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Continuous Learning and Internal Career Progression: A Quantitative Comparison of Formal, Informal, and Digital Training on Employee Advancement

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ABSTRACT

This master's thesis is dedicated to the quantitative investigation of employee career advancement in Russian organizations in response to formal, informal, and digital training. The relevance of the study is driven by current demands for workforce qualifications in a transitional era, increasing competition for talented employees, and the need for strategic human capital development. Despite the widespread implementation of corporate training programs, the comparative analysis of their success in terms of employees' career dynamics remains insufficiently explored.

The object of the study comprises processes of vertical employee mobility, while the subject is the specific effects of the three types of training on qualification enhancement and internal career trajectories with consideration of organizational and contextual factors.

A retrospective longitudinal design is employed, utilizing large secondary data sets and modern econometric methods. The primary methods include regression models with heteroskedasticity correction, least absolute deviation method, and quantile regression, allowing the detection of heterogeneous impacts of different training types on career advancement and the assessment of distributional effects among employees with varying growth potential. Restrictions are related to incomplete data, limited generalizability of results across sectors or regions, and the indirect nature of international comparisons due to the lack of microdata for Germany.

The academic novelty of this work lies in the quantitative comparison of the effects of the three training types, the development of an integrative model for assessing career growth considering organizational characteristics, and the identification of synergistic effects of combined educational programs. This is the first time an empirical evaluation of the relative contribution of each learning format is conducted using methods sensitive to distributional heterogeneity.

The practical significance of the study is expressed through specific recommendations for HR managers and strategists, emphasizing the strengthening of digital platforms as core tools for corporate learning and the implementation of analytical systems to evaluate program returns. The results confirm that digital training exerts the strongest and most sustainable positive influence on employees' vertical mobility, while combined formats generate a synergistic effect, enhancing the overall efficiency of investments in personnel development.

The paper expands both theoretical and practical understanding of the role of continuous learning in strategic human capital management. Organizations can use these insights to improve employee development quality and optimize training programs, thereby strengthening competitive advantages in a transformational environment.

KURZFASSUNG

Diese Masterarbeit widmet sich der quantitativen Untersuchung des Karrierefortschritts von Mitarbeitern in russischen Organisationen als Reaktion auf formelles, non-formelles und digitales Lernen. Die Relevanz der Studie ergibt sich aus den aktuellen Anforderungen an die Qualifikation der Arbeitskräfte in einer Übergangsphase, dem zunehmenden Wettbewerb um talentierte Mitarbeiter und dem Bedarf an strategischer Entwicklung des Humankapitals. Trotz der weit verbreiteten Implementierung von unternehmensinternen Weiterbildungsprogrammen bleibt die vergleichende Analyse ihrer Wirksamkeit in Bezug auf die Karriereentwicklung der Mitarbeiter bislang unzureichend erforscht.

Der Untersuchungsgegenstand umfasst Prozesse der vertikalen Mitarbeiterbewegung, während sich das Untersuchungsobjekt auf die spezifischen Effekte der drei Lernformen auf Kompetenzsteigerung und interne Karrierewege unter Berücksichtigung organisatorischer und kontextueller Faktoren konzentriert.

Es wurde ein retrospektives Längsschnittdesign angewendet, das große Sekundärdatensätze und moderne ökonometrische Methoden nutzt. Die wichtigsten Analysetechniken umfassen Regressionsmodelle mit Heteroskedastizitätskorrektur, das Verfahren der kleinsten absoluten Abweichungen und Quantilregression, wodurch heterogene Einflüsse der verschiedenen Lernformen auf den Karrierefortschritt festgestellt und Verteilungseffekte unter Mitarbeitern mit unterschiedlichem Wachstumspotenzial bewertet werden können. Die Einschränkungen ergeben sich aus unvollständigen Daten, der begrenzten Übertragbarkeit der Ergebnisse auf andere Sektoren oder Regionen sowie der indirekten Natur internationaler Vergleiche aufgrund fehlender Mikrodaten für Deutschland.

Die wissenschaftliche Neuheit der Arbeit liegt in der quantitativen Vergleichsanalyse der Effekte der drei Lernformen, der Entwicklung eines integrativen Modells zur Bewertung des Karrierewachstums unter Berücksichtigung organisatorischer Merkmale sowie der Identifikation synergistischer Effekte kombinierter Bildungsprogramme. Erstmals im russischen Kontext wird eine empirische Bewertung des relativen Beitrags jeder Lernform unter Verwendung methodisch verteilungssensitiver Ansätze durchgeführt.

Die praktische Relevanz der Studie zeigt sich in konkreten Empfehlungen für HR-Manager und Strategen, die die Stärkung digitaler Plattformen als Kerninstrumente des unternehmensinternen Lernens und die Implementierung analytischer Systeme zur Bewertung der Programmwirksamkeit betonen. Die Ergebnisse bestätigen, dass digitales Lernen den stärksten und nachhaltigsten positiven Einfluss auf die vertikale Mobilität von Mitarbeitern ausübt, während kombinierte Formate einen synergistischen Effekt erzeugen und die Gesamteffizienz von Investitionen in die Personalentwicklung erhöhen.

Die Arbeit erweitert das theoretische und praktische Verständnis der Rolle kontinuierlichen Lernens im strategischen Management von Humankapital. Organisationen können diese Erkenntnisse nutzen, um die Qualität der Mitarbeiterentwicklung zu verbessern und Weiterbildungsprogramme zu optimieren, wodurch Wettbewerbsvorteile in einem Transformationsumfeld gestärkt werden.

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INTRODUCTION

The relevance of this study is driven by the growing demands for employee qualifications in modern organizations. According to Decius et al. (2024), more than 70% of workers believe that various forms of professional instruction directly affect their employability and career prospects. As demonstrated by the meta-analysis by Cerasoli et al. (2018), informal learning explains up to 40% of variations in career progression through the development of professional capabilities and self-initiative. Digital learning is also gaining value: Castaño-Muñoz & Rodrigues (2021) found that participation in MOOCs increases promotion likelihood by 15–20%. At the same time, corporate formal training programs raise the probability of advancement to higher positions by 22% (McVicar et al., 2016). Consequently, comparing the returns of formal, informal, and digital training is pivotal for optimizing career strategies and promoting internal mobility among employees.

The degree of academic exploration of the topic reflects an escalating recognition of continuous learning as a foundation for career promotion in modern organizations (Drewery et al., 2020). Personnel engage in formal learning (structured programs and courses), informal learning (on-the-job experience, mentoring, peer knowledge sharing), and digital learning (online courses and e-learning platforms) to enhance their professional competencies (Manuti et al., 2015). These developmental activities support internal promotion and career advancement. Recent studies confirm that the majority of employees' skill growth and productivity improvements stem from learning by doing and informal learning (Cerasoli et al., 2018; Smet et al., 2022). Some papers even indicate that informal learning has a greater impact on human capital advancement than formal courses, reinforcing the importance of continuous development for career outcomes (De Grip, 2015; Kwon & Cho, 2020).

However, a clear gap remains in the literature concerning how different competence enhancement methods influence career progression within organizations. Previous studies have typically analyzed training in isolation focusing mainly on formal programs or continuous learning in general while paying less attention to comparisons with informal and digital learning (Manuti et al., 2015). Although on-the-job training is well-documented, its direct impact on internal promotion remains debatable. Some studies even suggest that formal training contributes minimally to career results (Pfeifer et al., 2013; Barrett & O'Connell, 2001).

Informal learning, which occurs much more frequently, is harder to quantify, and therefore often overlooked or only indirectly estimated (Cerasoli et al., 2018). As a result, many causal relationships between on-the-job informal training and career outcomes remain unclear. This research gap persists because informal learning achievements are less visible (e.g., lacking certification), which complicates their measurement and comparison (Smet et al., 2022). Further research is needed to clarify how informal learning translates into tangible career results, particularly within the individual organization.

Similarly, digital training is rapidly expanding through e-learning platforms, yet academic understanding of its effect on employees' internal mobility remains limited. Many organizations have embraced digital tools, but the question of what truly works is still debated; evidence on their effectiveness in workplace settings remains mixed or inconclusive (Brown, 2005; Bawazir et al., 2025). Comparative studies assessing whether digital training offers professional advantages equivalent to traditional training are scarce. Recent research highlights this gap: for instance, Decius et al. (2024) found that informal learning considerably increased internal mobility, while formal programs had minimal impact, and self-directed (often digital) competence building was associated primarily with external career opportunities. These findings suggest that different forms of training exert diverse impacts on career trajectories – a phenomenon that the existing literature has only begun to explore. Hence, there is no unified quantitative framework for evaluating the influence of formal, informal, and digital training on employees' internal career progression.

The aim of this master's thesis is to bridge this research gap by addressing questions related to both the overall impact of continuous learning and the specific influence of each training format on employees' internal career advancement.

To achieve this goal, the following **research tasks** have been defined:

1) Analyzing the theoretical foundations of continuous learning and its influence on internal career progression through formal, informal, and digital training methods.
2) Comparing the impact of different types of training on employee professional growth using empirical data and academic literature.
3) Examining organizational and contextual factors influencing internal promotion through company policies, managerial support, and access to learning resources.
4) Developing and applying an econometric model to quantitatively assess the influence of the three learning forms on promotion and test the proposed hypotheses.
5) Formulating practical conclusions and recommendations for optimizing training and career development programs, as well as proposing directions for future research on internal mobility.

Based on the identified gaps in the existing literature, this study addresses the following **research questions**:

RQ1: How does continuous learning (regardless of its format) influence employees' internal career trajectories within an organization?

RQ2: How do different types of training – formal, informal, and digital – vary in their effect on employees' internal promotion?

RQ1 examines the association between employees' engagement in continuous learning and internal career advancement, measured through promotion events and transitions into higher-level positions. Existing studies treat competence development as a driver of internal mobility, yet empirical evidence remains uneven across organizational settings. The present research tests this proposition with quantitative methods and links training participation to observed career moves inside the firm. The analysis clarifies whether training expenditure translates into a higher probability of advancement and, by extension, whether continuous learning correlates with measurable internal career outcomes.

RQ2 compares the effects of distinct training formats. This question addresses the lack of comparative data and aims to identify which type of learning – formal courses, informal on-the-job training, or digital training – most effectively fosters career growth. For instance, if informal learning demonstrates a significantly stronger effect on promotion than formal training, the focus of corporate training policies could be shifted with an emphasis on the value of on-the-job training. Analyzing digital training as an independent form of learning will allow for the assessment of its role in modern career development.

Object of the study is internal promotion and career advancement processes within organizations under the influence of different forms of training.

Subject of the study is the effect of formal, informal, and digital training on employee skill development and internal promotion, as well as the role of organizational and contextual factors in this process.

Academic novelty of the research is ensured by the following results:

1) A quantitative comparison of the effects of formal, informal, and digital training on employees' internal promotion – an aspect previously addressed only fragmentarily in scholarly research.
2) The paper incorporates organizational and contextual factors influencing training effectiveness and career progression, thereby broadening the understanding of internal mobility mechanisms.
3) An integrative model for assessing the influence of various training forms on promotion is developed, enabling identification of each type's relative contribution to employees' career progression.

Research methods. The study employs a quantitative approach using employee-level data on training participation and subsequent career outcomes. Based on a review of empirical literature, conceptual frameworks, and comparative analysis, a retrospective longitudinal design is developed to track employees' training participation and career progression over time. The primary analytical approach involves correlation and regression techniques, with efforts to identify causal relationships through control variables. The comparison covers three training forms: formal, informal, and digital.

Variables used:

1) Independent variables – participation in formal training, engagement in informal training, and use of digital training.
2) Dependent variable – proxy for career progression (binary).
3) Control variables – number of employees, average wage, industry, region, form of ownership, recruitment of university graduates, technical conditions, price dependency, share of labor costs, IT use, and year.

Data. To ensure representativeness, secondary analysis of large-scale datasets is employed. The main data sources include the NAFI database and questionnaires. These data enable a robust and generalizable assessment of the effects of different training forms on internal promotion.

Potential risks:

1) Limited data availability or incompleteness may affect result accuracy; therefore, multiple datasets are used for cross-validation.
2) Measuring informal training poses methodological challenges; it is assessed using validated instruments and survey-based indicators.
3) Limited generalizability across sectors or regions is mitigated through the inclusion of multi-sectoral and multi-regional data to enhance external validity.
4) Although the sampling methodology draws on German labor market studies, the comparison remains indirect and methodological, as lack direct empirical analysis with German microdata.
5) The findings remain limited by the survey-based biases, unobserved confounding, and the possibility of spurious correlations, which preclude definitive causal inferences and require cautious interpretation.

The structure of the thesis comprises several sections. The Introduction outlines the relevance of the topic, degree of its academic exploration, research aim and tasks, object and subject, academic novelty, applied methods, and overall structure. The Literature Review summarizes the theoretical foundations of professional training and career advancement, examining crucial directions and factors influencing employees' promotion. The Materials and Methods set out the research design and the procedures for hypothesis testing. The section also describes the analytical framework and the criteria applied to evaluate model performance and statistical reliability. The Results reports the core empirical estimates and documents the outcomes of data processing and model diagnostics. The Discussion interprets the assessed relationships and situates the findings within the relevant empirical literature, with attention to managerial implications that follow from the observed patterns. The Conclusion restates the main summary and emphasizes the contribution of the study, after which the paper provides recommendations for managerial practice. The thesis ends with the list of References and the Appendices, which contain supplementary materials and robustness outputs.

1. LITERATURE REVIEW

1.1. Theoretical Foundations of Continuous Learning and Career Development

The concept of continuous learning, framed as lifelong learning, entered academic and policy debate in the early twentieth century and later received a formal articulation in UNESCO reports, which presented learning as a lifelong process that reaches across social domains (Asundi & Karisiddappa, 2006). During the twenty-first century, lifelong development became a prominent theme in Europe, North America, and Oceania, because labour markets absorbed repeated shocks from globalization and digitalization and employers raised skill requirements (Evans et al., 2023; Le et al., 2023; Hirschi, 2018). Career trajectories now display weaker long-term security, while workers face recurrent reskilling demands in order to preserve employability and sustain productivity (De Vos et al., 2020). Economic research links growth to the accumulation and renewal of human capital, whereas psychological research emphasizes meaning, agency, and motivation within development decisions (Crane & Hartwell, 2018).

The literature on continuous learning and vocational training also connects professional development with the formation of expertise for entrepreneurial activity and inventive work. Experiential learning theory (Kolb, 2014) and andragogy (Knowles, 1970) help understand how vocational training cultivates creativity, adaptability, and entrepreneurial abilities. The relationship between continuous learning and entrepreneurial thinking demonstrates how continuous learning fosters risky yet strategically sound decisions and innovation. The application of game theory in the context of vocational training and entrepreneurship allows for an analysis of how the strategic decisions of governments, educational institutions, and entrepreneurs influence outcomes (Zuo et al., 2025).

Publication statistics exhibit a steady increase in research on the topics of Continuous Learning and Vocational Training, reflecting the growing academic interest and significance of these fields. Theoretical frameworks comprise experiential learning theory (Kolb, 2014), andragogy (Knowles, 1970), human capital theory (Becker, 2009), organizational learning (Argyris & Schön, 1997), and endogenous growth (Lucas, 1988; Romer, 1990), each of which supports the enhancement of professional competencies and adaptability. Economic and management theories demonstrate the strategic prominence of vocational training in building human capital that can drive innovation and sustainable growth. Within entrepreneurship, prospect theory (Kahneman & Tversky, 2013), real options (Dixit & Pindyck, 1994), perception of risk (Slovic, 1987), and radical innovation (Christensen, 2015) reveal how continuous learning builds the capacity for informed risk-taking and innovation activity.

Historical examples (such as the German dual vocational training system and Japanese retraining programs) illustrate the significance of lifelong training for economic sustainability and technological progress. International policy programs place digital literacy and adaptive competences at the center of vocational training agendas. The UN Sustainable Development Goals and the European Year of Skills illustrate this shift. Two gaps persist in the academic record. Firstly, empirical work concentrates on a limited set of countries, and secondly, the link between lifelong training and entrepreneurial risk-taking remains weakly specified. A game-theoretic framework offers a disciplined way to formalize strategic dependence among public authorities and education providers, while entrepreneurs face incentives that change with institutional design. The joint reading of theory, empirical measurement, and historical cases points to continuous learning as a channel through which entrepreneurial capacity and innovative activity expand (Zuo et al., 2025).

Recent research suggests that training should be viewed as transformational, aimed not only at gaining skills but also at developing the ability to apply them in new contexts (Frie et al., 2019).

However, definitions of continuous learning and lifelong development remain heterogeneous and often inapplicable in practice (Fouarge & Künn-Nelen, 2018). Contemporary authors note that development encompasses not only formal training but also informal and individual forms of growth throughout a career trajectory (Clardy, 2018; Jeong et al., 2018; Nijkamp et al., 2019). However, employees often perceive changes in the labor market as externally imposed and exhibit low activity in skills enhancement without intrinsic motivation (Grijpstra et al., 2019). To bridge this gap, researchers propose integrating economic and psychological perspectives into the overall concept of sustainable career, whereby organizations promote the lifelong development of employees through HR policies (Aust et al., 2020; Semeijn & Van der Heijden, 2021).

Lifelong development is traditionally viewed from an economic perspective as a tool for maintaining employment and productivity for the sake of public welfare (Council of the European Union, 2021). According to this viewpoint, it aims to prepare skilled workers for innovation and prevent talent shortages. The psychological perspective, in contrast, focuses on personal growth, adaptability, and the search for meaning in life, which enables individuals to realize their potential and achieve self-actualization (Weeks & Schaffert, 2019). Although EU policy strives to consider both economic and individual needs, it remains unclear how to reconcile them in practice (European Commission, 2018). Modern research links lifelong development with the concept of a sustainable career, where an employee's value is measured by their contribution to the organization, health, and happiness (De Vos et al., 2020). This career approach integrates economic and psychological perspectives to create a balance between the interests of the employer and the employee (Fugate et al., 2021; Van der Heijden et al., 2020). According to a new definition, continuous learning is the (pro)active enhancement of competencies throughout life, based on one's own interests and values, for the sake of a sustainable contribution to society, health, and happiness (Kuijpers et al., 2019). Accordingly, continuous learning should be understood as a dynamic process that requires dialogue between all participants and fosters a learning culture within organizations (Table 1).

Table 1: Components and Characteristics of the Continuous Learning Concept

Component	Characteristic	Purpose and Significance	Examples and Implementation Forms
1. Philosophical Basis	Learning as a continuous process throughout a person's life, grounded in the principles of humanism, self-development, and social responsibility.	Creating conditions for the harmonious development of individuals and society.	UNESCO's ideas of a learning society, 21st-century education concepts.
2. Historical Evolution	Emerged in the early 20th century; actively developed in the 1960s–1980s (Jacques Delors and Edgar Faure's reports, UNESCO).	Establishing the global understanding that education does not end after school or university.	Continuous education programs in Europe, OECD initiatives, UNESCO Global Report (1996).
3. Goals and Objectives	Adaptation to changes, development of critical thinking, enhancing competitiveness, and social inclusion.	Helping individuals remain resilient to changes and be active participants in society.	Retraining programs, soft skills development, civic education.
4. Forms of Learning	- Formal: schools, universities, academies.	Ensuring flexibility and accessibility of	Online courses (MOOCs),

	- Non-formal: trainings, courses, corporate learning. - Informal: self-education, experiential and peer learning.	education for all ages and social groups.	professional communities, self-training.
5. Technological Dimension	Use of digital technologies, the Internet, AI, and open educational resources.	Increasing accessibility and personalization of learning.	E-learning, mobile applications, digital libraries, platforms such as Coursera and edX.
6. Key Competencies	Ability to learn, critical and creative thinking, information literacy, communication skills, adaptability.	Developing flexible professionals capable of continuous growth.	Project-based learning, interdisciplinary approaches.
7. Socio-Institutional Support	Role of the state, employers, libraries, NPOs, and educational centers.	Creating conditions and infrastructure for the principle of learning everywhere and at all times.	National continuous learning strategies, corporate HR programs, educational hubs.
8. Outcomes and Effects	Development of human capital, personal self-realization, economic growth, and social cohesion.	Sustainable development of individuals and society.	Growth in digital literacy, increased employment, fostering a culture of self-education.

Source: compiled by the author based on literature review

Education begins with literacy but goes far beyond it, becoming a process of accumulating knowledge and skills necessary for life in a constantly changing society. Today's information- and technology-driven world requires people to continually update their expertise to keep pace with rapid change and remain competitive. In the face of information overload and technological revolution, people must be more than just knowledge holders, but active consumers of information, capable of seeking, evaluating, and using it effectively. This is why the concept of a learning society is emerging, where the whole environment – home, work, community – becomes a learning space (Kuijpers et al., 2025).

