.227

Colombo, M. G., & Grilli, L. (2010). On growth drivers of high-tech start-ups: Exploring the role of founders' human capital and venture capital. Journal of business venturing, 25(6), 610-626.

Cope, J. (2005). Toward a dynamic learning perspective of entrepreneurship. Entrepreneurship theory and practice, 29(4), 373-397.

Creswell, J. W., & Clark, V. L. P. (2017). Designing and conducting mixed methods research. Sage publications.

Creswell, J. W., & Creswell, J. D. (2017). Research design: Qualitative, quantitative, and mixed methods approaches (5th ed.). Sage Publications.

Dahlgaard-Park, S. M. (2011). The quality movement: where are you going?. Total Quality Management & Business Excellence, 22(5), 493-516.

Davidsson, P., & Honig, B. (2003). The role of social and human capital among nascent entrepreneurs. Journal of Business Venturing, 18(3), 301–331. https://doi.org/10.1016/S0883-9026(02)00097-6

Dorn, D., Schoner, F., Seebacher, M., Simon, L., & Woessmann, L. (2024). Multidimensional skills as a measure of human capital: Evidence from LinkedIn profiles. arXiv preprint arXiv:2409.18638.

Dossou-Yovo, A., & Keen, C. (2021). SMEs and the innovation management process: A multi-level process conceptual framework. Technology Innovation Management Review, 11(1), 22–33. https://doi.org/10.22215/timreview/1410

Dua, A., Ellingrud, K., Mahajan, D., & Silberg, J. (2020). Which small businesses are most vulnerable to COVID-19—and when [McKinsey & Company Social Sector Practice Report]. https://www.mckinsey.com/~/media/McKinsey/Featured%20Insights/Americas/Which%20small%20businesses%20are%20most%20vulnerable%20to%20COVID%2019%20and%20when/Which-small-businesses-are-most-vulnerable-to-COVID-19-and-when-final.pdf

Elo, S., & Kyngäs, H. (2008). The qualitative content analysis process. Journal of Advanced Nursing, 62(1), 107–115. https://doi.org/10.1111/j.1365-2648.2007.04569.x

Eraut, M. (2004). Informal learning in the workplace. Studies in continuing education, 26(2), 247-273.

Eriksson, T., Heikkilä, M., & Nummela, N. (2022). Business model innovation for resilient international growth. Small Enterprise Research, 29(3), 205–226. https://doi.org/10.1080/13215906.2022.2092890

European Commission. (2019). 2019 SBA fact sheet—Austria. https://ec.europa.eu/docsroom/documents/38662/attachments/2/translations/en/renditions/native

FasterCapital. (2025). Entrepreneurship: The Austrian entrepreneur—Driving forces of the market. https://fastercapital.com/content/Entrepreneurship--The-Austrian-Entrepreneur--Driving-Forces-of-the-Market.html

Fayolle, A., & Gailly, B. (2015). The impact of entrepreneurship education on entrepreneurial attitudes and intention: Hysteresis and persistence. Journal of small business management, 53(1), 75-93.

Felin, T., & Zenger, T. R. (2009). Entrepreneurs as theorists: On the origins of collective beliefs and novel strategies. Strategic Entrepreneurship Journal, 3(2), 127-146.

Field, A. (2024). Discovering statistics using IBM SPSS statistics (5th ed.). Sage Publications. http://vlb-content.vorarlberg.at/fhbscan1/330900091084.pdf

Fischer, E., & Reuber, A. R. (2014). Online entrepreneurial communication: Mitigating uncertainty and increasing differentiation via Twitter. Journal of Business Venturing, 29(4), 565-583. https://doi.org/10.1016/j.jbusvent.2014.02.004

Fisher, G. (2012). Effectuation, causation and bricolage: A behavioral comparison of emerging theories in entrepreneurship research. Entrepreneurship Theory and Practice, 36(5), 1019–1051. https://doi.org/10.1111/j.1540-6520.2012.00537.x

Fletcher, M., & Macuga, P. (2004). The Theory Practice Nexus in Teacher Education: Preparing Students for Work. In Educating: Weaving Research into Practice: Volume 2 (pp. 69–80). Griffith University, School of Cognition, Language and Special Education.

