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Contents

Future Issues

Editorial

The second open issue of our 80th anniversary volume of the *Swiss Journal of Business* (Established 1947 as *Die Unternehmung*) will focus on four current topics in leadership, governance, innovation management research and practice:

- In the first contribution of this open issue "Leading Across Languages: How Linguistic Diversity Moderates Leadership Impact in a Public Service Organization" *Bernhard Lang* and *Markus Gmür* examine how teams' linguistic proximity to their leader moderates the effects of servant and transformational leadership on leadership role occupancy in a multilingual public service context. Drawing on relational schema theory and inclusive leadership research, *Lang* and *Gmür* conceptualize linguistic proximity as a continuous cognitive–relational mechanism that shapes leader–team interactions. Data were collected from 68 platoon leaders and 755 followers in the Swiss Army, surveyed across four time points, and linked to objective career records. Their results show that linguistic proximity predicts leadership-role occupancy above and beyond leadership style and motivation, and conditions the effects of a common leadership core and style-specific components. Servant leadership exhibits a dual-channel, near-universal pattern of effectiveness across linguistic contexts, whereas transformational leadership follows a linguistically contingent, compensation-based trajectory. Their findings position language as a central relational mechanism in multilingual leadership and underline the importance of linguistic alignment in leadership development within public-service institutions.
- The second paper on "Executive Management Female Representation and Firm Performance in Switzerland" from *Lucas Knust*, *Patrick Chardonnens* and *Gabriela Nagel* shows a significant increase in female executive management members from 2005 through 2024 for Switzerland. Examining the association between substantive female representation and firm performance in terms of return on equity and revenue growth, *Knust*, *Chardonnens* and *Nagel* find no significant relation. However, decomposing the return on equity via a DuPont analysis reveals that substantive female representation (top quartile, >14.3 %) is associated with higher profit margins and lower financial leverage, though these associations are sensitive to threshold specification. Additional analyses indicate that these performance implications have become more pronounced over time.
- The third paper "VALORizing Innovation" from *Vanessa Orlando* develops based on classification methodology and by synthesizing four established innovation measurement models a holistic VALOR framework – encompassing values, activities, longevity, output, and return on innovation. For operationalization of the framework *Orlando* presents 62 distinct indicators to measure performance. Her research provides a comprehensive analytical framework which includes traditional as well as timely innovation aspects. The findings enable innovation managers and asset managers to evaluate and benchmark innovation performance of individual firms as well as to support their strategic decision-making.

- In the final contribution of this open issue on "Future-Relevant Technologies for Switzerland: Technological Priority Signals and Cross-Industry Robustness Based on Job Postings Analysis" *Marie Scheuffele* and *Leo Brecht* use online job postings from Switzerland to identify technologies frequently mentioned in connection with future-related terms in job description texts. Their novel approach provides a data-based perspective on the technology domains in which companies in Switzerland perceive future potential and actively recruit talent. Furthermore, *Scheuffele* and *Brecht* compare the recruiting dynamics for these technology fields across industries to identify robust technologies that are future-relevant in multiple sectors. Their methodology comprises text mining techniques – including keyword analysis and named entity recognition – and results in a data-driven trend study aimed at both innovation management researchers as well as business practitioners.

We hope that this issue will provide you with some inspiring summer readings as well as surprising and revealing "aha" moments for further research. Please have also a look on our new Call for Papers on "Recent Trends in Corporate Governance" by *Dušan Isakov* and *Nicolas Eugster* with a submission deadline of October 1st, 2026.
We would like to thank all the authors involved in this issue for their insightful contributions. We are especially grateful to our dedicated reviewers, who have made a significant contribution to ensuring the quality of this open issue. I wish you all a wonderful and relaxing summer!

Stefan Güldenberg, Prof. Dr. is Managing Editor of the Swiss Journal of Business, President of the Swiss Society of Business and Management and Full Professor as well as Academic Director at the Graduate School of the EHL Hospitality Business School, Lausanne.

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Leading Across Languages: How Linguistic Diversity Moderates Leadership Impact in a Public Service Organization

Bernhard Lang and Markus Gmür

Keywords: multilingual leadership, linguistic proximity, servant leadership, transformational leadership, leadership role occupancy, quasi-experimental study

Anstract: This study examines how teams' linguistic proximity to their leader moderates the effects of servant and transformational leadership on leadership role occupancy in a multilingual public service context. Drawing on relational schema theory and inclusive leadership research, we conceptualize linguistic proximity as a continuous cognitive–relational mechanism that shapes leader–team interactions. Data were collected from 68 platoon leaders and 755 followers in the Swiss Army, surveyed across four time points, and linked to objective career records. Hierarchical regressions show that linguistic proximity predicts leadership-role occupancy above and beyond leadership style and motivation, and conditions the effects of a common leadership core and style-specific components. Servant leadership exhibits a dual-channel, near-universal pattern of effectiveness across linguistic contexts, whereas transformational leadership follows a linguistically contingent, compensation-based trajectory. These findings position language as a central relational mechanism in multilingual leadership and underline the importance of linguistic alignment in leadership development within public-service institutions.

Führen über Sprachgrenzen hinweg: Wie sprachliche Vielfalt den Effekt von Führung in einer Public-Service-Organisation moderiert.

Zusammenfassung: Diese Studie untersucht, wie die sprachliche Nähe eines Teams zu seiner Führungskraft die Wirkungen von Servant Leadership und Transformational Leadership auf die Übernahme von Führungsrollen in einem mehrsprachigen Public-Service-Kontext moderiert. Auf Grundlage der Relational-Schema-Theorie und der Forschung zu inklusiver Führung konzeptualisieren wir sprachliche Nähe als einen kontinuierlichen kognitiv-relationalen Mechanismus, der die Interaktionen zwischen Führungskraft und Team prägt. Die Daten stammen von 68 Zugführern und 755 Angehörigen der Schweizer Armee, wurden über vier Messzeitpunkte hinweg erhoben und mit objektiven Karrieredaten verknüpft. Hierarchische Regressionen zeigen, dass sprachliche Nähe die Übernahme von Führungsrollen über Führungsstil und Motivation hinaus vorhersagt und sowohl die Effekte eines gemeinsamen Leadership-Kerns als auch die stilspezifischen Komponenten konditioniert. Servant Leadership weist dabei ein doppelkanaliges, nahezu universelles

Wirkmuster über sprachliche Kontexte hinweg auf, während Transformational Leadership einem sprachlich kontingenten, kompensatorischen Verlauf folgt. Die Ergebnisse positionieren Sprache als zentralen relationalen Mechanismus multilingualer Führung und unterstreichen die Bedeutung sprachlicher Passung für die Führungsentwicklung in öffentlichen Institutionen.

Stichwörter: mehrsprachige Führung, sprachliche Nähe, dienende Führung, transformationale Führung, Übernahme von Führungsrollen, quasi-experimentelle Studie

Introduction

Multilingual Leadership as a Relational Challenge

Leadership in multilingual contexts requires more than the application of universal leadership traits or culturally dominant prototypes, as commonly emphasized in cross-cultural leadership research (Chhokar et al., 2007; House et al., 2004; House et al., 2014). Multilingualism refers to the coexistence and use of multiple languages in organizations, across both formal and informal interactions. In such contexts, leaders and followers must continually navigate differences in values, expectations, and communicative styles. This relational complexity aligns with recent critiques in cultural research, which argue that contemporary workplaces are shaped not by single, nation-based cultural categories but by multiple, overlapping, and context-dependent cultural identities (Philipps & Sackmann, 2015; Sackmann & Phillips, 2004). Because these identities are enacted and negotiated through communication, language serves as a primary medium through which individuals express their belonging, interpret intentions, and manage relational boundaries. In multilingual teams, language therefore functions not only as a vehicle for information exchange but also as a salient socio-cultural cue that shapes interpersonal perceptions and leader–follower alignment (Henderson, 2005). Extending this perspective, research on multilingual teams demonstrates that language differences also give rise to emotional and relational dynamics, as language barriers can trigger anxiety, frustration, and interpersonal tensions among team members, thereby shaping interaction patterns and relational quality (Tenzer & Pudelko, 2015). Beyond these relational dynamics, emerging research highlights that language also plays an important role in shaping leadership effectiveness and team performance. Drawing on a micro-foundational perspective, studies show that managers' multilingual communication abilities enhance team performance by enabling more effective coordination, clearer communication, and stronger leadership influence, particularly in linguistically diverse settings (Szymanski et al., 2022). These dynamics are particularly consequential in public service organizations, where coordination, legitimacy, and sustained engagement depend on effective communication and shared understanding across diverse stakeholder groups. In such contexts, leaders and followers must continuously align expectations and interpret meaning across linguistic and cultural boundaries, making relational clarity central to organizational functioning. Despite these insights, existing research has primarily focused on institutional and policy-level aspects of multilingualism, whereas micro-level relational and psychological dynamics have been examined more fragmentarily and rarely integrated into leadership research on leader–follower interactions.

Building on this perspective, this study advances the discussion by examining teams' linguistic proximity with the leader as a relational mechanism that shapes leader–team interactions in multilingual settings. From this perspective, teams' linguistic proximity to the leader becomes a key contextual factor that structures how cultural meanings are negotiated in leader–team relationships. Building on this relational perspective, a team's linguistic proximity to the leader may shape the extent to which leaders and followers develop shared psychological schemas. When such schema congruence is achieved, alignment between leaders and followers enhances the quality of leader–member exchange, promoting trust, knowledge sharing, and reduced turnover intentions (Liu et al., 2025; Tsai et al., 2017; Zhang et al., 2023). When incongruence prevails, divergent expectations disrupt communication, reduce relational quality, and may even foster disengagement or dysfunctional behaviors (Tsai et al., 2017; Liu et al., 2024). Language is central to sensemaking processes, functioning not merely as a medium of communication but as a cognitive mechanism through which schemas, frames, and associations are activated, interpreted, and negotiated in organizational contexts (Whittle et al., 2023). While cross-cultural leadership research, such as the GLOBE study (Chhokar et al., 2007; House et al., 2004; House et al., 2014), has provided important insights into culturally endorsed leadership prototypes and value alignment, it has largely overlooked the relational and linguistic mechanisms through which leader–team schemas are enacted in practice, as well as variations within cultural contexts (Adler & Aycan, 2018; Hartog & De Hoogh, 2024; Schedlitzki et al., 2017). The social categorization model suggests that leadership moderates the effects of diversity by reducing subgroup distinctions and fostering information elaboration, thereby transforming linguistic diversity into a resource (van Knippenberg et al., 2004). This study addresses this gap by conceptualizing teams' linguistic proximity to the leader as a cognitive-relational contextual mechanism that shapes the quality of leader–team interactions in multilingual environments.

Building on a social-cognitive perspective (Tyler & Lind, 1992), we emphasize the role of relational schemas, implicit mental models that individuals use to interpret and respond to social interactions (Baldwin, 1992; Engle & Lord, 1997). These schemas serve as cognitive templates, shaped by cultural norms, past experiences, and contextual cues, that guide expectations regarding roles, authority, and interpersonal behavior. In leadership contexts, relational schemas influence how followers interpret leaders' actions and how leaders anticipate and respond to followers' needs. In multilingual settings, high teams' linguistic proximity to the leader may facilitate schema alignment through shared communicative norms, mutual understanding, and coordination. By contrast, low teams' linguistic proximity to the leader, arising from proficiency gaps, idiomatic variation, or culturally embedded styles, can disrupt schema activation, leading to misinterpretation, ambiguity, and weakened exchanges. By integrating relational schema theory with the dynamics of language use, this study offers a more nuanced understanding of how leaders and followers construct shared meaning, transcending static models of value alignment.

Inclusive Leadership in Multilingual Teams

To address schema misalignment, we focus on inclusive leadership approaches, particularly servant and transformational leadership. Though distinct in their theoretical roots (Stone et al., 2003; van Dierendonck et al., 2014), both styles promote inclusion by fostering trust, alignment, and identification (Assefa & Mujtaba, 2025; Gotsis & Grimani, 2016). Inclusion is defined as the simultaneous experience of belongingness and uniqueness (Shore et al., 2009; Shore et al., 2011). Inclusion is achieved through the recognition and integration of differences. Servant leadership supports this process by cultivating trust, mutual adjustment, and psychological safety through empathy, humility, and relational repair (Eva et al., 2019). Transformational leadership promotes alignment by articulating a compelling shared vision, reinforcing value congruence, and strengthening group identification (Bass & Riggio, 2006). Together, these styles provide relational mechanisms that may bridge linguistic barriers in multilingual teams.

The multicultural leadership literature offers important complementary insights. The GLOBE project (Chhokar et al., 2007; House et al., 2004; House et al., 2014) demonstrated that leadership effectiveness is shaped by culturally endorsed implicit leadership theories, or schemas of what constitutes effective leadership. More recently, Rockstuhl et al. (2023) identified three perspectives for understanding leadership effectiveness across contexts: (1) the cultural congruence perspective, which argues that leadership is most effective when aligned with culturally shared expectations; (2) the cultural compensation perspective, which suggests leadership can offset cultural gaps through structured behaviors; and (3) the near-universality perspective, which posits that certain styles, especially transformational and servant leadership, are broadly effective across cultures, partly due to converging global work norms (Mittal & Dorfman, 2012; Rockstuhl et al., 2023). However, despite these advances, most research has focused on alignment at the level of values or prototypes, while the relational, dyadic, and language-driven processes of schema congruence remain underexplored.

The Swiss Public Service Context

The Swiss context provides an ideal setting to investigate these dynamics. With four national languages and a tradition of receptive multilingualism, Switzerland institutionalizes linguistic diversity, particularly in public service organizations. Receptive multilingualism, in which individuals communicate in their own language while relying on others' partial comprehension and accommodation, is not only tolerated but also widely practiced in these organizations (Berthele & Wittlin, 2013). Unlike in many international or business firms, no lingua franca such as English is typically used, making communication contingent on mutual adjustment. Leaders and followers must therefore continually negotiate meaning across language boundaries. These dynamics are especially salient between Swiss Germanic, Swiss French, and Swiss Italian groups, which differ in communication styles and leadership prototypes (Brodbeck et al., 2000), making relational alignment both essential and fragile. Public service organizations, including non-profit associations, government bodies, civic institutions, and the Swiss Army, are characterized by a strong reliance on coordination, legitimacy, and sustained engagement rather than purely market-based performance logics. Their effectiveness depends not only on formal structures but also on shared understanding, trust, and voluntary commitment among members. In such contexts, communication plays a central role in aligning expectations and enabling cooperation across diverse stakeholder groups. This makes multilingual communication particularly consequential, as linguistic differences can shape how individuals interpret meaning, assess competence, and access opportunities. Evidence from comparable public service settings illustrates these dynamics. For instance, research on military organizations shows that language is not merely a neutral communication tool but can actively structure inequality and career trajectories. Peled (2000) demonstrates that language-based evaluation systems in the Israeli Defense Forces systematically disadvantaged certain linguistic groups, leading to their underrepresentation in leadership positions despite comparable capabilities. Such findings highlight how linguistic structures shape not only communication processes but also perceptions of competence and access to opportunities. As a compulsory and national institution, the Swiss Army not only reflects Switzerland's linguistic and cultural diversity but also depends heavily on multilingual coordination, intergroup cooperation, and inclusive leadership. Unlike profit-oriented firms, these organizations depend on sustained participation, volunteer engagement, and alignment with values. Their continuity, therefore, hinges not only on formal structures but also on members' willingness to assume leadership responsibility. In this environment, leadership role occupancy emerges as a decisive success factor: stepping into leadership roles ensures accountability, continuity, and strategic renewal, while signaling commitment and organizational identification (Avolio et al., 2009; Schuh et al., 2014). However, the conditions that foster or hinder such role transitions remain underexplored, particularly in multilingual public service settings where linguistic barriers and diverse expectations complicate relational dynamics. This study examines leadership in the Swiss Army, where multilingual interactions are a routine occurrence. Using the loci and mechanisms of leadership framework (Hernandez et al., 2011), this study investigates leadership at the dyadic level, focusing on how team members perceive their leader's style (servant or transformational) within relationships characterized by varying degrees of linguistic proximity. It further examines how these perceptions influence followers' willingness to assume leadership roles. In this context, language functions as a key mechanism through which relational schemas are formed, aligned, or disrupted.

Leadership in the Military

The military provides a particularly relevant context for studying multilingual leadership, as many armed forces operate in linguistically diverse environments that require continuous coordination across language boundaries. Comparative research shows that countries adopt different institutional, cultural, and structural approaches to managing linguistic diversity, particularly regarding the use of official languages as a language of work and the organization of units (Fourestier, 2010). Despite this contextual complexity, research on leadership in military settings has largely focused on the effects of established leadership styles, such as transformational and transactional leadership, on performance-related outcomes. For instance, Tremblay (2010) finds that transformational leadership can both strengthen and weaken soldiers' commitment and turnover intentions depending on perceived fairness, whereas transactional leadership tends to reduce commitment. Similarly, Swiss military research shows that transformational leadership elicits substantially more extra effort from subordinates than transactional leadership (Stadelmann, 2010). While these studies provide valuable insights into leadership effectiveness, they primarily emphasize performance outcomes and formal leadership styles, paying limited attention to the contextual and relational conditions under which leadership unfolds. More recent research has begun to address this limitation by focusing on relational leadership approaches. For example, Richardson et al. (2023) note that servant leadership behaviors are present in military contexts but remain underrepresented in formal leadership development programs. Likewise, Wuli et al. (2020) show that servant leadership can transform conflict management practices by fostering dialogue, mutual respect, and compassion. However, even this emerging focus on relational leadership largely overlooks how linguistic diversity shapes the relational processes through which leadership is enacted. In particular, the role of language in shaping shared understanding, relational alignment, and leadership outcomes remains insufficiently understood in multilingual military settings.

Contributions and Research Framework

Building on this contextual and theoretical foundation, the study makes two contributions. First, it introduces teams' linguistic proximity to the leader as a novel cognitive-relational contextual variable, extending cross-cultural and multilingual leadership research by conceptualizing language as a continuous, perception-based mechanism rather than a categorical demographic attribute. Second, it demonstrates that linguistic proximity serves as a contextual moderator, influencing the relationship between leadership style (servant and transformational) and the occupancy of leadership roles. By positioning leadership role occupancy as a novel outcome, the study contributes to understanding how inclusive leadership supports sustainable leadership development in multilingual public service organizations. From this theoretical integration, the study derives one core research question:

RQ: How does the team's linguistic proximity to the leader modify the relationship between teams' perception of servant or transformational leadership and teams' leadership role occupancy?

The model introduces teams' linguistic proximity to the leader as a continuous cognitive-relational variable capturing the perceived degree of linguistic alignment within leader–team dyads (see Figure 1). Rather than relying on categorical distinctions such as linguistic congruence or incongruence, linguistic proximity reflects the nuanced realities of multilingual interaction in which team members may differ in their fluency, comprehension, and communicative ease with their leader. Conceptualizing language in this way positions proximity as a theoretically grounded and empirically sensitive indicator of relational alignment, enabling a more fine-grained understanding of how language-based dynamics shape leader–team interactions in multilingual settings. This variable provides the foundation for investigating how linguistic alignment influences perceptions of leadership.

Figure 1: Teams' Linguistic Proximity to the Leader

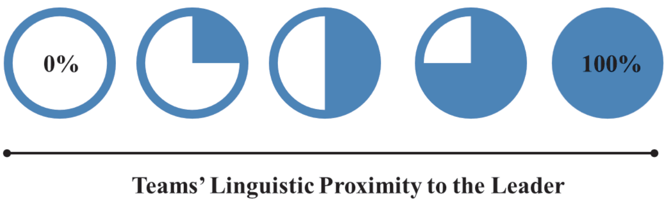
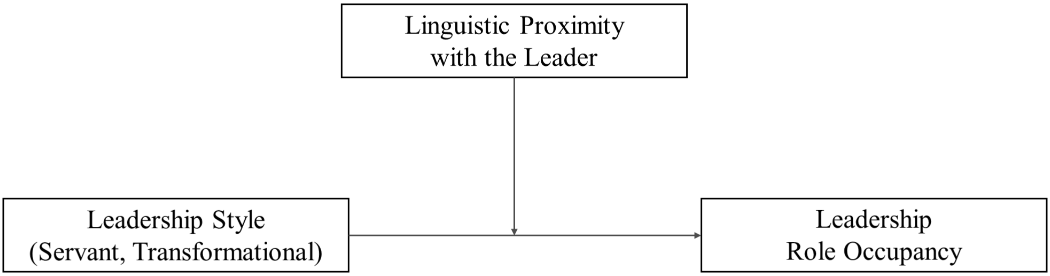


Figure 2 depicts the conceptual research model. Servant and transformational leadership serve as independent variables that predict leadership role occupancy, defined as a behavioral and objective indicator of followers' attainment of formal leadership positions within the organization (Avolio et al., 2009; Schuh et al., 2014). Teams' linguistic proximity to the leader is introduced as a contextual exogenous moderator that conditions this relationship. By capturing the degree of perceived linguistic alignment within the dyad, linguistic proximity reflects how communicative ease, shared understanding, and relational attunement shape the extent to which leadership behaviors translate into followers' willingness to assume leadership roles. This framework thus conceptualizes language not as a background demographic attribute but as a central relational mechanism through which leadership behavior influences followers' future occupancy of formal leadership roles.

Figure 2: Conceptual research model



Method

The Swiss Army is one of the country's largest public service organizations, with an active force of about 150,000 soldiers (VBS, 2025). As a militia-based institution, it depends on civic duty and, for leadership roles, on voluntary engagement. Most personnel serve part-time while balancing civilian careers or studies, creating a fluid leadership pipeline where individuals regularly transition between follower and leader roles. The willingness to assume formal leadership responsibility is, therefore, central to sustaining both operational effectiveness and organizational continuity. The Army is explicitly structured to integrate soldiers from all cultural regions, thereby promoting national cohesion and mutual understanding (Schweizer-Eidgenossenschaft, 2022). With four national languages (German, French, Italian, and Romansh), it mirrors the diversity of Swiss society. Historically, units were organized along territorial lines; however, ongoing restructuring and increased specialization have led to the creation of more mixed-language units, making multilingual collaboration a routine feature of training and operations (Jager, 2020). Regulations recognize this diversity: Article 57 of the Army's service code mandates that commanders address subordinates in their mother tongue whenever possible (Der Schweizerische Bundesrat, 2018). In practice, however, this principle is difficult to implement consistently. Mixed-language units often rely on the standardized written forms of German, French, or Italian (Jager, 2020). Spoken communication presents additional challenges: Swiss German dialects, widely used informally, differ substantially from the Standard German taught in schools, creating barriers for speakers of Latin languages. These linguistic hurdles can undermine communication, strain leadership, and erode cohesion, underscoring the importance of intercultural competence for operational effectiveness. Empirical studies in the Swiss Army context confirm that practice diverges from regulation. German dominates much of everyday interaction, while French is underrepresented outside Romandie, Italian is nearly absent, and Romansh plays a mostly symbolic role (Berthele & Wittlin, 2013). In response, the Army has come to rely heavily on receptive multilingualism: soldiers speak their own native language and rely on others' receptive abilities to follow. This practice is valued for protecting minority rights and fostering solidarity, but it is also criticized for imprecision and the risk of misunderstandings in operationally critical moments. Acceptance of receptive multilingualism increases with experience, suggesting that it is a learned practice rather than an innate ability (Berthele & Wittlin, 2013). Unlike in international and business organizations, where English often serves as a lingua franca, the Swiss Army has no neutral bridging language, making linguistic (in)congruence in leader–follower dyads a daily, unavoidable challenge. Beyond its multilingual composition, the Army offers unique methodological advantages for leadership research. Training conditions are highly standardized, and followers are randomly assigned to leaders, creating a quasi-experimental environment that allows for rigorous analysis of leadership effects. Soldiers' decision to pursue leadership training after basic service introduces an element of self-selection, making leadership role occupancy a meaningful behavioral outcome. Compulsory service for Swiss men aged 18 to 20 ensures a diverse pool of recruits, many of whom enter with varying levels of leadership motivation. Leadership service has historically been recognized as a valuable credential in civilian life, underscoring the Army's broader societal role. Although the Swiss Army has not engaged in warfare since 1848, it remains a vital civic institution contributing to disaster relief, infrastructure support, and national cohesion. The Swiss Army's leadership doctrine is grounded in mission command, which emphasizes decentralized decision-making: senior officers set objectives, while subordinates are entrusted with autonomous execution (Der Schweizerische Bundesrat, 2022). This approach aligns closely with servant and transformational leadership, which emphasize empowerment, responsibility, and initiative-taking (Knevelsrud et al., 2024). Empirical studies have shown that servant and transformational leadership behaviors among young Swiss officers are positively associated with their intrinsic motivation to assume leadership roles (Lang et al., 2022). Servant leadership is most effective in stable environments, such as structured training contexts. In contrast, transformational leadership proves especially effective in dynamic or crisis situations, inspiring followers through a shared vision and identification with the mission (Humphreys, 2005). In the Swiss Army, these two styles may operate in tandem: servant leadership strengthens motivation and continuity within the training system, while transformational leadership becomes critical in deployments such as disaster relief or peace support. Taken together, the Swiss Army combines the defining characteristics of a public service organization (purpose-driven mission, reliance on voluntary leadership, and civic significance) with the unique challenges of multilingual interaction in the absence of a lingua franca. Its standardized, quasi-experimental structure, coupled with the civic nature of leadership pathways, creates a natural laboratory for investigating how linguistic proximity to the leader and inclusive leadership styles shape perceptions of leadership and influence the filling of leadership roles.

Sample

The sample consisted of 68 leader–team dyads (68 leaders, 755 followers). The leaders were drawn from three officer training schools of the Swiss Army, where they had completed the standardized military training pathway, including basic training, the non-commissioned officer course, and the practical phase as group leaders, before entering the 15-week officer school and assuming formal command over a platoon. The average age of leaders was 20.9 years (SD = 1.25). Only male leaders were included in the analyses. Although three women served as platoon leaders in the sample, they were excluded because military service is voluntary for women but compulsory for men. This structural difference introduces systematic self-selection: women who choose to enlist are likely to differ from conscripted men in motivation, commitment, and career orientation. Including female leaders would therefore have introduced variance attributable to selection effects rather than leadership behavior itself. Restricting the analytical sample to male leaders reduces this source of bias and ensures comparability. Regarding linguistic background, the leaders closely reflected Switzerland's national distribution, with 61 % German-speaking, 34 % French-speaking, and 5 % Italian-speaking officers. In terms of education, 70 % of the leaders had not obtained a Swiss Federal Baccalaureate (Matura), while 30 % had. The Matura represents the highest secondary school qualification in Switzerland and constitutes the formal prerequisite for admission to university-level education. Followers also reflected Switzerland's multilingual composition, with 76 % of individuals being German-speaking, 18 % French-speaking, 4 % Italian-speaking, and 1 % Romansh-speaking. This distribution broadly aligns with national demographics, though German speakers were slightly overrepresented compared to their proportion in the general population. The average age of followers was 20.2 years (SD = 1.60). Female followers were likewise excluded for the same reason as female leaders, since voluntary service introduces systematic self-selection effects that differ from those of conscripted men. Team sizes varied from 2 to 34 members (M = 16.52, Median = 15).