Continuous learning helps people not only adapt to changes but also develop a holistic personality, critical thinking, and social responsibility. In the modern world, education cannot be limited to a diploma – one must be able to learn and relearn independently throughout life. This concept encompasses both formal and informal training – from childhood to old age, from schooling to self-development at work and in everyday life.

With the development of information technology, new forms of training have emerged – distance and online learning – making expertise accessible regardless of place and time. Information literacy and computer awareness have become fundamental elements of successful learning and professional growth. Libraries and information centers provide access to knowledge and help people become continuous learners. They are becoming spaces where people not only gain information but also learn to engage with it critically and meaningfully (Creswell & Guetterman, 2018).

Modern career pathing theories help understand how people make profession choices, adapt to changes, and balance personal goals with labor market demands. Theoretical approaches have evolved from the linear and predictable models of the 20th century to the more dynamic, contextual, and nonlinear frameworks of the 21st century (Read, 2025).

Table 2: Main Career Development Theories

Theory	Main Ideas	Concepts / Stages	Practical Significance	Features
Trait and Factor Theory (Parsons, 1909)	Matching personal traits with job requirements	1. Self-analysis 2. Job exploration 3. Rational choice	Basis for career guidance; used in assessments of personal suitability for a job	Underestimates the influence of external environment and labor market changes
Holland's Typological Theory (Holland, 1959)	Satisfaction and success depend on the compatibility between personality type and work environment	6 types: RIASEC – Realistic, Investigative, Artistic, Social, Enterprising, Conventional	Used in career counseling and vocational guidance	Simplifies the complexity of human motivation and context
Super's Career Development Stages Theory (Super, 1957)	Career is a process that progresses through stages of life	Stages: Growth, Exploration, Establishment, Maintenance, Decline	Accounts for age-related and personal changes	Requires adaptation for modern nonlinear careers
Social Cognitive Career Theory (Lent, Brown & Hackett, 1994)	Career choice depends on self-efficacy and outcome expectations	Belief in one's abilities, goals, environmental influence	Applied in counseling; helps develop confidence and adaptive skills	Does not always account for random or unpredictable elements
Planned Happenstance Theory (Krumboltz, 2009)	Random events affect careers but can be leveraged	Qualities: curiosity, persistence, flexibility, optimism, risk-taking	Helps utilize opportunities and unexpected events	Reduces predictability in career planning
Chaos Theory of Careers (Pryor & Bright, 2011)	Career trajectories are nonlinear and influenced by multiple factors	Small decisions – big consequences (ripple effect)	Encourages adaptability, flexibility, and acceptance of uncertainty	Difficult to apply practically due to abstract nature
Integrative (Modern) Career Approach	Combines personal, social, and random aspects	Readiness for changes, self-development, network support	Develops sustainable and adaptive career strategies	Requires continuous learning and self-awareness

Source: compiled by the author based on Read (2025)

The current understanding of professional trajectories is shifting from the idea of stability to the concept of dynamism and self-learning. A combination of the Planned Happenstance Theory and Chaos Theory most accurately reflects the realities of the 21st-century labor market. As a result, career planning is becoming less about choosing a profession and more about ongoing personal growth in the face of volatility and uncertainty.

Global changes in the organization of work and rising employer expectations have increased personnel responsibility for their own advancement through formal, informal, and digital training (Owusu-Agyeman, 2024). Modern careers have become less predictable, and workers are increasingly taking responsibility for their professional growth and incorporating technology into their work activities (Haenggli & Hirschi, 2020; Poquet & De Laat, 2021). According to the World Economic Forum, by 2025, 85 million jobs could disappear, while approximately 97 million new ones will emerge, involving the interaction of people, machines, and algorithms (World Economic Forum, 2020). The evolution of technology and artificial intelligence is creating new demands on staff skills, making their adaptability a pivotal factor in professional resilience (Poquet & De Laat, 2021). Training opportunities and access to resources directly impact employees' willingness to expand their expertise and competencies throughout their lives. Furthermore, human capital advancement is linked to economic growth and the achievement of global sustainable development goals (Zhou et al., 2020). According to Owusu-Agyeman (2024), continuous learning is not simply an educational system, but a socio-personal process closely tied to human development. Universities are seen as driving countries' transition to a knowledge-based economy and innovative advancement (Koryakina et al., 2015).

There are several reasons why institutions of higher education should support employee professional growth through continuous learning approaches:

1) The first reason is the technologization of work, which requires the continuous improvement of digital skills.

2) The second reason is the need for universities to design professional programs that combine formal, informal, and digital learning (World Economic Forum, 2020).

3) The third reason is the role of higher education in socio-economic development through the generation and dissemination of knowledge (Naidoo, 2003).

4) The fourth reason is the obligation of universities to establish policies and practices that promote personnel development and preparation for the digital environment (Antonopoulou et al., 2021; Vallo Hult & Byström, 2022).

Education serves as a tool for national development and economic prosperity (McCowan, 2019; Valero & Van Reenen, 2019). The concept of continuous learning encompasses all forms of instruction, from formal to non-formal and informal, and extends throughout the person's entire life cycle (UIL, 2010). Current research underscores three areas: learning abilities, conceptual framework or policies, and factors influencing continuous learning (Thwe & Aniko, 2024). However, Regmi (2023) points out the limitations of the continuous learning concept: an emphasis on the psychology of learning with insufficient attention to social aspects and life context. From the perspective of human capital theory, education is an investment that increases productivity and provides economic benefits (Tan, 2014; Schugurensky & Myers, 2003). Despite criticism for excessive economism (Marginson, 2019; Robeyns, 2006), human capital theory emphasizes the consequence of education as a form of social and market investment. This ultimately necessitates viewing personnel professional growth as an integrated system of continuous learning that ensures the expansion of knowledge, competencies, and competitiveness (Nair & Bhandare, 2024).

The following employee training theories should also be emphasized:

1) Constructionist learning theory (Piaget, 1971; Vygotsky, 1978) views knowledge as created by learners through interactions with the environment and colleagues and defines worker professional growth as an iterative process rather than the accumulation of isolated competencies. The approach encourages employees to see themselves as continuous learners and to apply new strategies and technologies (Fosnot, 2016). The constructionist approach enhances reflexivity and participation in collaborative learning, which contributes to long-term professional development.

2) Transformative learning theory (Mezirow, 2000) explains how adult learners are able to modify their belief systems through critical reflection on assumptions, which is required to cultivate reflective professionals. The process of transformative learning begins with a disorienting dilemma, in which previously accepted beliefs are challenged, for example, when collaborating with colleagues from different cultural backgrounds. Learning reveals instrumental mastery of tasks and communicative understanding of actions, which develops the ability to critically reconsider goals and methods.

3) Self-directed learning theory (Knowles, 1975) describes a process in which learners independently identify needs, set goals, select resources, and evaluate educational outcomes, fostering autonomy and self-regulation. Integrating self-directed learning into employee training promotes long-term career growth, proactive knowledge acquisition, and self-reflection.

4) Social cognitive theory (Bandura, 1986) explains how professional attitudes are formed through observation, interaction with colleagues, and participation in an educational environment, which defines the role of self-efficacy in motivating continuous learning. Collaborative learning and a culture of professional interaction strengthen collective efficacy and instill a habit of perpetual professional improvement in personnel.

Employees' orientation toward continuous learning follows from a specific set of behavioral mechanisms. Motivation and self-determination arise primarily from intrinsic drivers, since interest and satisfaction sustain learning participation more reliably than bonus-linked incentives. When competence, and social relatedness receive regular reinforcement inside the firm, commitment to development initiatives strengthens, and participation in internal mobility programmes becomes more frequent. A learner with strong intrinsic motivation tends to approach innovation with confidence and keeps a reflective discipline in professional routines. Persistence and resilience shape learning trajectories when training demands intensify. Obstacles appear in advanced courses and in new tasks at work, while persistence keeps attention on longer-term educational and career targets. Resilience supports recovery after setbacks and preserves learning continuity during periods of workload pressure. Under these conditions, professional development remains cumulative but not episodic, and the adoption of new methods becomes a regular practice rather than a one-off experiment (Debbarma & Shivam, 2025).

Curiosity and openness to experience direct attention toward unfamiliar ideas and unfamiliar tools and expand the range of learning strategies that employees consider. Exploration encourages trial and variation, which later translate into broader task competence and higher satisfaction with work content. An organizational climate that values inquiry and critical reasoning, and that accepts diverse practice formats, cultivates these traits and turns experimentation into a normal element of daily work. Self-regulation and self-management translate intentions into sustained behavior. Goal setting gives direction, planning structures time, and strategic choice links effort to measurable outcomes, while periodic self-assessment keeps learning aligned with performance requirements. Reflective routines and peer collaboration reinforce self-regulation, while mentoring strengthens accountability and clarifies standards. A stable combination of all personal parameters forms the behavioural foundation of long-term workforce development in organizations (Debbarma & Shivam, 2025).

The social and cultural context also notably influences the development of employees' propensity for continuous learning through participation in collaborative educational environments, professional communities, and supportive peer networks. Cultural factors (such as an emphasis on innovation and professional development) contribute to this tendency, while differences in educational traditions explain the variability of attitudes to continuous learning. Social support and public recognition of the profession increase engagement and retention among staff with a strong penchant for continuous learning.

Institutional support and resources (mentoring, internships, and access to modern educational technologies) enhance readiness for professional training. High-quality mentoring promotes reflective practice and a culture of continuous advancement. The formation of professional identity is a dynamic process in which personal beliefs, emotions, and self-insight evolve through autobiographical narratives and practical experience. A strong professional identity during the training stage increases self-efficacy and resilience to professional challenges.

Worker self-efficacy is directly related to participation in professional development and a desire for continuous learning. Employees' values and motivation determine their commitment to continuous learning, especially if their role is perceived as meaningful and autonomous. Professional commitment is formed through diverse educational and practical contexts, observation of effective work models, mentoring, and direct impact on company results, which strengthens the relationship between values, identity, and attitude to continuous learning (Debbarma & Shivam, 2025).

A literature review revealed that the concept of continuous learning and development reflects the need for constant knowledge and skill renewal to adapt employees to a dynamic labor market and digital transformation. Theoretical approaches demonstrate the relationship between continuous learning and strategic decision-making that fosters innovation and sustainable growth. Professional development is viewed as an integrative, transformative process that combines formal, informal, and self-directed training, as well as socio-cognitive mechanisms, enabling autonomy and adaptability in the face of unstable career trajectories. The outcomes of continuous learning depend on the joint action of intrinsic motivation and organizational arrangements, where mentoring practices and access to learning resources shape training intensity and the pace of internal advancement. When firms formalize guidance and allocate time for skill renewal, professional development links to measurable career movement and to broader productivity effects at the level of households and regions.

1.2. Formal, Informal, and Digital Learning: Comparative Effects

The notion of employability changed with the transition from industrial to post-industrial labour markets, since long-term job security lost primacy and individual responsibility for competence renewal gained prominence. Employability now refers to sustained accumulation of specialized knowledge and proactive behaviour that fits multiple work settings and shifting task demands. Van der Heijden (2016) defines employability through four components: professional expertise and adaptive flexibility, together with corporate sense and alignment between personal goals and career interests.

Research illustrates that employability is viewed from three perspectives: economic-social, individual, and organizational, with organizational culture supporting the development of employees' employability. Informal on-the-job social training promotes professional competence and the ability to anticipate change. Social interactions are embedded in modern work roles, making experiential and informal training particularly effective for improving employability.

Research in university and corporate settings reveal that active networking and knowledge exchange increase access to resources and data essential for employee career growth.

A learning climate (psychological safety, opportunities for experimentation, and a supporting infrastructure) enhances personnel engagement in social informal learning. A supportive learning climate encourages employees to proactively seek feedback and information, which in turn boosts their employability. Thus, social informal learning mediates between the learning climate and employability enhancement, fostering the integration of organizational context and individual competences (Crans et al., 2021).

Operational definitions of formal, non-formal, and informal learning are based on previous research (see Table 3). This study adopts a definition of online learning as the use of the Internet to access educational materials, interact with content, instructors, and other learners, and receive support throughout the learning experience, with the goal of acquiring knowledge, building personal understanding, and developing through learning experience.

Formal learning is characterized by the backing of an educational or training institution, the presence of structure (goals, schedule, learning support), supervision, and the possibility of obtaining certificate or other formal acknowledgment. In contrast, informal education is not supported by institutions, is primarily managed by the learner, lacks a fixed program, and does not offer certification. It takes place in everyday or social activities, but the learner must be aware that the educational process is actually occurring.

The main distinctions between formal and informal learning are observed along two axes: structural (institution, schedule, accreditation) and psychological (intention, control). The perception of learning depends on a person's comprehension of the learning process itself and reveals both cognitive and affective components (emotions, interests, opinions, and values) that arise during learning activities. Since informal learning has no formal conclusion, its evaluation is possible only through the learner's perception of the process.

Comparisons of formal and informal learning in online and face-to-face environments can reveal differences in student performance and satisfaction, but such investigations remain limited, particularly in the domain of informal learning (Levenberg & Caspi, 2010).

The scholarly literature provides a general overview of formal and non-formal learning, while informal learning has been less examined and requires further exploration. Formal learning is well-structured, has clear goals, and occurs in educational institutions, whereas non-formal and informal learning are more flexible and complex in nature. Non-formal education represents a blend of formal and informal learning, combining structured elements with learner initiative and creating unique educational opportunities (Johnson & Majewska, 2022).

Table 3: Comparative Characteristics of Formal, Non-Formal, and Informal Learning

Characteristics	Formal Learning	Non-formal Learning	Informal Learning
Structure	Structured (linear goals)	Can be structured	Unstructured
Delivery	Through direct teaching methods	Through indirect teaching methods	May not be intentionally delivered
Intention	Intended by both teacher and learner	Intended by the learner	May not be intended by the learner
Recognition	Recognized by teacher and learner	Recognized by the learner	May not be recognized
Motivation	Often external	Internal	May be unconscious

Location	Educational institutions	Educational institutions	Anywhere
Assessment	Measured through qualifications	Not measured through qualifications	Not measured
Knowledge Focus	Propositional knowledge	Propositional and procedural knowledge	Often cognitive focus
Curriculum	Documented	May be documented	Not documented
Process	Top-down, according to formal program	Bottom-up, learner-oriented	May not be linked to social integration

Source: Compiled by the author based on Johnson and Majewska (2022)

Formal learning is an institutionalized, structured, and hierarchically arranged system of education that spans stages from primary school to university or corporate levels. It relies on educational institutions and involves teachers who plan and guide the learning process, set consistent goals, and arrange classes according to a defined curriculum. The learning process in formal systems is typically hierarchical and is managed by teachers' timing and actions through explanation, demonstration, feedback, and goal setting. Formal learning is intentional on the part of both the teacher and the learner and often concludes with certificates, diplomas, or qualifications. It primarily emphasizes the acquisition of theoretical understanding and cognitive abilities, and the curriculum is fixed in written form and strictly adheres to an established plan. Formal learning ensures the standardization of educational practices, allows for the accumulation and sharing of general knowledge, supports social mobility, and provides access to prestigious knowledge regardless of social status. However, the formal system has limitations: it does not reflect all teacher actions and student experiences in the classroom, can be rigid, one-dimensional, and does not always address individual learner needs. Some students acquire understanding more effectively in informal settings; moreover, abstract concepts, isolated from life experience, can reduce motivation. In addition, formal learning limits teaching freedom and subject instructors to pressures related to examinations and curriculum requirements (Pienimäki et al., 2021).

Non-formal learning is organized and systematic educational activity that takes place outside the formal system and is targeted at specific groups of learners. It may have a particular structure and goals but is not always subject to a strict timetable or mandatory syllabus. Non-formal learning employs indirect teaching methods (gestures, intonation, and support from mentors), which foster a positive learning environment and motivate participants. This type of learning focuses on the needs and interests of learners, providing freedom of choice and the opportunity to participate voluntarily. Non-formal learning is intentional from the learner's perspective, and motivation is often internally driven. It emphasizes practical abilities and competencies in specific contexts through a combination of cognitive, emotional, social, and behavioral aspects. A defining characteristic of non-formal learning lies in process flexibility. Participants adjust tempo to personal capacity, while the schedule leaves room for experimentation and peer interaction. Programmes take place outside the classroom and rely on practice-oriented settings, for instance museum-based sessions or club activities, and community projects that complement school curricula. Authentic contexts tend to raise engagement and support critical judgement as well as interpersonal competence. Then confidence grows when progress becomes visible in real tasks rather than in test scores alone. Non-formal provision, however, faces structural constraints. Practices differ across institutions, and outcomes depend on local conditions and instructor preparation, which complicates standardization. Monitoring and assessment remain uneven, since many providers lack unified metrics and documentation routines, while public recognition of non-formal achievements stays limited in many education systems. A further tension emerges when non-formal programs align too tightly with formal targets, because learners with low baseline motivation disengage from additional activities that resemble compulsory schooling (Alnajjar, 2021).

Informal learning refers to the acquisition of skills and values across the life course through everyday experience and routine interaction with the surrounding environment. Formal timetables and predefined curricula remain absent, because learning episodes arise spontaneously and remain outside the learner's conscious attention. Meaningful situations anchor the learning process, while exchange with more experienced peers/mentors strengthens understanding and shapes practice. Learner initiative drives participation, as internal needs motivate engagement and sustain effort across settings that extend beyond classrooms and training centres (Allaste et al., 2021).

Informal learning typically remains voluntary and does not lead to formal certification, since the focus shifts toward practical judgement and social competence, and toward emotional regulation alongside knowledge application. Social processes structure informal learning, because socialization transmits norms and rules through everyday communication, while an implicit curriculum shapes attitudes and behaviour without direct instruction. High engagement accompanies informal learning, and active participation supports the development of competences that formal instruction rarely cultivates to the similar extent. At the same time, formal assessment fails to capture informal outcomes, and context dependence creates uneven quality across environments. Social inequalities also reproduce themselves when access to supportive networks differs across groups, which complicates inclusion for vulnerable learners (Allaste et al., 2021).

The development of digital technologies and online environments offers new opportunities for integrating formal and informal approaches to learning. Web platforms, virtual communities, and open educational resources (OERs) allow participants to interact with experts and independently navigate their educational experiences. Personal learning ecosystems (PLEs) provide access to diverse materials and support the creation of individualized learning trajectories. Open learning networks (OLNs) and mobile technologies facilitate the integration of formal and informal practices, making learning experiences interactive and personalized (Czerkawski, 2016).

However, successful implementation of these hybrid systems requires methodological guidance from teachers to help learners master digital resources and critically evaluate information. Unequal access to technology and differences in digital proficiency and motivation create risks of educational disparity. At the same time, combining structured formal instruction with the flexibility of informal and non-formal methods promotes holistic learner development, enhances metacognitive and communication skills, and enriches the educational experience. Nonetheless, empirical research analyzing the interplay of these methods and their impact on academic performance and professional development remains limited (Czerkawski, 2016).

Learning environments also play a significant role, shaping student educational achievements regardless of their abilities. These environments often fail to fully accommodate individual needs and preferences and rarely entirely meet societal expectations. Informal environments allow learners to acquire skills at their own pace and apply knowledge in real-world scenarios. They encourage autonomous learning through trial and error, as well as self-reflection. Informal environments also support the integration of advanced technologies and the development of 21st-century abilities such as creative thinking, collaboration, and leadership. Comparing formal and informal environments through cognitive and social perspectives clarifies learners' perceptions of the learning process and its effects on educational performance. Physical space also influences learners' perception of learning environment and shapes their self-efficacy, particularly in STEM disciplines. Moreover, participation in collaborative projects fosters social and cognitive skills, enhances understanding of professional roles, and increases interest in scientific and technical careers. Modern online environments must account for these aspects to balance structured learning and flexibility necessary for independent skill cultivation (Baucum, 2022).

Illeris (2011) identified two main individual factors of informal learning in the workplace: motivation and strategy of knowledge acquisition. Motivation is essential because learning requires effort, while strategy determines how individuals acquire knowledge. Unlike formal education, workplace knowledge is gained independently through interactions with colleagues, clients, or the execution of novel tasks. Decius et al. (2019) classified strategies of individual informal learning as trying and using one's own ideas, learning from examples, direct and indirect feedback, and anticipative and subsequent reflection. Organizational factors (work structure, autonomy, and learning culture) also shape the effectiveness of these strategies. Employee communities facilitate collaborative learning and knowledge exchange with external partners and clients. Digital tools enhance informal learning opportunities and blur the distinction between formal and informal processes. However, empirical data on the use of technology for informal workplace learning remains scarce. Investigating the interactions between individual strategies, organizational factors, and digital tools presents a pressing challenge in modern education and management (Amenduni et al., 2022).