Friedl, C.G., Frech, B., Mahajan, L., Wenzel, R., & Kirschner, E. (2023). Global Entrepreneurship Monitor 2022/2023: Bericht zur Lage des Unternehmertums in Österreich. Verlag der FH JOANNEUM Gesellschaft mbH. https://epub.fh-joanneum.at/obvfhjoa/download/pdf/11431220

Funder, D. C., & Ozer, D. J. (2019). Evaluating effect size in psychological research: Sense and nonsense. Advances in methods and practices in psychological science, 2(2), 156-168.

Gewirtz, C., Paretti, M., Case, J., Vinsel, L., Deters, J., & Zulfiqar, O. (2020). What do engineers do all day? Using LinkedIn profiles to study engineering work. 2021 IEEE Frontiers in Education Conference (FIE), 1–7. https://doi.org/10.1109/fie44824.2020.9273955

Gibbons, J. D., & Chakraborti, S. (2011). Nonparametric Statistical Inference, 5th Revised Edn. Boca Raton, FL, United States: Taylor & Francis Ltd, 10, 9781439896129.

Glickman, M. E., Rao, S. R., & Schultz, M. R. (2014). False discovery rate control is a recommended alternative to Bonferroni-type adjustments in health studies. Journal of clinical epidemiology, 67(8), 850-857.

Global Entrepreneurship Monitor. (2025). Entrepreneurial recovery on display in Austria: 2022/23 national report. GEM Consortium. https://www.gemconsortium.org/news/entrepreneurial-recovery-on-display-in-austria

González-Bailón, S. (2019, June). Decoding the social world. In Proceedings of the 10th ACM Conference on Web Science (pp. 131–139). https://doi.org/10.1145/3292522.3326021

Grech, A., & Camilleri, A. F. (2017). Blockchain in education. Publications Office of the European Union.

Gutschelhofer, A., Kailer, N., Taferner, J., Gaugeler, J., Painsi, P., & Wagenhofer, B. (2024). Empowering future entrepreneurs: The role of education and support in Austria's evolving entrepreneurial landscape—Global University Entrepreneurial Spirit Students' Survey 2023: National report Austria. University of Graz, 23–35.

Hallgren, K. A. (2012). Computing inter-rater reliability for observational data: an overview and tutorial. Tutorials in quantitative methods for psychology, 8(1), 23.

Hossain, M., & Rahman, M. S. (2018). Social networking sites and new entrepreneurs. Journal of Small Business and Enterprise Development, 25(6), 936–956. https://doi.org/10.1108/JSBED-02-2018-0043

Hsieh, C., Parker, S. C., & van Praag, C. M. (2017). Risk, balanced skills and entrepreneurship. Small Business Economics, 48(2), 287–302. https://doi.org/10.1007/s11187-016-9780-3

Jaca, C., Mateo, R., Viles, E., & Santos, J. (2019.). Proceedings QMOD Conference on Quality and Service Sciences. Journal of Change-Management, 5(4), 369-380.

Kerlinger, F. N. (1966). Foundations of behavioral research. Holt, Rinehart and Winston.

Kim, P. H., Aldrich, H. E., & Keister, L. A. (2006). Access (not) denied: The impact of financial, human, and cultural capital on entrepreneurial entryin the United States. Small business economics, 27(1), 5-22.

Klofsten, M., & Öberg, S. (2012). Chapter 4 Coaching versus Mentoring: Are There Any Differences? In New technology-based firms in the new millennium (pp. 39-47). Emerald Group Publishing Limited.

KMU Forschung Austria. (2022). SME Data. https://www.kmuforschung.ac.at/facts-and-figures/kmu-daten/?lang=en

Kock, H., & Ellström, P. E. (2011). Formal and integrated strategies for competence development in SMEs. Journal of European Industrial Training, 35(1), 71–88. https://doi.org/10.1108/03090591111095745

Kotey, B., & Folker, C. (2007). Employee training in SMEs: Effect of size and firm type—Family and nonfamily. Journal of Small Business Management, 45(2), 214–238. https://doi.org/10.1111/j.1540-627X.2007.00210.x

Krippendorff, K. (2018). Content analysis: An introduction to its methodology (4th ed.). Sage Publications.