Procedure

Data were collected at four points in time within the highly standardized training environment of the Swiss Army, which provides a unique quasi-experimental setting for leadership research. At the first measurement point (T1, June 2021), demographic information about the leader, including native language, was collected. At the second measurement point (T2, July 2021), followers evaluated their platoon leaders using validated scales of servant and transformational leadership. At the third point (T3, August 2021), approximately four weeks later, the same followers completed measures of motivational variables, specifically public service motivation and extrinsic motivation for a leadership career, which served as control variables in this study. At the fourth measurement point (T4, September 2022), leadership role occupancy was determined using objective administrative personnel records obtained from the Army's Personnel Service. These official data reflect whether individuals were promoted into formal leadership positions, thereby capturing an observable behavioral outcome rather than self-reported aspirations or intentions. The quasi-experimental design of the Swiss Army context enhances internal validity in several ways. First, followers were randomly assigned to leaders through standardized allocation procedures, eliminating self-selection and reducing common-source bias. Second, all participants were exposed to identical training schedules, shared accommodation, and uniform professional demands, creating an environment of controlled situational variance. Although leadership style was not experimentally manipulated, these structural conditions provide an as-if random assignment framework in which the effects of naturally occurring leadership behaviors can be observed under rigorously standardized circumstances. This allows for stronger causal inference than typical cross-sectional survey designs. To evaluate potential common method bias, Harman's single-factor tests were conducted separately for the leadership and motivational data. For the leadership variables (T2), the first unrotated factor explained 42 % of the total variance. For the motivational variables (T3), the first factor explained 43 %, which is well below the conventional 50 % threshold for factor loadings. These findings, combined with the temporal separation of measurement points and the inclusion of objective outcome data (T4), suggest that common method variance was not a major concern (Podsakoff et al., 2024). Overall, this multi-time and partially objective research design provides a robust quasi-experimental framework for examining how leadership style and the exogenous contextual variable of teams' linguistic proximity to the leader jointly predict leadership role occupancy within a real-world institutional setting.

Measures

This section outlines the procedures employed to assess the study's key constructs. Surveys were offered in German, French, and Italian to enable participants to respond in their preferred language. The original English questionnaire was translated into these languages using a back-translation process. To ensure linguistic precision and conceptual alignment, a panel of multilingual experts reviewed the translations for equivalence and clarity.

Linguistic Proximity with the Leader

Linguistic proximity was assessed based on the match between the leader's and followers' native languages. First, native language information was collected for all participants. For each leader–follower dyad, a binary match score was created (1 = same native language; 0 = different native language). These values were then aggregated at the team level by calculating the proportion of followers who shared the leader's native language. This resulted in a continuous percentage-based score ranging from 1 to 10, where a score of 1 represents 0–10 % linguistic proximity and a score of 10 represents 90–100 % linguistic proximity, reflecting the degree of linguistic alignment within each platoon leader.

Servant Leadership

Servant leadership was measured using the Servant Leadership Survey (van Dierendonck & Nuijten, 2011). The instrument consists of 18 items that capture five core dimensions: empowerment, stewardship, humility, standing back, and authenticity. Responses were recorded on a six-point Likert scale. The item wording was adapted to reflect the operational language of the military context, enhancing clarity and relevance. A representative item states, "*My platoon leader helps me to develop myself.*" Cronbach's alpha for the scale was.90. Followers' ratings of servant leadership were aggregated to the team level by computing the mean score within each platoon, reflecting shared team perceptions of the leader's behavior.

Transformational Leadership

Transformational leadership was measured using the Multifactor Leadership Questionnaire (B. Bass & Avolio, 1995). The instrument comprises 16 items that capture four core dimensions of transformational leadership: idealized influence (behavior), inspirational motivation, intellectual stimulation, and individualized consideration. Responses were recorded on a six-point Likert scale. The wording of the item was adapted to reflect the military context, enhancing clarity and relevance. A representative item states, *"My platoon leader makes it clear how important it is to commit 100 % to the mission."* Cronbach's alpha for the scale was.93. Followers' ratings were aggregated to the team level by computing the mean score within each platoon, reflecting the shared team perception of the leader's transformational leadership.

Leadership Role Occupancy

Leadership role occupancy was assessed using objective behavioral data from the Armed Forces Personnel Service, providing a valid and reliable indicator of leadership career pursuit within the Swiss Army. This measure captures enacted leadership behavior rather than self-reported intentions or aspirations. At the individual level, the variable was coded dichotomously (0 = did not pursue a cadre career; 1 = voluntarily continued into formal leadership training). These values were then aggregated at the team level by calculating the proportion of followers within each platoon who entered a leadership role. This resulted in a continuous percentage score reflecting each team's overall leadership advancement rate.

Control Variables

To account for contextual variation across platoons, leader education and two motivational variables were included in the analyses. Leader education was coded based on whether the platoon leader had completed the Swiss Federal Matura (0 = no Matura; 1 = Matura). Two motivational orientations toward leadership service were also considered. Public service motivation refers to an intrinsic commitment to the public interest and willingness to prioritize collective welfare over personal benefit. This construct was measured with five items adapted to the military context (Ritz & Brewer, 2013; Cronbach's α =.83). A representative item reads: *"It is important to me to contribute selflessly to the common good."* Extrinsic motivation, in contrast, reflects the external incentives associated with leadership training, such as its recognized value for future civilian careers (Schweizer Armee, 2025). It was measured using four items rated on a five-point scale (Cronbach's α =.90), for example: *"Pursuing leadership training is valuable because it benefits my future civilian career."* An exploratory factor analysis (principal axis factoring, oblimin rotation) confirmed that the two motivational constructs represent empirically distinct dimensions. Two factors with eigenvalues greater than one emerged, jointly explaining 71 % of the total variance (57 % and 14 %, respectively), with strong positive loadings for public service motivation items on the first factor and strong negative loadings for extrinsic motivation items on the second, and minimal cross-loadings (<.30), supporting conceptual distinction. Because the unit of analysis in this study is the leader–team dyad, the motivation scores were first aggregated at the team level by averaging the responses of followers within each platoon, resulting in shared motivational profiles for each team.

Analytical Strategy

All analyses were conducted at the team level. We began by computing Spearman rank-order correlations to explore the bivariate relationships among the control variables, teams' linguistic proximity to the leader, perceived leadership styles, team motivational variables, and leadership role occupancy. This initial step provided a descriptive overview of how these constructs relate to one another, before moving on to more complex modeling. To address the research question, we examined whether teams' linguistic proximity to the leader conditions the relationship between perceived leadership and leadership role occupancy. These analyses controlled for leader education and the team-level motivational variables. A methodological challenge arose due to the extremely high correlation between servant and transformational leadership (r =.91), which made it inappropriate to enter both variables simultaneously in their raw form. To disentangle their common and unique components, perceived leadership was decomposed into three elements: (a) a Common Leadership Core (CLC) capturing the variance common to both servant and transformational leadership, and (b) two residualized variables representing the unique variance specific to servant leadership and to transformational leadership, respectively. This decomposition allowed us to examine how both the common core and the style-specific aspects of leadership relate to leadership role occupancy, and how these relationships vary as a function of linguistic proximity. Using this decomposition, we estimated a series of hierarchical regression models. We first introduced the control variables, followed by an examination of linguistic proximity. We then entered the CLC and, in separate steps, the servant leadership residual and the transformational leadership residual. To test moderation effects, we added interaction terms between linguistic proximity and the leadership components, first with the CLC, and then with the style-specific residuals. Parallel sets of models were estimated for residual servant and transformational leadership. Changes in explained variance across successive models were used to evaluate whether linguistic proximity, leadership components, or their interactions contributed significantly to predicting leadership role occupancy. Taken together, this analytic strategy enabled us to assess both the direct influence of linguistic proximity on leadership perceptions and leadership role occupancy, as well as its moderating role in shaping how the common and style-specific components of perceived leadership translate into actual leadership advancement within teams.

Results

Table 1 presents the descriptive statistics and correlations among the primary study variables. Several consistent patterns emerge. Leader education shows meaningful associations with team motivation and leadership role occupancy, suggesting that more formally educated leaders tend to foster motivational climates linked to sustained leadership involvement. At the same time, leader education relates differently to linguistic proximity and servant leadership, indicating that formal education does not necessarily align with perceived relational closeness or servant leadership behavior. Team public service motivation correlates with both motivational and leadership-related variables, pointing to a broader attitudinal constellation in which a shared public service ethos accompanies more positive evaluations of leadership and a higher likelihood of assuming formal roles. A comparable pattern appears for extrinsic motivation. Linguistic proximity is systematically associated with perceptions of servant and transformational leadership, underscoring the role of language alignment as a relational mechanism shaping leadership evaluations. Finally, servant and transformational leadership are strongly interconnected, and both relate to leadership role occupancy.

	Variable	M ± SD	Range	1.	2.	3.	4.	5.	6.
1.	Leader's Education (0 = no Matura, 1 = Matura)	.71 ± .45	0 - 1						
2.	Teams' Public Service Motivation	2.98 ± .30	2.30 - 4.00	.17**					
3.	Teams' Extrinsic Motivation	2.65 ± .53	1.25 - 4.75	.11**	.80**				
4.	Teams' Linguistic Proximity with the Leader	7.54 ± 3.42	1 - 10	-.26**	-.24**	-.17**			
5.	Teams' Perception of Servant Leadership	4.41 ± .37	3.59 - 5.61	-.08**	.21**	.25**	.37**		
6.	Teams' Perception of Transformational Leadership	4.65 ± .38	3.50 - 5.95	-.01	.25**	.27**	.37**	.91**	
7.	Teams' Leadership Role Occupancy	.25 ± .14	0 - 1	.16**	.25**	.36**	.04	.13**	.15**

Note: Significance levels: $^{*}p < .05$; $^{**}p < .01$; N= 759; K=71

Table 1: Descriptive statistics and Spearman rank-order correlations among the study variables

To address the research question, we examined whether teams' linguistic proximity with the leader modifies the relationships between leadership perceptions and leadership role occupancy, while controlling for leader and team motivational characteristics (see Table 2). For this purpose, we decomposed teams' perceived leadership into three components: a Common Leadership Core (CLC) capturing the common variance between

Variables	Teams' Leadership Role Occupancy								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Leader's Education	.11**	.15**	.15**	.16**	.16**	.20**	.16**	.16**	.20**
Teams' Public Service Motivation	.06	.09†	.11*	.12*	.15**	.14**	.12*	.15**	.14**
Teams' Extrinsic Motivation	.33**	.31**	.32**	.31**	.30**	.25**	.31**	.30**	.25**
Teams' Linguistic Proximity with the Leader (LP)	-	.15**	.17**	.18**	.15**	.14**	.18**	.15**	.13**
Teams' Perceived Common Leadership Core (CLC)	-	-	-.08*	-.09*	.42**	.38**	-07*	.43**	.22
Teams' Perceived Servant Leadership Residual (SL-R)	-	-	-	.04	.05	.06†	-	-	-
Teams' Perceived Transformational Leadership Residual (TFL-R)	-	-	-	-	-	-	-.04	-.05	-.06†
LP ^{x} CLC	-	-	-	-	-.52**	-.48**	-	-.52**	-.27†
LP ^{x} SL-R	-	-	-	-		.24**	-	-	
LP ^{x} TFL-R	-	-	-	-	-	-	-	-	-.25**
F-Value	53.15**	45.74**	37.81**	31.81**	29.64**	35.10**	31.81**	29.64**	35.10**
R^2	.175	.196	.202	.203	.217	.274	.203	.217	.274
Adjusted R^2	.172	.192	.196	.197	.210	.266	.197	.210	.266
Adjusted ΔR^2		.021** (in relation to model 1)	.005* (in relation to model 2)	.002 (in relation to model 3)	.014** (in relation to model 4)	.056** (in relation to model 5)	.002 (in relation to model 3)	.014** (in relation to model 7)	.056** (in relation to model 8)

Note: Significance levels: $^{*}p < .05$; $^{**}p < .01$; N= 759; K=71

Table 2: Hierarchical Regression Model for the research question

servant and transformational leadership, and two residualized variables representing the unique servant-specific and transformational-specific components.

Across all analyses, leaders' education emerged as a stable and robust predictor: teams led by more highly educated leaders consistently showed higher rates of leadership role occupancy. In the baseline model with controls only, leaders' education and teams' extrinsic motivation were positively associated with occupying a leadership role, whereas public service motivation was not yet significant. When teams' linguistic proximity with the leader was added, the model improved, and linguistic proximity emerged as a positive predictor. In this extended specification, public service motivation also became positive, while extrinsic motivation remained robust. Introducing the teams' perceived leadership common variance index (CLC) led to a further improvement, with leader education, public service motivation, extrinsic motivation, and linguistic proximity all remaining significantly positive. At the same time, the CLC showed a small negative association with leadership role occupancy. Adding the teams' perceived servant leadership alongside the CLC did not change model fit. Leader education, public service motivation, extrinsic motivation, and linguistic proximity remained positive, the CLC remained negative, and the servant leadership residual was not significant. When the interaction between the CLC and linguistic proximity was introduced, the model improved, and the interaction was strongly negative, indicating that the positive effect of the common leadership core weakens as linguistic proximity increases. In a more comprehensive specification that included both the CLC and the servant leadership residual, the model improved further. Leader education, public service motivation, extrinsic motivation, and linguistic proximity all remained significant. The CLC showed a positive main effect, while the servant leadership residual showed a marginally positive tendency. Two interactions appeared: the CLC × linguistic proximity interaction remained negative, whereas the servant leadership residual × linguistic proximity interaction was positive. This pattern suggests that the common leadership core becomes less beneficial at higher linguistic proximity, while servant-specific components become more important as leaders and followers are linguistically closer.

The parallel set of models for transformational leadership showed a similar structure. Adding the teams' perceived transformational leadership residual to the CLC model did not improve model fit. In this model, leader education, public service motivation, extrinsic motivation, and linguistic proximity remained positive, the CLC was negative, and the transformational leadership residual was not significant. Adding the CLC × linguistic proximity interaction improved the model, yielding a negative interaction effect again. In the full specification, which included both leadership components and interactions, the model improved further. Leader education, public service motivation, extrinsic motivation, and linguistic proximity remained positive. The CLC was no longer significant as a main effect; the transformational leadership residual showed a marginally negative tendency; the CLC × linguistic proximity interaction was marginally negative; and the transformational leadership residual × linguistic proximity interaction was significantly negative. This indicates that the transformational-specific leadership component becomes increasingly negatively associated with leadership role occupancy as linguistic proximity increases. Across all models, leaders' education was consistently the strongest and most stable predictor. Teams' public service motivation became more robust once leadership variables were included, while extrinsic motivation remained positive but weakened slightly as model complexity increased. Overall, the analyses show that teams' linguistic proximity with the leader not only directly enhances leadership role occupancy but also systematically moderates how both the common leadership core and the style-specific components relate to leadership development within teams.

Discussion

The present study contributes to the emerging conversation on multilingual leadership as a relational challenge by demonstrating that linguistic proximity to the leader meaningfully shapes perceptions of leadership and its relationship to followers' willingness to assume leadership roles. Building on relational schema theory, multicultural leadership research, and inclusive leadership scholarship, the findings show that leadership in multilingual contexts is not simply a matter of universal leadership traits but depends on how leaders and followers navigate linguistic boundaries that structure relational alignment and expectations. This aligns with recent critiques in cultural research that emphasize that contemporary workplaces are shaped by multiple, context-dependent cultural identities rather than single national categories (Sackmann & Phillips, 2004; Phillips & Sackmann, 2020) and extends the emerging discourse on leadership in multilingual teams (Szymanski et al., 2022). A major insight of the study concerns whether linguistic proximity conditions the relationship between perceived leadership and leadership role occupancy. Because servant and transformational leadership are highly correlated at the team-perception level (r =.91), decomposing them into a common core (CLC) and style-specific residuals provided a more fine-grained perspective. Servant leadership shows a dual-channel pattern of effectiveness across linguistic contexts. The common leadership core is particularly influential under low proximity, supporting the compensatory view that value-based elements retain effectiveness when relational cues are difficult to decode (Rockstuhl et al., 2023). In contrast, the servant-specific residual becomes more influential when linguistic proximity is high, consistent with van Dierendonck's (2011) view that servant leadership activates followers' psychological needs through subtle cues that require clear communication to be perceived. Together, these dual patterns support the near-universality perspective, indicating that servant leadership remains effective across linguistic contexts, albeit through different relational mechanisms depending on the degree of linguistic alignment (Mittal & Dorfman, 2012; Rockstuhl et al., 2023). Transformational leadership follows a more linguistically contingent trajectory. Its style-specific component is more effective under low proximity, where followers rely on expressive or visionary cues to reduce uncertainty, again consistent with the compensation perspective. However, transformation-specific behaviors lose relevance and may be perceived negatively in proximity, particularly in cultural contexts such as the Germanic-Swiss setting, where restraint and factual objectivity are normatively preferred (House et al., 2004). Thus, transformational leadership can be effective in low-proximity contexts but lacks the dual-context adaptability characteristic of servant leadership. Taken together, these findings yield several theoretical implications. First, linguistic proximity emerges as a relational mechanism that shapes how leadership is interpreted and enacted in multilingual teams, rather than a binary condition—linguistic alignment functions as a continuous, relational process that structures the clarity and coherence of relational cues. Second, the results advance a relational-linguistic perspective on inclusive leadership, showing that servant and transformational leadership promote a sense of belonging and uniqueness (Shore et al., 2009) through distinct pathways, depending on linguistic context. Third, linguistic proximity predicts leadership role occupancy above and beyond leadership style and motivational factors, suggesting that linguistic alignment shapes developmental trajectories rather than merely perceptions. In multilingual public service environments, linguistic proximity therefore represents an overlooked dimension of leadership development and relational coordination.

Limitations

Despite its contributions, this study is subject to several limitations that warrant consideration in future research. First, the very high intercorrelation between servant and transformational leadership raises the possibility of multicollinearity. Although the two constructs have distinct theoretical roots (Stone et al., 2003; van Dierendonck et al., 2014), their substantial empirical overlap suggests that followers may perceive them as complementary facets of a broader inclusive leadership schema. While this study addressed the issue by decomposing the constructs into common and style-specific components, future research should apply more advanced analytical approaches to disentangle their unique and common variance more precisely. Alternatively, scholars may conceptualize servant and transformational leadership as formative rather than reflective constructs and examine their effects at the sub-dimensional level, thereby enabling a more granular understanding of which specific behaviors drive follower outcomes across varying linguistic conditions. Second, the study did not explicitly capture individual bilingualism or language proficiency gradients, which are highly relevant in multilingual environments, such as the Swiss Army. Linguistic proximity was operationalized as a continuous team-level variable, reflecting the percentage of followers who shared the leader's native language. This approach overlooks the fluidity of bilingual communication and receptive multilingualism, which are central to real-world interactions in Switzerland. Future research should adopt more fine-grained linguistic measures that account for self-assessed proficiency, habitual language use, and communicative switching behaviors. Third, the study did not include data on participants' migration backgrounds, a factor that substantially shapes linguistic identity, cultural orientation, and perceptions of leadership in Swiss public service contexts. Including this variable would allow for a deeper understanding of how intersectional forms of diversity, linguistic, cultural, and migratory, jointly influence leadership dynamics. Finally, while the quasi-experimental setting of the Swiss Army enhances internal validity through standardized structures and random assignment, it may also limit external validity. The hierarchical, male-dominated, and mission-oriented nature of this organization differs from that of many civilian public service institutions, nonprofit associations, or corporate environments. Replications across varied organizational and national contexts are therefore necessary to assess the generalizability of both the inverted-U relationship between linguistic proximity and leadership perceptions and the moderating role of linguistic proximity in shaping the relationships among different components of leadership and leadership role occupancy.

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Declaration of generative AI and AI-assisted technologies in the writing process

While preparing this work, the authors used ChatGPT to enhance clarity, improve readability, and refine certain theoretical explanations. After using this tool, the authors reviewed and edited the content as needed, taking full responsibility for the publication's content.

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Executive Management Female Representation and Firm Performance in Switzerland

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Abstract: We examine the evolution of female representation in Swiss executive management and its impact on firm performance. We show a significant increase in female executive management members from 2005 through 2024. Examining the association between substantive female representation and firm performance in terms of return on equity and revenue growth, we find no significant relation. However, decomposing the return on equity via a DuPont analysis reveals that substantive female representation (top quartile, >14.3 %) is associated with higher profit margins and lower financial leverage, though these associations are sensitive to threshold specification. Additional analyses indicate that these performance implications have become more pronounced over time.

Keywords: Female representation, gender diversity, corporate governance, Swiss executive management, firm performance, profitability, DuPont analysis.

Frauenrepräsentation in der Geschäftsleitung und Unternehmensleistung in der Schweiz

Zusammenfassung: Die vorliegende Studie untersucht die Entwicklung der Frauenrepräsentation in schweizerischen Geschäftsleitungen und deren Auswirkungen auf die finanzielle Unternehmensleistung. Der Frauenanteil in schweizerischen Geschäftsleitungen ist von 2005 bis 2024 signifikant gestiegen. Bei der Untersuchung des Zusammenhangs zwischen nennenswerter Frauenrepräsentation und Unternehmensleistung in Bezug auf Eigenkapitalrendite und Umsatzwachstum wurde kein signifikanter Effekt gefunden. Jedoch zeigt die Zerlegung der Eigenkapitalrendite mittels DuPont-Analyse, dass nennenswerte Frauenrepräsentation (oberstes Quartil, >14,3 %) mit höheren Gewinnmargen und geringerem Leverage verbunden ist, wobei diese Zusammenhänge von der Schwellenwertspezifikation abhängig sind. Zusätzliche Analysen deuten darauf hin, dass diese Leistungsauswirkungen im Laufe der Zeit ausgeprägter geworden sind.

Stichwörter: Frauenrepräsentation, Geschlechterdiversität, Corporate Governance, Schweizer Geschäftsleitung, Unternehmensleistung, Profitabilität, DuPont-Analyse.

1. Introduction

Diversity in corporate leadership has been extensively discussed in both academic literature and business practice (e.g., Ahern & Dittmar, 2012; Zattoni et al., 2023; Zeng et al., 2025). Such diversity, encompassing gender, ethnicity, age, and professional background, is often viewed as a driver of organizational success. Beyond the business context, female representation in leadership has also gained attention as a matter of societal and political importance. Switzerland's corporate governance regulation reflects this attention to female representation. New regulations implemented in 2021 establish representation targets of 30 % women on the board of directors and 20 % in executive management for listed companies, to be achieved by 2026 and 2031 respectively (Code of Obligations (CO), Art. 734f).

However, the relationship between female representation in executive management and firm performance remains empirically contested. While some studies document positive associations (e.g., Campbell & Mínguez-Vera, 2008; Carter et al., 2003; Conyon & He, 2017; Liu et al., 2014), others find negative relationships (e.g., Adams & Ferreira, 2009; Ahern & Dittmar, 2012; Zeng et al., 2025), and some report null results (e.g., Marinova et al., 2016; Rose, 2007). Moreover, research specifically examining Swiss firms is limited, with most studies either focusing on board or management characteristics without examining performance effects (Ruigrok et al., 2007) or including Switzerland only within broader international samples (Zeng et al., 2025). Given these conflicting findings, the scarcity of Swiss studies and the recent regulatory changes, this paper has two main objectives: first, to document the evolution of female representation in Swiss executive management over the past two decades, and second, to examine the female representation-performance relationship within the unique Swiss context.

We obtain comprehensive data on the executive management composition of Swiss firms from a data set provided by guido schilling ag, which annually publishes the schillingreport.[1] We merge this management data with financials from the LSEG database (formerly Refinitiv), and where LSEG data is unavailable, Moody's ORBIS, and annual reports (hand-collected). Our final sample comprises 1,566 firm-year observations and 109 unique firms from 2005 through 2024.

Our data shows a substantial increase in female executive management representation, with the average number of females on executive management teams rising from 0.2 in 2005 to 1.7 by 2024. In 2005, 84.7 % of firms had no female executive managers, and none had three or more female executive managers. In contrast, by 2024 only 20.2 % of firms lacked female representation, while 21.5 % had three or more female executive managers. The proportion of females in executive management has also increased significantly. The percentage of female executive management members grew steadily from 2.3 % in 2005 to 4.4 % in 2015, then more than doubled to 11 % by 2020, before reaching approximately 21 % in 2024.

Next, we assess the impact of female representation on firm performance using OLS regressions. As proxies for firm performance, our dependent variables include return on equity and revenue growth, with our variable of interest being substantive female representation, that is, a dummy variable equal to 1 for observations in the top quartile

1 We thank guido schilling ag for providing the data used in this study. The annual schillingreport is available at https://www.schillingreport.ch/en/.

of female executive representation (>14.3 % women; this 14.3 % cutoff corresponds to the sample's 75th percentile). Control variables account for firm size and executive management team size. We employ three models: one without fixed effects, one with year fixed effects only, and one with both year and firm fixed effects, thereby, controlling for time trends and time-invariant firm characteristics. We cluster standard errors at the firm-level. Across all regression specifications, we find no statistically significant association between substantive female representation and either return on equity or revenue growth.

Collectively, our results suggest that female representation in executive management neither enhances nor diminishes overall firm performance. Moreover, our findings indicate that the substantial growth in female representation in corporate leadership has not resulted in any significant negative or positive impact on firm performance.

To further explore the relationship between female representation and firm performance, we apply the DuPont identity to decompose the return on equity into its three components: profit margin, asset turnover, and equity multiplier. We find that substantive female representation is positively and statistically significantly associated with profit margins across all specifications, while it is negatively associated with financial leverage, though this effect is not statistically significant when including year and firm fixed effects.

Additional tests show marginal significance (at the 10 % level) in models using a 20 % threshold. However, all results become insignificant when using a 10 % threshold or a continuous percentage measure. These findings highlight the sensitivity of our results to threshold specification and indicate that a critical mass of female representation might be necessary. Overall, the DuPont analysis provides a more nuanced understanding of the relationship between female representation and firm performance. The countervailing effects on different components of ROE – increased profit margins offset by decreased leverage – could explain the absence of a significant net effect on overall return on equity.

Splitting our sample into two periods (2005–2014 and 2015–2024), we document that significant associations are only present in the recent decade. These results suggest that the performance implications of female representation have become more pronounced over time, though this pattern may also reflect increased statistical power as substantially more firms reach the threshold in the later period.

We note that our study documents associations rather than causal relationships. Despite employing multiple regression specifications with various fixed effects, we cannot eliminate concerns regarding time-varying omitted variables or reverse causality that may confound the documented relationships.

This study contributes to the literature in several ways. First, it documents the evolution of female representation in Swiss executive management teams over time. Second, it provides recent and comprehensive evidence on the association between female representation and firm performance. Third, by utilizing DuPont analysis, we unpack the aggregate relationship between female representation and return on equity, revealing potentially offsetting effects on operational efficiency (profit margin) and financial strategy (leverage) that could help explain the often-inconclusive findings on overall performance metrics. Fourth, our analysis over a twenty-year period highlights that the relationship between female representation and specific performance components may evolve over time, suggesting that the implications have become more pronounced in the recent decade.

The study's findings also offer a direct contribution to the debate surrounding Switzerland's new gender diversity law (Art. 734f CO). This "comply-or-explain" rule mandates that companies justify why they have not met gender targets for boards (30 % by 2026) and executive management (20 % by 2031). However, based on our analysis, we project this law is unlikely to substantially alter overall firm performance. This is for two reasons. First, from a compliance standpoint, our data shows many firms already meet the executive management threshold in 2024. Second, and more fundamentally, our DuPont analysis reveals that female representation is associated with compositional changes in financial performance. Rather than correlating with net changes in return on equity, it appears linked to specific, offsetting components – namely, profit margins and financial leverage. This suggests that regulatory effects may be more apparent in the individual components that drive firm performance rather than in aggregate performance measures.