Corporate culture can both foster and constrain employees' learning, with learning-oriented cultures supporting engagement in skill development. According to Schein's model, such an organizational culture comprises artifacts and underlying assumptions that guide behavior and facilitate learning. Artifacts are visible and tangible manifestations of culture, values define objectives and methods to achieve them, and underlying assumptions represent unconscious beliefs. Main characteristics of organizational learning cultures include openness to new ideas, readiness for experimentation, acceptance of mistakes, active participation of employees, and transparent communication. Research indicates that such cultures stimulate innovation and organizational adaptability, although their prerequisites are not fully studied. Learning rarely occurs in purely formal or informal modes; instead, these approaches complement and reinforce each other shaping organizational learning culture (Laubengaier et al., 2025).

Early theories of human capital recognized the importance of worker experience, but they placed the primary emphasis on formal education and training, as illustrated by Mincer earnings function from the 1960s. Modern research demonstrates that much of the productivity of new employees is shaped by learning by doing and interactions with colleagues and managers, especially in highly automated industries. Descriptive data reveal that in 2020, Dutch workers spent an average of 22% of their working time on activities facilitating learning, while formal training courses accounted for only 2% of their time. Informal learning is a priority for all age groups, but especially for younger workers: in the Netherlands, employees under 30 spent approximately 25% of their working time on informal learning, while older workers spent only 18%. The OECD PIAAC displays that the proportion of workers who participate in on-the-job training daily ranges from 12% in Korea to 53% in Spain, while learning from peers and managers ranges from 10% in Korea to 36% in Spain. In Germany, 26% of workers learn daily through work tasks, while in the US this figure reaches 44%, with learning from peers and managers accounting for 16% and 24%, respectively. Data from 28 European countries illustrate that low-skilled workers are more likely to participate in informal learning, compensating for the lack of formal training courses; on average, low-skilled workers spend 18% of their working time on learning, while highly skilled workers spend 25%. A 2013 analysis of work tasks in the Netherlands reflects that employees benefit most from learning when performing new and complex tasks, as well as when collaborating with more experienced colleagues. Studies of new employees across various EU industries present dramatic increases in productivity: auto glass installers increase their efficiency by 82% within the first year, while contact center recruits increase their productivity by 64% within the first year. The effect of knowledge transfer between colleagues is confirmed by data from contact centers: new agents in teams with more experienced colleagues become fully competent after 110 hours of on-the-job training, while in less experienced teams this process takes 161 hours (de Grip, 2024).

According to the research, since the 1970s, the priority of replaceable manual and routine cognitive tasks have decreased, while analytical and interactive non-routine tasks have increased in value (Autor et al., 2003; Spitz-Oener, 2006; Oesch & Rodriguez, 2011; Bachmann et al., 2018). Since the mid-2000s, some trends have leveled off (Autor & Price, 2013). New technologies, especially artificial intelligence, have the potential to automate tasks previously considered irreplaceable, such as truck driving (Brynjolfsson & McAfee, 2014; Frey & Osborne, 2017). The studies used data on 702 occupations from the O*NET database (Frey & Osborne, 2017), which found that participation in formal, non-formal, and informal learning is considered for workers at high risk of automation, that is, those with a share of routine tasks above the 75th percentile or a probability of automation above 70% (Nedelkoska & Quintini, 2018). According to the data of 2016, 43% of adults aged 18 to 64 engage in informal learning, 50% in non-formal learning, and only 10% in formal learning (Kaufmann-Kuchta & Kuper, 2017; Bilger & Strauß, 2017; Kuper et al., 2017). The study by Park & Choi (2016) involved 4,008 employees of small and medium-sized enterprises in South Korea. Both formal and informal training have been shown to have a positive impact on employee performance; the perceived value of on-the-job learning serves as a mediator in the relationship between learning and productivity. The results support the findings of previous studies on the relationship between learning and employee performance identifying the importance of perceived learning value in improving working efficiency.

Trainings increase employee productivity in analytical and interactive non-routine tasks and reduce the number of routine tasks (Autor et al., 2003). According to the PIAAC program, the likelihood of automation for workers in 70 manual labor occupations was assessed (Nedelkoska & Quintini, 2018). It was found that education and additional training help workers cope with technological changes and skill requirements (Autor, 2015; Nedelkoska & Quintini, 2018; Heß et al., 2019). To date, only three articles have examined the effect of learning on job tasks and the risk of automation (Tamm, 2018; Görlitz & Tamm, 2016; Nedelkoska & Quintini, 2018). In Germany, learning participation and its impact on the number of interactive non-routine tasks were studied from 2007 to 2010 (Tamm, 2018) and it was found that formal learning leads to officially recognized qualifications, non-formal learning leads to participation in courses and seminars, and informal learning leads to semi-structured learning (Eurostat, 2016). Technological change creates a need for retraining for workers with a high proportion of automatable tasks so that they can retain their jobs and increase productivity.

In the workplace studied by Finnish researchers, digital technologies were used in everyday work, leading to the development of established digital work practices. The analysis identified five categories of practices that facilitated informal learning: work communication, relationships, knowledge sharing, following and listening, and monitoring digital technology use. The practices were complex, and the categories overlapped, so a single practice could belong to several categories simultaneously. Employees used digital channels (Yammer and Teams) for work communication, both formal and spontaneous. Knowledge sharing through online chats facilitated collaborative knowledge construction and problem solving, and encouraged learning by doing. Relationships were maintained through online greetings for new employees, virtual coffee breaks, and the exchange of personal information, creating a positive learning atmosphere. Knowledge-sharing practices in digital workplaces take the form of experience exchange in online forums and screen-sharing sessions, where employees articulate routines and enable peers to learn through observation. Regular monitoring of internal communication channels and attentive participation in group discussions keep staff informed about current tasks and reveal how colleagues address operational challenges. Online meetings and discussion spaces widen access to knowledge, because participants draw on several sources and compare alternative approaches within a single workflow. Governance over digital tool usage aligns shared routines and reinforces complementary practices, since agreed rules structure interaction and reduce fragmentation in communication, which strengthens informal learning processes (Karhapää et al., 2023).

Recent scholarship identifies a coherent division of labour among formal, informal, and digital learning, because each modality contributes a distinct type of competence and supports employment stability. Formal training supplies conceptual foundations, whereas informal learning consolidates job-specific skills and supports adaptation under changing task conditions. In the same time, digital engagement broadens self-directed development and sustains the exchange of experience across teams. When organizations combine these modalities, a learning-oriented culture becomes embedded in daily operations, and productivity gains emerge through faster problem resolution and more consistent knowledge diffusion.

1.3. Organizational and Contextual Factors in Internal Promotion

Promotion within companies has drawn growing attention in organizational behaviour research, because advancement links directly to workforce sustainability and to long-run productivity. Sustainability as an analytical concept emerged from ecology, where it denotes the capacity of a system to persist while it develops and renews itself. Within labour settings, the same idea appears under social sustainability, where managerial practices shape employee wellbeing and sustain performance over time rather than in short cycles. The notion of thriving at work describes a psychological condition with two core dimensions. Vitality captures energy and engagement, whereas learning reflects personal development and the accumulation of knowledge through work experience. Both components operate synergistically and foster short-term development and long-term adaptability, with vitality motivating employees and learning cultivating skills. Thriving employees are more productive, innovative, engaged, and resistant to stress, and also display positive behaviors such as reduced turnover, higher job satisfaction, and overall well-being. Contextual elements (leadership coaching, trust, and perceived fairness) predict thriving because a supportive environment encourages energy and self-improvement. Leadership coaching provides mentoring, feedback, learning opportunities, and recognition, which enhances employee thriving and motivates reciprocal positive actions. Similarly, fairness and trust shape perceptions of the workplace and stimulate energy for learning, as well as promote engagement and a willingness to take risks for personal growth. Thriving at work positively influences affective organizational commitment because employees who feel energized and developing are more likely to identify with the organization and actively participate in its activities. According to the Socially Embedded Model of Thriving, career progression serves as a mediator through which contextual resources and support are transformed into commitment and other favorable organizational outcomes. Empirical evidence shows that career growth mediates the influence of leadership coaching and fairness on affective commitment, indicating its role as a self-regulatory mechanism. Understanding the determinants that contribute to promotion and its consequences is essential for sustaining employee performance and the long-term success of an organization (Abid et al., 2019).

Employee work activity encompasses both task performance and contextual performance, such as assisting colleagues or participating in process improvements. Task performance captures the achievement of organizational targets. Contextual performance describes the work climate that supports execution and cooperation. Human capital matters. Skills and job-specific knowledge shape output, while effort and motivation determine consistency across reporting periods. Corporate culture also matters. Norms that reinforce commitment reduce exit intentions, which stabilizes teams and protects accumulated expertise over time. Evidence from hotel settings in Malaysia and Thailand links higher engagement with stronger service delivery and with more stable work effort under demanding customer-facing conditions. Engagement and constructive cultural norms move together and raise both task outcomes and contextual behaviours, because employees invest more attention in core duties and maintain cooperation with colleagues. Managerial practice, therefore, benefits from structured learning investments and from governance that builds trust, since team results rise when capability formation and workplace climate align (Bhardwaj & Kalia, 2021).

Raising labor productivity remains a central objective for firms that seek stronger market positions and higher profit margins. To achieve this, enterprises allocate resources to developing individual competencies, considering the specific work setting that shapes employees' performance. Contextual factors encompass cultural norms, corporate values, and the adoption of emerging technologies, all of which directly influence the efficiency of work procedures and methods of team collaboration (see Table 4). Employees' performance appraisal systems should be tailored to the characteristics of each organization: for example, large manufacturing firms should consider the complexity of production processes and hierarchical management structures, while startups emphasize flexibility and prompt feedback. The internal organizational environment (availability of advanced equipment, software, materials, and infrastructure) directly affects productivity and employee motivation. Implementing a performance management framework is impossible without aligning appraisal methods with existing infrastructure, managerial support, and HR capabilities. When designing appraisal systems, managers must account for organizational culture, regulatory compliance, and corporate policies to ensure alignment with strategic objectives. Core features of proper appraisal reveal adaptability to changes in the organizational context, the ability to modify criteria according to circumstances, and coherence with the company's vision and mission (Rusu et al., 2016).

Table 4: Comparative Review of Employee Performance Efficiency Research Models

Research Model	Main Focus	Contextual Factors	Unit of Analysis
Armstrong and Ward (2005)	Effective performance management	Processes, culture and clarity of procedures, measurement and rewards, motivation, HR role	Employees and managers
Murphy and DeNisi (2008)	Employee performance improvement	Proximal factors (appraisal purpose, norms, system acceptance), distal factors (culture, strategy, legislation, technology), intervening and evaluative factors	Employees

Source: Compiled by the author based on literature review

The social context of appraisal, which reveals the quality of interactions between employees and management, the level of trust, and the corporate atmosphere, has a positive effect on employee behavior and motivation to achieve results. Modern approaches to performance management shift the emphasis from simply measuring results to a comprehensive appraisal that takes into account the organizational context, individual characteristics of employees, and their professional goals (see Table 5).

Table 5: Categories of Contextual Factors in Employee Performance Appraisal

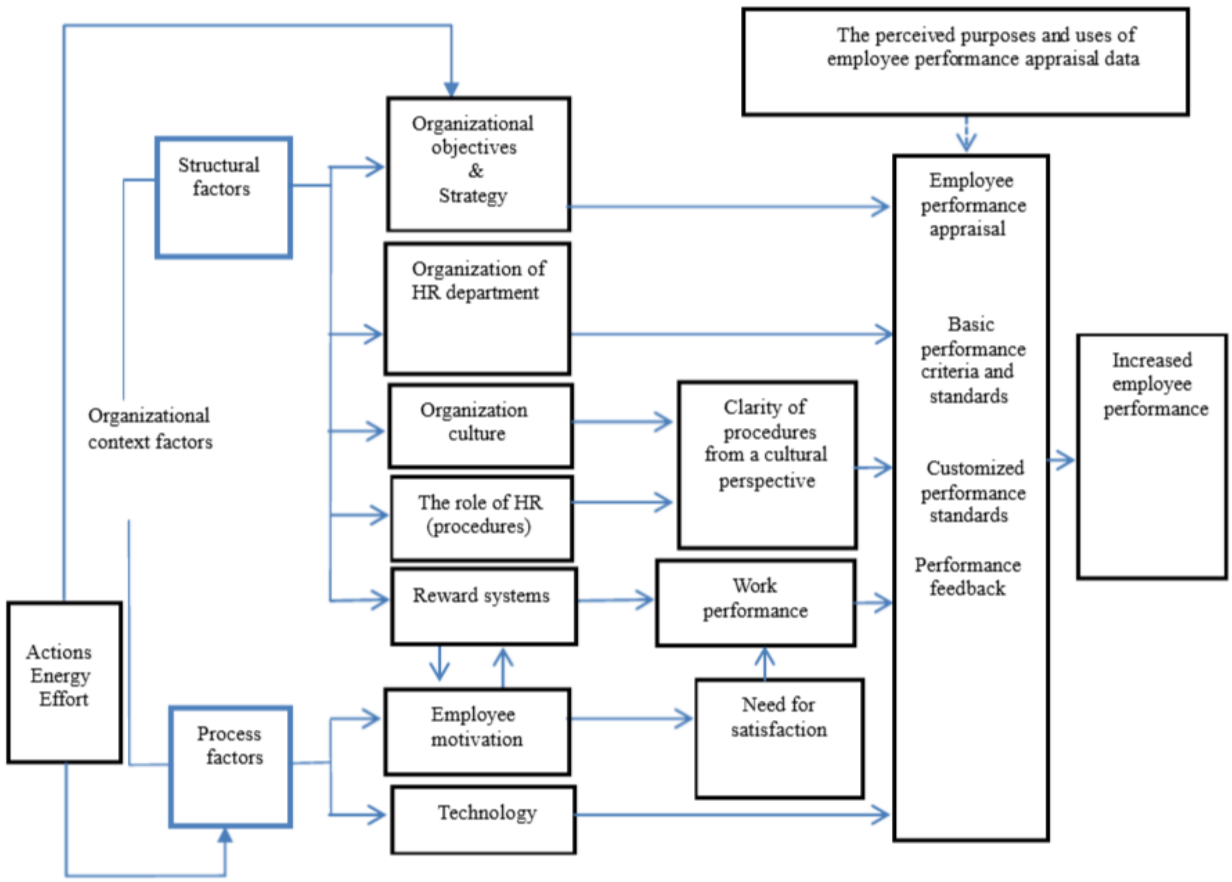
Category	Factors	Role in Appraisal	Examples of Application
Process factors	Motivation, technology	Increasing employee engagement and performance efficiency	Energy and effort, meeting employee needs, use of technological platforms
Structural factors	Organizational goals and strategy, culture, HR organization, rewards, clarity of procedures	Determining appraisal design and standards, ensuring alignment with organizational context	Individual appraisal standards, work criteria, reward and feedback systems

Source: Compiled by the author based on Rusu et al. (2016)

The performance appraisal process is viewed as a social and motivational mechanism arising from employee interactions with managers and the joint setting of goals (see Figure 1). Fundamental factors influencing appraisal success consist of company strategy, the technologies used, prevailing cultural norms, and the purpose of using appraisal data for management decision-making. Motivational elements (incentive systems, HR procedures, rewards, and the organization of the HR department) act as dynamic parameters that contribute to enhanced employee engagement and productivity. Organizational goals, corporate strategy, HR structure, and reward systems determine the design and implementation of appraisal systems, ensuring that processes align with strategic objectives and working conditions. A flexible research model identifies the significance of both process factors and structural factors in the organizational context that influence employee appraisal and improve overall company performance (Rusu et al., 2016).

The success of any organization depends heavily on the people who shape and manage it. Employee promotion is an effective strategy for motivating and retaining staff. Advancement symbolizes growth, recognition, and opens new opportunities for personnel. It is a moment when an employee's hard work and dedication are acknowledged by management and rewarded with increased responsibility. A career advancement is more than just a change in position; it has positive consequences for both employees and the organization. In countries with high unemployment, promotion is a primary factor in job satisfaction. Transparent promotions contribute to enhanced employee competence, engagement, and productivity. Career growth is accompanied by higher salary, authority, responsibility, and status (Mishra, 2025).

Figure 1: Relationship Between Organizational Context Factors and Employee Performance Appraisal



Source: Rusu et al. (2016)

There are four types of career advancements (Barman, 2024):

1) Internal promotion – appointment to a new position within the same organization.

2) Horizontal promotion – a salary increases while maintaining the same responsibilities.

3) Vertical promotion – moving to a higher level with increased authority, responsibilities, and status.

4) Dry promotion – increasing responsibility and status without financial bonuses.

An objective appraisal for career advancement contains metrics based on performance, experience, potential, and fit with corporate culture (see Table 6). Employee motivation increases when their efforts are recognized through promotion and associated rewards. Regular feedback and skill development help employees prepare for promotion. Unfair or delayed advancements can lead to demotivation and decreased performance. Strong strategies comprise establishing transparent criteria and considering team members' emotional intelligence and career goals. Implementing an advancement policy reduces staff turnover and supports the retention of talented employees. Career advancements directly impact job satisfaction, which in turn enhances overall company performance. In firms with a transparent promotion architecture, employees perceive recognition and fair valuation, which strengthens attachment to the employer. Promotion decisions also shape investment in firm-specific human capital, because advancement signals a credible horizon for career planning and reinforces internal labor-market capacity. Engagement persists when rewards match added responsibility and when managerial support accompanies the transition to higher-level tasks. Promotion policy, when executed on schedule and according to stated criteria, functions as an instrument of organizational governance that supports financial resilience and employee satisfaction (Mishra, 2025).

Table 6: Characteristics of Employee Promotion and Their Effects

Aspect	Description	Impact on Employee	Impact on Organization
Promotion Types	Internal, horizontal, vertical, dry	Defining career opportunities and motivation	Optimizing human resources
Criteria	Performance, experience, potential, emotional intelligence	Fair appraisal, competence development	Reducing turnover, increasing efficiency
Rewards	Salary, status, bonuses, privileges	Motivation, satisfaction	Enhancing productivity and loyalty
Feedback	Regular appraisal of work and skills	Supporting career growth	Preparing employees for future roles
Social Recognition	Acknowledgment of achievements	Increasing self-esteem and engagement	Improving corporate culture
Competency Development	Trainings, mentoring, new responsibilities	Strengthening professional skills	Increasing productivity and innovation

Source: Compiled by the author based on Mishra (2025)

The impact of career advancements on staff performance is an essential area of research, examining how promotions influence overall contribution to an organization. Career progression involves moving to a higher position with increased pay, status, responsibilities, and benefits, which motivates employees and enhances loyalty. The primary benefits of advancements involve increased career expectations, reduced staff turnover, enhanced productivity and motivation, cost-effectiveness for the organization, career development, a sense of control, and recognition of achievements. Promotion opportunities also boost morale, develop skills, strengthen loyalty, reduce recruitment costs, and facilitate faster team integration.

However, the disadvantages of promotions encompass the risk of favoritism, potential skill gaps, limitation of new ideas, increased workload per employee, decreased team morale, and additional training costs. The effectiveness of promotion is influenced by technical and organizational factors, encompassing performance indicators (40%), employment history (30%), professional competencies, adherence to diversity policies (20%), and personal biases (10%).

Employees' productivity is determined by the ability to transform acquired information and resources into work results and is directly linked to organizational culture, motivation, work environment, technology, time management, and health. Increased productivity contributes to improved financial outcomes, personnel retention, goal achievement, and business sustainability, while low productivity leads to missed deadlines, reduced quality, and burnout. Benchmarks (work quality, customer satisfaction, deadline adherence, employee retention) are used to assess productivity. Improving productivity is possible through setting clear expectations, training and development, maintaining a positive work environment, encouraging collaboration, recognizing achievements, using technology, and providing opportunities for career advancement.

Previous research conveys that promotion directly impacts motivation and productivity: studies from the University of Abuja, Nigeria, found increased performance after employee progression, and a meta-analysis by Gupta and Shaw confirmed increased performance after receiving bonuses and career growth. Lazear's tournament theory demonstrates that competition for career advancement motivates employees to achieve high performance (Aloufi et al., 2025).

Consequently, the analyzed studies demonstrate that internal promotion increase personnel motivation and productivity, strengthening their sense of worth and professional growth. Supportive management and a strong organizational culture create favorable conditions for employee development and commitment to the organization. Well-developed career promotion systems contribute to staff retention and overall organization's sustainability.