Kuratko, D., Hornsby, J., & McKelvie, A. (2023). Entrepreneurial mindset in corporate entrepreneurship: Forms, impediments, and actions for research. Journal of Small Business Management, 61(1), 132–154. https://doi.org/10.1080/00472778.2021.2011151

Lawson, C., & Tirado, M. M. (2023). LinkedIn use by academics: an indicator for science policy and research? https://doi.org/10.55835/6442eb73213d7f5155a70585

Lazear, E. P. (2005). Entrepreneurship. Journal of Labor Economics, 23(4), 649–680. https://doi.org/10.1086/491605

LinkedIn Engineering. (2023). Economic graph research project overview. https://engineering.linkedin.com/teams/data/projects/economic-graph-research

Markham, A., Buchanan, E., & with feedback from the AOIR Ethics Working Committee. (2012). Ethical decision-making and internet research: Recommendations from the AoIR Ethics Working Committee (Version 2.0).

Marsick, V. J., & Watkins, K. E. (2001). New directions for adult and continuing education (pp. 25-34).

Marvel, M. R., & Lumpkin, G. T. (2007). Technology entrepreneurs' human capital and its effects on innovation radicalness. Entrepreneurship Theory and Practice, 31(6), 807–828. https://doi.org/10.1111/j.1540-6520.2007.00209.x

McAdam, M., et al. (2020). Digital women entrepreneurs in the Gulf. Technological Forecasting and Social Change, 152, 119883. https://doi.org/10.1016/j.techfore.2019.119883

Meckling, W. H., & Jensen, M. C. (1976). Theory of the Firm. Managerial behavior, agency costs and ownership structure, 3(4), 305-360.

Mitchell, R. K., Smith, B., Seawright, K. W., & Morse, E. A. (2000). Cross-cultural cognitions and the venture creation decision. Academy of management Journal, 43(5), 974-993.

Morsing, M. (2023). Omnia Omnium Sunt – Everything belongs to everybody: Knowledge as a non-positional good in an education system governed by Human Capital Theory [Master's thesis, Malmö University]. 1–40.

Nambisan, S., Wright, M., & Feldman, M. (2019). The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes. Research Policy, 48(8), 103773. https://doi.org/10.1016/j.respol.2019.04.001

Nascimento, A. P. D., Santos, W. R. D., & Oliveira, M. P. V. D. (2020). The risk mentality in organizations: An analysis of inserting risk management in ISO 9001 and ISO 14001: 2015 standards. Gestão & Produção, 27(2), e4043. https://doi.org/10.1590/0104-530X4043-20

Neuendorf, K. A. (2017). The content analysis guidebook (2nd ed.). Sage Publications.

Nunnally, J. C., & Bernstein, I. H. (1994). Psychometric theory (3rd ed.). McGraw-Hill.

OECD. (2013). Skills development and training in SMEs. OECD Skills Studies. https://doi.org/10.1787/9789264169425-en

OECD. (2016). Innovating Education and Educating for Innovation: The Power of Digital Technologies and Skills. OECD Publishing. https://www.oecd.org/en/publications/innovating-education-and-educating-for-innovation_9789264265097-en.html

OECD. (2021). OECD economic surveys: Austria 2021. OECD Publishing. https://www.oecd.org/en/publications/2021/12/oecd-economic-surveys-austria-2021_b9942a66.html

Pernet, C. R., Wilcox, R., & Rousselet, G. A. (2013). Robust correlation analyses: false positive and power validation using a new open source matlab toolbox. Frontiers in psychology, 3, 606.

Piperopoulos, P., & Dimov, D. (2015). Burst bubbles or build steam? Entrepreneurship education, entrepreneurial self-efficacy, and entrepreneurial intentions. Journal of small business management, 53(4), 970-985.

Politis, D. (2005). The process of entrepreneurial learning: A conceptual framework. Entrepreneurship theory and practice, 29(4), 399-424.

Rae, D. (2006). Entrepreneurial learning: A conceptual framework for technology-based enterprise. Technology Analysis & Strategic Management, 18(1), 39-56.

Reuber, A. R., & Fischer, E. (1999). Understanding the consequences of founders' experience. Journal of Small Business Management, 37(2), 30-44.

Rosenbaum, P. R. (2010). Design of observational studies. Springer.