2. Background

The composition of executive management teams has undergone significant changes in recent decades, moving away from historically homogeneous groups toward greater diversity. Research on diversity encompasses multiple dimensions including gender, age, nationality, education, tenure, and expertise (see e.g., Borges et al., 2025; Zattoni et al., 2023 for reviews). While acknowledging this multifaceted nature, this study focuses specifically on gender diversity of executive management teams. Prior research has examined a broad range of organizational outcomes including firm performance, strategy and innovation, risk-taking behavior, and governance practices (Zattoni et al., 2023). Our study focuses specifically on firm performance outcomes, contributing to this central but still inconclusive stream of research.

2.1 Swiss context

According to Swiss corporate law, a corporation has three governing bodies: the general meeting of shareholders, the board of directors, and the external auditor. The board of directors is entrusted by the general meeting with the ultimate direction of the company (Art. 716a, paragraph 1, no. 1, CO). It may delegate the operational management of the company to an executive management team (Art. 716a, paragraph 1, no. 2 CO), termed in this paper EM.

The Federal Constitution commits to the principle of equality between women and men, explicitly including equality in the workplace.[2] This understanding of equality entails that both genders have equal opportunities in all work functions, particularly in leadership positions. Despite progress, Switzerland continues to lag behind international comparisons (guido schilling ag, 2025). According to the Global Gender Gap Index, initiated by the World Economic Forum in 2006, Switzerland ranked 20th in 2024 (World Economic Forum, 2024, p. 12).

To support the achievement of gender equality in the professional environment, Art. 734f of the CO, amended in 2020 and incorporated into law on January 1, 2021, stipulates that if each gender is not represented by at least 20 % in the executive management by 2031, publicly listed companies must disclose in their compensation report the reasons for non-compliance and the measures being taken to promote the underrepresent-

2 See Swiss Federal Constitution (2024), Art. 8 para. 3: “Men and women have equal rights. The law shall ensure their equality in law and practice, particularly in family, education and work. Men and women have the right to equal pay for work of equal value.”

ed gender.[3] This provision is intended to send a clear signal to the business community to "intensify efforts for active and comprehensive leadership development of women, who remain the significantly underrepresented gender in top management" (Forrer & Müller, 2022).

Prior to this legal requirement, gender diversity was merely listed as a recommendation in economiesuisse's Swiss Code of Best Practice for Corporate Governance, though without specifying a quota. The Swiss Code of Best Practice for Corporate Governance (Section 13) now explicitly refers to the CO, requiring that the board of directors aim to meet the legal targets for balanced gender representation on both the board and in executive management. In the context of personnel and succession planning, the board is expected to implement measures to promote the underrepresented gender.

While some prior studies have assessed Swiss board member characteristics, including gender (Ruigrok et al., 2007), they often do not explicitly link these attributes to firm performance. Other research connects board gender diversity to performance but includes Swiss firms only as part of broader international samples, potentially obscuring country-specific dynamics (Zeng et al., 2025). An exception is an unpublished working paper by Schmid & Urban (2015), who examine a broad international sample but additionally report countries separately. While they find a positive association between gender diversity and firm market value for Swiss firms, they do not report whether this association is statistically significant. Overall, there is a lack of studies focusing solely on Swiss executive management teams. Because the impact of gender diversity on Swiss firms' accounting performance remains unexplored, this study aims to close this gap by investigating the evolving role and impact of executive management gender diversity on firm performance, profitability, asset turnover, and leverage within the Swiss context.

2.2 Theoretical framework

The upper echelon theory (UET) provides our overarching theoretical framework. The theory's main premise is that organizations are a reflection of their top management. Observable demographic characteristics are proxies for their underlying cognitive bases and values, which arise from the accumulated experiences. Executives interpret complex situations and thus these cognitive bases directly influence the strategic choices (Hambrick & Mason, 1984). Gender serves in this context as a proxy for different life experiences, socialization patterns, and career paths. These divergent experiences lead to different knowledge bases, risk preferences, and value orientations, which can enrich or constrain decision-making.

Moving from the individual to the group level, the UET also emphasizes the importance of executive group heterogeneity (Hambrick & Mason, 1984), though heterogeneity can be a double-edged sword. A more diverse executive management could be better at generating new ideas through a higher level of creativity. By having wider ranges of

3 This requirement aligns with the corporate governance provisions set forth by SIX Exchange Regulation (Directive on Information relating to Corporate Governance – RLCG). It references Art. 732 CO, which mandates the preparation of a compensation report and specifies its content for listed companies. According to Section 3.8 of the annex to the RLCG, companies that are not subject to the provisions of company law under Art. 620 to 762 CO but exceed the thresholds defined in Art. 727, para. 1, no. 2 CO, are nevertheless required to comply with the disclosure obligations under the CO for both the board of directors and the executive management.

perspectives, diverse teams are better at analyzing complex problems and avoid the pitfalls of groupthink (Janis, 1972). Further, the information processing capacity with a higher variety of viewpoints is thought to lead to higher-quality decisions (Roberson & Park, 2007).

However, the potential downsides of diversity arise from challenges in social integration and group dynamics (van Knippenberg et al., 2004). The same differences that provide cognitive benefits can also create friction, conflict, and communication barriers that impede team effectiveness. Differences among the executive management can trigger interpersonal conflict. Heterogeneous teams may experience lower social integration, less frequent communication, and reduced group cohesiveness (Roberson & Park, 2007; Wiersema & Bantel, 1992).

Beyond these competing mechanisms, the level of female representation itself may matter. Tokenism suggests that individuals whose social category is underrepresented in particular contexts will face negative experiences such as increased visibility and social isolation. In the context of women, Kanter determined that women who composed less than 15 % of their work groups experienced negative processes (Kanter, 1977). This suggests a non-linear relationship where meaningful effects require substantive rather than token representation (critical mass), motivating our focus on substantive female representation in executive management.

2.3 Hypotheses

Hypothesis 1: Substantive Female Representation in EM and Overall Firm Performance

UET suggests that female representation in executive management influences firm performance through its effects on decision-making quality and team dynamics. However, the direction and the magnitude of these effects are ex-ante unclear.

On the one hand, female representation could enhance firm performance through improved group-level decision-making quality and problem-solving, as outlined earlier. Empirically, several studies find evidence supporting this positive relationship. A positive association between female representation and performance has been documented in Spain (Campbell & Mínguez-Vera, 2008), China (Liu et al., 2014), France (Sabatier, 2015), the US (Conyon & He, 2017), and the UK (Brahma et al., 2021).

On the other hand, the social integration challenges discussed earlier could impair performance. Beyond group dynamics, initiatives to increase female representation may influence the experience profile of appointed executives at the individual level. If these initiatives lead to the appointment of younger, less experienced executives, this could have negative performance implications (Ahern & Dittmar, 2012). Empirical evidence documents negative relationships between female representation and performance in various contexts: Adams & Ferreira (2009) in the US, Shehata et al. (2017) in the UK, and Zeng et al. (2025) across 40 countries in a cross-national study. Additionally, the introduction of mandatory gender quotas in Norway has resulted in a decline in firm performance (Ahern & Dittmar, 2012).

Finally, the competing mechanisms might offset each other, potentially explaining why some studies document null results (Marinova et al., 2016; Rose, 2007). In light of this tension and conflicting evidence, we formulate our hypothesis for the Swiss context in the null form:

H1: There is no statistically significant association between substantive female representation in executive management and firm performance among Swiss firms.

Hypothesis 2–4: Substantive Female Representation in EM and DuPont Analysis

To further explore the relationship between substantive female representation and firm performance, we apply the DuPont identity to decompose the return on equity (ROE) into its three components:

$$ROE = Profit\ Margin\ x\ Asset\ Turnover\ x\ Equity\ Multiplier \quad (1)$$

While overall ROE provides an aggregate view of profitability, decomposing it allows for a more nuanced understanding of *how* substantive female representation might influence performance through specific operational and financial channels.

Hypothesis 2: Substantive Female Representation in EM and Profit Margins

Profit margin reflects a firm's pricing strategy and its efficiency in controlling costs relative to sales. As with overall firm performance, the effect of female representation on profit margins is ex-ante unclear. On the one hand, improved group-level decision-making quality and problem-solving, as outlined earlier, could enhance operational efficiency and cost control, potentially increasing profit margins. On the other hand, group-level social integration challenges or individual-level factors such as less experienced appointments, as discussed earlier, could impair operational decision-making, potentially reducing profit margins. Given the tension, we formulate our hypothesis in the null form:

H2: There is no statistically significant association between substantive female representation in executive management and profit margins among Swiss firms.

Hypothesis 3: Substantive Female Representation in EM and Asset Turnover

Asset turnover measures how efficiently a company uses its assets to generate sales. The group-level decision-making improvements outlined earlier could enhance asset deployment efficiency and resource allocation, potentially increasing asset turnover. However, group-level social integration challenges discussed earlier could impair strategic asset management decisions. Moreover, individual-level risk preferences may influence asset deployment strategies, with some studies suggesting that female leaders might be more risk-averse (Perryman et al., 2016; Vo et al., 2023). This could translate into more cautious asset deployment (e.g., maintaining higher inventory or cash levels), potentially reducing asset turnover. Given these competing mechanisms, we formulate our hypothesis in the null form:

H3: There is no statistically significant association between substantive female representation in executive management and asset turnover among Swiss firms.

Hypothesis 4: Substantive Female Representation in EM and Equity Multiplier

The equity multiplier is a measure of financial leverage. A higher equity multiplier signifies higher leverage (more debt relative to equity). Individual-level risk preferences discussed earlier may influence financing strategies. Women in the general population are frequently associated with greater risk aversion (Faccio et al., 2016), suggesting more conservative financing strategies with lower debt levels. However, Adams & Funk (2012) document that female board members are less security oriented and *more* risk loving and Ahern & Dittmar (2012) report that the Norwegian gender quota led to an *increase* in firm leverage (thus a positive association with mandated female representation). Given these conflicting arguments, we formulate our hypothesis in the null form:

H4: There is no statistically significant association between substantive female representation in executive management and equity multipliers among Swiss firms.

3. Research design and data

3.1 Research design

To examine the relationship between female representation and firm outcomes (Hypothesis 1 to 4), we estimate the following OLS regression model:

$$Firm\ Outcomes_{i,\,t} = \beta_0 + \beta_1 High\ EM\ Female\ Share + Controls_{i,t} + \alpha_i + \theta_t + \varepsilon_{i,t} \tag{2}$$

where *i* denotes firm and *t* denotes year. We use two different dependent variables to measure firm performance (H1): *ROE*, i.e., return on equity (net income divided by total equity), and *Revenue growth* (year-over-year percentage change in revenue).[4] To further explore the relationship between female representation and firm performance, we decompose the return on equity into its three components according to the DuPont framework: *Profit margin* (Net Income / Revenue) for H2, *Asset turnover* (Revenue / Total Assets) for H3, and *Equity multiplier* (Total Assets / Total Equity) for H4.

Our variable of interest is *High EM Female Share*, a dummy variable equal to 1 for observations in the top quartile of female executive representation (>14.3 % women; corresponding to the 75th percentile of the sample). For Hypothesis 1, the coefficient β_1 captures the association between having substantive female representation and firm performance. A positive and statistically significant coefficient would suggest that substantive female representation is associated with better firm performance, while a negative coefficient would indicate that substantive female representation is associated with lower firm performance.[5]

We include control variables for firm size (*Log(Assets)* and *Log(Revenue)*) and executive management team size (*EM Size)* since prior literature states that these factors could affect firm outcomes, including firm performance (Carter et al., 2003; Dezsö & Ross, 2012; Liu et al., 2014; Yermack, 1996). We include firm fixed effects (α_i) to control for all time-invariant characteristics, both observable and unobservable, of each firm, such as industry, corporate culture, founding history, or other stable firm attributes that might affect female representation and firm outcomes. We also include year fixed effects (θ_t) to

4 We focus on accounting-based performance measures rather than market-based ones (e.g., abnormal stock returns, total shareholder returns or Tobin's Q), as not all firms in our sample are publicly listed and therefore lack market data.

5 Following previous literature (e.g., Adams & Ferreira, 2009; Dezsö & Ross, 2012), we use contemporaneous rather than lagged variables. We do so for two main reasons. First, when a manager is initially elected to executive management (typically in Q1), she has up to three quarters to influence performance within the same year, making lags unnecessary. Second, with lagged variables, a departing manager would still appear to influence firm performance after leaving.

absorb time trends. For Hypothesis 1, in the specifications with firm fixed effects included, our analysis focuses on how changes in substantive female representation within the same firm over time are associated with changes in that firm's performance. We employ firm-level clustered standard errors to account for potential within-firm correlation over time in our panel dataset.

3.2 Data

We use a proprietary dataset on executive management gender composition of the largest Swiss firms by number of employees from 2005 through 2024, provided by guido schilling ag, which represents the underlying data for their annual schillingreport. The panel is unbalanced, with firms observed for varying numbers of years due to corporate events such as mergers, spin-offs and data availability. The number of firms per year fluctuates between 111 and 122 firms, with the dataset covering 157 unique firms and 2,350 firm-year observations.[6] From this dataset, we extract the total number of members (*EM Size*), the number of female management members (*EM Female*) and industry membership. We then calculate the percentage of females (*EM Female %*).[7]

We obtain firm-level financial data – Net Income, Revenue, Total Assets and Total Equity – from LSEG database (formerly Refinitiv). For firms where financial data is unavailable in LSEG (Refinitiv), in particular for non-publicly listed companies, we turn to Moody's Orbis or hand-collect the information from annual reports as alternative sources.

After merging the executive management composition data with the financial data, we eliminate observations where financial data was unavailable and drop singletons.[8] Our final sample comprises 1,566 firm-year observations and 109 unique firms from 2005 through 2024. The sample covers both publicly listed (84 % of observations) and non-publicly listed (16 % of observations) companies. Descriptive statistics are reported in Table A1 in the Appendix. Panel A shows the distribution by industry and Panel B by year.

We provide definitions of all our variables in the Appendix. We winsorize all financial, non-logarithmic variables at the 0.5 % and 99.5 % levels to mitigate the influence of extreme observations. Table A1 Panel C presents summary statistics for the variables used in our analyses. Our sample firms have an average ROE of 13 % and revenue growth of 4 %. Average total assets in our sample are CHF 60 billion, consistent with the schillingreport's focus on major Swiss firms.

Female representation in executive management is limited, with an average of 0.62 women per EM-team. The distribution shows extreme concentration at zero, with 916 observations (58.5 %) having zero female executives and only the top quartile exceeding 14.3 % female representation (untabulated). Given this distribution pattern, continuous measures do not adequately capture meaningful variation, making a dummy variable approach more appropriate. We use the 75th percentile as our threshold for our dummy

6 Sample sizes for some selected years for the schillingreport are available at https://www.schillingreport.ch/en/schillingreport-databasis-9-1/ (see section 9.1.1 Analysed Sample, subsection Executive Boards/Senior Public Officials, row 'Companies/organisations actually included in the report' for private sector firms). Our study period 2005–2024 refers to fiscal years; these correspond to schillingreport publication years 2006–2025.

7 We acknowledge that our binary approach to gender (male/female) does not capture the full gender spectrum.

8 Singletons refer to cases where a fixed effect group contains only one data point (see Correia, 2015).

variable *High EM Female Share* to ensure sufficient observations for statistical analysis while capturing critical mass effects.[9]

4. Evolution of female representation

Figure 1 Panel A illustrates the average number of females in executive management of Swiss firms from 2005 through 2024. The data shows small growth from 2005 to 2015 as the average increased from approximately 0.2 females in EM in 2005 to about 0.35 by 2015. Growth accelerated as average number of females had risen to 0.8 by 2020 and reached approximately 1.7 by 2024.

Figure 1 Panel B examines the percentage of females in executive management over time. Looking at percentages helps distinguish whether the increase in absolute numbers seen in Panel A reflects actual changes in gender composition or merely larger management teams. The data shows similar growth patterns: minimal change from 2005 to 2015 (increasing from 2.3 % to 4.4 %), followed by acceleration to around 11 % by 2020, and reaching approximately 21 % by 2024. Both metrics demonstrate consistent increases in female representation in executive management throughout the sample period.

While Panels A and B track these changes annually across all firms, Panels C and D provide a more detailed comparison of the endpoints of our sample period. Figure 1 Panel C illustrates the changing female representation in executive management by comparing the distribution of firms in 2005 versus 2024. In 2005, 84.7 % of firms had no females in their executive management. By 2024, this distribution had shifted, with only 20.2 % of firms having no females, 23.8 % having one female, 34.5 % having two females, and 21.5 % having three or more females. Figure 1 Panel D confirms these shifts. By 2024, firms with females representing more than 20 % of their executive management had become prevalent, with 32.1 % of firms having 21–30 % females, 19.0 % having 31–40 % females, and 8.3 % having over 40 % females.

An increasing representation of women in leadership positions could be driven by multiple factors. These include the gender diversity recommendation in the 2014 Swiss Code of Best Practice for Corporate Governance, and a heightened corporate focus on diversity initiatives, often linked to enhancing legitimacy or perceived performance benefits (Lückerath-Rovers, 2013; Vo et al., 2023; Zattoni et al., 2023).[10]

Figure 1: Female managers over time

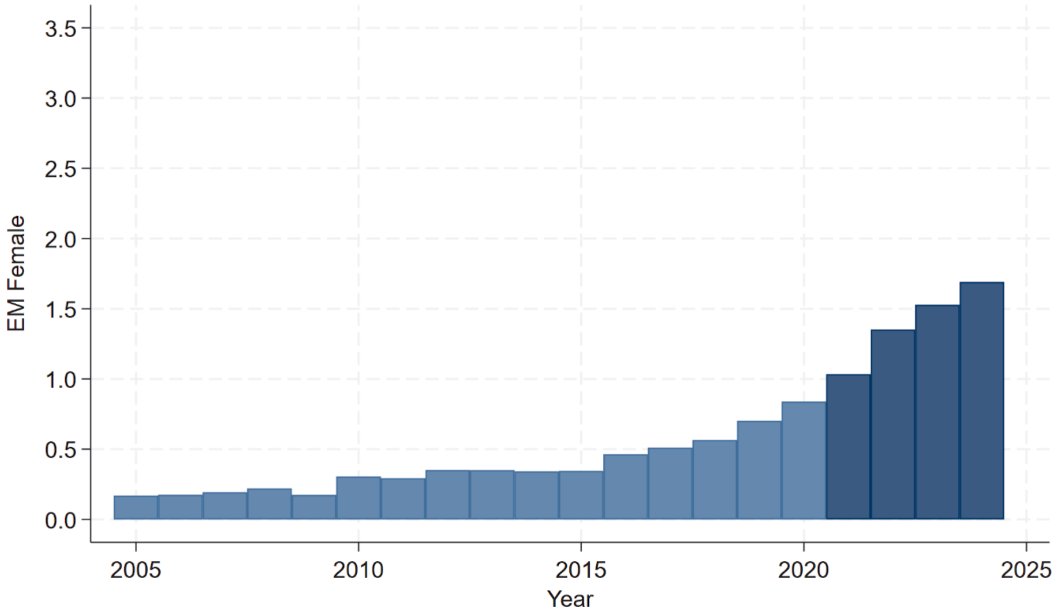
These figures present the evolution of female representation in Swiss executive management (EM) over time. Panels A and B report the average number and percentage of females in executive management per year, respectively. Panels C and D compare the distributions in 2005 versus 2024. The sample includes Swiss firms from 2005 through 2024. The color change to dark blue beginning in 2021 reflects the year following the

9 A potential concern with our dummy variable approach is that firms with very high female representation (e.g., 100 %) could have different effects due to reduced diversity. However, only 3 observations (0.19 %) exceed 50 % female representation, with a maximum of 66.7 %.

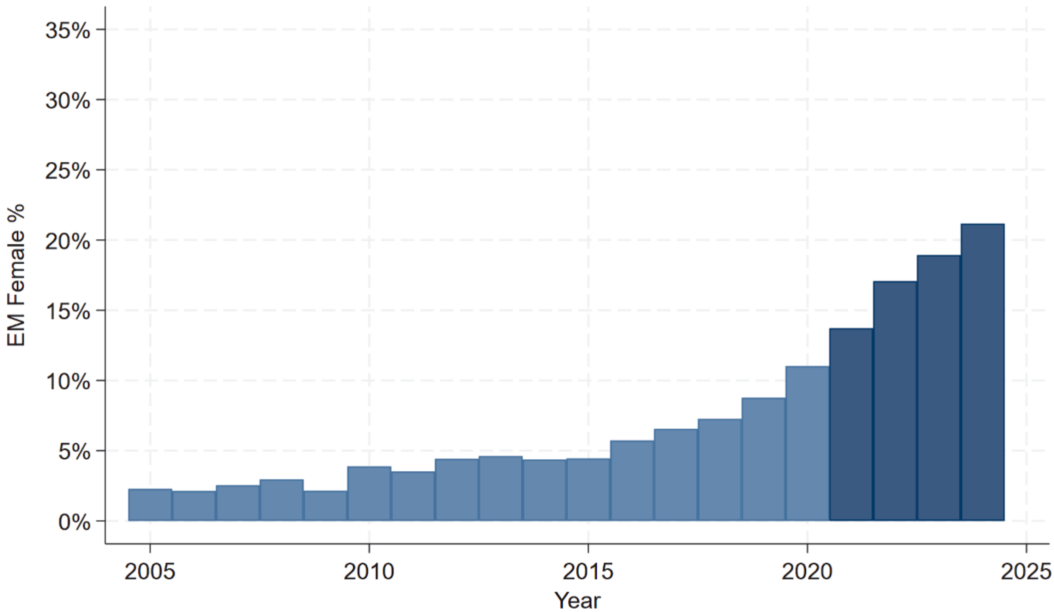
10 Consistent with our findings, numerous studies empirically document an upward trend in female representation in leadership positions. For example, Zeng et al. (2025) document an increase in the percentage of female board members from 8.42 % in 2009 to 19.07 % in 2018 across 40 countries. Single country studies find similar trends (e.g., Farrell & Hersch, 2005; Dezsö & Ross, 2012; Liu et al., 2014; Shehata et al., 2017; Brahma et al., 2021; Vo et al., 2023).

2020 amendment of Art. 734f of the CO, which set a 20 % gender quota target for executive management by 2031.

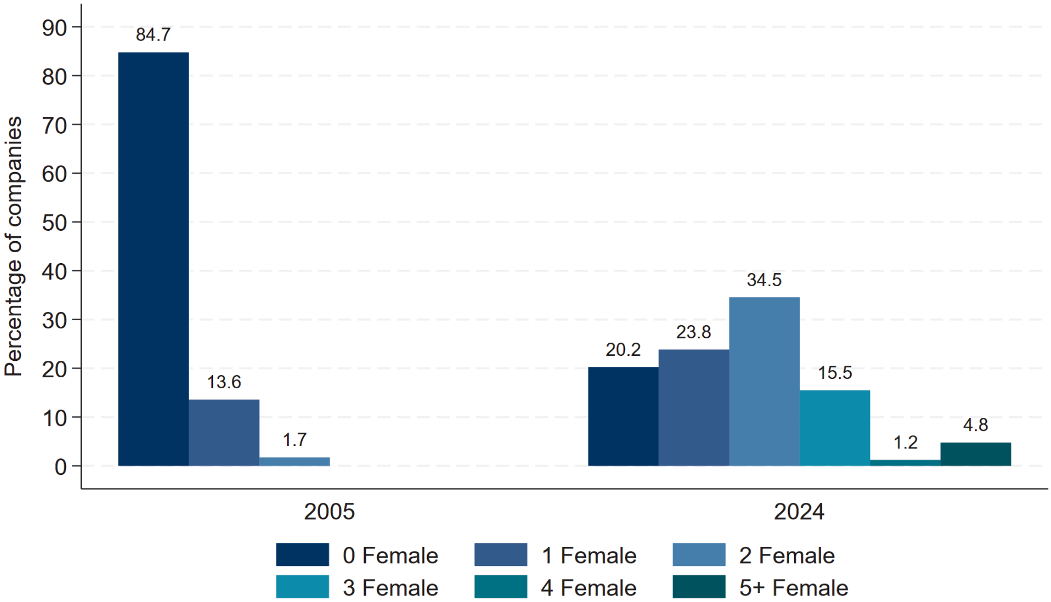
Panel A: Number of female managers over time



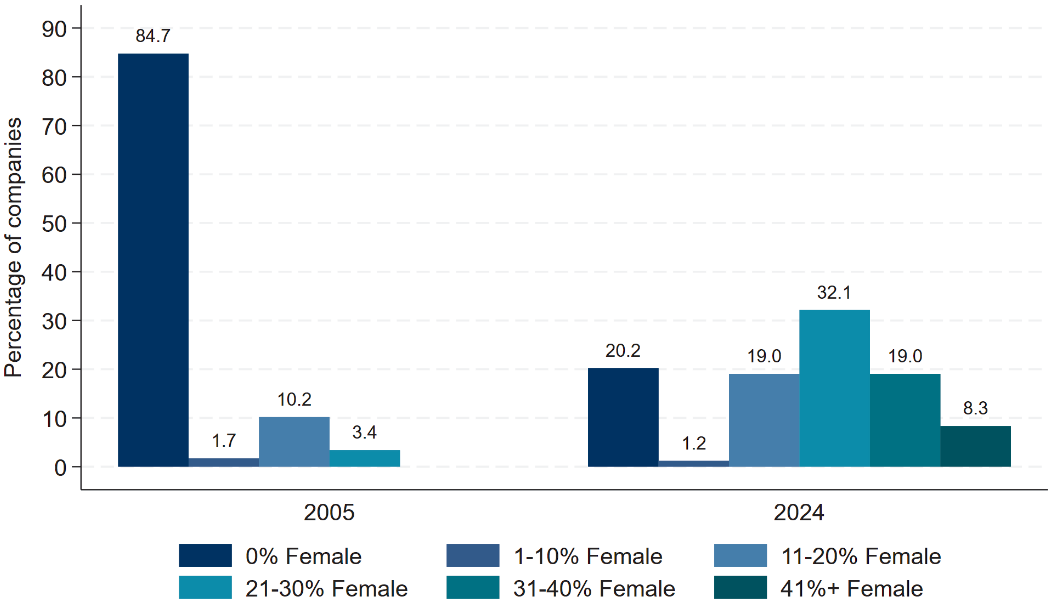
Panel B: Percentage of female managers



Panel C: Number of female managers 2005 vs. 2024



Panel D: Percentage of female managers 2005 vs. 2024



5. H1: Female representation and firm performance

We assess the impact of female representation on firm performance by estimating the OLS regression model defined in Equation (2). We present our results in Table 1. In Columns (1), (2), and (3), the dependent variable is *ROE*. In Columns (4), (5), and (6), the dependent variable is *Revenue growth*. The variable of interest in all regressions is *High EM Female Share*, a dummy variable which is equal to 1 if female executive representation is in the top quartile (>14.3 % women). For each dependent variable, we run three different regression models: without fixed effects, with year fixed effects only, and with both year and firm fixed effects. Standard errors are clustered at the firm-level.

In Column (1), the coefficient of our variable of interest *High EM Female Share* is positive (0.001) but not statistically significant. When we add year fixed effects (Column (2)) to control for time trends, or both year and firm fixed effects (Column (3)), to control for time trends and time-invariant firm characteristics (such as industry affiliation) the coefficient of our variable of interest remains insignificant. The results in Columns (1) through (3) show that substantive representation of females in executive management is not associated with the firm's return on equity. We note that in specifications with firm fixed effects included (Column (3)), our analysis focuses on within-firm changes. That is, we document that changes to substantive female representation within the same firm are not associated with changes in that firm's return on equity.

For *Revenue growth*, the coefficient of *High EM Female Share* is also insignificant across all specifications. The regressions in Columns (4) through (6) indicate that substantive female representation in executive management is not associated with the firm's revenue growth.