2. MATERIALS AND METHODS

2.1. Research Design, Sample, Data Sources

2.1.1. Basic Characteristics of the Study Design

According to Batchelor & Soylu (2025), talent development is a priority element of human resource management (HRM), aimed at identifying and maximizing employee potential to achieve an organization's strategic goals. Historically, HRM has evolved from an administrative function to a strategic tool for increasing competitiveness through personnel development. Modern practices highlight individualized training programs, mentoring, and the use of digital technologies to build personal development trajectories (e.g., GE Leadership Program, Google G2G, Deloitte University). In the context of digitalization, such aspects as continuous learning, the development of soft skills, and the development of adaptable employees prepared for internal career advancement are becoming increasingly noteworthy.

Based on the data by Schislyaeva & Saychenko (2022), the attention of employers and researchers to the development of employees' soft skills has increased profoundly in the context of the digitalization of the economy. The authors used statistics from the NAFI Research Centre and found that the share of jobs requiring soft skills increased from 22% in 2000 to 52% in 2020, with forecasts for 2025–2035 projecting growth to 56–64%. In Russia, the greatest soft skills shortage is observed among specialists, particularly in teaching, communication, coordination, complex problem-solving, and time management. Soft skills training programs have shown productivity gains of up to 20% and a 258% increase in company profits eight months after training completion.

Shiri et al. (2023) conducted a systematic review using PRISMA guidelines which included search in PubMed, Embase, and Google Scholar without restrictions on age, gender, and publication language, followed by independent relevance checking by two reviewers. The review included 27 studies (4 cohort and 23 cross-sectional) with participants ranging from 81 to 88,948, primarily working in healthcare. The data covered professional education, job retention, intention to leave a job, and turnover intention. A cohort study found that participation in professional development programs increased the likelihood of job retention by 11% (67% vs. 56%, $p = 0.04$), while for workers with disabilities, additional training reduced the likelihood of leaving their jobs (OR 0.5, 95% CI 0.4–0.8). Satisfaction with development opportunities was found to reduce intention to leave, with the effect dependent on gender, occupation, and employment history; professional education reduced the time to return to work by 3 weeks and increased the likelihood of employment.

The study by Islam et al. (2020) analyzed the effectiveness of employee training programs in state-owned banks in Bangladesh, where nine state-owned banks account for more than 70,000 employees with 5,043 branches; the sample size was 205, calculated using the Yamane formula with an accuracy of 0.07. Structured questionnaires with a 5-point scale were used to collect data, and the reliability of the measurement instruments was confirmed (Cronbach's $\alpha = 0.858$). Factor analysis (PCA with Varimax rotation) and multiple regression were used for the analysis, which calculated six factors of training effectiveness: general skill development, stress reduction, technical skill development, need-based programs, long-term productivity, and instructor quality; the total explained variance was 65.07%. Multiple regression illustrated that five of the six factors were significantly associated with overall return on training (Adjusted $R^2 = 0.570$, $F = 43.431$, $p < 0.001$), while general skills development was not statistically significant.

This research's methodology is based on a retrospective longitudinal design aimed at identifying the relationships between employees' participation in three forms of continuous learning and their subsequent internal career advancement. This approach allows for a comprehensive understanding of employee professional development as a dynamic phenomenon, encompassing formal, informal, and digital learning trajectories, and for assessing their long-term effects in the context of organizational structures and HR strategies.

A longitudinal design tracks career mobility across multiple observation points and links training participation with later promotion events and the assignment of broader duties. Human capital studies require this temporal lens, because skill formation accumulates across several cycles of work and learning and because internal connections develop through repeated interaction rather than within a single reporting period.

Cross-sectional designs register one moment and therefore leave ordering unclear. Panel data, by contrast, permit estimation of lag structures between training episodes and later career outcomes while control for worker heterogeneity and firm conditions that shape advancement. Divergent trajectories appear once learning modalities enter the model separately, since each channel builds competencies through a different mechanism and enters the promotion process through a dissimilar organizational filter.

Formal training covers corporate programs and certified courses that align with qualification standards and internal job ladders. Informal learning develops through self-directed acquisition of new routines during task execution and through problem solving on the job. Digital learning draws on ICT-based platforms and adaptive systems that structure continuous development. Comparative evaluation of the three modalities identifies the strongest pathway to advancement and also detects complementarities when modalities reinforce each other within the same career spell.

The empirical analysis is based on secondary quantitative enterprise-level data covering the period of 2019–2024. The use of secondary data was driven by the need for a broad and representative sample, as well as comparisons with other international sources. The primary dataset is the Russian NAFI panel database, which contains indicators on employee participation in training and organizational characteristics. To enhance reliability and external validity, the results were additionally verified using open datasets, which allowed for cross-validation of primary relationships and expanded interpretation of the findings beyond a single national sample.

The Interaction of Internal and External Labor Markets survey, commissioned by Laboratory for Labor Market Studies, has been conducted by NAFI since 2009 and annually covers 1,000–2,000 enterprises from most sectors of the Russian economy and regions. The sampling methodology was developed based on the experience of German labor market studies (IAB and Hannover Firm Panel). Since 2011, the survey has comprised a set of questions on the availability and lack of employee skills, developed with support from the World Bank and based on international standards. This survey forms a unique database reflecting the HR policies of Russian enterprises and the state of the labor market. However, it should be emphasized that the comparison remains indirect and serves a methodological purpose rather than providing a direct empirical assessment, as the study does not incorporate German microdata for quantitative analysis. Any conclusions about parallels or divergences between Russian and German labor market patterns are provisional and must be interpreted with caution.

The combination of two data sources ensures the representativeness and generalizability of the results at the industry and region levels and helps assess the stability of patterns across different institutional and technological contexts. The panel nature of the NAFI database makes it possible to observe the dynamics of enterprise development and their HR strategies over a six-year period, facilitating a more accurate determination of the effects of continuous learning. The simultaneous use of corporate and open data enhances the analytical power of the study, enabling the use of high-level quantitative methods – correlation, regression, and comparative analyses – aimed at testing hypotheses about the cause-and-effect relationships between participation in different forms of learning and the likelihood of internal employee promotion.

2.1.2. Panel Structure and Sample Size

The total number of observations is 8,425, each representing a single employee (*id*) in a specific year of observing. The unit of analysis is an individual working at a specific company, which forms a panel of employees within companies and facilitates the analysis of both intercompany differences and the dynamics of individual trajectories.

The data are structured as a partial panel for the period of 2019–2024, with some respondents and companies re-represented in different years, allowing for the possibility of tracking changes in learning participation and career outcomes over time. The estimated number of unique employees is approximately 2,500–5,000, and the number of companies is approximately 1,000–2,000, reflecting the balanced multi-level structure of the sample.

The study is based on a retrospective longitudinal design aimed at identifying the impact of the analyzed forms of continuous learning (formal, informal, and digital) on internal career promotion. This approach allows for the consideration of time lags between learning and career changes, as well as for assessing the sustainability of the identified effects. The database integrates secondary quantitative sources, the primary one being the NAFI panel, supplemented by verification data from open datasets, ensuring the representativeness and external validity of the results for the industries and regions covered.

The model data structure allows for the capture of hierarchies: employees are nested within companies, and observations are nested within time periods. This system opens the potential for the application of panel regression methods (logit, probit, and linear models with fixed and random effects) capable of controlling for unmeasured individual characteristics (motivation and ability).

The sample variables consist of:

1) participation in formal, informal, and digital learning (independent factors);

2) career advancement (dependent variable);

3) controlling company characteristics – number of employees, average salary, ownership structure, technical conditions, industry, region, share of labor costs, and price dependence;

4) time and individual effects (year of observation and *id*).

The data structure and chosen design enable calculating causal relationships between learning and professional growth, as well as analyzing differences across industries, levels of technological development, and types of enterprise ownership.

2.1.3. Structural, Industrial, and Economic Indicators of Companies

To ensure accurate representativeness, the data uses a weight variable reflecting regional and industry-specific weighting. This weighting adjustment is applied when calculating aggregate indicators to balance the impact of large and small enterprises and avoid biasing the results toward more represented regions and industries. Observations outside the main representative population (test records, incomplete data) are assigned a weight of zero.

The sample covers 8,425 observations from companies with 30 to 100,000 employees, of which 7,404 are private (see Table 7). The following industries are the most widely represented: wholesale and retail trade, vehicle and household goods repair – 1,309 companies (15.5%); real estate transactions, rent and service provision – 947 companies (11.2%); construction – 870 companies (10.3%); financial activities – 675 companies (8%); and transportation and communications – 672 companies (8%). Among the industrial sectors, the following stand out: mining (except fuel and energy) – 581 (6.9%), fuel and energy extraction – 345 (4.1%), electricity, gas, and water production and distribution – 586 (7%), metallurgy – 165 (2%), wood processing and wood product manufacturing – 461 (5.5%), and food and beverage manufacturing – 374 (4.4%).

Table 7: Sample Characteristics by Industry, Technological Level, Price Dependence, and Export Status (N = 8,425)

Category	Subcategory	Number of Companies	% of Sample
Industry – Most Represented	Wholesale & retail trade, vehicle & household goods repair	1,309	15.5%
	Real estate, rent, service provision	947	11.2%
	Construction	870	10.3%
	Financial activities	675	8.0%
	Transportation & communications	672	8.0%
Industry – Industrial Sectors	Mining (except fuel & energy)	581	6.9%
	Fuel & energy extraction	345	4.1%
	Electricity, gas, water production & distribution	586	7.0%
	Metallurgy	165	2.0%
	Wood processing & manufacturing	461	5.5%
	Food & beverage manufacturing	374	4.4%
Technological Level (*sibjtechcond*, 1–5)	Profoundly lag behind	115	1.4%
	Slightly lag behind	394	4.7%
	Meet industry standards	4,929	58.5%
	Slightly exceed	2,103	25.0%
	Significantly exceed	729	8.7%
Price Dependence (*pricedepend*, 1–4)	Strong influence	1,798	21.4%
	Moderate influence	4,025	47.8%
	Insignificant influence	1,566	18.6%
	No influence	574	6.8%
	Undecided	617	7.3%
Export Status	Exporters	679	8.1%
	Non-exporters	7,746	91.9%

Source: compiled by the author

According to the *sibjtechcond* parameter (level of technological development), 115 companies substantially lag behind industry standards, 394 slightly lag behind, 4929 meet industry standards, 2103 slightly exceed, and 729 substantially exceed them. For the price dependence parameter (*pricedepend*), 1,798 companies indicated a strong influence, 4,025 indicated a moderate effect, 1,566 indicated an unsignificant impact, 574 indicated no influence at all, and 617 were undecided. Of the sample, 679 companies were exporters.

2.1.4. Data Processing and Analysis Methods

To prepare the data for statistical analysis, computational procedures were implemented to ensure correctness, representativeness, and the minimization of systematic errors. First, the data was checked and cleaned: observations with missing company identifiers or observation years, as well as records with unrealistic values, such as negative wages or headcount, were excluded from the sample. Second, qualitative variables (technical condition indicators and price dependence) were recoded into numerical format to enable their use in regression analysis. Third, omission checks were performed: for quantitative parameters, the proportion of missing values did not exceed 10%, and in such cases, single imputation was used using the mean or median value within the industry and year.

Within this panel model, single imputation provides a precise method to address limited missing values while respects the data structure and temporal consistency. Missing entries for quantitative indicators did not exceed 10%, and substituting them with the industry-year mean/median preserved comparability across firms and prevented distortions in longitudinal patterns. This approach safeguarded the panel's conditional balance to avoid the exclusion of firms with sporadic gaps in reporting. That is why, the estimated impact of training participation on promotion outcomes reflects genuine economic variation rather than artifacts from incomplete data and sample reduction.

In the original analysis, the concept of a "balanced panel" was applied in a simplified manner. In strict econometric terms, a balanced panel implies that the same units are observed in every period without any missing data. In this dataset, several observations were absent in some years and different units of measurement used for a number of variables, that indicates that the panel does not meet this definition. It is more precise to characterize the procedure as an attempt to increase comparability across years rather than constructing a fully balanced panel in the technical sense.

To achieve greater year-to-year comparability, the data were adjusted using weights normalized for each year. This adjustment ensured that aggregated values represented the overall structure of the population of firms and accounted for variations in observation counts across periods. Accuracy of the adjusted figures was further confirmed by cross-referencing with official sources (Rosstat and HSE), thereby validating the consistency and reliability of the calculations.

Data analysis was performed using quantitative methods, encompassing primary descriptive analysis (distributions, means, standard deviations), correlation analysis to determine pairwise relationships between training types and career outcomes, and multiple regression (logit/probit/PE/FE/RE) to estimate the likelihood of employee promotion based on participation in the presented training types while controlling for structural factors. Control variables, year dummies, and robustness procedures (repeated analyses on subsamples by industry and region) were used to test causal relationships.

The ethical aspects of the study incorporate complete anonymization of company data; identification codes do not allow identification of specific companies, and the use of secondary data from NAFI and the open Kaggle dataset complied with the requirements for the scientific processing of personal and corporate data. Handling incomplete and missing data involved the following steps: missing values for quantitative parameters (e.g., *wage* and *sharelaborc*) were handled using imputation at the industry-year level; a separate "no data" category was created for categorical attributes to avoid missing observations; and, if data on training participation were missing, the value "no participation" was assumed. This approach allowed us to preserve sample size and minimize systematic biases when estimating the parameters of the regression models.

The main limitations and risk mitigation measures are as follows:

1) Incomplete data – observations are sometimes missing in some years; this risk was minimized by using panel methods with control for individual effects.

2) The methodological complexity of measuring informal learning was addressed through validated indicators from questionnaire data.

3) Limited generalizability of the results, offset by the breadth of industry and region coverage and the inclusion of control variables that enhance the external validity of the model.

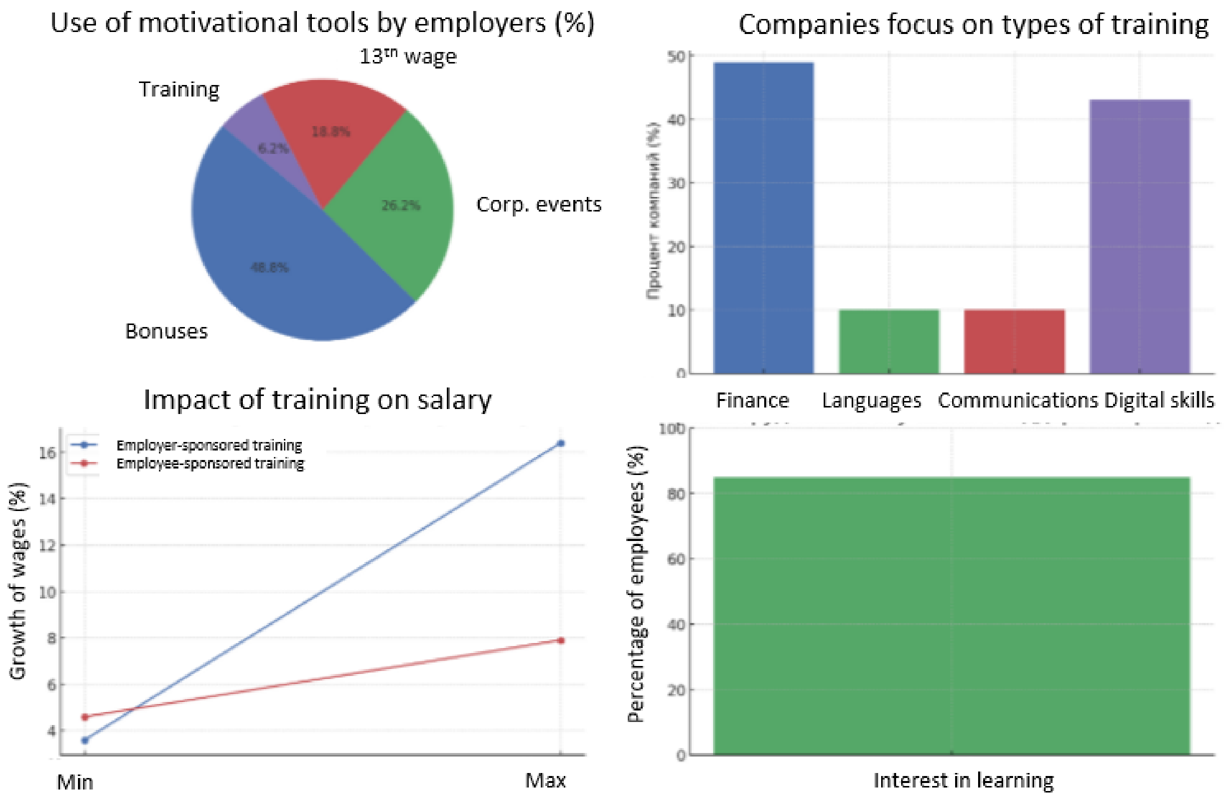
Therefore, this section describes a systematic, empirically grounded, and methodologically rigorous approach to studying the relationship between employee participation in various forms of training and their elevation. The panel data structure, high variability of company characteristics, and accurate statistical analysis ensure the reliability and replicability of the obtained results.

2.2. Description of Variables (Independent, Dependent, Control)

2.2.1. Review of the Works and Statistics of Predecessors

Empirical evidence from Russia confirms the meaningful role of company characteristics in the organization of workplace training and its impact on employee career advancement. Analysis of NAFI data presents that innovation activity, the technological level of production, and competition in the product market determine both the availability and intensity of training programs, with innovative and technologically advanced companies more likely to provide formal and informal training opportunities (Roshchin & Travkin, 2015; 2017). Quantitative studies of the effect of further vocational education suggest that training has a positive impact on wages and labor productivity: according to various assessment methods, employer-sponsored training increases wages by 3.6–16.4%, while employee-sponsored training increases wages by 4.6–7.9%, confirming a direct link between skill development and promotion (Travkin, 2013; 2014). Sectoral analysis illustrates that highly skilled and managerial personnel are predominantly involved, while low-skilled workers and agricultural sectors (agriculture and fisheries) have limited access to training, reflecting structural differences in opportunities for professional development (Vasiliev et al., 2013; Roshchin & Travkin, 2015). Corporate training priorities in Russia are similar to international ones: courses in financial management, accounting, and labor law predominate, while digital and soft skills (IT, foreign languages, and communications) remain less in demand, despite being essential for career advancement (Roshchin & Travkin, 2017; NAFI & LIRT HSE, 2017). Despite the high returns, employer involvement in further vocational education is low: only 10–15% of employees in medium and large companies receive training at their employer's expense, while in OECD countries this figure is 35–60%, which is due to high costs, risks, and information asymmetries (Travkin, 2013; Roshchin & Travkin, 2015). Analyses also show that a high level of employee education and company growth positively influence the likelihood of providing training, which indicates the consequence of organizational capacity and workforce composition for the development of continuous learning (Travkin, 2014; Roshchin & Travkin, 2017). Studies of the effect of continuing professional education on wages using regression and difference-in-differences (DID) methods confirm that investments in human capital through formal, informal, and digital training facilitate internal elevation, increase productivity, and provide measurable returns for employers. Furthermore, government support can expand access to training for a wider range of workers and industries (Travkin, 2013; Vasiliev et al., 2013; NAFI & LIRT HSE, 2017). Overall, Russian experience demonstrates that a multi-format training system combining formal courses, on-the-job training, and digital upskilling is a major factor in employee career advancement and the innovative development of companies (see Figure 2).

Figure 2: Statistics on Training in Russian Companies



Source: NAFI (2017; 2018)

According to the survey by NAFI (2018), 69% of employed Russians noted that their employers use additional motivational tools beyond salary. The most common are bonuses and incentives (39%) and employee benefits (39%), followed by corporate events (21%) and a thirteenth salary (15%), while only 5% of companies provide employee training. Almost a third of employees (31%) indicated a lack of incentive systems, and paid training is considered a desirable form of compensation by only 5% of employees (NAFI, 2018). Additional education is perceived as a means of promotion: 77% of respondents consider it useful, and 79% believe that retraining courses are sufficient for changing careers, without a second higher education (NAFI, 2017a). Reduced-training formats are viewed as a reliable career boost for those currently employed (81%) and those with a higher education (83%). 85% of employees are interested in training in their field with the support of their employer, and 71% would like to undergo training unrelated to their current job, with 48% considering a career change as a motivated learning opportunity (NAFI, 2017a). Half of medium and large companies that provide training focus on courses in financial management and accounting (49%), while foreign languages and mass communications are used less frequently (<10%) (NAFI, 2017b). Digital skills motivate 43% of Russians for career advancement or salary increases, while the fear of digital lag is expressed by 25% of respondents, especially men and young people aged 25–34 (NAFI, 2018b). Among Russian SMEs, 79% of companies are concerned about unforeseen circumstances: 49% invest in employee training, 48% create a financial safety net, and 34% use insurance (NAFI, 2024). According to NAFI and HSE Laboratory for Labor Market Studies (2016–2017), skills shortages were reported by 69–70% of specialists and 67% of blue-collar workers, while the soft skills deficit among managers is 37%. More than half of companies train their employees: 54% of managers, 57% of specialists, and 58% of entry-level workers (NAFI & LIRT HSE, 2016–2017). Therefore, motivation, corporate training, and skills development remain core factors in increasing employee productivity and career growth in the Russian economy.