Sagala, G. H., & Őri, D. (2025). Exploring digital transformation strategy to achieve SMEs resilience and antifragility: A systematic literature review. Journal of Small Business & Entrepreneurship, 37(3), 495–524. https://doi.org/10.1080/08276331.2023.2270368

Santamaría, L., & Mihaljević, H. (2018). Comparison and benchmark of name-to-gender inference services. PeerJ Computer Science, 4, e156. https://doi.org/10.7717/peerj-cs.156

Sarstedt, M., & Mooi, E. (2018). Descriptive statistics. In A Concise Guide to Market Research: The Process, Data, and Methods Using IBM SPSS Statistics (pp. 91-150). Berlin, Heidelberg: Springer Berlin Heidelberg.

Sarasvathy, S. D. (2001). Causation and effectuation: Toward a theoretical shift from economic inevitability to entrepreneurial contingency. Academy of Management Review, 26(2), 243–263. https://doi.org/10.5465/amr.2001.4378020

Schober, P., Boer, C., & Schwarte, L. A. (2018). Correlation coefficients: appropriate use and interpretation. Anesthesia & analgesia, 126(5), 1763-1768.

Soluk, J., & Kammerlander, N. (2021). Digital transformation in family-owned Mittelstand firms: A dynamic capabilities perspective. European Journal of Information Systems, 30(6), 676–711. https://doi.org/10.1080/0960085X.2021.1948687

Spence, M. (1973). Job market signaling. The Quarterly Journal of Economics, 87(3), 355–374. https://doi.org/10.2307/1882010

Statista. (2022). Number of small and medium-sized enterprises (SMEs) in Austria from 2008 to 2022, by size. Retrieved June 19, 2025, from https://www.statista.com/statistics/878685/number-of-smes-in-austria/

Stuart, E. A. (2010). Matching methods for causal inference: A review and a look forward. Statistical science: a review journal of the Institute of Mathematical Statistics, 25(1), 1-12.

Tan, E. (2014). Human capital theory: A holistic criticism. Review of Educational Research, 84(3), 411–445. https://doi.org/10.3102/0034654314532696

Tidd, J. (2001). Innovation management in context: Environment, organisation and performance. International Journal of Management Reviews, 3(3), 169–183. https://doi.org/10.1111/1468-2370.00062

Trieu, H. D. X., Nguyen, P. V., Tran, K. T., Vrontis, D., & Ahmed, Z. (2023). Organisational resilience, ambidexterity and performance: The roles of information technology competencies, digital transformation policies and paradoxical leadership. International Journal of Organisational Analysis, 32(7), 1302–1321. https://doi.org/10.1108/IJOA-02-2023-3645

Unger, J. M., Rauch, A., Frese, M., & Rosenbusch, N. (2011). Human capital and entrepreneurial success: A meta-analytical review. Journal of Business Venturing, 26(3), 341–358. https://doi.org/10.1016/j.jbusvent.2009.09.004

Van Der Heijden, B., Boon, J., Van der Klink, M., & Meijs, E. (2009). Employability enhancement through formal and informal learning: An empirical study among Dutch non-academic university staff members. International Journal of Training and Development, 13(1), 19–37. https://doi.org/10.1111/j.1468-2419.2008.00313.x

Van Der Heijden, B. I., & Bakker, A. B. (2011). Toward a mediation model of employability enhancement: A study of employee-supervisor pairs in the building sector. The Career Development Quarterly, 59(3), 232-248.

Wasserstein, R. L., Schirm, A. L., & Lazar, N. A. (2019). Moving to a world beyond “p< 0.05”. The American Statistician, 73(sup1), 1-19.

Whishaw, I. Q., & Kolb, B. (1984). Decortication abolishes place but not cue learning in rats. Behavioural Brain Research, 11(2), 123-134.

Wilcox, R. R. (2011). Introduction to robust estimation and hypothesis testing. Academic press.

Williamson, O. (1985). The economics of governance: framework and implications. En RN Langlois. Economics as a Process: Essays in the New Institutional Economics, 171-202.

Wilson, J. P., & Beard, C. (2013). Experiential learning: A handbook for education, training and coaching. Kogan Page Publishers.

WKO - Wirtschaftskammer Österreich. (2024). Unternehmensneugründungen 1993–2023. Endgültige Ergebnisse. Wien.

Yahaya, H. D., & Nadarajah, G. (2023). Determining key factors influencing SMEs' performance: A systematic literature review and experts' verification. Cogent Business & Management, 10(3), 2284168. https://doi.org/10.1080/23311975.2023.2284168

Zahra, S. A., & George, G. (2002). Absorptive capacity: A review, reconceptualization, and extension. Academy of management review, 27(2), 185-203.