Table 1. Female representation and firm performance

This table presents regressions to test the association between female representation in Swiss executive management and firm performance with the dependent variables being *ROE* (Columns (1)-(3)) and *Revenue growth* (Columns (4)-(6)). The sample includes Swiss firms from 2005 through 2024. All variables are defined in the Appendix. We winsorize all continuous, non-logarithmic variables at 0.5 % and 99.5 % levels. Standard errors are clustered at the firm-level. ***, **, * indicate the significance at the 1 %, 5 %, and 10 % levels, respectively.

Dependent variable:	ROE	ROE	ROE	Revenue growth	Revenue growth	Revenue growth
	(1)	(2)	(3)	(4)	(5)	(6)
High EM Female Share	0.001	-0.005	-0.014	-0.007	-0.006	0.001
	(0.068)	(-0.197)	(-1.002)	(-0.715)	(-0.605)	(0.104)
Log(Assets)	-0.030***	-0.029***	-0.101*	-0.007*	-0.005	-0.128***
	(-4.332)	(-4.147)	(-1.979)	(-1.885)	(-1.511)	(-3.216)
Log(Revenue)	0.029**	0.029**	0.151***	0.019***	0.017***	0.322***
	(2.416)	(2.378)	(2.941)	(3.204)	(2.944)	(6.718)
EM Size	0.013***	0.013***	-0.001	0.001	0.001	-0.000
	(2.845)	(2.806)	(-0.400)	(0.598)	(0.596)	(-0.156)
Observations	1,566	1,566	1,566	1,481	1,481	1,478
Adjusted R-squared	0.052	0.059	0.319	0.006	0.070	0.180
Year FE	No	Yes	Yes	No	Yes	Yes
Firm FE	No	No	Yes	No	No	Yes

Previous research provides mixed results regarding the relationship between female representation in EM and firm performance. The UET suggests that female representation could enhance firm performance through improved group-level decision-making quality and problem-solving, which has been documented in Spain (Campbell & Mínguez-Vera, 2008), China (Liu et al., 2014), France (Sabatier, 2015), the US (Conyon & He, 2017), and the UK (Brahma et al., 2021). In contrast, challenges related to social integration could impair performance, which was documented by Adams & Ferreira (2009) in the US, Shehata et al. (2017) in the UK, and Zeng et al. (2025) across 40 countries in a cross-national study. Finally, competing mechanisms might offset each other, potentially explaining null results (Marinova et al., 2016; Rose, 2007).

Overall, our results indicate that we cannot reject Hypothesis 1. We find no significant relationship across multiple specifications and performance measures, suggesting that female representation in executive management neither enhances nor diminishes overall firm performance.

These findings are also important in the context of the significant increase in female representation documented in Section 4. The substantial growth in female representation in corporate leadership does not seem to have resulted in any significant negative or positive impact on firm performance, whether measured by return on equity or revenue growth.

While our results suggest no significant relationship between female representation and firm performance, we acknowledge potential omitted variable bias and reverse causality concerns. Despite controlling for firm and executive management team size, as well as including year and firm fixed effects, unobserved time-varying factors might still influence both executive management composition and performance metrics. Though our comprehensive fixed effects mitigate some concerns, endogeneity issues limit causal interpretations of our findings.

6. H2-H4: DuPont analysis

6.1 Main results

To further explore the relationship between female representation and firm performance, we decompose the return on equity into its three components according to the DuPont framework: *Profit margin* (Net Income / Revenue), *Asset turnover* (Revenue / Total Assets), and *Equity multiplier* (Total Assets / Total Equity). Using the OLS regression model defined in Equation (2), we then examine the association between female representation and each of these components separately. Table 2 presents the results of this analysis.

In Columns (1), (2), and (3), the dependent variable is *Profit margin*. The coefficient of *High EM Female Share* is positive and statistically significant at the 5 % level in Columns (1) and (2) (the coefficients equal 0.027 and 0.032, respectively). In the model with year and firm fixed effects in Column (3), the coefficient of the variable of interest is positive (0.012) and significant at the 5 % level. These results suggest that firms with substantive female representation on their executive management tend to have higher profit margins, even after controlling for firm and year fixed effects.

Given the consistently positive and significant coefficients found in our regressions, we reject the null hypothesis (H2). Instead, our results indicate that female representation is associated with higher profit margins, suggesting that firms with more female executive management members are more efficient in controlling costs or pricing their products and services.

In terms of economic significance, in Column (3), the coefficient of 0.012 indicates that when a firm changes from non-substantive to substantive female representation in executive management, profit margin increases by 1.2 percentage points, or 15 % relative to the mean. These findings suggest that the relationship between female representation and profit margin is not only statistically significant but also economically relevant.

In Columns (4), (5), and (6), the dependent variable is *Asset turnover*. The coefficient of *High EM Female Share* is statistically insignificant throughout all regressions. This suggests that there is no association between female representation in executive management and asset turnover. We therefore cannot reject the null hypothesis (H3).

In Columns (7), (8), and (9), the dependent variable is *Equity multiplier*. The coefficient of *High EM Female Share* is negative and statistically significant at the 5 % level in Columns (7) and (8) (the coefficients equal -1.097 and -1.203, respectively). In the model with year and firm fixed effects in Column (9), the coefficient is negative (-0.203) but statistically insignificant at conventional levels. The consistently negative coefficients across all specifications, with statistical significance in two of the three models, provide partial support against the null hypothesis (H4). Our results suggest that firms with substantive female leadership tend to maintain more conservative financing strategies with lower debt levels. This finding is consistent with arguments linking female representation to risk aversion and more conservative financial policies.

In terms of economic significance, in Column (8), the coefficient of -1.203 indicates that a change from non-substantive to substantive female representation is associated with a 22.9 % decrease in the equity multiplier relative to its sample mean, suggesting an economically meaningful effect. For Column (9), when a firm changes from non-substantive to substantive female representation, the equity multiplier decreases by 0.203, or 3.9 % relative to the mean, though this effect is statistically insignificant.

Table 2: DuPont analysis

This table presents regressions to test the association between female representation in Swiss executive management and firm performance with the dependent variables being *Profit margin* (Columns (1)-(3)), *Asset turnover* (Columns (4)-(6)), and *Equity multiplier* (Columns (7)-(9)). The sample includes Swiss firms from 2005 through 2024. All variables are defined in the Appendix. We winsorize all continuous, non-logarithmic variables at 0.5 % and 99.5 % levels. Standard errors are clustered at the firm-level. ***, **, * indicate the significance at the 1 %, 5 %, and 10 % levels, respectively.

Dependent variable:	Profit margin	Profit margin	Profit margin	Asset turnover	Asset turnover	Asset turnover	Equity multiplier	Equity multiplier	Equity multiplier
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
High EM Female Share	0.027**	0.032**	0.012**	-0.035	0.009	0.004	-1.097**	-1.203**	-0.203
	(2.055)	(2.194)	(2.065)	(-0.710)	(0.139)	(0.270)	(-2.533)	(-2.438)	(-0.576)
Log(Assets)	0.024***	0.024***	-0.072***	-0.424***	-0.422***	-0.608***	3.628***	3.642***	2.343**
	(2.835)	(2.856)	(-2.952)	(-9.456)	(-9.490)	(-7.606)	(9.362)	(9.379)	(2.431)
Log(Revenue)	-0.033***	-0.033***	0.121***	0.416***	0.414***	0.549***	-2.945***	-2.951***	-1.104
	(-2.683)	(-2.723)	(3.667)	(6.371)	(6.348)	(5.692)	(-7.932)	(-7.934)	(-1.350)
EM Size	0.005***	0.005***	0.001	-0.006	-0.005	-0.002	-0.072	-0.078	-0.067
	(2.852)	(2.869)	(0.826)	(-0.712)	(-0.662)	(-0.795)	(-0.717)	(-0.773)	(-1.072)
Observations	1,566	1,566	1,566	1,566	1,566	1,566	1,566	1,566	1,566
Adjusted R-squared	0.105	0.109	0.562	0.672	0.673	0.969	0.478	0.476	0.814
Year FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Firm FE	No	No	Yes	No	No	Yes	No	No	Yes

Overall, the findings from the DuPont analysis provide a more nuanced understanding of the relationship between female representation and firm performance. While we do not find a significant association between female representation and total ROE, we do find that female representation is positively associated with profit margins and negatively associated with financial leverage (though not consistently significant across all specifications). These opposing effects on different components of ROE might explain why we do not observe a significant net effect on overall ROE.

As with our previous performance regressions, we acknowledge similar omitted variable bias and reverse causality concerns in these component analyses. Although our fixed effects specifications help mitigate endogeneity issues, unobserved time-varying factors could still influence both female representation and these financial ratios, limiting causal interpretations of the documented associations.

6.2 Alternative measurements for female representation

Next, we examine alternative measures to examine how our findings are sensitive to our choice of the top-quartile threshold. All specifications employ firm and year fixed effects, our most stringent econometric specification. We present our results in Table A2 in the Appendix.

First, we employ a 20 % threshold (*EM Female: >20 %*) to test the robustness of our main results (this threshold also corresponds to the Swiss legislative benchmark). The coefficient for *Profit margin* (Column 1) is positive and statistically significant at the 10 % level, consistent with but providing weaker support than our main findings.

Second, we examine a 10 % threshold (*EM Female: >10 %*) to test whether lower representation levels below the critical mass threshold show significant effects. The coefficient for *Profit margin* (Column 4) is positive but statistically insignificant, consistent with tokenism theory that minimal female representation is insufficient to generate meaningful effects.

Third, we use the continuous proportion of females in executive management (*EM Female %*) to examine whether female representation effects operate linearly rather than through threshold mechanisms. The coefficient for *Profit margin* (Column 7) is positive but statistically insignificant, consistent with our data section finding that continuous measures do not adequately capture meaningful variation given the extreme concentration at zero and limited variation above the 75th percentile.

For *Asset turnover*, all alternative measures are statistically insignificant, consistent with our main results. For *Equity multiplier*, results are insignificant, consistent with our main results. An exception is the 20 % threshold (Column 3) which is negative and statistically significant at the 10 % level, while this variable was statistically insignificant in our main results using the 14.3 % threshold.[11]

6.3 Analysis over time

To examine whether the relationship between female representation and DuPont components has evolved over time, we conducted separate analyses for two periods: 2005–2014 (Table A3 Panel A) and 2015–2024 (Table A3 Panel B). We chose this sample split to create two equal time periods for comparison. Moreover, the revised 2014 Swiss Code of Best Practice for Corporate Governance (Section 12), issued by economiesuisse, introduced a recommendation that boards of directors should include both male and female members. However, the later decade features substantially more firms reaching the 14.3 % threshold: 79 firm-years (11.1 %) in 2005–2014 compared to 359 firm-years (41.8 %) in 2015–2024. Similarly, the number of within-firm switches from below to above the threshold increased from 21 in the earlier period to 70 in the later period. The increased prevalence could provide greater statistical power to detect existing relationships.

Panel A (2005–2014) shows statistically insignificant results for the variable of interest (*High EM Female Share*) across specifications for *Profit margin*, *Asset turnover* and *Equity multiplier*.

Panel B (2015–2024) reveals a different pattern. For *Profit margin*, the coefficient of *High EM Female Share* is positive and significant at the 5 % level in Columns (1) and (2) without firm fixed effects. The coefficient is positive and statistically significant at the 10 % level in the specification with year and firm fixed effects in Column (3).

For *Asset turnover*, the coefficient is negative and statistically significant at the 5 % level in Column (4) and at the 10 % level in Column (5), but becomes insignificant when year and firm fixed effects are included in the model in Column (6). For *Equity multiplier*, the coefficients are negative and significant at the 5 % level in models without firm fixed effects (Columns (7) and (8)), but this effect is statistically insignificant with firm fixed effects in Column (9).

Overall, these analyses reveal an evolving relationship between executive management female representation and firm performance components over time. The associations between female representation and the components of return on equity are only present in the last decade. These findings suggest that the performance implications of executive management female representation may have become more pronounced over time.

Several factors could contribute to the more pronounced relationships observed in the 2015–2024 period. Statistically, while the overall sample size difference between both periods is moderate, the later decade features significantly more firms with female executives

11 In untabulated results, we use the Blau Index (Blau, 1977), which measures the probability that two randomly selected management members would be of different genders. Results using the Blau Index are statistically insignificant across all performance measures, consistent with our findings that continuous measures do not adequately capture the relevant variation in our empirical context.

and more firms reaching the female representation threshold (exceeding 14.3 % female executives). This could provide greater statistical power to detect existing relationships.

7. Conclusion

This study analyzes the evolution and impact of female representation in Swiss executive management. We document a significant increase in female representation in executive management between 2005 and 2024. Despite this growth, our regression analyses reveal no consistent or statistically significant association between executive management female representation and firm performance in terms of ROE and revenue growth. However, a deeper look through DuPont analysis suggests that substantive female representation (top quartile, >14.3 %) may be linked to higher profit margins and lower financial leverage, though these associations are sensitive to how female representation is measured.

This study does not come without limitations. First, we document associations, not causal relations. While we include year and firm fixed effects, we cannot rule out that time-varying omitted variables or reverse causality drive our results. Second, our sample is limited to larger Swiss firms. Hence, the study results might not generalize to smaller Swiss firms. Third, like much of the existing literature, we use gender as a demographic proxy for underlying cognitive bases and experiences, which may only imperfectly capture the mechanisms through which executive characteristics influence firm outcomes.

These limitations open several avenues for future research. First, studies employing quasi-experimental designs could help establish causal relationships. Second, extending this analysis to smaller Swiss firms would test the generalizability of our findings. Third, future research could move beyond gender as a demographic proxy to examine how specific executive experiences and backgrounds shape decision-making and firm outcomes.

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Appendix: Variable definitions

Variable	Definition [source]
EM Size	Total number of individuals in executive management (EM). [guido schilling ag]
EM Female	Total number of females in the executive management (EM). [guido schilling ag]
EM Female %	Proportion of females in executive management, calculated as *(EM Female / EM Size)*. [guido schilling ag]
High EM Female Share	A dummy variable which is equal to 1 if female executive representation is in the top quartile (>14.3 % women).

Variable	Definition [source]
EM Female: > 10 %	A dummy variable which is equal to 1 if more than 10 % of executive managers are female.
EM Female: > 20 %	A dummy variable which is equal to 1 if more than 20 % of executive managers are female.
ROE	Return on equity, calculated as Net income / Total Equity [LSEG (Refinitiv), Orbis, hand-collected from annual reports]
Revenue growth	Percentage change in revenue compared to the previous year, calculated as (Revenue / Revenue in the previous year) – 1. [LSEG (Refinitiv), Orbis, hand-collected from annual reports]
Profit margin	Net income divided by revenue. [LSEG (Refinitiv), Orbis, hand-collected from annual reports]
Asset turnover	Revenue divided by total assets. [LSEG (Refinitiv), Orbis, hand-collected from annual reports]
Equity multiplier	Total assets divided by total equity. [LSEG (Refinitiv), Orbis, hand-collected from annual reports]
Log(Assets)	The logarithm of total assets. [LSEG (Refinitiv), Orbis, hand-collected from annual reports]
Log(Revenue)	The logarithm of revenue. [LSEG (Refinitiv), Orbis, hand-collected from annual reports]

Table A1. Descriptive statistics

These tables report descriptive statistics of the main variables used in our regressions. Panel A displays the distribution of firms in our sample by industry and Panel B by year. Panel C shows the summary statistics of the variables used. The sample includes Swiss firms from 2005 through 2024. All variables are defined in the Appendix. We winsorize all continuous, non-logarithmic variables at 0.5 % and 99.5 % levels.

Panel A: Distribution of firms by industry

Industry	N	Percent
Banks	144	9.20
Insurance	154	9.83
Media/ICT	81	5.17
Business Services	42	2.68
Transport/Logistics/Tourism	91	5.81
Real Estate	3	0.19
Manufacturing Industry	491	31.35
Energy	49	3.13
Life Sciences	184	11.75
Retail/Consumer Goods	279	17.82
Wholesale/Raw Materials	48	3.07
Total	1,566	100.00

Panel B: Distribution of firms by year

Year	N	Percent
2005	59	3.77
2006	63	4.02
2007	62	3.96
2008	68	4.34
2009	69	4.41
2010	72	4.6
2011	75	4.79
2012	77	4.92
2013	80	5.11
2014	82	5.24
2015	84	5.36
2016	82	5.24
2017	86	5.49
2018	85	5.43
2019	84	5.36
2020	87	5.56
2021	87	5.56
2022	91	5.81
2023	89	5.68
2024	84	5.36
Total	1,566	100.00

Panel C: Summary statistics

	N	mean	sd	p25	p50	p75
EM Size	1,566	7.16	2.94	5.00	7.00	9.00
EM Female	1,566	0.62	0.90	0.00	0.00	1.00
EM Female %	1,566	0.08	0.11	0.00	0.00	0.14
High EM Female Share	1,566	0.28	0.45	0.00	0.00	1.00
EM Female: > 10 %	1,566	0.38	0.48	0.00	0.00	1.00
EM Female: > 20 %	1,566	0.17	0.38	0.00	0.00	0.00
ROE	1,566	0.13	0.21	0.06	0.11	0.18
Revenue growth	1,481	0.04	0.19	-0.03	0.02	0.09
Profit margin	1,566	0.08	0.12	0.03	0.06	0.11
Asset turnover	1,566	0.87	0.67	0.36	0.77	1.23
Equity multiplier	1,566	5.26	6.76	1.98	2.69	4.06
Total Assets (mio CHF)	1,566	60,041	175,256	2,139	6,019	37,748
Log(Assets)	1,566	16.02	1.87	14.58	15.61	17.45
Revenue (mio CHF)	1,566	11,557	22,588	2,071	3,915	9,863
Log(Revenue)	1,566	15.39	1.24	14.54	15.18	16.10

Table A2. Alternative measurements for female representation

This table presents regressions to test the association between female representation in Swiss executive management and firm performance. In Columns (1), (4), and (7), the dependent variable is *Profit margin*. In Columns (2), (5), and (8), the dependent variable is *Asset turnover*. In Columns (3), (6), and (9), the dependent variable is the *Equity multiplier*. In Columns (1), (2) and (3), we construct a dummy variable which is equal to 1 if more than 20 % of executive managers are female. In Columns (4), (5) and (6), we construct a dummy variable which is equal to 1 if more than 10 % of executive managers are female. In Columns (7), (8) and (9), we include the proportion of females in executive management. The sample includes Swiss firms from 2005 through 2024. All variables are defined in the Appendix. We winsorize all continuous, non-logarithmic variables at 0.5 % and 99.5 % levels. Standard errors are clustered at the firm-level. ***, **, * indicate the significance at the 1 %, 5 %, and 10 % levels, respectively.

Dependent variable:	Profit margin	Asset turnover	Equity multiplier	Profit margin	Asset turnover	Equity multiplier	Profit margin	Asset turnover	Equity multiplier
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
EM Female: > 20 %	0.012*	0.005	-0.692*						
	(1.686)	(0.290)	(-1.796)						
EM Female: > 10 %				0.003	0.011	-0.059			
				(0.634)	(0.682)	(-0.204)			
EM Female %							0.043	0.033	-1.823
							(1.447)	(0.412)	(-1.146)
Log(Assets)	-0.073***	-0.608***	2.363**	-0.072***	-0.608***	2.330**	-0.072***	-0.607***	2.325**
	(-2.963)	(-7.602)	(2.428)	(-2.949)	(-7.603)	(2.390)	(-2.967)	(-7.611)	(2.425)
Log(Revenue)	0.122***	0.549***	-1.107	0.122***	0.549***	-1.118	0.121***	0.549***	-1.101
	(3.658)	(5.697)	(-1.360)	(3.672)	(5.688)	(-1.364)	(3.667)	(5.692)	(-1.347)
EM Size	0.001	-0.003	-0.064	0.001	-0.002	-0.067	0.001	-0.002	-0.062
	(0.721)	(-0.875)	(-1.113)	(0.769)	(-0.805)	(-1.108)	(0.715)	(-0.824)	(-1.058)
Observations	1,566	1,566	1,566	1,566	1,566	1,566	1,566	1,566	1,566
Adjusted R-squared	0.561	0.969	0.815	0.561	0.969	0.814	0.561	0.969	0.814
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A3: DuPont analysis over time

These tables present regressions to test the association between female representation in Swiss executive management and firm performance. In Columns (1), (2), and (3), the dependent variable is *Profit margin*. In Columns (4), (5), and (6), the dependent variable is *Asset turnover*. In Columns (7), (8), and (9), the dependent variable is the *Equity multiplier*. The sample includes Swiss firms from 2005 through 2024. We estimate our regressions separately for two time periods: in Panel A 2005–2014 and in Panel B 2015–2024. All variables are defined in the Appendix. We winsorize all continuous, non-logarithmic variables at 0.5 % and 99.5 % levels. Standard errors are clustered at the firm-level. ***, **, * indicate the significance at the 1 %, 5 %, and 10 % levels, respectively.

Panel A: 2005–2014

Dependent variable:	Profit margin	Profit margin	Profit margin	Asset turnover	Asset turnover	Asset turnover	Equity multiplier	Equity multiplier	Equity multiplier
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
High EM Female Share	0.024	0.026	-0.007	0.205	0.211	0.012	-0.880	-0.783	0.294
	(1.280)	(1.384)	(-0.856)	(1.239)	(1.260)	(0.611)	(-1.165)	(-1.056)	(0.912)
Log(Assets)	0.023**	0.024**	-0.080**	-0.465***	-0.464***	-0.627***	3.756***	3.769***	2.354**
	(2.215)	(2.214)	(-2.177)	(-8.239)	(-8.208)	(-5.548)	(8.347)	(8.293)	(2.150)
Log(Revenue)	-0.029*	-0.030**	0.115**	0.465***	0.464***	0.540***	-3.305***	-3.307***	-0.450
	(-1.987)	(-2.002)	(2.043)	(5.534)	(5.504)	(4.014)	(-7.387)	(-7.314)	(-0.559)
EM Size	0.005**	0.005**	0.002	-0.007	-0.008	0.002	-0.018	-0.020	-0.072
	(2.560)	(2.568)	(0.750)	(-0.734)	(-0.737)	(0.513)	(-0.202)	(-0.222)	(-1.100)
Observations	707	707	704	707	707	704	707	707	704
Adjusted R-squared	0.093	0.106	0.482	0.667	0.665	0.972	0.541	0.540	0.841
Year range	2005–2014	2005–2014	2005–2014	2005–2014	2005–2014	2005–2014	2005–2014	2005–2014	2005–2014
Year FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Firm FE	No	No	Yes	No	No	Yes	No	No	Yes

Panel B: 2015–2024

Dependent variable:	Profit margin	Profit margin	Profit margin	Asset turnover	Asset turnover	Asset turnover	Equity multiplier	Equity multiplier	Equity multiplier
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
High EM Female Share	0.034**	0.034**	0.012*	-0.099**	-0.089*	-0.001	-1.098**	-1.368**	-0.093
	(2.225)	(1.998)	(1.793)	(-2.375)	(-1.842)	(-0.103)	(-2.152)	(-2.251)	(-0.290)
Log(Assets)	0.024***	0.024***	-0.081**	-0.385***	-0.385***	-0.664***	3.572***	3.591***	2.218*
	(2.740)	(2.717)	(-2.282)	(-9.990)	(-9.921)	(-8.437)	(7.257)	(7.236)	(1.903)
Log(Revenue)	-0.035***	-0.035***	0.180***	0.380***	0.379***	0.574***	-2.708***	-2.715***	-1.831
	(-2.665)	(-2.666)	(3.264)	(6.766)	(6.719)	(6.777)	(-6.723)	(-6.685)	(-1.115)
EM Size	0.006**	0.006**	-0.001	-0.005	-0.005	-0.002	-0.123	-0.132	-0.045
	(2.278)	(2.302)	(-0.744)	(-0.602)	(-0.565)	(-0.514)	(-0.719)	(-0.765)	(-0.738)
Observations	859	859	857	859	859	857	859	859	857
Adjusted R-squared	0.113	0.110	0.656	0.693	0.691	0.983	0.433	0.430	0.841
Year range	2015–2024	2015–2024	2015–2024	2015–2024	2015–2024	2015–2024	2015–2024	2015–2024	2015–2024
Year FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Firm FE	No	No	Yes	No	No	Yes	No	No	Yes

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VALORizing Innovation

Vanessa Orlando

Abstract: Innovation measurement remains fragmented across existing frameworks, creating ambiguity about effective approaches for assessing company level innovation performance. Drawing on classification methodology, this study synthesizes four established innovation measurement models to develop the holistic VALOR framework—encompassing Values, Activities, Longevity, Output, and Return on Innovation. For operationalization of the framework 62 distinct indicators are presented to measure performance. This research provides a comprehensive analytical framework which includes traditional as well as timely innovation aspects. The findings enable innovation managers and asset managers to evaluate and benchmark innovation performance of individual firms as well as to support their strategic decision-making.

Keywords: Innovation measurement, innovation performance evaluation, innovation efficiency, innovation controlling, classification, literature review.

VALORisieren von Innovation

Zusammenfassung: Die Messung von Innovation ist in bestehenden Modellen fragmentiert, was zu Unklarheiten hinsichtlich wirksamer Ansätze zur Bewertung von Innovationsleistung führt. Mithilfe der Klassifizierungsmethode fasst diese Studie vier etablierte Modelle zur Innovationsmessung zusammen, um das ganzheitliche VALOR Framework zu entwickeln, welches Values, Activities, Longevity, Output sowie Return on Innovation umfasst. Zur Operationalisierung des Frameworks werden 62 Indikatoren vorgestellt, mit denen die Leistung der Innovationskategorien gemessen werden können. Diese Forschung bietet einen umfassenden analytischen Rahmen, der sowohl traditionelle als auch zeitgemässe Innovationsaspekte umfasst. Die Ergebnisse ermöglichen es Innovationsmanagern und Vermögensverwaltern, die Innovationsleistung einzelner Unternehmen zu bewerten und zu benchmarken sowie ihre strategischen Entscheidungen zu unterstützen.

Stichwörter: Innovationsmessung, Bewertung der Innovationsleistung, Innovationseffizienz, Innovationscontrolling, Klassifizierung, Literaturrecherche.

1 Introduction

Global R&D expenditures reached USD 2.4 trillion in 2019, representing 17% of Europe's GDP for the same year (Burke et al., 2022; Eurostat, 2020). Corporate R&D investments from the top global R&D spenders increased from USD 840 billion in 2019 to USD 1.117 trillion in 2022, which corresponds to a 33 % growth rate (WIPO, 2023). This substantial capital deployment highlights the central role innovation plays for corporations.

Since Schumpeter's (1934) argumentation about innovation as the primary driver of economic growth, research has demonstrated its impact on organizational and economic performance. Innovation enables firms to maintain a competitive advantage (Singhal et al., 2022), generates employment (Lachenmaier & Rottmann, 2011), drives macroeconomic growth (Dempere et al., 2023), and explains variations in stock returns (Ganbaatar et al., 2024). Despite this prevalent recognition of innovation's impact and importance, the multifaceted nature of innovation makes it difficult to measure (Möller et al., 2016).

Scholars emphasize that measuring and evaluating innovation performance requires a comprehensive approach due to innovation's multifaceted nature (Adams et al., 2006; Möller et al., 2016). Available innovation performance management frameworks, however, fail to holistically capture performance. For example, the IPOO (Brown & Svenson, 1998) does not include open-innovation relevant dimensions such as external investments, partnerships, or co-creation. The R&D Framework (Foster et al., 1985) fails to include the non-financial benefits derived from innovation such as corporate value increase from reputation and brand recognition. On the other hand, the Innovation Balanced Scorecard (IBS) (Kerssens-van Drongelen & Cooke, 1997) leaves out values – the basis for innovation to flourish – and activities that lead to innovation output. A throughout evaluation of innovation requires a holistic framework which captures all aspects relevant to innovation and which reflects current corporate innovation practices.