2.2.2. Analysis of Variables and Descriptive Statistics

This research develops an empirical model aimed at assessing the effect of three forms of employee training on career advancement, taking into account the structural and contextual characteristics of companies. Three groups of variables are used for the analysis: dependent, independent, and control ones.

A binary proxy dependent variable, *CareerGrowthProxy*, captures internal career advancement at "employee-year" level. The indicator takes the value 1 when an employee receives a promotion/moves to a higher hierarchical position, whereas 0 denotes the absence of changes in professional status. This operationalization allows the empirical framework to identify how different learning channels relate to measurable career outcomes.

The set of explanatory variables consists of three analytically separated training dimensions. Formal training (*train_formal*) reflects employee participation in structured educational formats. Informal training (*train_informal*) describes competence development embedded in everyday work activities through mentoring arrangements and internal knowledge-sharing initiatives. Digital training (*ittech_1–ittech_11*) captures engagement with learning technologies implemented within the firm. All training variables are also measured annually and linked to the same year t, i.e., they describe the intensity in the corresponding observation period.

To address heterogeneity across firms, the model incorporates a range of control variables. Workforce size (*nempl*) reflects organizational scale and internal mobility capacity. Average wages (*wage*) approximate financial incentives embedded in compensation structures. Industry affiliation (*industry*) isolates sector-specific labor patterns, while regional indicators (*region*) account for spatial differences in economic development and access to educational infrastructure. Ownership structure (*shareprivrus, shareprivfor, sharestate, shareother*) distinguishes between Russian private, foreign-owned, state-owned, and other enterprise forms. Graduate hiring intensity (*hiredvuz*) characterizes workforce qualification at entry. Technological condition (*sibjtechcond*) reflects the state of production equipment. Exposure to input price volatility is captured by *pricedepend*. Labor cost intensity is measured by *sharelaborc*. Operational digitalization enters through *ittech_block*, while calendar effects and institutional shifts are absorbed by *year*.

Selected interaction terms link learning variables with firm characteristics. For example, interactions between digital learning indicators and *nempl* reveal how training outcomes vary with organizational complexity and coordination requirements.

The dataset covers most federal districts of the Russian Federation, supporting regional representativeness. Regional controls isolate differences in economic conditions, educational availability, and digital infrastructure across territories.

Summary statistics are reported in Table 8, which presents means, standard deviations, and ranges.

Table 8: Descriptive Statistics of Main Variables

Variable	Mean	Std. Dev.	Min	Max	N
CareerGrowthProxy (promotion)	0.32	0.47	0	1	8,425
Formal Training (train_formal)	0.27	0.44	0	1	8,425
Informal Training (train_informal)	0.35	0.48	0	1	8,425
Digital Training (ittech_sum)	3.2	2.1	0	11	8,425
Number of Employees (nempl)	2,850	12,450	30	100,000	8,425
Average Wage (wage, RUB)	58,200	23,400	10,000	250,000	8,425

Hiring of University Graduates (hiredvuz, %)	36	18	0	100	8,425
Technological Condition (sibjtechcond, 1–5)	3.4	0.9	1	5	8,425
Price Dependence (pricedepend, 1–4)	3.1	1.1	1	4	8,425

Source: author's calculations

The distribution foregrounds substantial heterogeneity. *CareerGrowthProxy* records a mean of 0.32 with a standard deviation of 0.47, indicating that promotions occur in roughly one third of observations and vary markedly across firms. *Train_formal* covers, on average, 27 percent of employees, while *train_informal* reaches about 35 percent, suggesting broader diffusion of workplace-based development. Digital learning intensity, measured by *ittech_sum*, averages 3.2 courses per employee per year and ranges up to 11, pointing to uneven adoption of IT-based training. Firm size (*nempl*) spans from 30 to 100 000 employees, with a mean of 2 850. Average wages (*wage*) amount to 58 200 rubles and show wide dispersion. The share of university graduates (*hiredvuz*) averages 36 percent, reflecting diverse recruitment strategies. The technological condition index (*sibjtechcond*) centers around 3.4 out of 5, while *pricedepend* averages 3.1, indicating moderate sensitivity to input price fluctuations.

Overall, the data demonstrate high heterogeneity across all core variables, which should be taken into account when constructing regression models to estimate the effect under analysis.

2.3. Econometric Model, Analysis Methods, Data Preparation

To quantitatively assess the impact of the analyzed training forms and the introduction of digital technologies on employee career outcomes, econometric models were constructed using panel data on employees at Russian companies. The primary goal of the study is to identify the effect of formal, informal, and digital training on the likelihood of employee career advancement, taking into account structural, industrial, and regional factors.

2.3.1. Econometric Approaches and Model Specifications

The study utilized three approaches to estimating probabilistic relationships.

1. Panel models with fixed, random, and pooled effects. Panel models with time and individual effects allow for time-invariant company/employee characteristics that can influence employee promotion, thereby minimizing the bias in coefficient estimates caused by omitted/constant determinants. In such models, company fixed effects control for all time-invariant organizational characteristics (corporate culture, management structure, and internal career paths), resulting in more accurate estimates of regression coefficients. Random effects models, in contrast, treat individual company characteristics as random variables, allowing for differences between companies to be accounted for, provided they are independent of the regressors. Pooled effects models combine the advantages of both approaches. These regressions are applicable to panel data analysis, where the same companies are observed over multiple periods, and allow identifying the net effect of educational programs and separate it from the unchanging structural factors of companies that can distort the analysis results. This is fully consistent with approaches recommended in the econometric literature (Abid et al., 2019; Bawazir et al., 2025).

The general equation of the fixed effects (FE) model is:

$$CareerGrowthProxy_{it} = \beta_0 + \beta_1 train\_off_{it} + \beta_2 train\_on_{it} + \sum_{k=1}^{11} \beta_{2+k} ittech_{k,it} + \delta' X_{it} + \alpha_i + \gamma_t + \varepsilon_{it} \quad (1)$$

where:

X_{it}={*nempl,wage,industry,region,shareprivrus,shareprivfor,sharestate,shareother,hiredvuz,sibjtechcond,pricedepend,sharelaborc,ittech_block*};

α_i – company fixed effects, γ_t – year dummies, ε_{it} – random error.

In the random effects (RE) model, individual characteristics of the company are considered as a random variable (μ_i), independent of the regressors:

$$CareerGrowthProxy_{it} = \beta_0 + \beta_1 train\_off_{it} + \beta_2 train\_on_{it} + \sum_{k=1}^{11} \beta_{2+k} ittech_{k,it} + \delta' X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \quad (2)$$

where:

$\mu_i \sim N\ (0, \sigma_\mu^2)$ – is the random effect of the company, $\varepsilon_{it} \sim N\ (0, \sigma^2)$;

The control variables X_{it} remain the same.

The pooled model (PE) does not take into account individual and time effects; all variance is explained by the regressors:

$$CareerGrowthProxy_{it} = \beta_0 + \beta_1 train\_off_{it} + \beta_2 train\_on_{it} + \sum_{k=1}^{11} \beta_{2+k} ittech_{k,it} + \delta' X_{it} + \varepsilon_{it} \quad (3)$$

There are no α_i and γ_t here, because the model assumes that differences between companies and years do not affect the results, which simplifies estimation but can produce biased coefficients if the effects are pivotal.

2. Pooled logit and probit models with year and industry dummy variables. These regressions are discrete models designed to analyze the probability of a binary event, in this case, an employee's career growth. To accurately estimate the effect of training on such outcomes in panel data, these models contain year and industry dummy parameters, allowing for control for both time shocks and industry differences. This is done due to the fact that economic conditions, regulatory changes, and industry-specific characteristics can markedly impact the availability of career opportunities and the results of educational programs. The addition of dummy determinants ensures that the training effect is measured purely, without confounding with time and industry fluctuations, and allows for a reliable interpretation of the coefficients. This approach is consistent with modern recommendations for econometric analysis of discrete panel data (Wooldridge, 2010).

Since the dependent variable is binary, it is preferable to use a logit or probit model:

$$Pr(CareerGrowthProxy_{it} = 1 \mid train, X) = F(\beta_0 + \beta_1 train\_off_{it} + \beta_2 train\_on_{it} + \sum_{k=1}^{11} \beta_{2+k} ittech_{k,it} + \delta' X_{it}) \quad (4)$$

where F(·) – distribution function:

- Logit: $F(z) = \frac{e^z}{1+e^z}$
- Probit: $F(z) = \Phi(z)$ – standard normal distribution function.

The model comprises year and industry fixed effects through dummy parameters.

3. Use of lagged variables (t-1). To account for the fact that the effect of educational programs on employee promotion is not immediate but rather occurs with a time lag, lagged variables (t-1) are encompassed in the models. This approach captures the realistic impact of training, since courses, mentoring, and digital educational initiatives require time for knowledge to be absorbed and applied before they influence an employee's likelihood of promotion. The use of lags also reduces the risk of endogeneity associated with reverse causality between career advancement and training participation and allows the models to more accurately estimate career trajectory dynamics. This approach is fully consistent with the practice of analyzing human capital and career development, where a time lag between training and its effect on work outcomes is a natural and expected phenomenon (Cascio & Boudreau, 2016).

To take into account the fact that training affects career promotion with a delay, lagged variables are used:

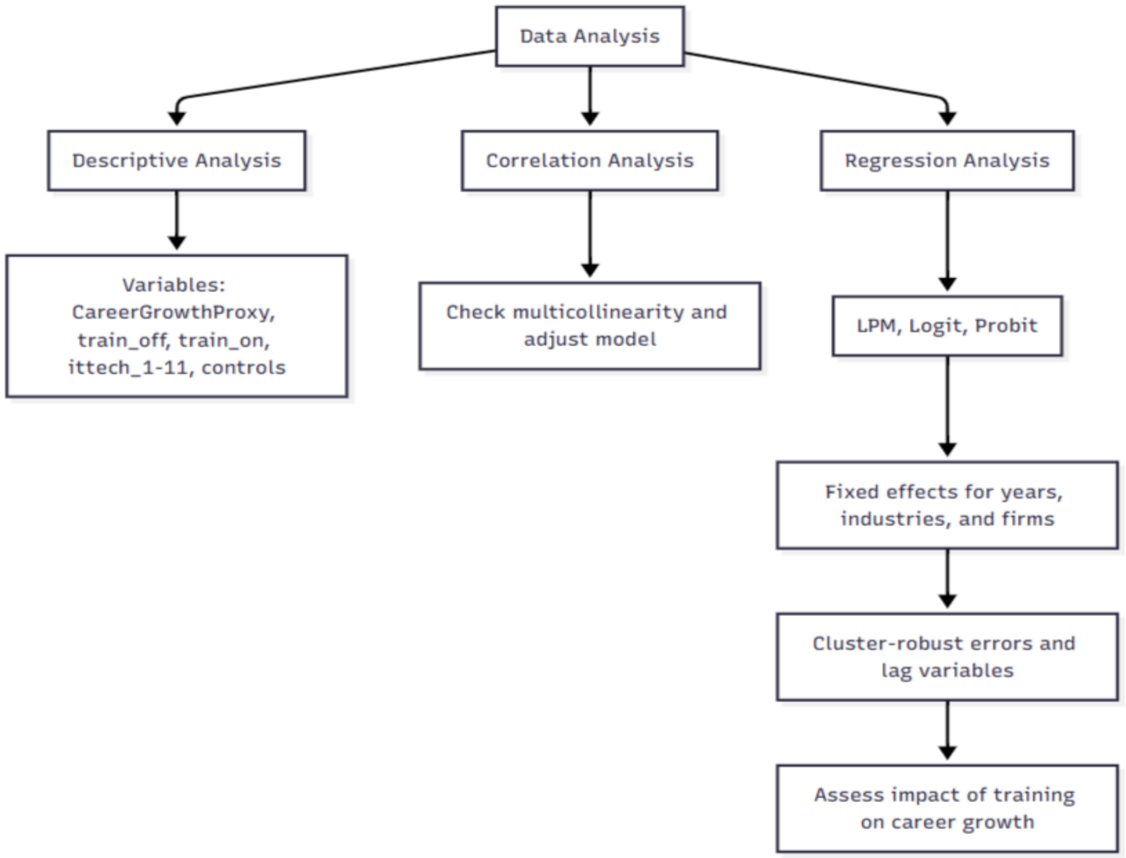
$$CareerGrowthProxy_{it} = \beta_0 + \beta_1 train\_off_{it-1} + \beta_2 train\_on_{it-1} + \sum_{k=1}^{11} \beta_{2+k} ittech_{k,it-1} + \delta' X_{it} + \alpha_i + \gamma_t + \varepsilon_{it} \tag{5}$$

Consistently, panel econometric models accounting for the structural and time-varying characteristics of companies are used for the analysis. The use of models with fixed effects, random effects, and pooled effects, as well as discrete-time models (logit/probit), allows isolating the net effect of educational programs while minimizing the influence of constant parameters and industry-specific fluctuations. The addition of lagged variables indicates a time-lag effect, reflecting realistic dynamics of knowledge acquisition and its practical application.

2.3.2. Analysis Methods and Model Testing

To analyze the data, the four stages of complex statistical methods were used, aimed at a comprehensive assessment of the impact of the three forms of training on the career growth of employees and ensuring the reliability of the results obtained (see Fig. 3).

Figure 3: Data Analysis Stages



Source: compiled by the author

The first stage involves a primary descriptive analysis, which contains constructing distributions and calculating means, medians, quartiles, and standard deviations for all variables under study. This helps identify the nature of the data distribution and the presence of outliers and assess the overall status of variables reflecting formal, informal, and digital learning, as well as the binary proxy indicator CareerGrowthProxy, used as the dependent variable.

The second stage involves correlation and graphical analysis, aimed at calculating pairwise relationships between forms of training and career outcomes, as well as between control parameters. This step allows for a preliminary assessment of the strength and direction of the relationship between indicators, identifying potential multicollinearity issues, and determining which variables may have a significant effect on the likelihood of employee career advancement. Variance Inflation Factors (VIFs) are additionally used to check for multicollinearity, allowing for the calculation of potentially redundant or highly correlated regressors and, if necessary, for adjustments to the model specification.

In the third stage, the primary tool of quantitative analysis is multiple regression. A linear panel model (LPM) is used to estimate linear relationships, while logit and probit models (logit/probit) with year and industry fixed effects are used to analyze the probability of career promotion in binary relationships, allowing for accurate control for time shocks and industry differences. Incorporating company fixed effects ensures that time-invariant organizational characteristics are taken into account.

In the fourth (final) stage, cluster-robust standard errors (SE) are used to improve the reliability of statistical inferences. These errors correct for intra-cluster correlations among observations at the company level and reduce the risk of underestimating standard errors. Furthermore, a panel balance check is performed to ensure that the data covers time comparable observations across different companies, while the use of lagged variables ensures an accurate estimate of the time lag in the effect of training on employee career advancement. The study also incorporates tests for the stability, specification, and robustness of models:

1. Hausman test checks the choice between fixed and random effects models.

2. Wald test assesses the joint significance of regressors and dummy variables across time periods; also used to test for heteroscedasticity.

3. Breusch-Pagan test checks for the presence of observation-specific error variance.

4. Nonlinearity test (LM test for squares and logarithms) evaluates the correctness of the linear specification of the model.

5. Ramsey test (RESET) validates the adequacy of the model specification.

6. White test checks for heteroscedasticity of the errors.

7. Normal Error Distribution Test examines the distribution of model residuals.

8. Wooldridge Test checks first-order autocorrelation in panel data.

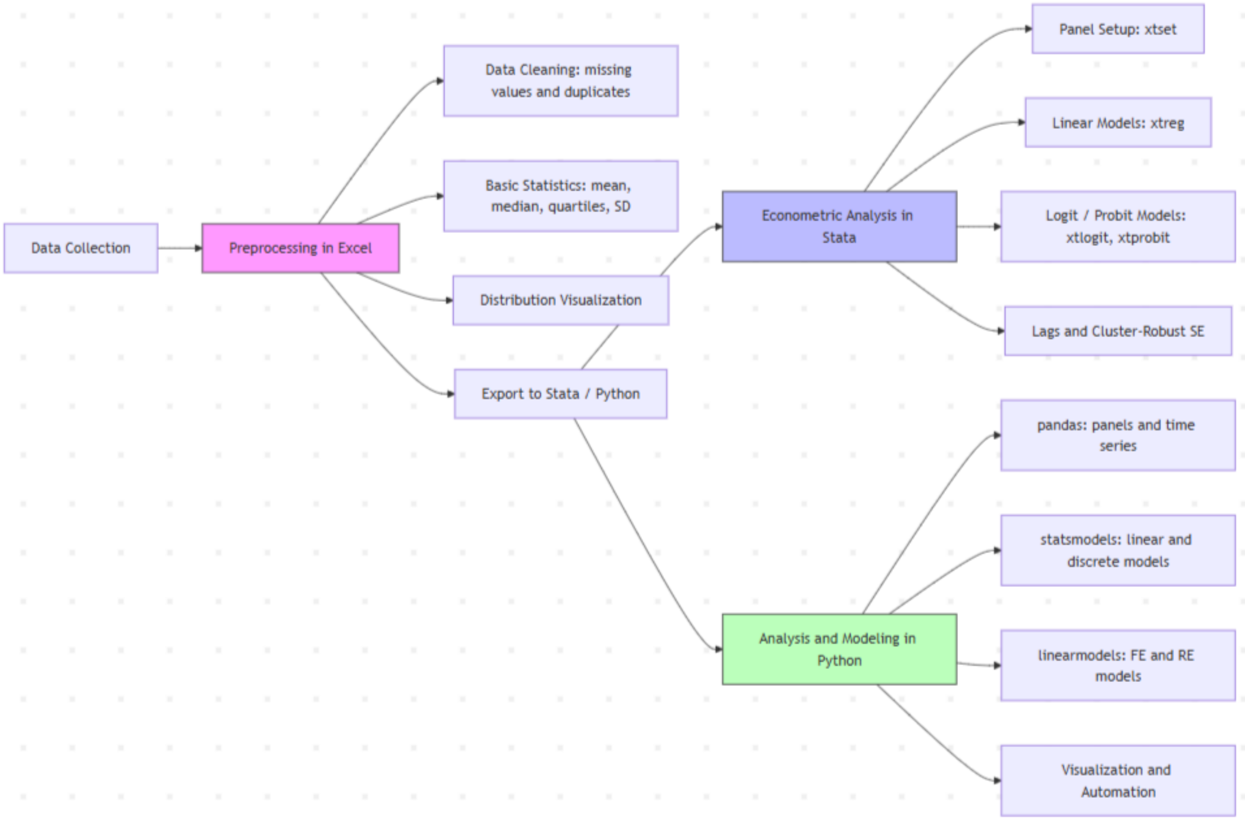
9. Pesaran CD Test inspects cross-sectional dependence.

Overall, this set of methods helps to conduct a correct empirical study on an econometric basis and control for the internal structure of the data.

2.3.3. Software Implementation

Econometric data analysis is performed using specialized software that ensures accurate and reproducible results. Stata is used for working with panel data and implementing fixed and random effects models. The major commands are *xtset* for defining the panel data structure, *xtlogit* and *xtprobit* for estimating logit and probit models with fixed effects, and *xtreg* for linear panel models. These tools help correctly account for individual company effects and time shocks, utilize lagged variables, and apply cluster-robust standard errors to correct for intra-cluster correlations (see Figure 4).

Figure 4: Software Implementation of the Analysis



Source: compiled by the author

Microsoft Excel is used for data preprocessing and preparation for analysis. Excel is used for data validation and cleaning, removing missing and duplicate data, creating pivot tables, calculating basic statistics (means, medians, quartiles, and standard deviations), as well as visualizing distributions and plotting graphs for initial variable assessment. Excel is also used to export data from the Stata statistical package and then format the results for reporting and presenting purposes.