30countries.com. (2025). Thriving in Austria: Key insights for entrepreneurs on Austrian business culture. https://30countries.com/austria/understanding-austrian-business-culture-key-insights-for-entrepreneurs/

Appendices

Appendix A - Survey Instrument (LinkedIn coding protocol)

Coding protocol used to analyze LinkedIn profiles	
Gender	
Male	0
Female	1
Age	
up to 40	0
over 40	1
Experience	
up to 20	0
over 20	1
Education	
High School	0
Bsc, Msc	1
Enterprenurship determinants	
Likert five-point scale - rating from 1 to 5 according to the determinants risk management, innovation management, flexibility	
1,2	0
3,4,5	1

Appendix B - A summarized overview of all analyzed LinkedIn profiles - in accordance with the coding protocol

Profile nr	Male/Female	Age	Experience year	Entrepreneur/non-entrepreneur	School Education	Business Education	Enteprene. Focus	Board Experience	Senior Management Experience	Enterprenurship determinants - analyze risk management, innovation management, flexibility - data on profile
1	0	1	1	Entrepreneur	1	1	1	0	0	1
2	0	1	1	Entrepreneur	1	0	1	1	1	1
3	0	0	0	Entrepreneur	1	1	1	0	1	1
4	0	0	0	Entrepreneur	1	1	1	0	0	1
5	0	1	1	Entrepreneur	1	0	1	0	1	1
6	0	0	0	Entrepreneur	1	1	1	0	1	1
7	0	1	1	Entrepreneur	1	0	1	1	1	1
8	0	1	1	Entrepreneur	1	0	1	0	0	1
9	0	0	0	Entrepreneur	1	1	1	1	1	1
10	0	1	1	Entrepreneur	1	1	1	1	1	1
11	0	0	0	Entrepreneur	1	0	0	0	0	1
12	0	0	0	Entrepreneur	1	0	1	1	1	0
13	0	0	1	Entrepreneur	1	1	1	1	1	1
14	0	1	1	Entrepreneur	1	1	1	1	1	1
15	1	1	1	Entrepreneur	1	0	0	0	1	1
16	0	0	0	Entrepreneur	1	1	1	0	0	1
17	0	0	0	Entrepreneur	1	0	0	0	0	1
18	0	1	1	Entrepreneur	0	0	0	1	0	1
19	0	1	1	Entrepreneur	1	1	1	1	1	1
20	0	0	0	Entrepreneur	1	1	1	1	1	1
21	0	0	0	Entrepreneur	1	1	1	0	1	1
22	0	0	0	Entrepreneur	1	0	0	0	1	0
23	0	1	1	Entrepreneur	1	1	1	1	1	1
24	0	1	1	Entrepreneur	0	1	0	1	1	1
25	1	1	1	Entrepreneur	1	1	1	0	1	1
26	0	0	0	Entrepreneur	1	1	1	0	0	1
27	0	0	0	Entrepreneur	1	1	1	0	0	1
28	0	1	1	Entrepreneur	1	0	1	0	1	1
29	0	0	0	Entrepreneur	1	0	1	0	0	1
30	1	1	1	Entrepreneur	1	0	1	0	1	1
31	0	1	1	Entrepreneur	1	0	1	0	1	1
32	0	1	1	Entrepreneur	1	1	1	1	1	1
33	0	0	0	Entrepreneur	0	0	1	0	0	1
34	0	1	0	Entrepreneur	1	0	1	0	0	0
35	0	1	1	Entrepreneur	1	0	1	1	1	0
36	0	1	1	Entrepreneur	1	1	1	0	1	1
37	0	0	0	Entrepreneur	1	1	1	0	0	1
38	0	1	0	Entrepreneur	0	0	0	0	0	1
39	0	0	0	Entrepreneur	1	1	1	1	0	0
40	0	1	1	Entrepreneur	0	0	1	0	0	0
41	0	1	1	Entrepreneur	1	1	1	0	1	1
42	1	1	0	Entrepreneur	0	1	1	0	0	0
43	1	1	0	Entrepreneur	1	1	1	0	0	1
44	0	1	0	Entrepreneur	0	0	1	0	1	0
45	0	1	1	Entrepreneur	1	1	1	1	1	1
46	0	1	1	Entrepreneur	1	1	1	1	1	1