Developing a holistic framework that enables measurement, evaluation, and benchmarking of firms' innovation performance represents a significant contribution to both academic literature and practitioners. The developed VALOR framework adopts a holistic approach that acknowledges the multifaceted nature of innovation by capturing relevant dimensions throughout the value chain of innovation performance. Its process-based structure encompasses four key components: (1) Values, which capture the foundational resources and capabilities that enable innovation; (2) Activities, which encompass innovation initiatives pursued within and outside of the corporation; (3) Output, which includes inventions generated from innovation activities and (4) Return on Innovation, which captures the financial and non-financial benefits derived from innovation. The VALOR framework addresses the limitation of existing frameworks which fail to capture the multifaceted nature of innovation and are increasingly outdated.

1.1 Existing Innovation Performance Management Frameworks

Innovation represents the creation of new products and services [as well as processes] that generate economic value for society (Foray, 2023). Various theoretical and empirical models have been developed to measure and manage innovation (Möller et al., 2016). Among the most established frameworks are the Input-Process-Output-Outcome (IPOO) Model (Brown & Svenson, 1998), the Innovation Balanced Scorecard (Kerssens-van Drongelen & Cooke, 1997), the R&D Framework (Foster et al., 1985), and the Innovation Management Measurement Framework (Adams et al., 2006). These frameworks represent significant contributions to the innovation performance management literature (Davila et al., 2006; Möller et al., 2016; Walcher & Wöhrl, 2018). These frameworks align with the broader performance management discipline by seeking to measure innovation performance for corporate steering and achievement of objectives. However, analyzing these models comparatively reveals significant heterogeneity in their conceptual foundations, measurement approaches, and levels of granularity.

The Input-Process-Output-Outcome (IPOO) Model developed by Brown and Svenson (1998) represents one of the most well-known innovation management frameworks in literature (Möller et al., 2016). This process-based model comprises eight distinct steps: Inputs, processing system, outputs, receiving system, outcomes, in-process measurement and feedback, output measurement and feedback, and outcome measurement and feedback (Brown & Svenson, 1998). The process-based structure provides analytical value because it describes "the causal relationships behind an innovation model" (Davila et al., 2006, p. 150). Therefore, it offers a causal approach to understanding how innovation inputs are transformed into outcomes.

The Balanced Scorecard (BSC) serves as a strategic implementation tool that links financial and non-financial objectives to key performance indicators (Davila et al., 2006; Möller et al., 2016). Building upon the BSC, Kerssens-van Drongelen and Cooke (1997) developed an innovation-specific model that addresses the unique challenges of measuring innovation activities. Their Innovation Balanced Scorecard encompasses four strategic perspectives: The financial perspective, the internal business perspective, the innovation and learning perspective, and the customer perspective. The framework serves organizations to translate innovation strategies into measurable objectives.

Foster et al. (1985) introduced an innovation measurement framework that focuses on financial inputs and outcomes relating to innovation performance. The framework's central focus is to optimize returns on R&D. The objective is operationalized as the ratio of profits to R&D investment, which is decomposed into two components namely, R&D productivity and R&D yield (Foster et al., 1985). This framework demonstrates a fundamentally mathematical and rational approach to innovation measurement (Möller et al., 2016).

Adams et al. (2006) synthesized six innovation management models following an inductive approach. The resulting framework encompasses seven categories for innovation measurement namely, inputs, knowledge management, innovation strategy, organization and culture, portfolio management, project management, and commercialization (Adams et al., 2006).

As Adams et al. (2006) point out, the fragmentation of different innovation management and measurement models hinders further theoretical development and creates ambiguity regarding effective innovation measurement and management in practice. While their study contributes to the field by synthesizing existing approaches, their categorization does not offer a process-based logic, nor does it include innovation outcomes. So even their synthesized model seems incomplete for measuring and managing performance holistically. A holistic approach to innovation evaluation is critical, to capture resources and activities on which innovation is grounded as well as outputs and return on innovation to evaluate the added value of the resources and the activities employed. The IPOO as the most well-known model offers this process-based structure, however it is outdated, given the lack of open innovation relevant dimensions. A holistic approach that integrates structural causality, coherence and that reflects current innovation practices is essential for effective innovation performance management.

1.2 Objectives

The purpose of this paper is to synthesize and enhance existing innovation performance measurement and management frameworks by developing a holistic and coherent framework that enables comprehensive measurement of company-level innovation performance. The framework is designed to enable measuring, evaluating, and benchmarking innovation performance across corporations. While the framework serves multiple stakeholder groups, it targets analysts, investors, and innovation managers who require systematic tools for evaluating innovation performance. This research contributes a novel methodology for holistic innovation performance evaluation. The framework provides both a structured conceptual model as well as performance indicators for comprehensive assessment of innovation performance at the company level.

This paper is structured as follows: Section two outlines the research methodology employed for the framework development and indicator collection. Section three presents the VALOR innovation measurement framework and section four details the innovation performance indicators that are collected through a systematic literature review. Finally, section five discusses the framework's implications and limitations, along with directions for future research.

2 Research Method

To develop a holistic and coherent innovation performance measurement framework, this study employs a two-stage methodology comprising framework construction followed by indicator collection, standardization, and mapping. First, the IPOO model structure is used as the basis for the newly developed VALOR framework. Second, using classification methodology the framework is created by recycling and recombining performance categories from four existing innovation performance measurement frameworks. Third, from 56 empirical studies 263 innovation performance indicators are collected and decoded. Fourth, these indicators are clustered and standardized into 62 performance indicators for performance evaluation of the VALOR innovation performance categories.[1]

2.1 Classification Methodology

The framework development follows classification methodology, which is defined as the "general process of grouping entities by similarity" (Bailey, 1994, p. 4). Classification enables systematic structuring and understanding of complex occurrences. They can be grounded in conceptual foundations, empirical evidence, or a combination of both (Bailey, 1994). This study adopts a mixed classification approach, integrating both theoretical and empirical concepts. The framework is required to be holistic – accounting for innovation's multifaceted nature – and coherent, providing a logically sound measurement approach. To ensure practical applicability and user accessibility a lean model design is necessary. This prevents cognitive overload of users and facilitates implementation. The aim is to ensure that the framework captures innovation's multifaceted nature while remaining operationally manageable for practitioners and researchers. The newly created framework reflects traditional as well as current corporate innovation practices holistically and closes the gaps present in available innovation performance management models.

The framework adopts a nested hierarchical structure with the highest level designed to represent the innovation process based on the IPOO framework. The IPOO model serves as the basic structure given its predominance among established innovation performance measurement frameworks (Möller et al., 2016). Additionally, the benefit of the IPOO structure includes its ability to capture causal relationships within innovation systems (Davila et al., 2006). Compared to the other frameworks presented in section 1.1 (with the exception of the IPOO model), none of them offers this causal relationship in combi-

1 Note that to improve readability and clarity of the text AI was utilized (Anthropic, 2025).

nation with a holistic model character. Following classification methodology, innovation performance categories from four existing frameworks are decomposed and recombined. The four models are the IPOO Model (Brown & Svenson, 1998), the Innovation Balanced Scorecard (Kerssens-van Drongelen & Cooke, 1997), the R&D Framework (Foster et al., 1985) and the Innovation Management Measurement Framework (Adams et al., 2006). The framework is created while adhering to Gregor's (2006) criteria for the application of classification methodology.

2.2 Literature Review

After the creation of the framework, performance indicators are collected from empirical research through a systematic literature review and are mapped to the model's structure. For the collection of research papers five academic databases – Econbiz, JSTOR, Scopus, Swiss Discoveries, and Google Scholar – are employed to source relevant articles from the innovation performance management and measurement literature. The search strategy makes use of Boolean operators combining innovation-specific keywords (innovation management, innovation measurement, innovation performance, balanced scorecard, business structures, and capital costs) with accounting and finance terminology (accounting, forecasting, asset pricing, capital, coefficients, earnings, financial, and performance). For each database, the first 50 results are screened, yielding an initial sample of 250 research papers. Studies are ranked by relevance since it indicates a paper's quality and suitability with respect to the keywords utilized. Case studies, literature reviews, and meta-analyses are excluded to ensure indicators were validated through large-scale empirical testing. Title and abstract analysis identify studies that empirically investigate innovation performance or impact, resulting in 134 studies for detailed examination. Thereafter, quality screening is applied using established journal rankings. Studies published in B rated journals or higher according to VHB criteria, or appearing on the FT50 journal ranking (Ormans, 2016) are saved. For unranked journals, inclusion requires an SJR rating exceeding 1.0 on Scopus. Working papers are included to capture recent developments in innovation management and measurement research. This filtering reduces the sample to 73 studies. Final screening excludes studies that do not focus on company-level analysis, resulting in a final sample of 56 research papers for indicator extraction and analysis. The utilized indicators from these studies are decoded and subsequently a bottom-up analytical approach examines the indicators based on similarity. The indicators are clustered and standardized into relevant performance indicators to measure each of the VALOR innovation performance categories.

3 VALOR Innovation Measurement Framework

Four established innovation performance measurement models have provided the foundation for the newly created innovation performance measurement framework. The resulting framework is called the VALOR innovation measurement framework. The framework consists of a three-level nested hierarchy structure that includes innovation processes, innovation dimensions, and innovation measurement categories. At the highest level, the framework encompasses the following four innovation processes that have been adapted from the IPOO model (Brown & Svenson, 1998): *Values*, *Activities*, *Output*, and *Return on Innovation*. The categories have largely been recycled from the four innovation performance measurement frameworks. The innovation dimensions resulted by clustering the categories by similarity.

The framework's theoretical hypothesis rests on the premise that corporations with superior innovation performance are better positioned to maintain competitive advantage and achieve long-term success. Accordingly, *Longevity* (*L*) is positioned at the centre as organizing principle of the framework, reflecting the ultimate objective of innovation efforts. The integration of the four process steps with the Longevity principle, results in the acronym VALOR. Figure 1 illustrates the VALOR innovation measurement framework, with detailed descriptions of each component provided in the subsequent paragraphs.

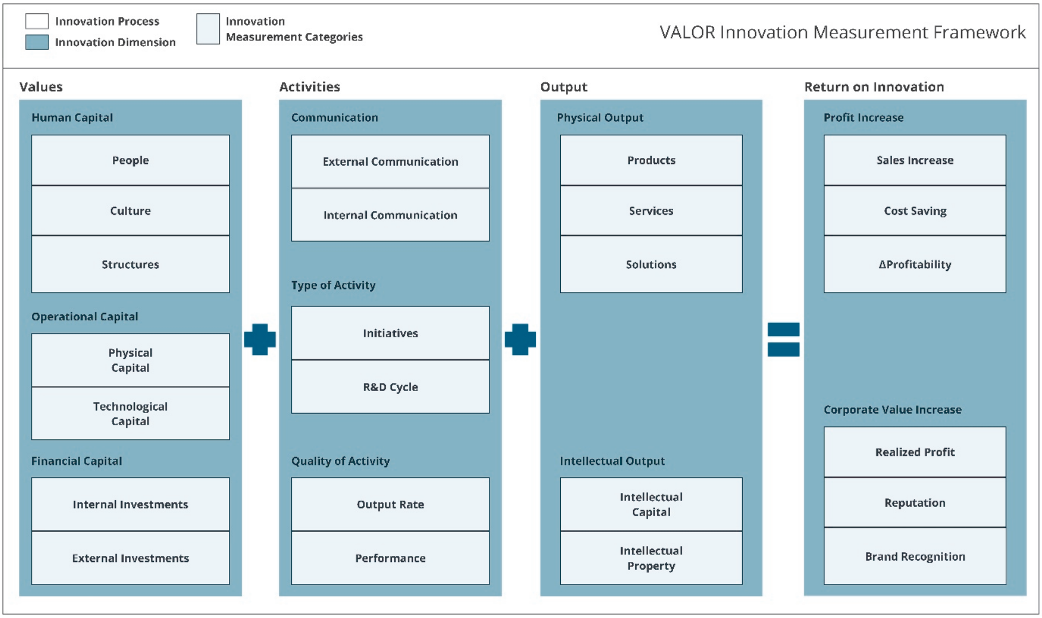

Figure 1: The VALOR Innovation Measurement Framework

Note. The figure presents the VALOR innovation measurement framework that was created using classification methodology by synthesizing four established innovation performance measurement and management models.

Values encompasses resources controlled by the corporation as a result of past events that are used for innovation activities and serve as enablers, from which future economic benefits are expected to flow. This conceptualization adapts the standard definition of assets from literature (CFA Institute, n.d.) to the specific context of innovation management. The *Values* process step comprises three innovation dimensions: *Human Capital*, *Operational Capital*, and *Financial Capital*. *Human Capital* encompasses three innovation measurement categories—*People*, *Culture*, and *Structures*—that capture human-centered resources and capabilities essential for innovation performance. *Operational Capital* includes *Physical Capital* and *Technological Capital*, representing the tangible and intangible assets corporations possess to enable innovation activities. *Financial Capital* encompasses the monetary resources that corporations allocate to innovation. The framework differentiates between *Internal Investments* (internally invested funds) and *External Investments* (externally deployed capital) to reflect the diverse investment mechanisms available to corporations.

The innovation process step *Activities* encompasses R&D initiatives pursued internally within the organization or through external collaborations with third parties. This process is structured into three innovation dimensions: *Communication*, *Type of Activity*, and *Quality of Activity*. *Communication* captures both *Internal Communication* and *External Communication* mechanisms that enable, enrich, and promote R&D activities across organizational boundaries and stakeholder networks. *Type of Activity* encompasses *Initiatives* and *R&D Cycle* components, which characterize the nature and scope of innovation activities, including collaborative efforts with external partners. *Quality of Activity* incorporates *Output Rate* and *Performance* measures that assess the efficiency, effectiveness, and productivity of R&D investments and activities, providing indicators about how well organizations convert innovation inputs into measurable innovation outcomes.

Longevity represents the competitive position of an organization over time. The framework posits that companies with superior innovation performance are better positioned to maintain competitive advantage in dynamic market environments, thereby ensuring long-term organizational value creation.

Output encompasses innovations created internally within the corporation or in collaboration with third parties, that are expected to generate benefits to the company while delivering economic value to society. This process comprises two innovation dimensions: *Physical Output* and *Intellectual Output*. *Physical Output* represents tangible innovations resulting from R&D activities that can be commercialized in the form of *Products*, *Services*, or *Solutions*. *Intellectual Output* encompasses intangible innovations namely *Intellectual Capital* and *Intellectual Property*, which emerge from R&D activities as abstract assets including new concepts, methodologies, and processes that contribute to superior organizational capabilities and competitive positioning.

Return on Innovation represents the tangible and intangible benefits derived from innovation outputs that are captured by the company. This process encompasses two innovation dimensions: *Profit Increase* and *Corporate Value Increase*. *Profit Increase* captures direct financial gains resulting from innovation outputs, measured through: *Sales Increase* (revenue growth attributable to innovation), *Cost Saving* (operational efficiencies achieved through innovation), and *ΔProfitability* (changes in profitability margins resulting from innovation). *Corporate Value Increase* encompasses broader value creation mechanisms through which organizations capture benefits from their innovation performance. These include *Realized Profits* (financial returns converted to shareholder value), *Reputation* (enhanced organizational standing and credibility), and *Brand Recognition* (increased market awareness and brand equity derived from innovation).

The four innovation processes include ten innovation dimensions and twenty-four innovation measurement categories. While the majority of categories were recycled from the four established frameworks, the existing categorizations proved insufficient for comprehensive evaluation of company-level innovation performance. Consequently, additional categories were incorporated to address the gaps in the measurement structure. The framework optimization process integrated insights from the systematic literature review, domain expertise, and collaborative discussions with innovation and investment managers to ensure comprehensive coverage of relevant innovation performance dimensions while maintaining theoretical coherence and practicality.

External Investments was incorporated as an innovation category alongside the established *Internal Investments* category to reflect present practices where corporations acquire innovative capabilities through external sourcing rather than solely relying on internal R&D development. Additionally, *Services* and *Solutions* were added to complement *Products*, recognizing that modern corporations deliver value through service offerings and solutions rather than exclusively through physical products. The *Return on Innovation* process step was structured according to a clear conceptual logic that distinguishes between direct and indirect value capture mechanisms. Within *Profit Increase*, all categories represent direct financial gains. On the other side, *Corporate Value Increase* encompasses both direct financial returns and indirect value creation through *Reputation* and *Brand Recognition*, which capture consumer sentiment and market awareness as intermediate drivers of long-term financial performance. This comprehensive categorization enhances confidence in the framework's ability to capture the complete value chain of innovation from initial investments through value realization.

The VALOR innovation measurement framework provides a comprehensive analytical foundation that can be applied independently of specific performance indicators. Users may draw upon diverse data sources including company reports and external databases based on individual preferences and data accessibility to extract innovation relevant information as outlined by the framework. The VALOR adheres to the process-based logic to obtain the causal relationship of innovation performance. Its holistic nature is achieved by the synthesis of existing innovation performance measurement frameworks and is updated to reflect current corporate innovation practices. The VALOR framework includes open-innovation relevant aspects, which the IPOO lacks. It includes the financial view of the R&D framework but also adds non-financial dimensions that were missing. It includes the resources fundamental to innovation which the IBS lacks and innovation outcomes which are missing in Adams et al.'s (2006) framework.

While the framework ensures holistic and comprehensive capture of innovation performance across all relevant dimensions, practical implementation requires standardized performance indicators to enable systematic measurement, comparison, and benchmarking across organizations. Consequently, the development of a standardized indicator set is essential for translating the framework's conceptual structure into an operational measurement tool that supports innovation performance evaluation.

4 VALOR Indicators

Empirical indicators have been systematically collected from 56 studies which have been clustered and standardized into 62 indicators for measuring the VALOR innovation performance categories. Initially 309 performance indicators were extracted. During the mapping process, 46 indicators could not be allocated to any VALOR innovation measurement categories, resulting in a final sample of 263 innovation indicators. The excluded indicators represent exogenous variables beyond direct organizational control, such as market competition intensity, competitor actions, and regulatory factors such as tax benefits.

The temporal distribution of the 56 included studies spans from 2006 to 2023, with two earlier publications from 1994 and 2003. The most relevant studies during this timeframe were selected for analysis and indicator collection. Figure 2 in Appendix A illustrates the distribution of study publications over the period. The quality distribution of the 56 included studies are as follows: 20% were published in A+ or A-rated journals, 34% in B-rated journals, and 11% in journals with SJR ratings exceeding 1.0. The remaining 36% are conference proceedings, SSRN publications, and working papers from academic institutions, ensuring inclusion of emerging research. Indicator extraction yielded an average of 4.7 indicators per study (median = 4). Journal rankings and bibliography for all 56 studies are provided in Table 2 in Appendix A. Studies utilized for indicator collection are identified in the reference section with an asterisk (*) for transparency purposes.

Mapping the 263 indicators to the VALOR innovation measurement categories reveals significant variation in research attention across different performance dimensions. The categories with the highest representation are *Sales Increase* (31 indicators), *People* (25 indicators), and *Performance* (22 indicators), indicating substantial scholarly focus on revenue-based outcomes, human capital factors, and R&D efficiency measures. Conversely, the least studied categories are *Brand Recognition* (0 indicators), *Reputation* (1 indicator), and *Cost Saving* (2 indicators), highlighting notable research gaps in intangible value creation and operational efficiency measurement within the innovation performance literature. Figure 3 in Appendix A presents the complete distribution of indicators across all VALOR innovation measurement categories, illustrating the uneven research emphasis across different innovation performance dimensions.

The 263 indicators extracted underwent systematic analysis and standardization, resulting in 62 distinct performance indicators that serve as operational measures for the individual VALOR framework categories. Table 1 presents the complete set of standardized indicators with their corresponding mapping to innovation measurement category, dimension, and process step. Practitioners and researchers may choose the indicators that are most relevant for their objective and use them with consistency across time and corporations. A holistic framework does not set forth that the employment of more indicators is better than less indicators, but that all categories are measured and evaluated. The indicators should always relate to innovation values, -activities, output- or return from innovation activities.

Innovation Process Step	Innovation Dimension	Innovation Category	Indicator
Values	Human Capital	People	Diversity
Values	Human Capital	People	Knowledge
Values	Human Capital	People	Size
Values	Human Capital	Culture	Training and Development
Values	Human Capital	Culture	Innovation Spirit
Values	Human Capital	Culture	Motivation
Values	Human Capital	Culture	Leadership
Values	Human Capital	Structures	Foreign Ownership
Values	Human Capital	Structures	R&D Internationalization
Values	Human Capital	Structures	Organizational Structures
Values	Operational Capital	Physical Capital	Physical Capital Stock
Values	Operational Capital	Physical Capital	Physical Capital Investment
Values	Operational Capital	Technological Capital	Technological Diversity

Innovation Process Step	Innovation Dimension	Innovation Category	Indicator
Values	Operational Capital	Technological Capital	Intangible Assets
Values	Financial Capital	Internal Investments	R&D Investment
Values	Financial Capital	Internal Investments	R&D Investment Intensity
Values	Financial Capital	External Investments	M&A Activity
Values	Financial Capital	External Investments	R&D Outsourcing
Values	Financial Capital	External Investments	External Business Development Activities
Activities	Communication	Internal Communication	Information Flow
Activities	Communication	External Communication	External Linkages
Activities	Type of Activity	Initiatives	R&D Collaboration
Activities	Type of Activity	Initiatives	Open Innovation
Activities	Type of Activity	Initiatives	Partner Variety
Activities	Type of Activity	Initiatives	R&D Outsourcing Intensity
Activities	Type of Activity	R&D Cycle	R&D Monitoring
Activities	Quality of Activity	Output Rate	Patent Applications
Activities	Quality of Activity	Output Rate	Product Output
Activities	Quality of Activity	Output Rate	Patents Granted
Activities	Quality of Activity	Performance	Forward Citations
Activities	Quality of Activity	Performance	R&D Intensity
Activities	Quality of Activity	Performance	Speed of Innovation
Activities	Quality of Activity	Performance	Success Ratio
Output	Physical Output	Product Services Solutions	New Products, Services, Solutions Launched
Output	Physical Output	Product Services Solutions	Modified Products, Services, Solutions
Output	Intellectual Output	Intellectual Capital	Process Innovation
Output	Intellectual Output	Intellectual Capital	New Knowledge Generated
Output	Intellectual Output	Intellectual Capital	Innovativeness
Output	Intellectual Output	Intellectual Property	Patent Stock
Output	Intellectual Output	Intellectual Property	Reuse of Patent
Output	Intellectual Output	Intellectual Property	Patent Diversity
Output	Intellectual Output	Intellectual Property	Patent Longevity
Output	Intellectual Output	Intellectual Property	Protection Strength

Innovation Process Step	Innovation Dimension	Innovation Category	Indicator
Return on Innovation	Profit Increase	Sales Increase	Sales Growth
Return on Innovation	Profit Increase	Sales Increase	Innovative Sales
Return on Innovation	Profit Increase	Sales Increase	CFO
Return on Innovation	Profit Increase	Sales Increase	Volatility of CFO
Return on Innovation	Profit Increase	Cost saving	Gross Margin
Return on Innovation	Profit Increase	Cost saving	Cost Reduction
Return on Innovation	Profit Increase	Profitability	Profit Margin
Return on Innovation	Profit Increase	Profitability	Volatility of EBITDA
Return on Innovation	Profit Increase	Profitability	ROA
Return on Innovation	Profit Increase	Profitability	EBITDA
Return on Innovation	Corporate Value Increase	Realized Profit	Assets to Market
Return on Innovation	Corporate Value Increase	Realized Profit	Market Return
Return on Innovation	Corporate Value In-crease	Realized Profit	Net Income
Return on Innovation	Corporate Value Increase	Realized Profit	Variability of Income
Return on Innovation	Corporate Value Increase	Realized Profit	Market Share
Return on Innovation	Corporate Value Increase	Realized Profit	EPS
Return on Innovation	Corporate Value Increase	Realized Profit	Firm Value
Return on Innovation	Corporate Value Increase	Reputation	Customer Satisfaction
Return on Innovation	Corporate Value Increase	Brand Recognition	Brand Awareness

Table 1: Standardized Indicators

Note. This table presents the 62 indicators that have been standardized from 263 initial indicators that have been decoded from 56 studies.

The VALOR framework together with the indicators enables systematic innovation performance analysis at the company level through a standardized four-point evaluation scale. For each category one or more indicators from Table 1 need to be utilized with consistency. Employing the indicators, each category is assessed with the ratings *insufficient (1)*, *poor (2)*, *sufficient (3)*, or *good (4)*. Numbers are always used as integers. Detailed definition for each rating is provided in Table 3 Appendix B. This four-point scale design eliminates neutral rating options, ensuring that evaluations provide clear directional guidance regarding organizational innovation performance rather than an ambiguous middle-ground assessment. The evaluation process follows a hierarchical aggregation structure whereby rated categories are equally weighted before summing them up to their respective innovation measurement dimension. The dimensions are then equally weighted to aggregate them into their respective process step. The four innovation process step ratings are aggregated equally to an overall organizational innovation performance rating. This multi-level evaluation approach enables both granular analysis and comprehensive assessment of overall innovation performance. The rating requires professional judgement. Therefore, the person conducting the analysis is required to have relevant experience in the field. Additionally, it is recommended to perform the analysis longitudinally (focusing on one company) or comparatively (multiple companies).

By employing the VALOR innovation performance measurement framework together with a selection of the 62 performance indicators innovation as well as asset managers are equipped to measure and evaluate a company's innovation performance holistically. By providing performance indicators to the innovation measurement categories, operationalization of the framework is ensured. An innovation manager is enabled to comprehensively capture and report corporate innovation performance whereby the VALOR evaluation provides the basis for discussing strategic decisions. Asset managers are given a framework to evaluate and benchmark innovation performance of different corporations, which serves as a decision-making tool given an innovation focused investment strategy.

To demonstrate the applicability of the VALOR innovation measurement framework, two companies from the aerospace and defense sector are analyzed using selected indicators based on the perspective of an investment analyst. These case studies illustrate the framework's operational utility for systematic innovation performance evaluation and benchmarking of two companies. The framework application, including company analyses and innovation performance assessments, are presented in Appendix C. Additionally, practitioners interested in using the VALOR framework find an evaluation template in Appendix D.

5 Discussion

The VALOR framework synthesizes and extends traditional innovation performance management and measurement models to a holistic analytical framework, offering comprehensive information to decision-makers. Unlike existing models, this updated framework includes financial, non-financial, closed- and open-innovation relevant aspects throughout the value chain of innovation. A holistic, comprehensive approach to innovation performance evaluation is important for identifying and understanding the aspects that shape and influence innovation performance.

Conceptually, the VALOR framework is providing a process-based approach like the IPOO model. The R&D framework, the IBS and the innovation performance model from Adams et al. (2006) do not offer this causal relationship. However, as with any analytical model, the VALOR framework constitutes an abstraction of reality and cannot fully encompass the complete complexity of innovation phenomena. Users must therefore be aware of the limitations presented in section 5.2. The VALOR framework does not specify an absolute efficiency metric like the R&D framework. The evaluation based on the VALOR framework builds the ground for further discussion and decision-making. Also, the VALOR framework does not help to define the innovation strategy, but needs to be defined independently of the framework. However, unlike the traditional models, the VALOR framework supports users in finding weaknesses, inefficiencies, gaps, and opportunities for improvement holistically. By aggregating the individual categories into the process steps, gaps and inefficiencies are recognized by comparing Values, Activities, Output and Return on Innovation ratings.