For more complex analysis and modeling, Python is used: pandas libraries for working with panel data structures and time series, statsmodels for estimating linear and discrete models, and the linearmodels package, specifically designed for analyzing panel data with fixed and random effects. Using Python provides flexibility in data preparation, visualization of correlations and distributions, and automation of repetitive analysis procedures.

The proposed methodology integrates complementary tools in order to estimate training effects with higher precision. Structural heterogeneity across firms enters the specification through the control set, while industry and year absorb sectoral patterns and macro-level shifts. Firm-invariant features remain outside direct measurement, yet the empirical design reduces their influence on coefficient bias.

The same framework supports substantive inference on how educational initiatives relate to CareerGrowthProxy. Statistical identification rests on transparent variable construction and consistent model structure, while managerial relevance follows from coefficients that translate into HR policy choices and internal mobility planning.

2.4. Hypothesis Testing Plan, Risk Mitigation Measures

The study relies on the human capital framework formulated by Becker (2008) and on empirical evidence regarding corporate training practices in Russia reported by NAFI for the period 2019–2024. On this basis, four empirically testable assumptions related to career advancement is formulated.

H0: Continuous learning activities (formal, informal, and digital training) have no statistically significant effect on internal career progression (measured by internal promotion).

The empirical basis for the "effectiveness" of informal learning is sometimes ambiguous and in cases overestimated, so it is logical to assume a zero effect on internal promotion (Clardy, 2018). Work-related learning formats yield varying career outcomes, and for part of outcomes, formal learning does not appear to contribute at all, which supports the H0 hypothesis (Decius et al., 2024). The effect of training depends on the context and valence (perceived usefulness), so without the right conditions, the impact on internal promotion may not be statistically apparent (van den Elsen et al., 2022).

H1: Formal training (train_formal) positively influences the likelihood of internal promotion.

This hypothesis draws on numerous studies demonstrating the direct impact of formal training on career outcomes and productivity. For example, Arthur et al. (2003) found that structured training programs in organizations have a positive impact on employee performance. Similarly, Barrett and O'Connell (2001) illustrated that corporate training generally has a positive effect on career promotion and income. Research in the contexts of Russia and other countries confirms that participation in formal training increases the likelihood of promotion and improves professional competencies (Roshchin & Travkin, 2015; 2017). Islam et al. (2020) noted the effectiveness of formal training programs in the banking sector, which indirectly indicates improved career prospects.

H2: Informal training (train_informal) through internal practices and mentoring increases employees' chances of internal promotion.

Empirical studies by Cerasoli et al. (2018) reveal stable links between informal training formats and observable changes in professional conduct. Manuti et al. (2015) together with Clardy (2018) identify workplace-based knowledge exchange as a mechanism shaping employability trajectories. Evidence presented by Decius et al. (2019) differentiates outcomes across training formats and reports stronger career expectations among participants of informal initiatives. Kwon and Cho (2020) associate such initiatives with promotion dynamics, while Abid et al. (2019) identify organizational commitment as a transmission channel through which engagement in informal development translates into advancement decisions.

H3: The use of digital training technologies boosts the likelihood of internal promotion, especially when combined with other forms of training.

Research by Antonopoulou et al. (2021) identifies digital competence as a determinant of performance in knowledge-intensive settings. Park and Choi (2016) demonstrate that digital integration within formal and informal training environments intensifies workplace development effects. Laubengaier et al. (2025) further show that blended training infrastructures reinforce internal development cultures, while Poquet and De Laat (2021) trace sustained competence accumulation to systematic digital engagement during periods of technological change.

Hypothesis verification follows a structured sequence intended to secure empirical consistency and analytical rigor (see Table 9).

Table 9: Summary of Hypothesis Testing Stages and Control Methods

Stage	Description
1. Data and Panel Structure Preparation	Comparability of annual comparisons in the panel, missing value checks and imputation, standardization and recoding of qualitative variables
2. Preliminary Descriptive Analysis	Assessment of variable distribution, checking correlations between training and career outcomes, data visualization to identify anomalies
3. Regression Analysis	LPM with effects, logit/probit with year and industry dummies, lagged variables (t-1), control for structural and industry factors
4. Significance and Effect Size Evaluation	Testing coefficients at 5% and 1% significance levels, interpretation of marginal effects
5. Robustness Checks	Subsamples by industry, size, and region; cluster-robust standard errors; multicollinearity diagnostics (VIF); alternative model specifications; checking lagged effects (t-1 and t-2)
6. Instrumental Variables (IV)	Use of instruments to address self-selection endogeneity
7. Assumption Control and Risk Mitigation	Single imputation for missing data, fixed effects for time-invariant factors, endogeneity check, external validity, model diagnostics (VIF, heteroskedasticity, autocorrelation)
8. Study Limitations	Possible data incompleteness, limited measurement accuracy for informal training, limited generalizability for small or non-representative companies

Source: compiled by the author

The initial phase constructs a firm-level panel by year, aligns observations across periods, and resolves missing values in order to preserve sample comparability. Quantitative variables undergo normalization, while categorical attributes receive numerical encoding.

The subsequent phase evaluates descriptive patterns, examines pairwise associations between training indicators and CareerGrowthProxy, and detects distributional irregularities. This preparatory analysis informs model specification and narrows attention to relationships that justify econometric testing.

The third stage engages regression analysis, using linear panel models (LPM) with effects, as well as logit and probit models with year and industry dummy variables, to estimate the likelihood of employee career promotion. The model contains lagged variables for the previous period (t-1) to reflect the time lag of the training effect, as well as control variables to account for the influence of structural and industrial factors.

The fourth stage requires assessing the statistical significance and size of the effects by testing the regression coefficients at the 5% and 1% significance levels, as well as interpreting the marginal effects for the logit and probit models. This allows for a quantitative assessment of the effect of each form of training on the likelihood of promotion.

As part of the fifth stage, robustness checks comprise analyzing subsamples by industry, company size, and region, using cluster-robust standard errors to account for the correlation of observations within companies, diagnosing multicollinearity using VIF, comparing alternative specifications of the LPM and logit/probit models, and testing the time effect of training using lags t-1 and t-2 to assess the long-run impact.

At the sixth stage, to minimize endogeneity, an instrumental approach (IV) is used whenever possible. Additional variables are used as instruments to estimate the net effect of training on career growth and separate it from employee self-selection bias.

Furthermore, the seventh stage considers risk mitigation measures and assumption control through single imputation for missing data, the use of fixed-effects panel models to control for unchanging factors, endogeneity testing using IVs, ensuring external validity through broad industry and region coverage, and model diagnostics for multicollinearity, heteroscedasticity, and autocorrelation.

At the eighth stage, the study's main limitations are considered which comprise possible incomplete data for individual years or companies, limited accuracy of measuring informal training, and the potential limited generalizability of the results for small and non-representative companies. Despite this, a combination of countermeasures helps minimize the influence of confounding factors and improve the reliability of conclusions about the effect under study.

3. RESULTS
3.1. Sample Description and Initial Analysis

The transition from the initial variables (*id*, *nempl*, *industry*, *year_found*, *shareprivrus*, *shareprivfor*, *sharestate*, *shareother*, *sibjtechcond*, *ittech_1… ittech_11*, *pricedepend*, *export*, *sharelaborc*, *hiredvuz*, *wage*, *train*, *train_formal*, *train_informal*, *year*, *weight*, *CareerGrowthProxy*) to a structured dataset reveals the creation of meaningful and interpretable variables (see Table 10). For example, company age (*comp_age*) was calculated based on *year_found*, shares of ownership were combined into a weighted index (*own_balance*), and training indicators (*train_formal*, *train_informal*, *train_dig*) were used both separately and aggregated into an overall training intensity measure (*train*). Categorical variables were encoded: industry, export activity, and technological/market conditions (*sibjtechcond*, *pricedepend*), while continuous indicators such as wages, labor cost share, and number of employees were standardized. Digital training (*train_dig*) was consolidated into comparable metrics through the sum of individual parameters (*ittech_1… ittech_11*), and the career growth proxy (*CareerGrowthProxy* and *WCareerGrowthProxy*) was represented by binary and weighted variables, respectively. Observation years were limited to the 2019–2024 range, and observation weights (*weight*) were preserved. All technical variables were cleared, recoded, and clearly labeled to ensure consistency, interpretability, and analytical readiness. The sample was reduced from 8,420 to 2,460 observations due to the exclusion of missing, incorrect, and logically inconsistent data.

Table 10: Description of Structured Variables for Analysis

Variable	Description	Type / Unit of Measurement	Interpretation
id	Unique employee identifier	Text (string)	Used to identify each observation
nempl	Number of employees in the organization	Quantitative (number)	Reflects company size (scale of operations)
industry	Industry code	Categorical (number)	1 – Manufacturing, 2 – Extractive, 3 – Energy, 4 – Construction and Real Estate, 5 – Services and Infrastructure
comp_age	Company age	Quantitative (years)	Indicates company experience and stability in the market
own_balance	Weighted ownership index (private, foreign, state, other)	Share (0–1), calculated as (1*(shareprivrus + shareprivfor) + 0.5*shareother + *0**sharestate)/100	1 = fully private, 0 = fully state-owned, intermediate values indicate mixed ownership
sibjtechcond	Technological condition (estimate)	Ordinal scale (1–5)	1 – low technological level, 5 – high technological level
pricedepend	Dependence on prices / market fluctuations	Ordinal scale (1–4)	1 – low dependence, 4 – high dependence

export	Export activity	Binary (0/1)	1 – company exports products, 0 – does not export
sharelaborc	Share of labor costs (%)	Quantitative (%)	Reflects the structure of company costs
hiredvuz	Share of employees hired from universities (%)	Quantitative (%)	Indicator of academic or young workforce presence
wage	Average wage in rubles	Quantitative (rubles)	Proxy for workforce development and employer attractiveness
train	Overall training intensity	Quantitative (% of participants)	Aggregate measure of all types of training
train_formal	Share of formal training	Quantitative (% of participants)	Courses, trainings, certifications
train_informal	Share of informal training	Quantitative (% of participants)	Mentoring, on-the-job learning
train_dig	Volume of digital training	Quantitative (number of courses)	Online learning, e-learning, LMS, etc.
year	Observation year	Quantitative	Covers 2019–2024
weight	Observation weight	Quantitative (0–2.82)	Regional and sectoral weighting factor
CareerGrowthProxy	Career growth proxy	Binary (0/1)	1 – internal promotion observed; 0 – no promotion
WCareerGrowthProxy	Weighted career growth proxy	Quantitative (weight * binary metric)	Weighted indicator adjusted for sample homogeneity

Source: compiled by the author

The analysis of the sample's descriptive statistics illustrates that the observations cover a wide range of company and employee characteristics (see Table 11). The sample is highly heterogeneous in terms of company size, industry, age, ownership structure, and technological level, as well as employee wages, training, and career trajectories. The weighted proxy for career growth, *WCareerGrowthProxy*, averages 0.461, indicating that internal promotion is observed for less than half of employees; the variance is higher which suggests heterogeneity in career trajectories depending on region, industry, and company scale. *CareerGrowthProxy* approximates a balanced binary indicator, with a mean value of 0.495, which allows its interpretation as an unbiased marker of upward mobility. Firm scale, expressed through *nempl*, extends from 30 to 100,000 employees, while the average level equals 598, which indicates the simultaneous presence of small enterprises and large corporations. Sectoral affiliation captured by *industry* covers five categories and concentrates mainly within manufacturing and extractive activities, where the mean reaches 2.44. Organizational maturity, reflected by *comp_age*, spans from three to 202 years and averages 24.6 years, which reveals coexistence of recently established firms and long-standing market participants. Ownership structure measured by *own_balance* shows predominance of private capital with an average of 0.914, although state and mixed forms also appear in the sample. The technological state assessed by *sibjtechcond* varies between zero and five and reaches a mean of 3.43, which characterizes an intermediate level of equipment modernization. Price sensitivity proxied by *pricedepend* equals 2.63 on a four-point scale and indicates moderate exposure to market volatility. Export participation remains limited, since only 18.6 percent of firms report external sales. Considerable dispersion emerges for *sharelaborc* and *hiredvuz*, which points to heterogeneity in cost composition and human capital profiles. Wage levels measured by *wage* range from 999 to 210,000 rubles, which signals pronounced differentiation in compensation incentives. Training activity demonstrates uneven intensity. *Train_informal* reaches 32 percent, *train_formal* remains at 17.9 percent, and *train_dig* stays restricted with a mean value of 5.43. All observations refer to 2024, while weight averages 0.922 and corrects for sample representativeness.

Table 11: Descriptive Statistics (Observations Used: 1:1–410:6)

Variable	Mean	Median	Std. Dev.	Min	Max
WCareerGrowthProxy	0.461	0.000	0.579	0.000	2.82
CareerGrowthProxy	0.495	0.000	0.500	0.000	1.00
nempl	598.0	150.0	2940.0	30.0	100000.0
industry	2.44	2.00	1.54	1.00	5.00
comp_age	24.6	21.0	19.3	3.00	202.0
own_balance	0.914	1.00	0.255	0.000	1.00
sibjtechcond	3.43	3.00	0.943	0.000	5.00
pricedepend	2.63	3.00	1.08	0.000	4.00
export	0.186	0.000	0.389	0.000	1.00
sharelaborc	24.7	23.0	22.5	0.000	100.0
hiredvuz	7.61	0.000	83.9	0.000	2100.0
wage	32,100.0	30,000.0	18,000.0	999.0	210,000.0
train	22.9	15.0	26.2	0.000	100.0
train_formal	17.9	3.00	29.5	0.000	100.0
train_informal	32.0	10.0	38.1	0.000	100.0
train_dig	5.43	5.54	1.79	0.000	10.0
year	2024.0	2024.0	1.63	2019.0	2024.0
weight	0.922	0.980	0.489	0.150	2.82

Source: author's calculations

Distributional diagnostics uncover marked asymmetry across several variables. *WCareerGrowthProxy* displays positive skewness equal to 1.07 alongside moderate kurtosis of 0.48, which indicates a slight concentration at higher values. *CareerGrowthProxy* shows near symmetry with skewness of 0.02, whereas kurtosis of -2.00 signals a flattened distribution with extended tails. Firm size captured by *nempl* reveals extreme right skewness of 21.42 and kurtosis of 608.23, which highlights the dominance of a small group of very large organizations against a broad base of smaller entities. Sectoral affiliation measured by *industry* presents moderate asymmetry at 0.50 and negative kurtosis of -1.35, which reflects concentration within a limited number of leading sectors. Company age (*comp_age*) displays strong positive skewness (3.46) and high kurtosis (17.17), indicating the presence of rare, very old companies. The ownership index (*own_balance*) is highly negatively skewed (−2.94) with high positive kurtosis (7.26), presenting the dominance of fully private companies. Technological condition (*sibjtechcond*) and price dependence (*pricedepend*) have moderate negative skewness, suggesting that most companies exhibit medium-to-high technology levels and moderate price sensitivity. Export activity (*export*) displays positive skewness (1.62) and kurtosis (0.61), confirming that exporters are relatively rare. Labor cost share (*sharelaborc*) and the share of hired university graduates (*hiredvuz*) vary widely, with the latter illustrating extreme values that accentuate the coexistence of firms with almost no or very high academic workforce concentration. Wages (*wage*) have positive skewness (1.07) and kurtosis (5.05), revealing income variation and the presence of highly paid employees. Training intensity – particularly formal training (*train_formal*) and overall training (*train*) – shows high positive skewness and kurtosis, indicating that while most employees receive limited training, only a few engage in highly intensive programs. The variable distributions demonstrate strong heterogeneity and the presence of outliers, necessitating caution (additional tests and adjustments) during further analysis and interpretation.

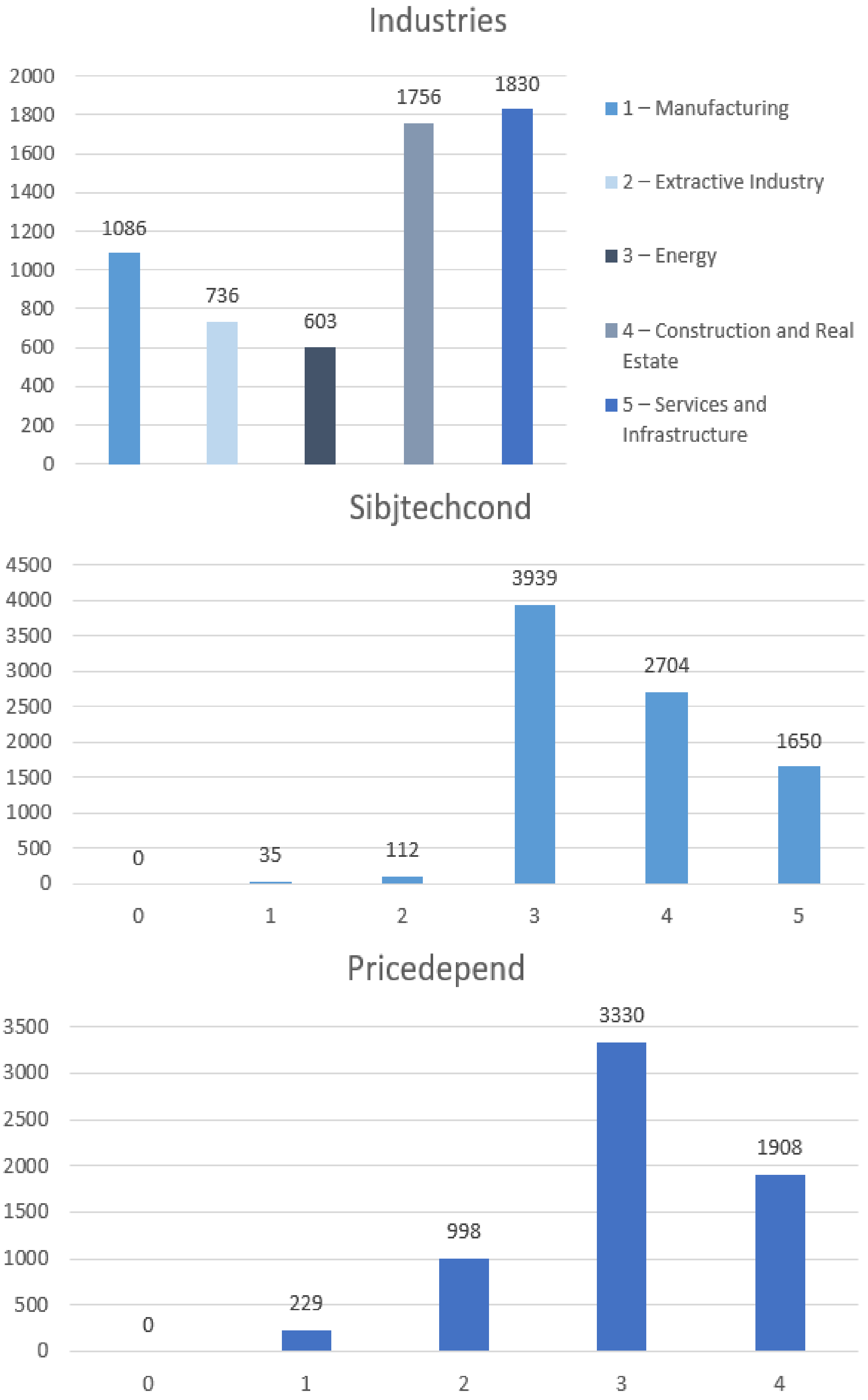
Table 12: Distribution Statistics

Variable	Var	Skew	Kurt	5th Perc	95th Perc	Interquartile Range	Missing
WCareerGrowthProxy	1.26	1.07	0.48	0.00	1.45	0.98	0
CareerGrowthProxy	1.01	0.02	−2.00	0.00	1.00	1.00	0
nempl	4.92	21.42	608.23	32.00	2096.70	290.00	0
industry	0.63	0.50	−1.35	1.00	5.00	3.00	0
comp_age	0.79	3.46	17.17	9.00	65.00	11.00	0
own_balance	0.28	−2.94	7.26	0.00	1.00	0.00	0
sibjtechcond	0.27	−0.68	2.41	2.00	5.00	1.00	0
pricedepend	0.41	−0.80	0.11	0.00	4.00	1.00	0
export	2.09	1.62	0.61	0.00	1.00	0.00	0
sharelaborc	0.91	0.73	0.01	0.00	70.00	40.00	0
hiredvuz	11.02	22.88	544.01	0.00	20.00	2.00	0
wage	0.56	1.07	5.05	999.00	62,000	20,950	0
train	1.14	1.51	1.57	0.00	90.00	26.00	0
train_formal	1.65	1.88	2.33	0.00	100.00	20.00	0
train_informal	1.19	0.83	−0.93	0.00	100.00	60.00	0
train_dig	0.33	−0.14	1.93	1.00	9.00	0.32	0
year	0.00	0.41	−1.11	2019	2024	3.00	0
weight	0.53	0.66	1.15	0.23	1.79	0.71	0

Source: author's calculations

The graphs below illustrate the distributions of the ordinal variables, clearly visualizing the trends described earlier.