Equal to the models presented in section 1.1 users of the framework must customize the VALOR for their own use. First, performance indicators must be selected. Second, corresponding data needs to be collected. Third, each category is evaluated based on the indicators before aggregating the evaluation to the final rating. This process requires professional judgement and leaves a certain freedom to users which may imply personal biases. Therefore, for proper utilization it is recommended to work in teams. Additionally, the quality and comprehensiveness of the evaluation are dependent on data availability. Enhanced data quality (for example through direct data sourcing) and completeness across innovation measurement categories improves the reliability and validity of the assessments. Users must also recognize that comparability across companies decreases when information availability varies significantly between them. Compared to existing approaches the VALOR framework is more extensive and therefore requires greater effort for performance evaluation. While the process steps are comparable and efforts were made to keep the model lean, compared to the R&D framework for example, it requires more data (sources).

The VALOR framework is useful for corporations with established innovation practices. It supports identifying gaps and avenues for improvement. For example, one might encounter that satisfactory innovation performance is achieved within the company, but the impact on perceived corporate value (such as customer satisfaction and brand recognition) is unknown providing direction for further investigation. The VALOR framework can be utilized also for corporates which do not pursue innovation. It can serve as a starting point and help to implement the innovation strategy by defining resource allocation, activities, and key performance indicators besides others. For example, starting within the process step Values and the category people, managers may define the number of employees to allocate to innovation, how diverse their backgrounds should be, and what knowledge is required from them to succeed innovating. The VALOR framework hereby enables systematic thought through decision-making.

5.1 Implications

The VALOR framework challenges traditional innovation performance measurement frameworks by offering a more holistic and comprehensive approach. For today’s complex world we need more than isolated, quantitative models for decision-making. We need to understand the interconnections and interdependencies of innovation performance. For this we need a framework and tools which support capturing information in a comprehensive manner. This basis is what the VALOR framework and the underlying indicators offer. It surpasses traditional approaches because it is timely, holistic, and captures financial, non-financial, quantitative, as well as qualitative data. Researchers are equipped with a framework which was consolidated based on four innovation performance measurement and management models, making the VALOR framework the most comprehensive of them. Researchers and practitioners benefit from this paper since it provides them the most timely and comprehensive version of an innovation performance measurement model as of to date.

The VALOR framework supports innovation managers in assessing the performance of their subject and corresponding decision-making. The framework also serves as a reporting tool and basis for discussion with the upper management and employees involved. The evaluation supports innovation managers in identifying gaps and inconsistencies across the innovation value chain. Key implementation challenges for innovation managers include the time and resources involved in conducting the analysis and the subjectivity of their performance assessment. It is recommended to perform the analysis in teams and periodically to recognize trends and efficiency of past decision-making.

The VALOR framework also serves asset managers with an innovation-based investment hypothesis in their decision-making process. The holistic innovation performance evaluation acts as a filter for identifying the most innovative companies from an investment universe. The implementation challenges for asset managers are primarily data availability. Public available data may be insufficient for comprehensive innovation assessment which would require asset managers to source data directly from the corporation. Data needs to be normalized for size and industry when comparing different companies. This requires extensive efforts for a high-quality assessment. The VALOR framework includes an extensive and throughout analysis compared to other innovation-based investment hypotheses (see for example Hirshleifer et al. 2013; 2018). However, indicators have not been tested for forecasting in this paper.

5.2 Limitations

The following limitations should be noted by users of the VALOR framework. First, as a single author study, the screening, analysis, and selection of categories and indicators are affected by personal biases and individual professional experience. Second, the VALOR framework emphasizes internal organizational innovation performance and excludes macroeconomic influences and external environmental factors. This limitation is demonstrated by the 46 sourced indicators that could not be allocated to the VALOR framework categories, despite their established use in innovation performance measurement literature. Consequently, the framework's scope is constrained to company internal variables that can be directly influenced and controlled. Third, no empirical utilized measure for brand recognition was sourced from the structured literature review. Brand awareness was added as indicator to measure the category that is measuring market awareness and brand equity of a company which results out of its innovation performance. Fourth, regarding data availability constraints, users are recommended to conduct sensitivity analyses to examine how alternative scenarios – both positive and negative – for missing categories influence the overall conclusion. Sensitivity analyses are conducted by rating categories with a 1 in the worst case and a 4 in the best case scenario before summing up the rating to each of the next levels of the framework and overall innovation rating. The difference in the rating from these sensitivity analyses to the base case provide an approximation of the company's innovation performance robustness. Fifth, meaningful application of the framework requires professional judgment in applying the four-point evaluation scale to each measurement category, introducing an element of subjectivity that must be carefully managed through consistent application criteria and evaluator expertise. Sixth, the two case studies in Appendix C show that information relating to the categories internal communication, products, services, and solutions, as well as intellectual capital and brand recognition are difficult to collect from the utilized sources. Innovation managers will likely have more information than asset managers when it comes to evaluating innovation performance, since innovation managers are employed by the company and have direct data access unlike asset managers.

5.3 Further Research

The present study establishes a foundation for further research directions that enhance the understanding of company level innovation performance. First, quantitative analyses that empirically validate the indicators and examine their interrelationships represent potential for future research. Second, research focusing on aggregated analyses – across industries or countries – presents opportunities to extend the framework's application beyond individual company evaluation. Third, the development of industry specific benchmarks based on the VALOR framework could significantly enhance its practical utility. Fourth, future research could address one of the framework's acknowledged limitations by exploring the integration of macroeconomic influences into innovation performance analysis. Incorporating external factors such as regulatory environments, government incentives, market dynamics, competitive pressures, and broader economic trends could provide a more comprehensive understanding of factors that influence company level innovation success.

6 Appendices

Appendix A

Figure 2: Publication Year of Studies Included

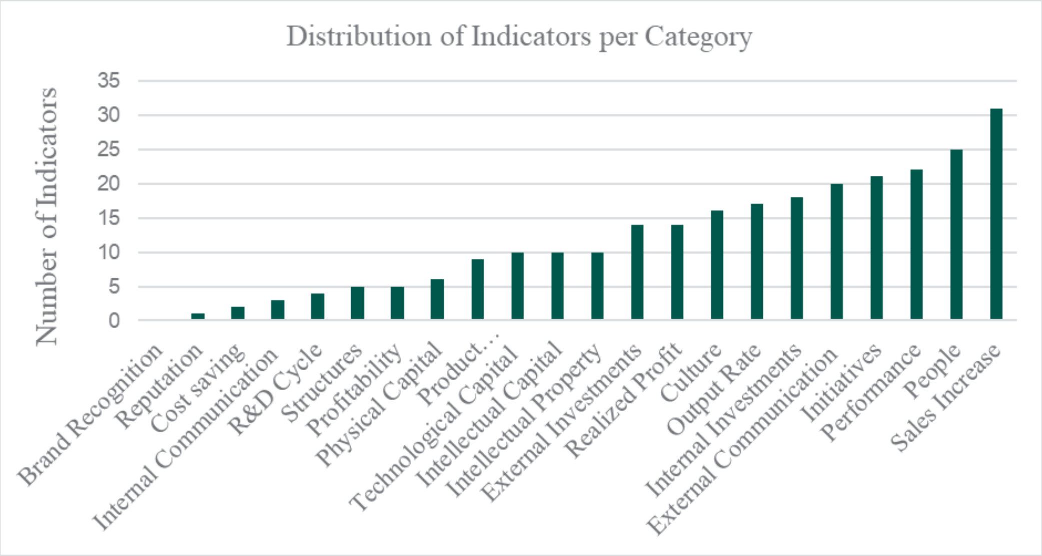

Figure 3: Distribution of 263 Sourced Indicators per Category

Performance Indicators

Journal Name	#	%	% cum	VHB Rank	SJR
The Review of Financial Studies	1	2 %	2 %	A+	
The Accounting Review	1	2 %	4 %	A+	
Strategic Management Journal	4	7 %	11 %	A	
Research Policy	2	4 %	14 %	A	
Journal of Management Studies	1	2 %	16 %	A	
Review of Accounting Studies	1	2 %	18 %	A	
Journal of Organizational Behavior	1	2 %	20 %	A	
IEEE Transactions on Engineering Management	3	5 %	25 %	B	
Small Business Economics	3	5 %	30 %	B	
Finance Research Letters	2	4 %	34 %	B	
European Journal of International Management	1	2 %	36 %	B	
International Journal of Production Economics	1	2 %	38 %	B	
Journal of Accounting, Auditing & Finance	1	2 %	39 %	B	
Journal of Business Finance & Accounting	1	2 %	41 %	B	
Journal of Business Research	1	2 %	43 %	B	

Journal Name	#	%	% cum	VHB Rank	SJR
Journal of International Management	1	2 %	45 %	B	
Journal of International Marketing	1	2 %	46 %	B	
The International Journal of Accounting	1	2 %	48 %	B	
R&D Management	1	2 %	50 %	B	
Managerial and Decision Economics	1	2 %	52 %	B	
Omega	1	2 %	54 %	B	
Cambridge Journal of Economics	1	2 %	55 %		1.156
Global Journal of Flexible Systems Management	1	2 %	57 %		1.072
Industrial Management and Data Systems	1	2 %	59 %		1.219
Journal of Innovation & Knowledge	1	2 %	61 %		2.649
Scientometrics	1	2 %	63 %		1.019
Review of Industrial Organization	1	2 %	64 %		1.009
Working Paper	13	23 %	88 %	-	
Conference Paper	4	7 %	95 %	-	
SSRN	3	5 %	100 %	-	
Total	56	100.0 %			

Table 2: Paper Publication and Distribution

Appendix B

Evaluation Scale

The VALOR framework employs a standardized four-point evaluation scale—insufficient, poor, sufficient, and good—applied systematically across innovation measurement categories, innovation dimensions, innovation processes, and overall organizational assessment. The evaluation process follows an equally weighted hierarchical aggregation structure that ensures systematic and comprehensive performance assessment. Initially, individual innovation measurement categories are evaluated using the four-point scale based on available data and performance evidence. Subsequently, category-level ratings are aggregated to generate innovation dimension scores, which are then consolidated to produce innovation process evaluations. Finally, process-level assessments are synthesized to derive an overall organizational innovation performance rating. This multi-level evaluation approach requires professional judgment at each aggregation stage to ensure that ratings accurately reflect company performance across different innovation domains.

Rating	Numeric Rating	Description
Good	4	The company demonstrates operationalized innovation activities and quantifiable progress toward strategic innovation objectives
Sufficient	3	The company exhibits innovation initiatives, though implementation remains limited or outcomes have not yet materialized substantially
Poor	2	The company displays minimal innovation efforts with limited strategic integration or measurable outcomes
Insufficient	1	There are no recognizable innovation activities, or the company exhibits declining innovation performance indicators

Table 3: Definitions of the Four-Point Scale Used for Evaluating Organizational Innovation Performance Using the VALOR Innovation Measurement Framework

Note. Colors may be used in conjunction with the four-point evaluation scale to facilitate rapid visual assessment and intuitive understanding of innovation performance.

Appendix C

Application of the Framework

The following analysis demonstrates the practical application of the VALOR framework through evaluation of two publicly listed companies from the aerospace and defense sector: OHB Group and Thales Group. These organizations were selected based on their active participation in the space industry, an emerging sector characterized by increasing commercialization activities within the New Space Economy (ESA, n.d.). Thales Group represents one of the largest aerospace and defense companies by market capitalization, while OHB Group operates as a smaller organization serving as a key supplier to the European Space Agency (ESA). This size differential provides valuable insights into how innovation performance varies across organizations of different scales and market positions.

The framework application process involves consulting publicly available data sources, including annual reports, corporate disclosures, and database information, which are systematically attributed to the corresponding innovation measurement categories within the VALOR framework. Each category is analyzed using one or more of the indicators out of Table 1 based on data availability and evaluated using the four-point scale as detailed in Appendix B. This process enables systematic comparison of innovation performance across the two organizations while demonstrating the framework's practical utility for real-world organizational assessment and benchmarking purposes. The evaluation process follows a hierarchical aggregation structure whereby rated categories are equally weighted for summing up to their respective innovation measurement dimension, respective process step to an overall organizational innovation performance rating. The categories were rated by the authors professional judgement.

OHB SE represents a European space and technology group headquartered in Germany, established in 1981 (OHB SE, 2023a; PitchBook, n.d.-a). The organization operates through three primary business verticals: Space Systems, Aerospace, and Digital services. As of 2022, the OHB Group maintains a diversified portfolio structure encompassing multiple subsidiaries alongside minority and majority equity positions in more than twenty companies (OHB SE, 2023a).

The comprehensive evaluation draws upon data sourced from OHB SE's Annual Report (OHB SE, 2023a), Corporate Report (OHB SE, 2023b), and Sustainability Report (OHB SE, 2023c), supplemented by PitchBook data (n.d.-a) where information gaps exist in official corporate disclosures. The analysis focuses on 2022 performance data with 2021 serving as the comparative baseline for trend assessment. Figure 4 presents a visual summary of the evaluation findings, while Table 4 provides detailed tabular documentation of ratings across each innovation measurement category, innovation dimension, innovation process, and the overall organizational assessment derived through systematic application of the VALOR framework.

Consolidating the individual category ratings through systematic aggregation as detailed in Table 4, OHB receives an overall poor rating for innovation performance. This comprehensive assessment reflects consistent weaknesses across multiple framework dimensions, with poor performance in foundational resources (Values), poor effectiveness in R&D execution (Activities), and insufficient innovation outcomes (Output). However, OHB reports sufficient financial returns (Return on Innovation) for the year under consideration. Key performance indicators are depicted in Figure 4 and the detailed evaluation summary is presented in Table 4.

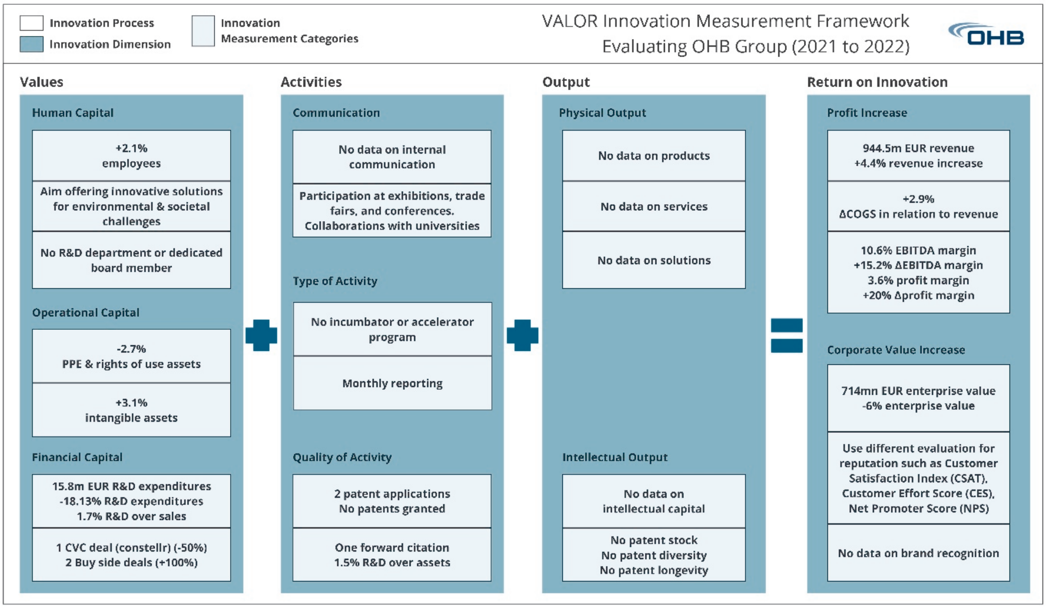

Figure 4: OHB Group Analysis Based on the VALOR Framework

Note. This is a visual representation of OHB's innovation performance for the year 2021/2022.

The second organization analyzed is Thales Group, a global technology leader providing comprehensive solutions and services across Defense, Aeronautics, Space, and Digital Identity and Security sectors (Thales Group, 2023a). Founded in 1986 with headquarters in France, Thales operates across 68 countries and maintains market leadership positions as the foremost defense electronics company in Europe and the global leader in data protection, payment cards, and SIM card technologies (PitchBook, n.d.-c; Thales Group, 2023a).

The comprehensive evaluation utilizes data sourced from Thales Group's Integrated Report (Thales Group, 2023a) and Consolidated Financial Statements (Thales Group, 2023b), supplemented by PitchBook information (n.d.-c) where gaps existed in official corporate documentation. The analysis examines 2022 performance data with 2021 serving as the comparative baseline for trend assessment and performance evaluation. Figure 5 provides a visual summary of the evaluation findings. Table 5 presents detailed tabular documentation of ratings across each innovation measurement category, innovation dimension, innovation process, and overall organizational assessment derived through systematic application of the VALOR framework to Thales Group's innovation performance.

Consolidating the individual category ratings through systematic aggregation as detailed in Table 5, Thales receives an overall sufficient rating for innovation performance. This comprehensive assessment reflects consistent performance across framework dimensions, with sufficient ratings in Values, Activities, and Return on Innovation as well as good performance in Output. The aggregated results and key performance indicators for Thales Group are presented visually in Figure 5.

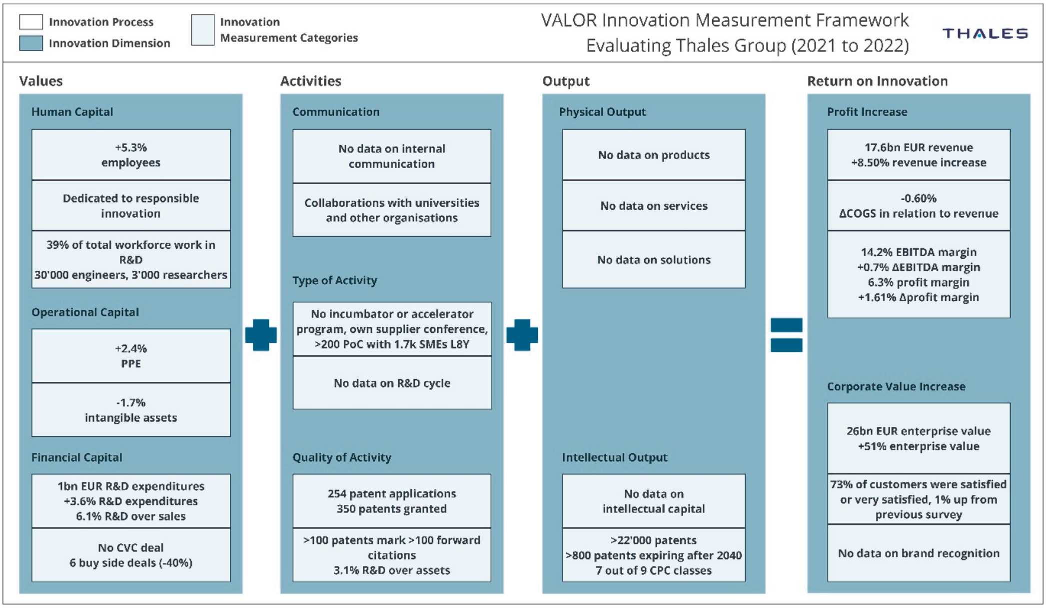

Figure 5: Thales Group Analysis Based on the VALOR Framework

Note. This is a visual representation of Thales's innovation performance for the year 2021/2022.

The comparative analysis demonstrates that Thales Group's innovation performance substantially exceeds that of OHB Group across multiple framework dimensions. Systematic evaluation of all VALOR framework components using the four-point scale yields an overall sufficient rating for Thales compared to a poor rating for OHB, indicating significant performance differentiation between the two organizations. While both companies achieve sufficient performance in Return on Innovation, Thales consistently outperforms OHB across remaining process steps. Thales achieves sufficient ratings in both Values and

Activities alongside good performance in Output, reflecting strong foundational resources, effective R&D execution, and substantial innovation outputs. Conversely, OHB demonstrates poor performance in both Values and Activities, with insufficient performance in Output, indicating fundamental weaknesses in innovation capabilities and execution.

Data limitations prevented complete evaluation of certain innovation dimensions as documented in Tables 4 and 5. Particularly for the internal communication, the product, services, and solutions as well as the brand recognition categories. However, available information provides sufficient basis for comparative assessment. These evaluation results offer practical decision-making insights for multiple stakeholder groups. Innovation managers at OHB can benefit from the assessment to make strategic decisions based on comparative analysis. Asset managers pursuing innovation-focused investment strategies may rationally prefer Thales over OHB based on superior comprehensive innovation performance, assuming market premiums for innovation performance. Policy makers may leverage Thales's innovation performance as a benchmark or best practice example for promoting industry-wide innovation development, utilizing the organization's systematic approach to R&D investment, external collaboration, and intellectual property development as reference standards for innovation excellence within the aerospace and defense sector.

<table>
<tr><th colspan="3">Measurement Category</th><th colspan="2">Dimension</th><th colspan="2">Process</th><th>Overall</th></tr>
<tr><td>People</td><td>Increase of 2.1 % in employees from 2021 to 2022 counting 3,025 employees as of December 2022</td><td>Sufficient</td><td rowspan="3">Human Capital</td><td rowspan="3">Sufficient</td><td rowspan="7">Values</td><td rowspan="7">Poor</td><td rowspan="13">Poor</td></tr>
<tr><td>Culture</td><td>Aims offering innovative solutions for environmental and societal challenges. Do not demonstrate how.</td><td>Sufficient</td></tr>
<tr><td>Structures</td><td>No R&D department or dedicated board member</td><td>Poor</td></tr>
<tr><td>Physical Capital</td><td>Decrease in PPE and rights of use assets by 2.7 %</td><td>Insufficient</td><td rowspan="2">Operational Capital</td><td rowspan="2">Poor</td></tr>
<tr><td>Technological Capital</td><td>Increase in intangible assets by 3.1 %</td><td>Sufficient</td></tr>
<tr><td>Internal Investments</td><td>EUR 15.8m, 18.13 % less than in 2021, 1.7 % R&D over sales</td><td>Insufficient</td><td rowspan="2">Financial Capital</td><td rowspan="2">Insufficient</td></tr>
<tr><td>External Investments</td><td>One CVC follow on investment and two corporate deals</td><td>Poor</td></tr>
<tr><td>Internal Communication</td><td>NA</td><td>NA</td><td rowspan="2">Communication</td><td rowspan="2">Sufficient</td><td rowspan="6">Activities</td><td rowspan="6">Poor</td></tr>
<tr><td>External Communication</td><td>Participation at exhibitions, trade fairs, and conferences. Pursuing collaborations with universities.</td><td>Sufficient</td></tr>
<tr><td>Initiatives</td><td>No incubator nor accelerator program.</td><td>Insufficient</td><td rowspan="2">Type of Activity</td><td rowspan="2">Poor</td></tr>
<tr><td>R&D Cycles</td><td>Monthly reporting</td><td>Sufficient</td></tr>
<tr><td>Output Rate</td><td>2 patent applications, no patents granted</td><td>Poor</td><td rowspan="2">Quality of Activity</td><td rowspan="2">Poor</td></tr>
<tr><td>Performance</td><td>One forward citation, 1.5 % R&D over assets</td><td>Poor</td></tr>
</table>

Measurement Category			Dimension		Process		Overall
Products	NA	NA	Physical Output	NA	Output	Insufficient	
Services	NA	NA					
Solutions	NA	NA					
Intellectual Capital	NA	NA	Intellectual Output	Insufficient			
Intellectual Property	No patent stock, no patent diversity, no patent longevity	Insufficient					
Sales Increase	944.5m EUR revenues, 4.4 % more than in 2021	Good	Profit Increase	Sufficient	Return on Innovation	Sufficient	
Cost Saving	2.9 % higher costs in relation to revenues	Insufficient					
ΔProfitability	EBITDA margin 10.6 % with 15.2 % increase from 2021. Profit margin 3.6 % with 20 % increase compared to 2021.	Good					
Realized Profit	714mn EUR enterprise value, 6 % less compared to 2021	Poor	Corporate Value Increase	Poor			
Reputation	Different metrics in place to evaluate customer satisfaction. However, without any conclusion or reporting specific numbers.	Poor					
Brand Recognition	NA	NA					

Table 4: Evaluation of the OHB Group Based on the VALOR Innovation Measurement Framework

Note. Data sources for the evaluation includes OHB Group's Annual Report (OHB SE, 2023a), Corporate Report (OHB SE, 2023b), Sustainability Report (OHB SE, 2023c), PitchBook (n.d.-a; n.d.-b), and Refinitiv Eikon (n.d.-a).

Measurement Category			Dimension		Process		Overall
People	5.3% increase in number of employees marking 85,253 employees in 2022	Sufficient	Human Capital	Good	Values	Sufficient	Sufficient
Culture	Dedicates itself to responsible innovation and R&D is at the core of their business	Good					
Structures	39 % of their total workforce works in R&D counting 30,000 engineers and 3,000 researchers in 2022	Good					
Physical Capital	Increase of 2.4 %	Sufficient	Operational Capital	Poor			
Technological Capital	Decrease of 1.7 %	Insufficient					
Internal Investments	1bn in R&D amounting to 6.1 % R&D expenditures over sales, expenditures are 3.6 % higher than in 2021	Good	Financial Capital	Sufficient			
External Investments	No external investments since 2017 with their CVC. 6 buy side deals, -40 % from 2021.	Poor					

Measurement Category			Dimension		Process		Overall
Internal Communication	NA	NA	Communi-cation	Sufficient	Activities	Sufficient	
External Communication	Collaboration with four universities and the CNRS	Sufficient					
Initiatives	No accelerator or incubator but worked on over 200 PoCs with SMEs and startups counting a network of over 1,700 ventures for the past eight years. Own supplier conference.	Sufficient	Type of Activity	Sufficient			
R&D Cycles	NA	NA					
Output Rate	254 patent applications, 350 patents granted	Good	Quality of Activity	Good			
Performance	>100 patents mark >100 forward citations, 3.1 % R&D over assets	Good					
Products	NA	NA	Physical Output	NA	Output	Good	
Services	NA	NA					
Solutions	NA	NA					
Intellectual Capital	NA	NA	Intellectual Output	Good			
Intellectual Property	>22,000 patents, >800 patents expiring after 2040, 7 out of 9 CPC classes	Good					
Sales Increase	17.6bn EUR revenues with 8.5 % increase from 2021	Good	Profit Increase	Good	Return on Innovation	Sufficient	
Cost Saving	0.6 % decrease in cost of sales in relation to revenues	Sufficient					
ΔProfitability	EBITDA margin 14.2 % with 0.7 % increase from 2021. Profit margin of 6.3 % which is 1.6 % higher than 2021.	Good					
Realized Profit	26bn EUR enterprise value, +51 % from 2021	Good	Corporate Value Increase	Sufficient			
Reputation	73 % of customers are satisfied and very satisfied with 1 % increase from last survey	Sufficient					
Brand Recognition	NA	NA					

Table 5: Evaluation of the Thales Group Based on the VALOR Innovation Measurement Framework

Note. Data sources for the evaluation includes Thales Group's Integrated Report (Thales Group, 2023a), Consolidated Financial Statements (Thales Group, 2023b), PitchBook (n.d.-c; n.d.-d), and Refinitiv Eikon (n.d.-b).

Appendix D

Evaluation Template

Measurement Category			Dimension		Process		Overall
People			Human Capital		Values		
Culture							
Structures							
Physical Capital			Operational Capital				
Technological Capital							
Internal Investments			Financial Capital				
External Investments							
Internal Communication			Communi-cation		Activities		
External Communication							
Initiatives			Type of Activity				
R&D Cycles							
Output Rate			Quality of Activity				
Performance							
Products			Physical Output		Output		
Services							
Solutions							
Intellectual Capital			Intellectual Output				
Intellectual Property							
Sales Increase			Profit Increase		Return on Innovation		
Cost Saving							
ΔProfitability							
Realized Profit			Corporate Value Increase				
Reputation							
Brand Recognition							

Table 6: Template for the Usage of the VALOR Innovation Performance Measurement Framework

Note. This template can be used for evaluating a company of choice using the four-point scale presented in Appendix B. Indicators are selected from Table 1.

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Future-Relevant Technologies for Switzerland: Technological Priority Signals and Cross-Industry Robustness Based on Job Postings Analysis

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Abstract: Foresight research constantly strives to identify and utilize new data sources for its technological trend analyses. In addition to long-established data sources such as patents and scientific publications, job postings data have recently proven to be an insightful data source for foresight purposes, reflecting the adoption of emerging technologies in practice without major time or publication delays. In our research we use online job postings from Switzerland to identify technologies frequently mentioned in connection with future-related terms in job description texts. This novel approach provides a data-based perspective on the technology domains in which companies in Switzerland perceive future potential and actively recruit talent. Furthermore, we compare the recruiting dynamics for these technology fields across industries to identify robust technologies that are future-relevant in multiple sectors. Our methodology comprises text mining techniques – including keyword analysis and named entity recognition – and results in a data-driven trend study aimed at both innovation management researchers as well as business practitioners.

Keywords: Trend Analysis, Technology Foresight, Data-Driven Foresight, Robust Technologies, Industry Trends, Job Postings Analysis, Text Mining, Named Entity Recognition

Zukunftsrelevante Technologien für die Schweiz: Technologische Prioritätssignale und branchenübergreifende Robustheit basierend auf der Analyse von Stellenausschreibungen

Zusammenfassung: Die Foresight-Forschung ist ständig danach bestrebt, neue Datenquellen für ihre Technologietrendstudien zu identifizieren und zu nutzen. Zusätzlich zu den etablierten Datenquellen wie Patenten und wissenschaftlichen Publikationen haben sich auch Stellenausschreibungen als aussagekräftig für die Vorausschau erwiesen. In unserer Forschung nutzen wir Stellenausschreibungen aus der Schweiz, um Technologien zu identifizieren, die häufig im Zusammenhang mit zukunftsbezogenen Begriffen genannt werden. Dieser neuartige Ansatz liefert eine datenbasierte Perspektive auf Technologiebereiche, in denen Unternehmen in der Schweiz Zukunftspotenzial sehen und für welche sie aktiv Personal einstellen. Zusätzlich vergleichen wir die Einstellungsdynamiken für diese Technologiebereiche über Industrien hinweg, um robuste Technologien zu identifizieren, die in mehreren Sektoren zukunftsrelevant sind. Unsere Forschungsmethode umfasst verschiedene Text-Mining-Techniken und resultiert in einer datengetriebenen Trendstudie mit Wissenschafts- und Praxisrelevanz.

Stichwörter: Trendanalyse, Technologievorausschau, Data-Driven Foresight, Robuste Technologien, Industrietrends, Stellenausschreibungsanalyse, Text Mining, Named Entity Recognition

Legend

AI	Artificial Intelligence
AR	Augmented Reality
DDF	Data-Driven Foresight
FTE	Full-Time Equivalent
GPTs	General-Purpose Technologies
IoT	Internet of Things
LLM	Large Language Model
ML	Machine Learning
NAICS	North American Industry Classification System
NER	Named Entity Recognition
NLP	Natural Language Processing
TRL	Technology Readiness Level
VR	Virtual Reality

1. Introduction

Technology trend studies with a regional focus and practical implications are widespread in the literature and show a high relevance for the scientific discourse on corporate and technology foresight. A lot of these studies, however, apply qualitative foresight methods such as scenario techniques, expert interviews, or the Delphi method to set trend signals into national or regional contexts (Blind et al., 1999; Bassani et al., 2016; Kindras et al., 2019). Data-driven foresight (DDF), on the contrary, is a specialized stream within the foresight discipline that exploits quantitative data analyses to derive weak signals from various data sources for potential future trend developments and helps companies in proactively identifying and seizing emerging competitive advantages (Rohrbeck et al., 2015, p. 2; Scheuffele et al., 2024, p. 132). With the latter, DDF pursues the same goal as strategic foresight, only that it is usually more focused on the identification of emerging technologies and innovation fields rather than on the organizational integration of futures thinking into strategic decision-making processes (Müller-Stewens & Müller, 2010, p. 245).

In terms of the data sources used, scientific publications and patents are the most established and extensively utilized in DDF, with many examples of successfully conducted trend studies in a variety of analysis contexts (Block et al., 2021; Han et al., 2021; Niknejad et al., 2021; Wider et al., 2023). Nevertheless, while these data sources provide valuable insights into emerging technologies and their early downstream maturing phases, the later development phases are not sufficiently covered by scientific publications or patents, as the focus shifts from technical to strategic and market-related factors. Especially scientific publications lack the ability to represent practical relevance or anticipate application success because scientific success of a technology or research field does not necessarily lead to market success or innovation breakthroughs (Stelzer et al., 2015, p. 144). Also, science- and technology-heavy data sources alone do not contain all the information needed to anticipate an innovation's market success, nor can they single-handedly cover all aspects of a multi-perspective foresight (Mühlroth & Grottke, 2018, pp. 673–674; Cagnani et al., 2023). Finally, scientific publications and patents usually require considerable time before their information can be utilized effectively, due to lengthy application and publication processes, which can lead to a timely disconnection from real market needs (Gerken et al., 2015; Zhang et al., 2017).

This is why, in both foresight science and practice, constant efforts are being made to identify alternative data sources from various perspectives and to analyze them for weak signals on emerging innovation fields. Bonaccorsi et al. (2020), for example, use Wikipedia pages as a data source to identify emerging technologies and industrial leadership in the context of Industry 4.0. Laurell and Sandstrom (2022), moreover, present social media analytics of multiple platforms as an innovative foresight approach. In our research, we use online job postings as an alternative data source to identify priority signals for future-relevant technologies for Switzerland. For this purpose, we examine over one million job postings from Switzerland from September to December 2024 for the technologies they mention in connection with future-related terms in their job description texts. Although job postings data are not yet fully established in the foresight discipline, they have recently proven to be an insightful data source for trend identification, reflecting the early business practice perspective of technology adoption and development efforts without major review or publication delays (Zhang et al., 2017; Goldfarb et al., 2023, p. 2; Scheuffele et al., 2025).

Based on the approach by Goldfarb et al. (2023), who analyze job postings across various industries to compare emerging technologies for their potential as general-purpose technologies (GPTs), we also examine the occurrence of our identified future-relevant technologies across industries. Our aim, however, is to assess the technologies' potential robustness in terms of cross-industry future relevance. Robust technologies in foresight are usually characterized by the fact that they occur in various future scenarios and play a dominant role for future competitive advantages without being too sensitive to changes in future conditions (Maier et al., 2016, p. 159; McPhail et al., 2020). Applied to our study, technologies are robust if they are identified as future-relevant technologies in many different industries through keyword analysis and named entity recognition (NER) of technologies frequently mentioned in connection with future-related terms in job descriptions. Importantly, we do not conceptualize future-relevant technologies as innovations that are guaranteed to remain dominant in the long term. Instead, we use the term to describe technologies and innovation fields that exhibit early widespread and cross-industry relevance signals in labor market data. Specifically, we focus on technologies for which firms articulate forward-looking skill requirements and capability needs, as reflected in job postings. From a foresight perspective, such signals are commonly interpreted as proxies for future strategic importance, rather than as deterministic predictions of technological success (Gilmore et al., 2023, p. 1).

Proposing our novel methodology for data-driven foresight to the scientific discourse and following the outlined approach, we strive to answer the following research question: Which technologies and innovation fields are future-relevant for Switzerland based on job postings analysis and cross-industry robustness evaluation?

2. Theoretical background

Our research bridges the gaps between the scientific discourses on technology foresight in Switzerland, methodological advancements in DDF, and the utilization of job postings for anticipatory trend studies. Recent academic foresight studies and technology trend analyses for Switzerland identify digital technologies as further emerging and highly relevant for the Swiss economy and its core industries (Tsesmelis et al., 2022; Niggli & Rutzer, 2023). In their data-driven trend study on cybersecurity technologies in Switzerland and abroad, Tsesmelis et al. (2022) evaluate 5G, big data, machine learning, blockchain, and contact-tracing methods as emerging technologies based on job openings, patents, and publications analysis. Most of these technologies are also mentioned in a national trend study by the Swiss Academy of Engineering Sciences SATW (2023) as well as in a focused market study by Deloitte (2021). Although non-academic, both studies provide valuable insights into current technology trends for Switzerland and underscore the need for further technology foresight research within the country. Another literature stream in the Switzerland-related foresight discourse examines how foresight activities are implemented in different national business practice contexts (Peter, 2019; Baumgartner & Peter, 2022). Baumgartner and Peter (2022), for example, analyze how international Swiss banks incorporate strategic foresight into their innovation activities and develop a new framework for enhanced innovation activity through collaborative foresight. While the latter research stream does not provide any insights into actual technology or innovation trends, the formerly mentioned trend studies do not only identify specific emerging technologies and innovation fields but also explain the data sources and analysis methods in use. Table 1 summarizes the findings of these studies and gives an overview of the relevant research methodologies and data sets.

Emerging technologies and innovation fields	*Data sources and analysis methods used*	*Authors*
Artificial intelligence, digital personalized health, robotics, advanced manufacturing, blockchain	Expert opinions (qualitative data) collected through interviews	Deloitte, 2021
5G, big data & machine learning, blockchain, contact tracing	Patent analysis of granted patents per technology field in Switzerland Publication analysis of scientific publications uploaded to arXiv Analysis of Google search history for technologies and insights from Google Trends	Tsesmelis et al., 2022

Emerging technologies and innovation fields	*Data sources and analysis methods used*	*Authors*
Digitalization: 5G applications, blockchain, Internet of Things (IoT), extended reality, connected machines, quantum computing, quantum and post-quantum cryptography, autonomous vehicles, photonic integrated circuits, digital twins Energy and environment: photovoltaics, sustainable food production, artificial photosynthesis, carbon capture and storage, geothermal energy, mobility concepts Manufacturing processes and materials: low-carbon concrete, sustainable adhesives and sealants, bioplastics, thermal interface materials, fiber-optic sensors, antimicrobial surfaces	Technology Outlook 2021 reassessed through Technology Readiness Level (TRL) evaluation Expert opinions (qualitative data) collected through semi-structured interviews Economic importance for Switzerland evaluated by sales revenue data of companies based in Switzerland Research competence in Switzerland evaluated through publications of academic and industrial research in Switzerland plus monitoring of X accounts of Swiss universities	Swiss Academy of Engineering Sciences SATW, 2023

Table 1: Technologies and innovation fields identified in recent trend studies for Switzerland

The brief review of trend studies for Switzerland already shows a variety of data sources and analysis methods used for technology foresight purposes. An even broader perspective emerges when considering the foresight literature without regional limitations. In this context, the body of literature also contains trend studies that compare the content validity of different data sources (Mikova & Sokolova, 2019; Bonaccorsi et al., 2020; Laurell & Sandstrom, 2022) and examine their individual foresight horizons (Cozzens et al., 2010; Segev et al., 2015; Mühlroth & Grottke, 2018).

Much of this discourse builds on two leading studies that classify foresight data sources from different perspectives according to their technology lifecycle predictiveness (Watts & Porter, 1997; Martino, 2003). Orienting towards the observable sequence of technological change – from theoretical proposal to commercial introduction – it is possible to determine a technology's maturity and anticipate its transition to the next lifecycle phase based on publication peaks in specific types of data sources. Scientific publications, for example, are best suited to represent emerging technologies in their basic research phase. Patents, on the other hand, reflect technologies that are already in the development stage, and newspapers, business press, and popular press allow for trend insights regarding the daily application and social impacts of a technology (Martino, 2003, pp. 720–721). Specialized studies show that an increase in scientific publications within a specific technology field can predict a subsequent rise in patent activity in the same field by up to six years. With regard to marketability and application success of technologies, scientific publications can even be nine years ahead. This makes them the earliest-phased data source for foresight purposes but not necessarily the most practice-oriented (Segev et al., 2015, p. 7; Stelzer et al., 2015, p. 144; Block et al., 2021; Hsieh et al., 2024).

These findings, along with the argument that different data sources offer different foresight potential (Watts & Porter, 1997, p. 29), provide the rationale for using job postings data as an innovative foresight data source. Goldfarb et al. (2023, p. 2) argue that job postings should reflect a company's intentions to engage with a new technology or innovation field earlier than patent data because human capital is an input into technology development, and technological innovations must be developed by employees before a company can file a patent. Hence, job postings data can be seen as the most forward-looking data source of the business practice perspective, reflecting exactly when a company or industry starts adopting emerging technologies or innovation fields.

Nevertheless, it is important to acknowledge that hiring activities may also be reactive in nature. Companies may start recruiting for certain technological capabilities only once these have already proven strategically important in the market. Prior research highlights that labor demand signals – particularly in technology-intensive contexts – often reflect a combination of anticipatory and responsive organizational behavior (Carnevale et al., 2014; Hershbein & Kahn, 2018). But rather than contradicting their value for foresight, this dual role of job postings strengthens their relevance as an anticipatory data source. Reactive job postings indicate that a technology has reached a level of maturity and organizational salience that necessitates dedicated human capital, whereas proactive job postings reflect early experimentation and capability-building (Bakhshi et al., 2017). In both cases, recruitment behavior provides timely and resource-backed evidence of technological importance within firms, complementing publication- or patent-based indicators that capture earlier stages of the innovation lifecycle but are less indicative of organizational commitment and market-driven relevance.

Despite this potential, job postings are not yet fully established in the foresight discipline. Most studies using this data source focus on the identification of future skills required in specific countries, technology fields, or job domains. For example, Brasse et al. (2024) analyze job advertisements to identify future skills for the manufacturing industry in Baden-Württemberg, Germany, while Firpo et al. (2021) reveal a skills mismatch in the labor market of Tunisia and highlight the demand for specific digital competencies based on online job ads. The seminal study by Goldfarb et al. (2023), which uses online job postings to assess the potential of different emerging technologies to become GPTs, illustrates that even the metadata of job postings can be leveraged for foresight purposes. In their study, the authors analyze the North American Industry Classification System (NAICS) codes associated with job postings for the various emerging technologies to derive their *widespread use* and *innovation in application industries* as part of the GPT assessment (Goldfarb et al., 2023, p. 4). This approach to measuring cross-industry robustness, combined with the text mining techniques described in the following chapter, forms the basis for our own identification and evaluation of priority signals for future-relevant technologies for Switzerland.

3. Research methodology

3.1 Data retrieval and preparation

Next to the brief literature review of the theoretical background of technology trend analysis in Switzerland, its utilized data sources and methods, and the analysis of job postings data in general, our paper presents a data-driven trend study on priority signals for future-relevant technologies for Switzerland based on job postings analysis. For this purpose, we acquired an extensive set of online job postings from the commercial data provider LinkUp, which is updated daily and sourced directly from employer websites worldwide. The data provider has indexed 315 million jobs from 80,000 companies across 195 countries (LinkUp, 2026). Both numerical and textual data are available in different file types, which can be merged depending on the focus of the analysis. For our analysis, we utilized the job record files, the job description files, as well as the company reference files. Each job posting is assigned an individual job hash that serves as the unique identifier for merging the different files and for removing duplicates. Table 2 summarizes the contents and structures of the file types and gives an overview of the data preparation steps.

File name	*Information contained*	*Relevance for analysis*
Job Records	hash, title, company_id, company_name, city, state, zip, country, created, last_checked, last_updated, delete_date, unmapped_location, url	hash: merge files, remove duplicates company_id: merge files (with company reference files) country: filter by CHE created: filter by analysis period delete_date: exclude inactive records
Descriptions	job_hash, description	job_hash: merge files, remove duplicates description: basis for text mining
Company PIT Reference	company_id, start_date, end_date, company_name, company_url, lei, open_perm_id, naics_code	company_id: merge files end_date: exclude inactive references naics_code: basis for industry analysis

Table 2: Overview of LinkUp data files relevant for the analysis

3.2 Two-phase text mining approach

The cleansed data set of 1,079,079 job postings from Switzerland that were online between 1 September and 31 December 2024, forms the basis for our two-phase text mining analysis. In the first phase of the analysis, we use Python-based keyword analysis to automatically scan the job description texts for the co-occurrence of future-related terms and technology topics. In the second phase, we extract specific technologies mentioned in the relevant job descriptions by applying both a NER in Python and a ChatGPT-assisted technology identification approach. To illustrate how these steps operate on the original data, Figure 1 presents a representative, fully anonymized excerpt of a job posting from our data set. The example shows how future-related and technology-related terms trigger inclusion in the first analysis phase and how specific technologies can subsequently be detected in the second phase, with the relevant segments highlighted accordingly.

hash	98a54ff9f7634bc9be6ae450795244e5
title	**Technology** Strategy Consultant (all genders)
description (excerpt)	As a Strategy Consultant, you will work with us to develop strategies for a smarter, digital ***future*** and use your expertise and innovative ideas to convince potential clients to work with us. You will work closely with managers and our interdisciplinary teams to develop an agile operating model. Together, you will design integration/carve-out strategies as part of an M&A process, analyse IT cost optimisation potential using current benchmarks and design industry-specific **cloud** strategies to develop new business models. Based on sound qualitative and quantitative analyses, you will develop new solutions, taking expert and careful account of disruptive ***trends*** (e.g., **blockchain**, **artificial intelligence**, **IoT**).
company_id	1425
company_name	Anonymized
naics_code	541519
city	Zürich
state	Zürich
zip	8000
country	CHE
created	01.12.2024 04:09:00
last_checked	01.12.2024 04:09:00
last_updated	N/A
delete_date	N/A
unmapped_location	FALSE
url	Anonymized

Figure 1: Anonymized excerpt from a sample job posting from the original data set

3.3 Future-term filtering logic

The use of future-related terms in our first analysis phase serves to identify job postings that explicitly reference technologies in a forward-looking or strategic context. Without such a filter, the analysis would include a substantial number of job postings in which technologies are mentioned only incidentally, operationally, or without any strategic relevance (e.g., routine IT support, maintenance, or generic software use). Prior studies emphasize that distinguishing between strategic and operational technological skills is essential, as only the former provide meaningful insights into emerging innovation trajectories (Bakhshi et al., 2017; Carnevale et al., 2014). By requiring the co-occurrence of future-oriented terminology and technology-related terms, our approach intentionally narrows the focus to job postings in which firms articulate technological change, capability expansion, or innovation intentions. We acknowledge that this introduces a controlled sampling bias. However, this bias is theoretically motivated and strengthens the validity of our foresight perspective. Including all job postings that mention a technology – even if the reference is purely operational – would risk overwhelming weak signals with contextually irrelevant noise, thereby decreasing the precision of the resulting trend insights. Our analysis approach therefore follows established principles in text mining-based foresight, where identifying future-relevant narratives is a prerequisite for extracting meaningful trend signals (Laurell & Sandstrom, 2022, p. 566; Rohrbeck et al., 2015, p. 4).

In this sense, the future-term filter does not exclude strategically important technologies, instead it improves the signal-to-noise ratio by focusing the analysis on job postings where companies actively articulate technological development, transformation, or innovation-related intentions. At the same time, our methodological design incorporates an explicit future orientation by restricting the analysis to technologies that are mentioned in direct conjunction with future-related terminology in job postings. This co-occurrence filter serves as a first-order proxy for future-oriented intent in firms' recruitment communication and helps to reduce purely reactive hiring signals. By focusing on job postings in which companies explicitly articulate technological change, capability expansion, or innovation intentions, this design choice strengthens the foresight orientation of the analysis and further improves the signal-to-noise ratio. Nevertheless, the use of future-oriented language cannot fully eliminate the possibility that some postings reflect responses to already emerging or established technological needs. Accordingly, while this filter enhances the forward-looking perspective of our approach, it does not replace ex-post validation of future technological relevance.

3.4 Quantitative analysis and robustness assessment

Following the above analysis steps, we conduct in-depth analyses and result visualizations in Excel to determine how the identified technologies are represented in job postings

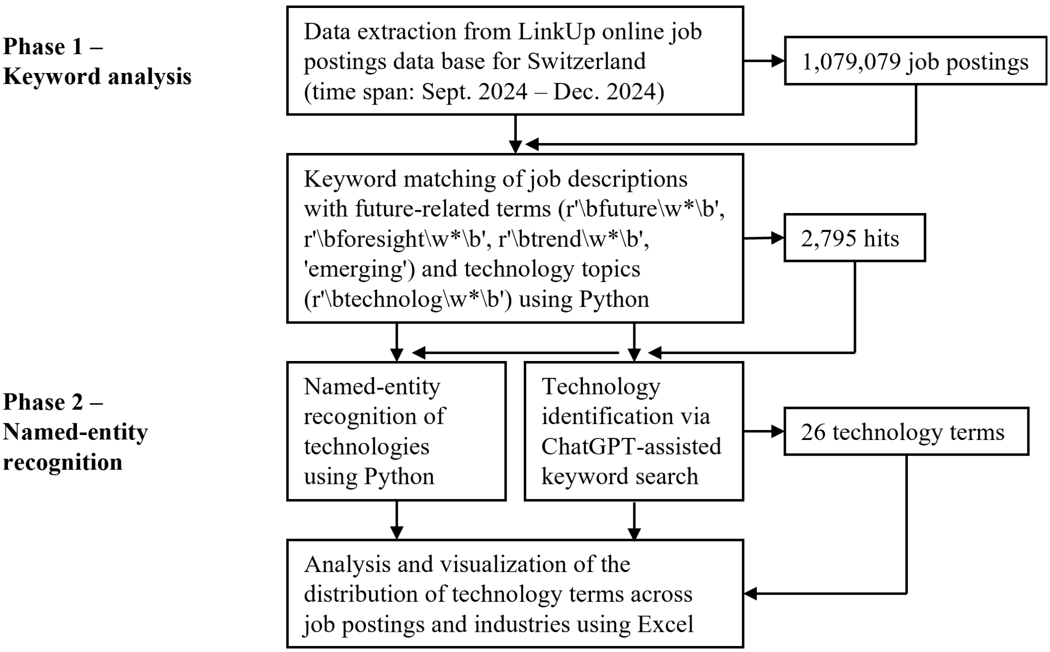


Figure 2: Flowchart of the two-phase research methodology

across industries. Finally, we calculate the entropy of this distribution to assess the technologies' potential futures robustness. Figure 2 visualizes the outlined approach in a methodology flowchart and shows how the analysis phases and individual steps are linked with each other.

4. Job postings analysis

4.1 Keyword-based filtering of job postings

Since automated keyword matching with a predefined directory is a proven methodology for analyzing job postings data (Brancatelli et al., 2020, p. 12; Brasse et al., 2024, p. 482), we also employed a keyword-based text mining approach in the first phase of our analysis. Rather than restricting the search to a fixed list of terms, we developed the following custom search query using logical operators to minimize bias in the detection of technologies:

future* OR foresight* OR trend* OR emerging AND technolog*

The initial data set of 1,079,079 job postings from September to December 2024 in Switzerland was available in .xlsx format after downloading the files from the LinkUp server. Without additional preprocessing, the monthly job description texts could be matched against the search query from above using the following Python code in Google Colab:

```
future_terms_patterns = [r'\bfuture\w*\b', r'\bforesight\w*\b',
r'\btrend\w*\b', 'emerging']
technology_term_pattern = r'\btechnolog\w*\b'
df['description'] = df['description'].fillna('')
def find_future_terms_with_technology(text):
      found_terms = []
      text_lower = text.lower()
      if re.search(technology_term_pattern, text_lower):
            for pattern in future_terms_patterns:
                  if re.search(pattern, text_lower):
                        found_terms.append(re.search(pattern,
                        text_lower).group())
      return found_terms
df['future_terms'] =
df['description'].apply(find_future_terms_with_technology)
filtered_df = df[df['future_terms'].str.len() > 0]
filtered_df['future_term'] = filtered_df['future_terms'].apply(lambda x:
x[0] if x else None)
output_df = filtered_df.copy()
output_df.to_excel('', index=False)
```

After this analysis step, the remaining data set was manually cleansed of duplicates and outdated or inactive job postings in Excel. Only job offers published and active in Switzerland between 01.09.2024 and 31.12.2024 were retained for the further analysis. In doing so, we did not impose any language restrictions on the description texts, as job advertisements in Switzerland are often multilingual due to the country's linguistic diversity, and as our defined keywords can appear across different languages. Nevertheless, given the English-language search string, the majority of job postings in the resulting data set were written in English, with fewer postings in German, French, and Italian. In total, 2,795 unique job postings were identified as simultaneously containing technology- and future-related terms in their job descriptions and qualifying for the second analysis phase.

4.2 Named entity recognition for technology extraction

Since the aim of the second analysis phase was to extract the specific technologies and innovation fields targeted in these job postings, we applied the following NER analysis to their job description texts using spaCy's standard model for natural language processing (NLP) in Python via Google Colab:

```
import spacy
nlp = spacy.load("en_core_web_sm")
descriptions = df['description'].dropna().tolist()
entities = []
for desc in descriptions:
      doc = nlp(desc)
      for ent in doc.ents:
            if ent.label_ in ["ORG", "PRODUCT", "TECHNOLOGY"]:
            entities.append(ent.text.lower())
from collections import Counter
entity_counts = Counter(entities)
import pandas as pd
tech_df = pd.DataFrame(entity_counts.most_common(),
columns=["Technology", "Count"])
tech_df.head(20)
tech_df.to_excel('', index=False)
```

4.3 LLM-assisted technology consolidation

To complement the NER-based extraction, we applied a ChatGPT-assisted technology identification step. Importantly, ChatGPT was not used to generate new data or to define technologies a priori, but rather to systematically filter and consolidate the large set of several thousand named entities extracted in the previous step. Specifically, the unfiltered list of named entities obtained through NER was provided to ChatGPT-4o with a structured prompt instructing the model to identify technologies and innovation fields relevant in a business and technology foresight context. The model was asked to exclude generic terms, company names, and non-technological entities and to return a consolidated list of distinct technology domains. To ensure transparency and reproducibility, the prompt used for the ChatGPT-assisted step is provided in Appendix A. While the use of an LLM introduces an element of algorithmic interpretation, this approach aligns with recent methodological advances in text-based foresight and labor market analysis, where LLMs are increasingly used as supplementary tools for extracting and consolidating structured concepts from unstructured text, supporting downstream analysis steps rather than replacing researcher-defined decisions (Li et al., 2025; Norouzi et al., 2025; Sioziou et al., 2024). Accordingly, this step served as a supportive classification and aggregation mechanism, enabling us to reduce noise and to derive a manageable and interpretable set of future-relevant technology topics for Switzerland from the NER results, which are presented below in alphabetical order along with their common abbreviations:

- Artificial Intelligence (AI)
- Automation
- Big Data
- Biotechnology
- Cybersecurity
- Digital Twins
- Fintech
- Internet of Things (IoT)
- Machine Learning (ML)
- Natural Language Processing (NLP)
- Robotics

4.4 Verification of LLM results

To assess the robustness of the LLM-assisted technology consolidation step, we conducted an additional verification using alternative LLMs. Specifically, the original list of named entities extracted through the NER procedure was processed using the same prompt with three additional models, namely ChatGPT Auto, Gemini 3, and Claude Sonnet 4.6. The resulting technology domains were then compared with the domains obtained in the original ChatGPT-4o-based analysis. The comparison showed that all technology and innovation fields included in our original analysis were consistently identified by the alternative models as well. While the additional models suggested some further candidate technologies and synonyms for existing domains, the core set of technology fields remained stable across models. This indicates that the technology topics shown above are not driven by a single model choice but reflect robust patterns in the underlying entity list. Addressing further potential prompt-induced bias in the LLM-assisted technology consolidation step, we additionally tested several alternative prompt formulations that differed in how technological relevance and exclusion criteria were specified. Across these prompt variants, the resulting technology domains showed a high degree of overlap with the domains obtained using the original prompt formulation. In particular, all technology and innovation fields shown above were consistently identified across the prompt variants. Differences between prompts were limited to minor variations in terminology or additional candidate technologies suggested by some prompts. However, all identified technology domains were manually reviewed and validated by the authors to ensure conceptual coherence and analytical relevance before inclusion in the final analysis. Overall, these results indicate that the technology consolidation step is robust to moderate variations in prompt wording and model choice.