Figure 5: Distribution Charts by Industrial, Technological, and Market Conditions

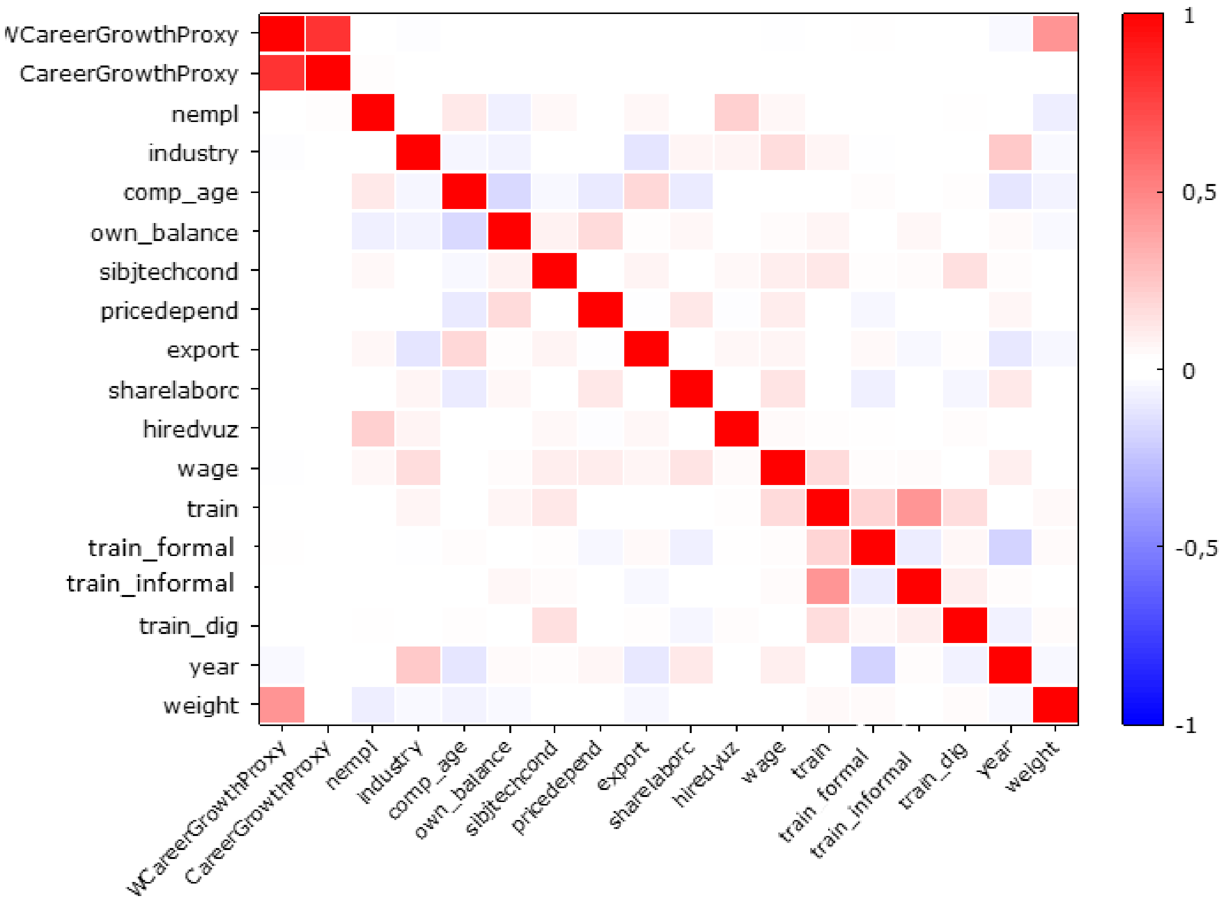


Source: compiled by the author

The correlation matrix analysis demonstrates that the variable *WCareerGrowthProxy* is most strongly associated with the binary career growth indicator *CareerGrowthProxy* (0.80), confirming that both metrics reflect similar aspects of employee promotion (see Fig. 6). The relationship with company size (*nempl*), industry (*industry*), and company age (*comp_age*) is nearly nonexistent, indicating that structural characteristics of organizations have little effect on observed career growth. The ownership index (*own_balance*), technological condition (*sibjtechcond*), and price dependence (*pricedepend*) reveal very low correlations with *WCareerGrowthProxy*, suggesting that internal promotions are not significantly influenced by these factors. Export activity (*export*) and labor cost share (*sharelaborc*) are also almost unrelated to the career growth proxy, implying a limited role of external orientation and cost structure.

The share of employees with higher education (*hiredvuz*) and wage level (*wage*) exhibit a slight positive correlation, hinting at a modest influence of qualification and compensation on promotion. Training intensity measured by *train* reveals a weak positive association with *WCareerGrowthProxy*, which allows identification of a limited link between aggregated learning activity and internal advancement. Separate indicators of formal instruction (*train_formal*) and informal development (*train_informal*) show almost no correlation with career outcomes, which indicates that participation alone does not translate automatically into promotion. Digital education proxied by *train_dig* also demonstrates only a marginal positive relationship, which suggests restrained influence on upward mobility within the observed firms. At the same time, internal associations among train, *train_informal*, and *train_formal* remain moderate, which reflects coordinated planning of development initiatives rather than isolated programs. Temporal variable *yea*r and weighting factor *weight* display near-zero correlation with the core indicators, which confirms stability of the dataset across time and correctness of regional and sectoral adjustments.

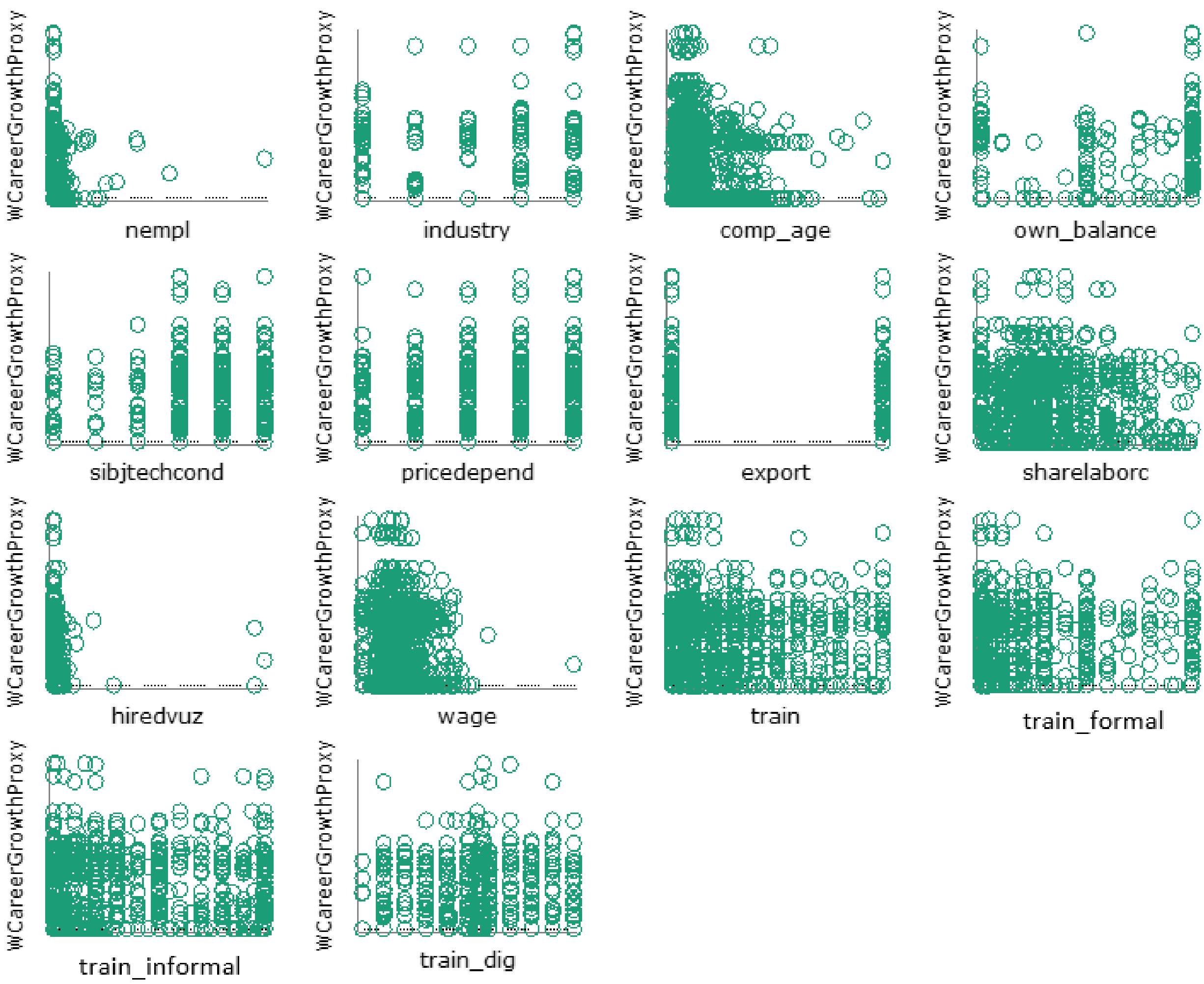
Figure 6: Correlation Matrix



Source: compiled by the author

The scatterplot analysis of *WCareerGrowthProxy* against major variables illustrates a weak dependence of career growth on company size (*nempl*) and industry (*industry*), confirming the findings from the correlation analysis (see Fig. 7). A moderate positive trend is observed with company age (*comp_age*), indicating a higher likelihood of promotion in more mature organizations. The relationship with private ownership share (*own_balance*) and the company's technological condition (*sibjtechcond*) appears weak and scattered, without any clear linear pattern. Dependence on price sensitivity (*pricedepend*) and export activity (*export*) is virtually absent, foregrounding minimal influence of external orientation on career progression. Labor cost share (*sharelaborc*) and employee education level (*hiredvuz*) display dispersed data, indicating variability within companies. Average wages (*wage*) show a moderate clustering of points at higher *WCareerGrowthProxy* values, suggesting an effect of compensation on promotion. General training (*train*) and its components (*train_formal*, *train_informal*, *train_dig*) form dense but scattered clouds, reflecting heterogeneous impacts of training programs. The general visualization confirms that career growth in the sample is determined in a complex manner, without a strong dependence on any single variable.

Figure 7: Scatterplots



Source: compiled by the author

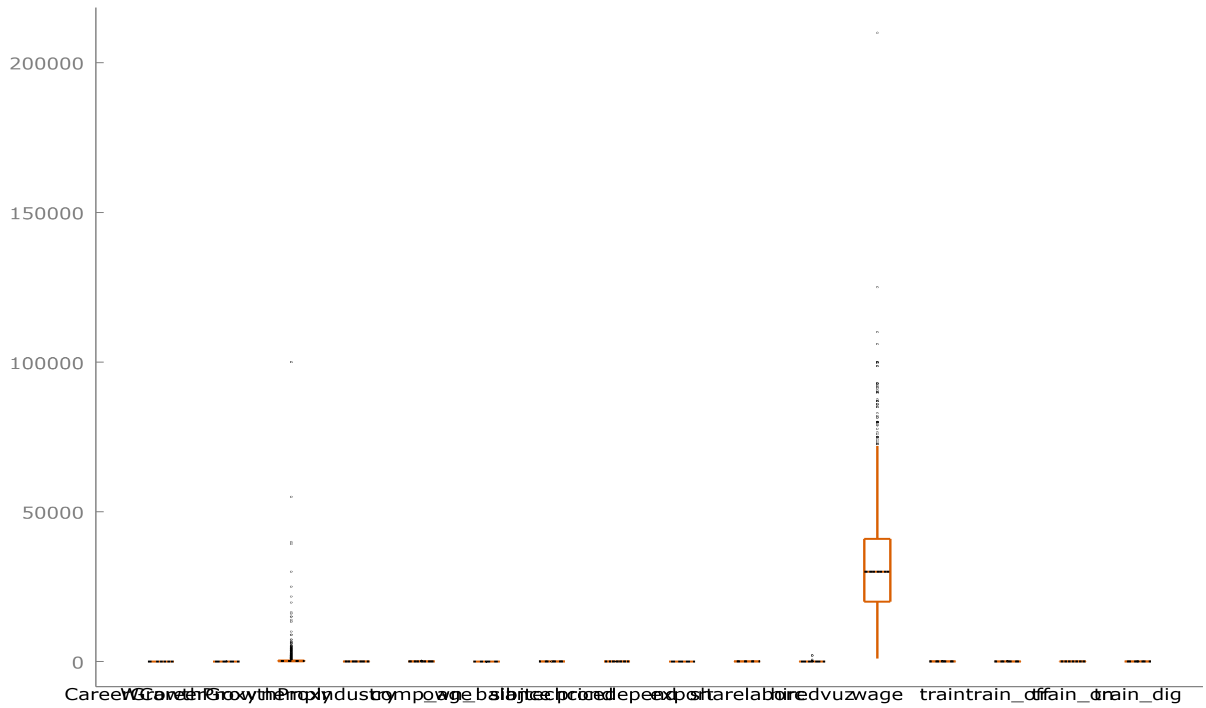
Figure 8 presents the frequency distributions of all variables included in the empirical specification and emphasizes pronounced heterogeneity across firms. Most indicators demonstrate clear concentration points alongside extreme values, which points to uneven structural conditions among enterprises. *Wage* and *comp_age* span particularly wide intervals, which illustrates sharp contrasts in remuneration systems and organizational maturity. Training-related measures (*train, train_formal, train_informal, train_dig*) share comparable distribution shapes, although asymmetry remains visible in several cases. Such patterns justify transformation procedures, since normalization and logarithmic scaling reduce distortion effects prior to estimation.

Figure 8: Variable Distribution Charts

Source: compiled by the author

Boxplot diagnostics displayed in Figure 9 clarify the position of medians and the dispersion of values across variables. The majority of indicators cluster tightly around central values, whereas *wage* and *nempl* stand apart due to extreme observations. Similar deviations appear for *train* and *train_formal*, which signals that certain organizations allocate exceptionally high resources to staff development. Narrow interquartile ranges reveal dense concentration of observations near medians, while distributional imbalance complicates estimation procedures. Data cleaning through outlier treatment and smoothing therefore becomes necessary to stabilize model behavior and improve interpretability of results.

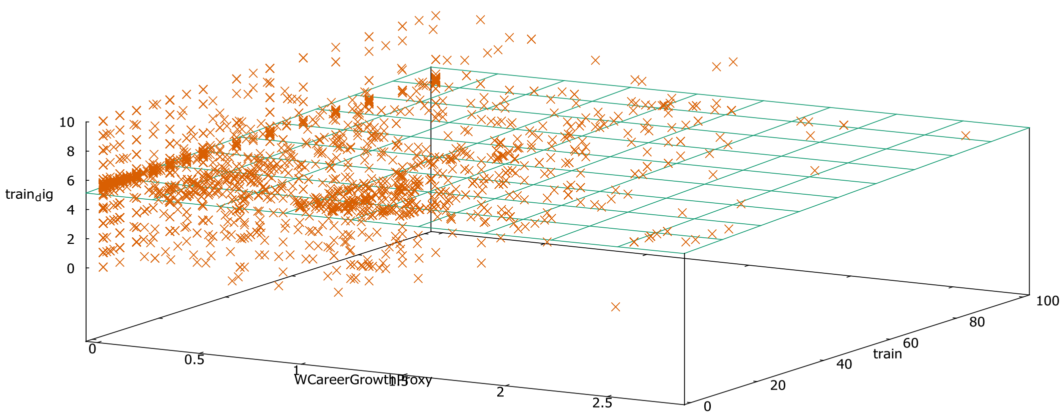
Figure 9: Boxplots



Source: compiled by the author

The 3D plot illustrates the relationship between *train*, *train_dig*, and *WCareerGrowthProxy* (see Fig. 10). A positive trend is observed: higher investment in training is associated with an increase in the career growth indicator. However, the points are unevenly distributed, indicating the presence of clusters. This suggests differences in companies' strategies regarding employee training. Some point groups deviate strongly from the overall trend, spotlighting potential anomalies. There is a high density of data at lower levels of training. At the same time, the plot supports the hypothesis that training has a positive impact on career development.

Figure 10: 3D Plot of Training Variables and Career Growth



Source: compiled by the author

Transforming the original variables into a structured dataset allowed the creation of informative indicators, facilitating interpretation and subsequent analysis. The sample demonstrates high heterogeneity in company size, age, technological level, industry, wages, and training parameters, reflecting a wide range of corporate strategies and career trajectories. Correlation and graphical analyses showed that internal employee promotion is weakly dependent on structural company characteristics but moderately associated with training and wage levels, confirming the value of human capital for career growth. Distribution analysis revealed strong skewness and the presence of extreme values, particularly for wages, employee numbers, and training metrics, necessitating log-transformation, standardization, and outlier mitigation for proper estimation of panel models, logit and probit models, as well as specifications with first differences and heteroskedasticity adjustments. Visualization of interactions between training and career growth revealed clusters and anomalies, featuring differences in corporate personnel development strategies and supporting the proposed hypotheses, demonstrating the need to account for these effects in the development of further model specifications.

3.2. Comparison and Trend Analysis

Examination of the eigenvalue spectrum shows a one-to-one correspondence between the fifteen extracted components and the original set of variables, arranged in sequential order (Table 13). The dominant position belongs to the first component, whose eigenvalue reaches 5.285. This element captures the core configuration of the dataset and concentrates the strongest loading on *WCareerGrowthProxy*, which emerges as the central dimension of variation. The second and third parts, with eigenvalues of 1.318 and 1.167, extend the explained structure to a lesser degree and reflect the contribution of firm scale and sectoral affiliation to dispersion within the sample. All remaining components, from the fourth to the fifteenth, display sharply declining eigenvalues and describe residual patterns of limited analytical weight. Accumulated explanatory power attains full coverage at the fifteenth component, while the first five components already account for roughly two thirds of total variance. This concentration allows identification of redundant dimensions and supports dimensional reduction without loss of substantive information on employee advancement.

Table 13: Eigenvalues for the Correlation Matrix

Component	Eigenvalue	Proportion	Cumulative Proportion
1	5.285	0.352	0.352
2	1.318	0.088	0.440
3	1.167	0.078	0.518
4	1.062	0.071	0.589
5	0.961	0.064	0.653
6	0.886	0.059	0.712
7	0.775	0.052	0.764
8	0.696	0.046	0.810
9	0.600	0.040	0.850
10	0.560	0.037	0.887
11	0.484	0.032	0.920
12	0.407	0.027	0.947
13	0.329	0.022	0.969
14	0.261	0.017	0.986
15	0.210	0.014	1.000

Source: author's calculations

Results of the principal component decomposition clarify the internal logic of factor groupings (Table 14). The first principal component demonstrates a tight association between ownership balance, technological condition, and *WCareerGrowthProxy*, which together outline the structural backbone of organizational development. Workforce size and the share of newly hired university graduates dominate the second component and underline the relevance of personnel composition. The third component brings together indicators of employee training activity and export orientation, revealing a link between skill formation and external market exposure. Company maturity, combined with training intensity and export share, shapes the fourth component and points to evolutionary trajectories of established firms. Formal training and labor cost share define the fifth component and highlight cost-skill interactions. Subsequent components isolate narrower configurations, where career growth intersects with training patterns and ownership structure or where industry affiliation aligns with labor expenditure. Concentration of explanatory power within the first seven components narrows the analytical focus to variables with strategic relevance for managing internal mobility.