4.5 Recall-oriented technology screening and final data set construction

To further increase the completeness of the technology identification, we applied an additional complementary screening step using ChatGPT-4o. This step was not intended to independently define or classify emerging technologies but to flag potentially relevant technology-related concepts that may not have been consistently captured by the spaCy standard NER model due to linguistic variation, context dependence, or domain-specific phrasing. For this purpose, ChatGPT-4o was prompted to support a recall-oriented screening of the job description texts of all 2,795 postings identified in the first analysis phase and to highlight technology-related terms and innovation fields mentioned therein. The model was explicitly instructed to operate in a supportive, recall-oriented manner, returning candidate technologies without performing any ranking or evaluative judgement. To ensure transparency and reproducibility, the exact prompt used for this recall-oriented screening step is provided in Appendix B. All suggested concepts were subsequently manually reviewed, consolidated, and validated by the authors and cross-checked against the NER-based results. Through this complementary screening, ChatGPT-4o flagged several additional technology domains that were underrepresented or not consistently detected in the initial NER output. After removing overlaps with previously identified technologies and excluding concepts that did not meet our analytical criteria (e.g., overly broad terms such as data science), the following technology domains were added to the final list of future-relevant technology topics for Switzerland:

- 5G
- Augmented Reality (AR)
- Blockchain
- Cloud Computing
- Cryptography
- Drones
- Nanotechnology
- Smart Devices
- Virtual Reality (VR)

As this step was designed to increase recall rather than to determine the final set of technologies, minor variations in extracted candidate terms do not affect the final analysis, which is based on manually validated and consolidated technology domains. Importantly, the ChatGPT-assisted steps described did not determine whether a technology is emerging or future-relevant. Instead, the identification of future-relevant technologies and innovation fields in our study is based on the co-occurrence of technology-related terms with future-oriented terminologies in job postings, followed by an assessment of cross-industry dispersion using an entropy-based measure. ChatGPT was used solely to support the consolidation and recall of technology-related concepts extracted via NER, thereby reducing noise and linguistic variation. All decisions regarding which technology domains are included in the final analysis were made by the authors based on predefined criteria. Consequently, the role of ChatGPT is supportive rather than decision-making and does not define the core construct of future relevance.

4.6 Quantitative analysis and entropy-based robustness assessment

After successfully identifying the above technologies and innovation fields as co-occurring with future-related terms in Swiss job postings using a combination of query analysis, NER, and ChatGPT-assisted technology extraction, we proceeded with a two-step quantitative hit evaluation in Excel. First, we conducted a descriptive frequency analysis to assess how often each technology appeared in the job description texts. Using conditional Excel formulas (e.g., IF, SEARCH, ISNUMBER, SUM, and IFERROR), we marked which job postings mentioned which technologies and counted the total number of occurrences per technology or innovation field. Second, we performed an industry-level comparison by leveraging the six-digit NAICS codes assigned to each job posting. These were aggregated at the two-digit level to determine how frequently each technology or innovation field appeared across different industries. When interpreting industry-level job postings frequency, it is important to acknowledge that industries differ substantially in size, employment levels, and overall hiring intensity. Larger industries may naturally generate more job postings, which could influence the absolute frequency counts of technology mentions. To address this structural effect, our analysis does not only rely on absolute frequencies alone but focuses on the distribution of future- and technology-related job postings across industries, operationalized through an entropy-based measure. Entropy captures how evenly the technology mentions are spread across industries and is therefore largely independent of the absolute industry size. A technology that appears across many industries – even if each industry contributes relatively few job postings – will yield a higher entropy value than a technology concentrated in a single large industry. By emphasizing dispersion rather than volume, our approach mitigates size-related bias and aligns with prior labor market-based foresight research that assesses cross-industry relevance instead of raw hiring intensity (Goldfarb et al., 2023, p. 2). Consequently, our robustness assessment reflects cross-industry technological relevance rather than the dominance of large industries in the labor market.

Our outlined approach was inspired by Goldfarb et al. (2023), who used Gini coefficients to evaluate the distribution of enabling technologies in job postings. In their study, the authors calculated Gini values across industry sectors to assess both the *widespread use* of a technology (based on all job postings) as well as its *innovation in application industries* (based on research-related job postings). Similar to the Gini coefficient, entropy also serves as a measure of dispersion or concentration within a distribution. To calculate the entropy of technology occurrence across industries in our data set, we applied the following formula:

$$H = -\sum_{i=1}^{n} p_i * \log_2(p_i)$$

where p_i denotes the proportion of hits in industry i relative to the total number of hits for a given technology field, and n represents the total number of industries included in our analysis. The entropy value H reaches its maximum, $\log_2(n)$, when the distribution of hits is perfectly uniform, indicating equal representation of a technology field across all industries. Based on the entropy values calculated for each technology or innovation field, we were finally able to draw data-driven conclusions regarding the cross-industry relevance and potential futures robustness of our future-relevant technologies for Switzerland. These insights, along with the results of the preceding analysis steps, are presented in the following chapter.

5. Results and discussion

The descriptive evaluation of job posting hits per innovation field provides a clear indication of which technologies are most frequently mentioned in connection with future-related terms in our data set. Artificial intelligence – along with its common abbreviation, AI – generates by far the most keyword matching hits, followed by automation, machine learning (and its abbreviation ML), cybersecurity, and robotics. Other innovation fields such as drones, cryptography, smart devices, or nanotechnology generate only a few hits. This does not necessarily imply that these technologies are not future-relevant, but it indicates that they are currently less established in everyday business practice or that they are highly specialized niche technologies which are subject to other modes of capability acquisition, such as outsourcing or strategic partnerships. Figure 3 shows for all technologies and innovation fields identified above in how many job postings from our data set they are mentioned in connection with future-related terms in the job description texts. For that, the frequency of a specific keyword within a single job posting is not considered, however, a single posting may be assigned to multiple innovation fields if it includes more than one relevant term. In addition to displaying the total number of matching job postings per technology across the full analysis period, Figure 3 also provides a breakdown of monthly occurrences, capturing potential seasonal dynamics in recruitment activity.

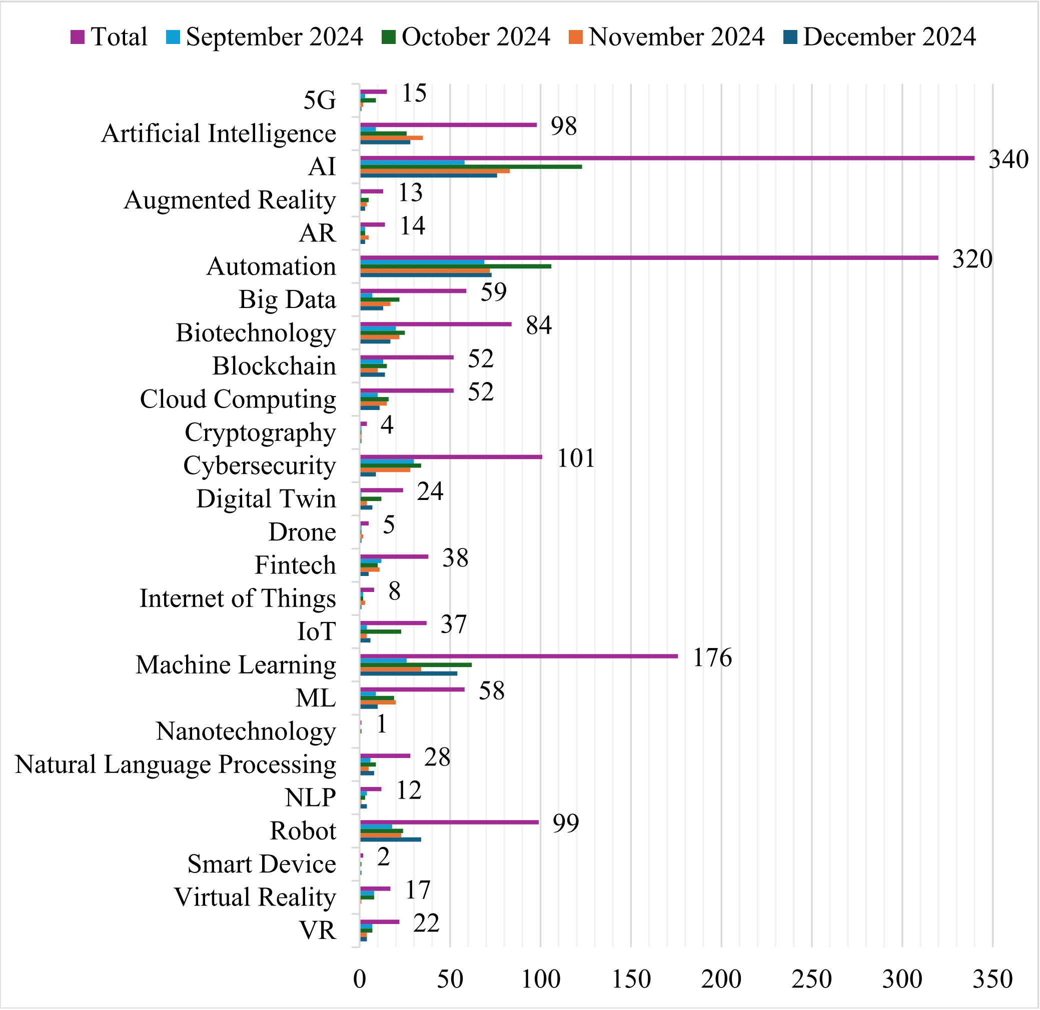
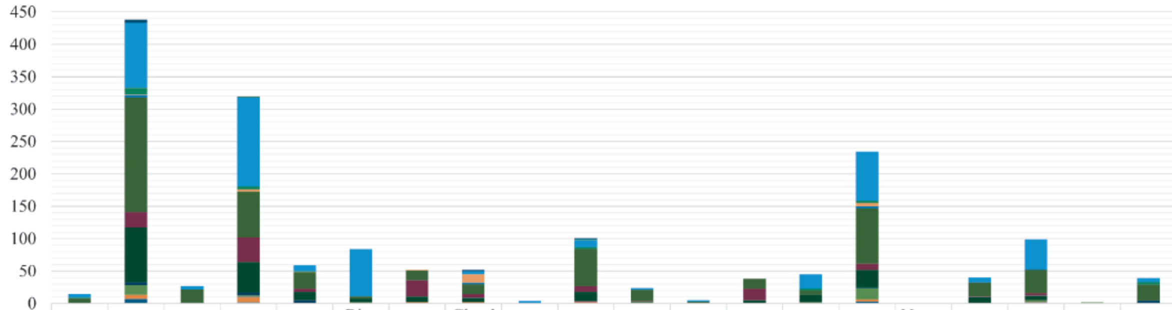


Figure 3: Descriptive evaluation of job posting hits per technology field

Regarding the technologies' general recruiting or adoption intensity, Figure 3 reveals some striking disparities. The combined mentions of artificial intelligence and its abbreviation, AI, add up to 438 hits, outpacing automation (320 hits) and machine learning, including ML (234 hits), by a significant margin. This dominance suggests that AI is not only a central topic in the current technological and public discourse but also actively drives recruitment efforts across Swiss companies. In contrast, technology fields such as cybersecurity, robotics, biotechnology, blockchain, and cloud computing (around 50–100 job posting hits) show only moderate levels of demand, pointing to their more selective, domain-specific adoption. The long tail of technologies and innovation fields (e.g., drones, cryptography, smart devices, and nanotechnology) illustrates that many emerging technologies have not yet reached widespread application in the Swiss labor market or are too specific to be hired for and are therefore rather outsourced. Interestingly, the monthly breakdown shows relatively stable demand for the leading technologies across the observation period. Except for the occasional peaks in October 2024, there are no strong seasonal spikes, implying that the predominance of these technologies is not driven by short-term campaign effects but by structural demand.

While Figure 3 provides a useful overview of which technologies and innovation fields from our analysis context are currently in high demand on the Swiss labor market, it does not offer insights into their cross-industry relevance or potential futures robustness. These aspects can only be assessed by examining how job postings referencing specific technologies are distributed across different industries, as illustrated in Figure 4.

To enhance the readability and clarity of the industry-specific analysis, technologies with commonly used abbreviations – such as AI or ML – are consolidated into a single technology category, and their respective hits from Figure 3 are combined accordingly. The industry labels shown in Figure 4 are based on NAICS, using the broader two-digit level rather than the more detailed six-digit classification typically available in the LinkUp data set. Also from Figure 4, we can easily determine the technology fields that are most frequently mentioned in connection with future-related terms in Swiss job postings from September to December 2024. The top three in descending order are AI, automation, and ML. With these findings and our identified technologies and innovation fields in general, we do not deviate from previous trend studies discussed in the theoretical background of this paper. We do, however, add contextual depth to the trend results, such as the industry-specific insights from Figure 4.



	5G	AI	AR	Automation	Big Data	Biotechnology	Blockchain	Cloud Computing	Cryptography	Cybersecurity	Digital Twin	Drone	Fintech	IoT	ML	Nanotechnology	NLP	Robot	Smart Device	VR
11 - Agriculture, Forestry, Fishing, and Hunting																				
21 - Mining, Quarrying, and Oil and Gas Extraction		5		1				2		2										
22 - Utilities				1						1										
23 - Construction																				
31-33 - Manufacturing	6	100	5	137	9	73		5	3	11	3	2		22	75		7	46		6
42 - Wholesale Trade	1	10		5	1					3				3	4					4
44-45 - Retail Trade		1		3	1		1	13							5					
48-49 - Transportation and Warehousing		4						2							3		1	1		
51 - Information	7	177	22	71	25	4	15	15	1	57	17	3	15	7	86		21	36		24
52 - Finance and Insurance		23		38	5		25	6		9	1		18		9		1	4		
53 - Real Estate and Rental Leasing																				
54 - Professional, Scientific, and Technical Services		86		47	13	5	9	7		15	1		4	11	27		9	7		1
55 - Mangement of Companies and Enterprises																				
56 - Administrative Support and Waste Management		4		5	4										1					4
61 - Educational Services	1	15		2		1					2			1	18	1		3	2	
62 - Health Care and Social Assistance				1						1				1				2		
71 - Arts, Entertainment, and Recreation																				
72 - Accommodation and Food Services																				
81 - Other Services (except Public Administration)		6		7			2	1		2			1		3					
92 - Public Administration		7		2	1	1		1							3		1			

Figure 4: Distribution of job posting hits per technology field across industries

A first look at the distribution of the job posting hits across industries reveals that especially in the top three technology fields, the hits extend across many sectors. The same impression applies to cloud computing and cybersecurity but not to biotechnology, blockchain, or NLP. Unsurprisingly, technology fields with only a few total hits, such as cryptography, drones, or smart devices, do not show a broad distribution of hits across industries, depicting them as less robust in our foresight context. Definitive statements about the dispersion of the job posting hits – and thus the potential futures robustness of individual technologies – can only be drawn after calculating the entropy for each innovation field. Table 3 presents the results of these calculations based on the previously defined formula, along with a corresponding robustness rating ranging from low to high.

Technology field	*Entropy score*	*Robustness rating*
5G	1.56	Medium
Artificial Intelligence (AI)	2.39	High
Augmented Reality (AR)	0.69	Low
Automation	2.32	High
Big data	2.28	Medium
Biotechnology	0.78	Low
Blockchain	1.75	Medium
Cloud Computing	2.67	High
Cryptography	0.81	Low
Cybersecurity	2.04	Medium
Digital Twin	1.41	Low
Drone	0.97	Low
Fintech	1.52	Medium
Internet of Things (IoT)	1.92	Medium
Machine Learning (ML)	2.38	High
Nanotechnology	0	Low
Natural Language Processing (NLP)	1.81	Medium
Robot	1.84	Medium
Smart Device	0	Low
Virtual Reality (VR)	1.66	Medium

Table 3: Entropy of job posting hits distribution per technology field including robustness rating

Given that the maximum possible entropy for the 20 industries under consideration is

$$H_{max} = \log_2(20) \approx 4.32$$

and the highest observed entropy score in our data is 2.67 for cloud computing, the robustness ratings must be defined in relation to the empirical data distribution. Accordingly, we classify robustness as high for entropy scores ≥ 2.3, medium for scores between 1.5 and 2.29, and low for scores < 1.5.

As shown in Table 3, the technologies and innovation fields with the highest entropy scores in our analysis are cloud computing, AI, ML, and automation. This indicates that job postings referencing these technologies are spread across a broad range of industries, suggesting the highest cross-industry relevance for these innovation topics within the scope of our study. For AI, ML, and automation, the high entropy scores and corresponding robustness ratings could be expected, given their overall high number of job posting hits. In contrast, cloud computing ranks only mid-range in terms of total job posting hits, yet it achieves the highest entropy score and indicates the broadest cross-industry relevance among all innovation fields in our analysis. The moderate number of job posting hits suggests that cloud computing currently lacks recruitment momentum compared to AI, automation, and ML – either because it is not yet fully established in business practice or because companies perceive less need to hire specialized staff in this area. Nevertheless, its broad cross-industry relevance indicates that it is of strategic interest across all industries examined. From a technology foresight perspective, these findings highlight the importance of closely monitoring developments in the cloud computing field and encourage further trend studies on this innovation topic using diverse data sources and applying complementary foresight methods. Just below the threshold for a high robustness rating are big data and cybersecurity, whose job posting hits show a notable concentration in a limited number of industries – especially in the Information industry and the Professional, Scientific, and Technical Services sector in the case of big data, and in the Information industry in the case of cybersecurity.

An entropy value of zero occurs when all job posting hits for a technology or innovation field stem from a single industry, as is the case with nanotechnology and smart devices. For these and other innovation fields with low robustness ratings in Table 3, we find little to no cross-industry relevance within our analysis and argue that also their futures potential may remain confined to the associated industries from Figure 4.

In this context, it is important to note that our robustness criterion is intentionally defined in terms of cross-industry relevance. As a result, technologies that may be indispensable for the future of a single industry but remain highly specialized are not prioritized as robust within our analytical framework. Such industry-specific technologies may be critical for sectoral competitiveness and long-term viability, yet they do not exhibit the cross-sectoral diffusion that is central to our robustness concept. Accordingly, our findings should be interpreted as identifying technologies and innovation fields with broad, economy-wide future relevance signals, rather than technologies that are future-critical within individual industries.

In relation to our research question, the results of our job postings analysis can be summarized in three key findings: First, we successfully identified twenty technology and innovation fields that are frequently mentioned in connection with future-related terms in recent job postings from Switzerland. Second, we provided an overview of the industries that are actively recruiting for these fields. Third, we conducted a futures robustness assessment for the identified technologies and innovation fields, based on a statistical evaluation of their cross-industry relevance. Referring back to the definition of robust technologies within the context of strategic foresight and our analysis, we conclude that cloud computing, AI, ML, and automation emerge as the most relevant innovation fields across all industries represented in our data. Accordingly, these technologies can be considered future-relevant for Switzerland in the context of our study. Nevertheless, our findings do not claim to identify technologies that are inherently future-relevant in a deterministic sense. Rather, they reveal current technological priorities and capability signals across Swiss industries based on firms' articulated demand for future-oriented skills. By analyzing these priorities across industries and assessing their dispersion, our approach provides an indicator-based assessment of technologies that are robustly positioned across the Swiss economy, which is a central concern in business-oriented foresight research.

Overall, our findings align with those of previous trend studies for Switzerland, which also highlight digital technologies as further emerging and highly relevant for the Swiss economy (Deloitte, 2021; Tsesmelis et al., 2022; Niggli & Rutzer, 2023; Swiss Academy of Engineering Sciences SATW, 2023). In contrast to these studies, however, our findings are derived from a purely quantitative data analysis and reflect the early-stage business practice perspective of companies engaging with emerging technologies and innovation fields, free from expert opinion bias. Furthermore, the cross-industry relevance and resulting futures potential of cloud computing for Switzerland have, to our knowledge, not been highlighted to this extent in previous research. With these findings and our proposed analytical approach, we contribute to the scientific foresight discourse by presenting a data-driven trend study for Switzerland and demonstrating the feasibility of using online job postings data for this purpose. In addition to foresight scholars and trend researchers, also business practitioners from various fields can gain insights into future-relevant technologies for Switzerland as well as into the quantitative utilization of job postings data based on our study. This includes technology and innovation managers, foresight professionals, and human resources specialists, highlighting not only the academic but also the practical relevance of our research.

6. Limitations and future research

Our study adopts a novel approach by analyzing online job postings from Switzerland to identify priority signals for future-relevant technologies for the Swiss economy. Specifically, we examine the co-occurrence of technologies and future-related terms in job description texts and assess cross-industry relevance, using a combination of keyword analysis, NER, and entropy-based evaluation. As one of the first trend studies to test this method combination in a technology foresight context by applying and expanding previous job posting analysis efforts from different application fields, our work is naturally subject to certain limitations.

One of these limitations is the relatively short analysis period of four months. A longer observation window would allow for more detailed insights into shifts in demand for future-relevant technologies and facilitate the monitoring of newly emerging innovation topics over time. Another limitation concerns the evaluation of the NER results, which we conducted using a ChatGPT-based prompt. This step introduces an additional layer of algorithmic interpretation, as LLMs may apply implicit classification patterns based on their training data. Recent research highlights that outputs of LLMs may vary across models and prompt formulations (Camuffo et al., 2026). Although we conducted additional robustness checks using alternative models and prompt variations and manually validated the resulting technology and innovation domains, some degree of model-dependent interpretation cannot be fully excluded. Accordingly, while the ChatGPT-assisted step was used solely to support the consolidation of NER results and not to generate or rank technologies, full reproducibility cannot be guaranteed. Future research could compare LLM-assisted extraction with manual expert coding or alternative NLP-based classification approaches.

Further limitations arise in the industry-level analysis. These include the restriction to two-digit NAICS codes, which limits sectoral granularity, and the exclusive focus on hit frequencies without deeper insights into the companies posting the jobs or the occupational groups associated with them. Additionally, we acknowledge that differences in industry sizes and employment structures may influence the observed number of hit-generating job postings. While our entropy-based approach reduces size-related effects by focusing on cross-industry dispersion rather than absolute frequencies, future research could further normalize job postings data using industry-level employment or full-time equivalent (FTE) statistics to refine robustness assessments. Consequently, our approach also does not capture industry-specific technologies whose future importance may be high within a single sector but limited in cross-industry scope. Such technologies may be critical for sectoral competitiveness and long-term viability, yet they fall outside the scope of our robustness concept, which is intentionally oriented toward identifying technologies with broad, economy-wide future relevance signals.

Another limitation of our approach relates to the distinction between internal hiring and external sourcing of technological capabilities. For certain highly specialized or niche technologies, firms may deliberately refrain from recruiting dedicated in-house staff and instead rely on external service providers, consultants, or technology partners. As a result, these technologies may appear never or rarely in job postings, despite being strategically important for specific firms or industries. This sourcing behavior is particularly relevant for technologies that require rare expertise, exhibit high fixed costs, or are only intermittently needed. Consequently, a low number of mentions in job postings does not necessarily imply low strategic relevance but may reflect alternative organizational strategies for accessing technological capabilities.

We also acknowledge that job postings may capture both proactive and reactive recruiting activities. While they can reflect forward-looking skill requirements and anticipated capability needs, they may equally represent reactive hiring responses to already emerging or established technological demands. As a result, our approach cannot fully disentangle future-oriented technology anticipation from responses to manifested skill gaps, nor can it empirically verify to what extent the identified technology signals anticipate future technological developments as opposed to reflecting current labor market needs. This limitation is inherent to labor market-based foresight approaches and underscores that our findings should be interpreted as indicator-based priority signals, rather than as validated predictions of future technological dominance. Nevertheless, both proactive and reactive recruitment activities indicate organizational recognition of technological importance and therefore provide valuable foresight-relevant signals. Future research could address this limitation by combining job postings data with longitudinal innovation indicators or ex-post validation analyses.

Another limitation of our approach is that the use of future-related terminology as a filtering criterion may exclude job postings that reference strategically relevant technologies without framing them explicitly in a future-oriented context. This constitutes a deliberate, theoretically motivated bias intended to distinguish strategic technological signals from routine operational references and to mitigate the aforementioned limitation. Future research could relax or vary this filtering requirement to examine how different levels of future-orientation affect the identification of technology trends.

Looking ahead, we also encourage future research to build upon our proposed approach by incorporating additional analysis steps that enable a more fine-grained examination of technologies and by applying the methodology to other national or regional contexts. For forthcoming trend studies and foresight research in general, we recommend fully acknowledging the potential of job postings data as a valuable foresight data source and continuing to enhance existing analysis methods or develop new ones. Beyond these methodology-related recommendations, we also propose comparing the trend insights derived from job postings with those obtained from other semi-structured data sources, particularly scientific publications and patents. Future research could investigate whether these data sources reveal overlapping or distinct thematic trends and how the temporal dynamics of trend emergence differ across them. In this context, it would be especially valuable to explore potential time lags between the different data sources, shedding light on how trend topics evolve with respect to their maturity and position within the technology lifecycle.

Finally, we encourage future research to examine the relationship between data-driven foresight, innovation efficiency, and firm performance. In particular, it would be worthwhile to investigate whether and how a company's financial and innovation-related performance is linked to its recruitment behavior concerning emerging technology domains or innovation fields, and whether firms that hire experts in emerging fields at an early stage achieve superior performance.

Appendix

Appendix A: Prompt used for the ChatGPT-assisted technology consolidation of NER results

The following prompt was used to support the identification and consolidation of technology-related concepts mentioned in the unfiltered NER output derived from job description texts:

> *"You are provided with a list of named entities extracted from job descriptions using a Named Entity Recognition (NER) model.*
> *Please identify and extract only technology and innovation fields relevant in a business and technology foresight context.*
> *Exclude company names, job titles, software tools with purely operational relevance, and generic terms.*
> *Consolidate closely related concepts under a common technology domain (e.g., "AI" and "Artificial Intelligence").*
> *Return a concise list of distinct technology and innovation fields.*
> *Do not rank, evaluate, or assess the future importance of the identified technologies."*

Appendix B: Prompt used for the ChatGPT-assisted technology screening of job descriptions

The following prompt was used to support the identification of additional technology-related concepts directly from job description texts in a recall-oriented manner:

> *"You are provided with job description texts that have already been filtered to include both future-related and technology-related terminology.*
> *Your task is to identify and extract any explicitly mentioned technology-related concepts, innovation fields, or technological domains.*
> *Include only technologies that are directly mentioned in the text.*
> *Exclude company names, job titles, soft skills, generic business or management terms.*
> *Return a list of candidate technology and innovation fields mentioned in the text.*
> *Do not rank, evaluate, or assess the importance of the technologies and do not infer technologies that are not explicitly mentioned in the text."*

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Design of compensation contracts and pay–performance sensitivity; say-on-pay and shareholder engagement; non-financial performance metrics and ESG-linked pay; managerial short-termism, risk-taking, and classic agency conflicts between managers and shareholders.

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Timeline

Submission of contributions	October 1, 2026
Feedback on initial submission	December 1, 2026
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Second feedback on revised papers based on reviews	March 1, 2027
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