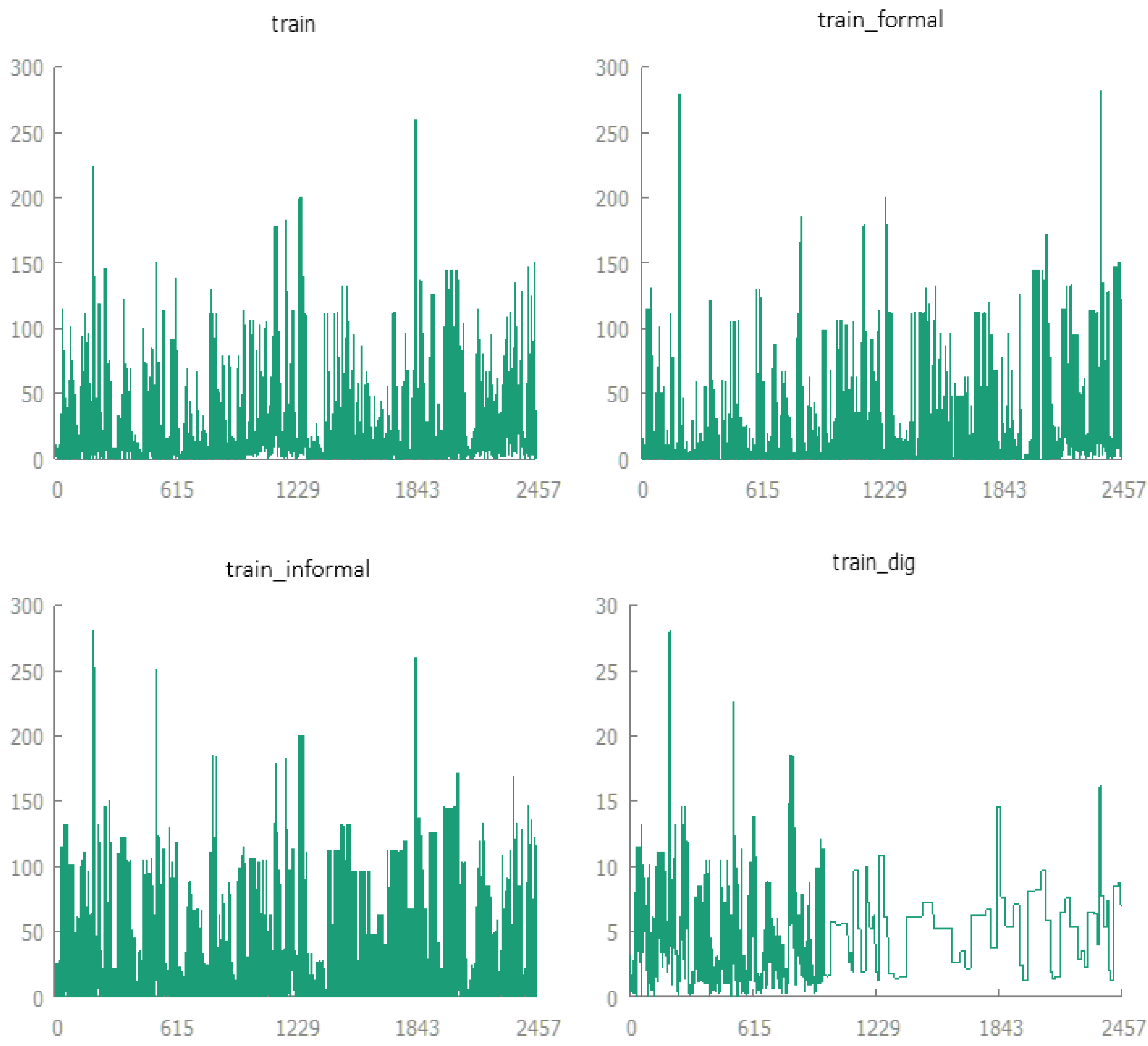
Table 14: Eigenvectors (Component Loadings)

Variable	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12	PC13	PC14	PC15
WCareerGrowthProxy	-0.206	-0.023	0.188	0.069	0.103	-0.611	0.632	0.127	-0.230	0.238	0.065	0.043	-0.008	0.010	0.033
nempl	0.001	-0.667	-0.092	-0.192	0.075	-0.207	-0.238	0.616	0.123	-0.075	-0.034	0.026	0.003	-0.045	0.032
industry	-0.295	0.021	-0.033	-0.256	-0.064	-0.096	-0.168	-0.172	0.376	0.648	-0.392	0.004	0.244	-0.021	-0.010
comp_age	-0.199	-0.200	0.228	0.386	0.068	-0.281	-0.583	-0.301	-0.425	0.055	0.061	-0.040	0.106	-0.064	0.033
own_balance	-0.372	0.080	0.052	-0.089	0.058	0.016	0.056	-0.056	0.141	-0.324	-0.048	-0.041	0.013	-0.623	0.564
sibjtechcond	-0.380	-0.006	0.066	-0.039	0.028	-0.043	-0.018	-0.057	0.129	-0.159	-0.062	-0.127	-0.476	-0.271	-0.694
pricedepend	-0.350	0.099	0.040	-0.149	0.106	-0.015	0.032	0.037	0.047	-0.408	0.132	0.007	0.716	0.224	-0.286
export	-0.078	-0.263	0.384	0.512	0.385	0.457	0.218	0.082	0.246	0.119	-0.141	0.024	0.086	0.023	-0.014
sharelaborc	-0.241	0.099	-0.034	-0.331	0.261	0.409	-0.008	0.244	-0.665	0.172	-0.227	-0.025	-0.053	-0.000	0.009
hiredvuz	-0.018	-0.637	-0.216	-0.224	-0.058	0.157	0.314	-0.586	-0.136	-0.064	0.021	-0.042	0.033	0.025	-0.002
wage	-0.321	-0.012	-0.018	-0.117	0.069	0.184	-0.092	0.010	0.128	0.289	0.790	0.262	-0.164	0.087	0.091
train	-0.242	-0.020	-0.417	0.366	-0.326	0.123	0.092	0.207	-0.044	0.151	0.137	-0.636	0.104	-0.013	0.027
train_formal	-0.150	-0.106	0.358	0.043	-0.790	0.194	0.070	0.145	-0.133	-0.019	-0.085	0.344	0.050	-0.043	-0.036
train_informal	-0.200	0.035	-0.625	0.375	0.064	-0.034	0.027	0.016	-0.036	-0.065	-0.206	0.609	-0.017	-0.009	-0.038
train_dig	-0.370	0.004	0.075	-0.013	-0.037	-0.061	-0.052	-0.050	0.117	-0.245	-0.222	-0.107	-0.371	0.686	0.322

Source: author's calculations

Graphical inspection of temporal paths for *train*, *train_formal*, *train_informal*, and *train_dig* reveals comparable oscillatory movements across observation periods (Fig. 11). Each series follows recurrent rises and declines that coincide with planned cycles of skill development. Internal learning, proxied by *train_informal*, displays the smoothest trajectory, which reflects the routine nature of in-house practices. Digital training, measured by *train_dig*, fluctuates more sharply, which indicates uneven diffusion of technological learning tools across firms. Formal instruction occupies an intermediate position between stability and volatility. The synchronized rhythm observed across all four indicators points to institutional scheduling rather than random variation in training activity.

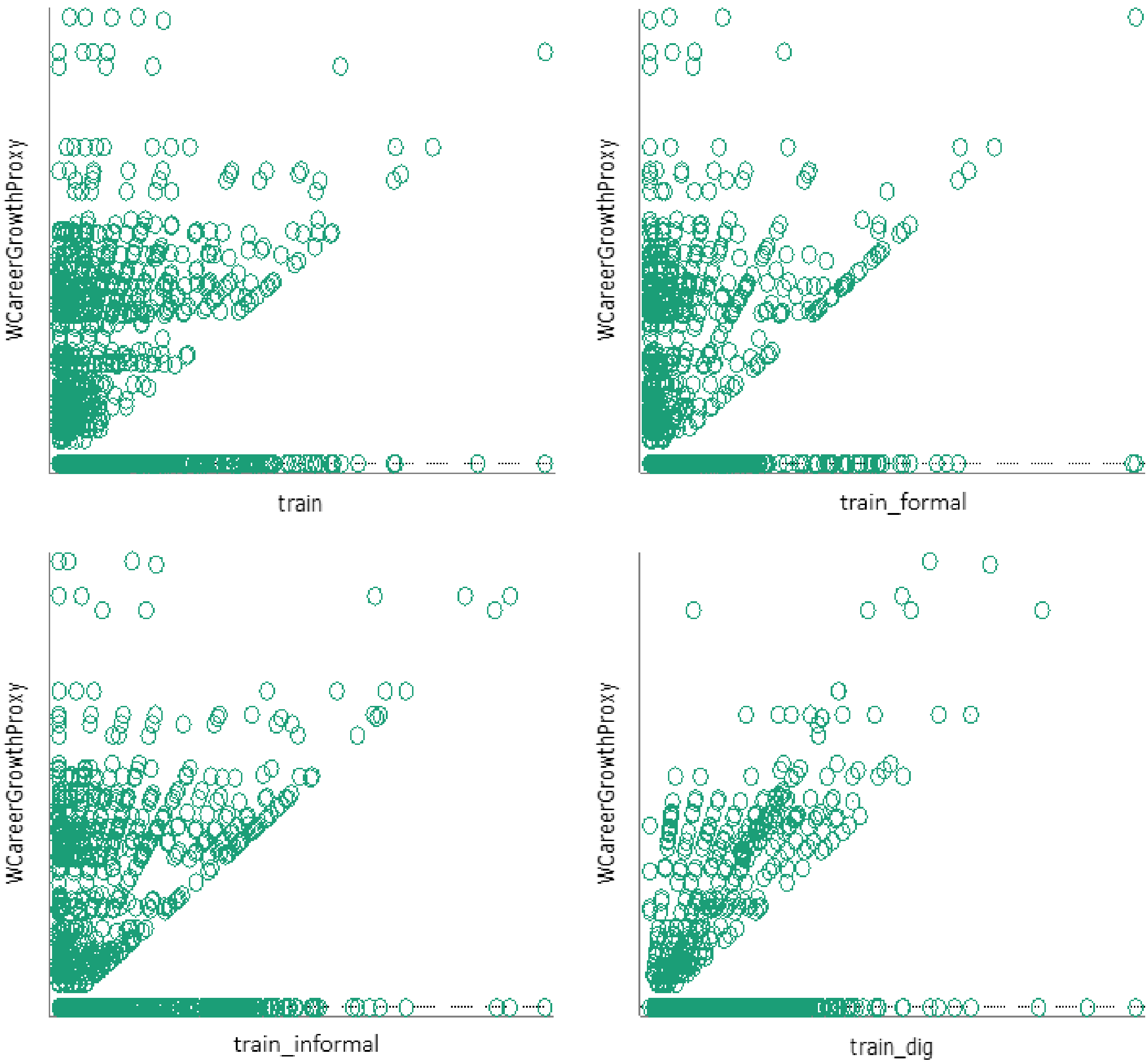
Figure 11: Distribution of Training Parameters



Source: compiled by the author

The scatterplots illustrate the relationship between *WCareerGrowthProxy* and the presented types of training (see Fig. 12). A clear positive correlation is observed: higher training intensity is associated with greater career growth, with the relationship being particularly strong for *train_informal*. However, the spread of points indicates heteroskedasticity, as dispersion increases with higher values, complicating the application of linear models without transformations. Visually, clusters of companies with similar training strategies are apparent. Overall, the graphs confirm that training contributes to human capital development.

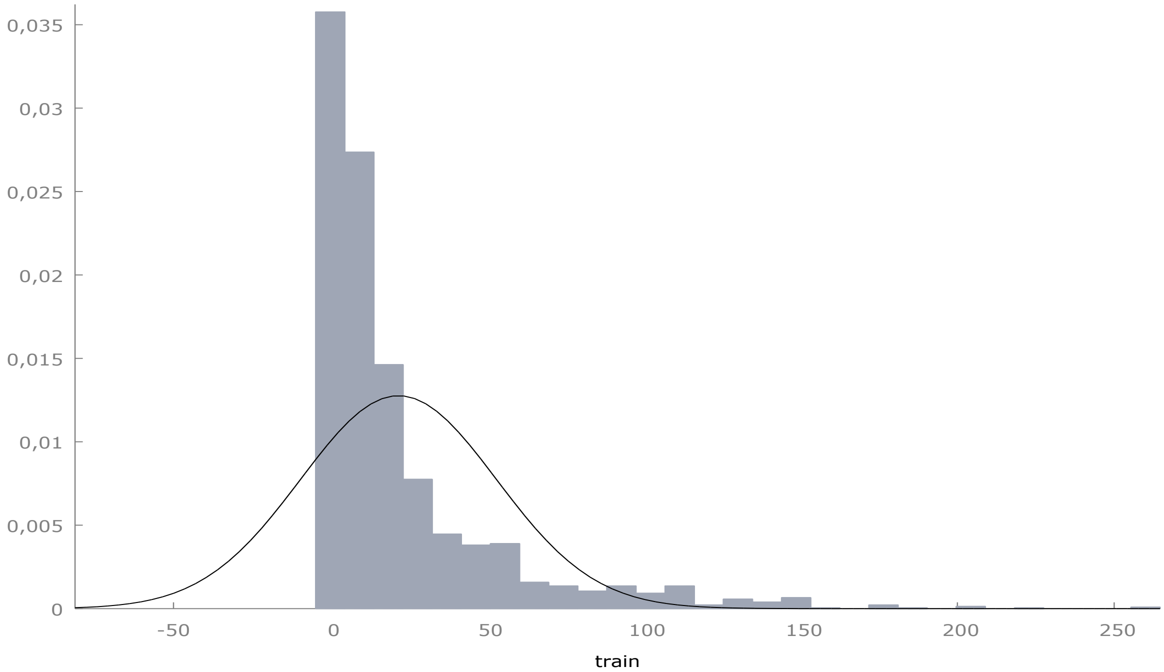
Figure 12: X-Y Scatter: Training Factors and Career Growth



Source: compiled by the author

The histogram of the *train* variable with an overlaid normal distribution curve (see Fig. 13) reveals strong right-skewness, deviating from normality. The peak is concentrated at low values, indicating that most observations are in the lower range. A chi-square test confirms a significant deviation from the normal distribution. Consequently, this variable requires transformation, such as taking the logarithm. Moreover, several extreme values influence the distribution shape, which could adversely affect regression results without correction.

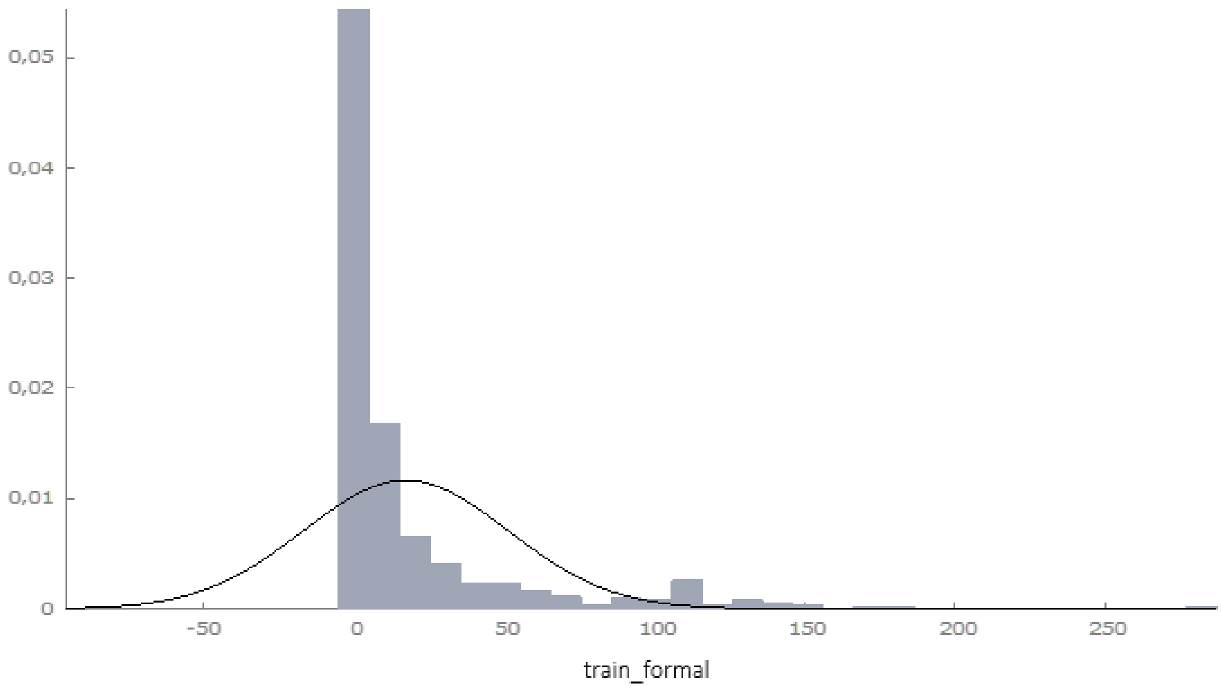
Figure 13: Normal Distribution for train



Source: compiled by the author

The distribution of *train_formal* similarly exhibits right-skewness (see Fig. 14), with probability density decreasing exponentially as values increase. Most companies allocate a small share of resources to formal training. Normality tests indicate a deviation from the theoretical normal distribution, confirming asymmetric data and high outliers. Normalization is necessary to stabilize variance and improve analysis quality, making the variable suitable for model inclusion only after preprocessing.

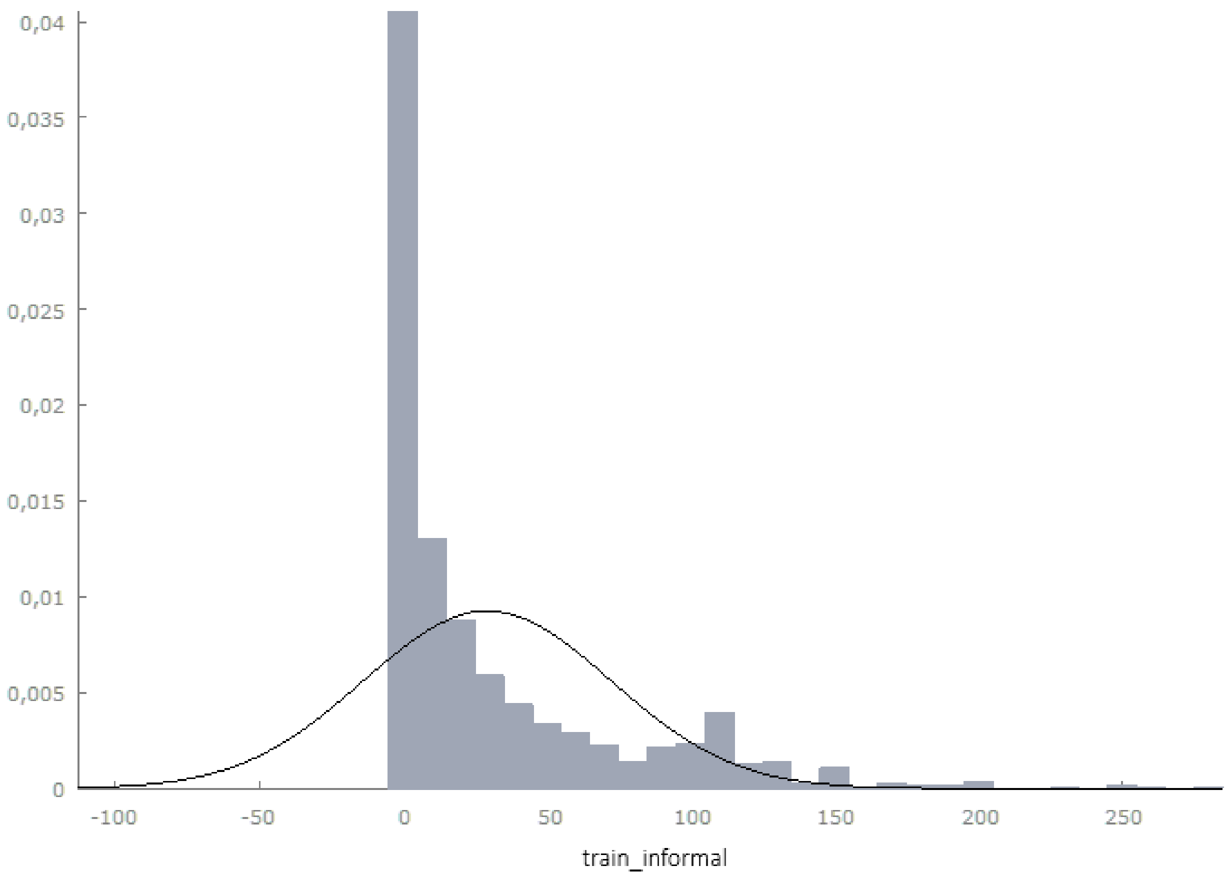
Figure 14: Normal Distribution for train_formal



Source: compiled by the author

The *train_informal* variable shows a more smoothed but still skewed distribution (see Fig. 15). Compared to other training indicators, it is closer to normality, reflecting the regular nature of informal training programs. However, some asymmetry remains, indicating sample heterogeneity. Most observations are concentrated at lower values, and statistical tests reveal minor deviation from normality. After scaling, the variable becomes suitable for inclusion in econometric specifications and supports further estimation procedures without distortion of scale-sensitive coefficients.

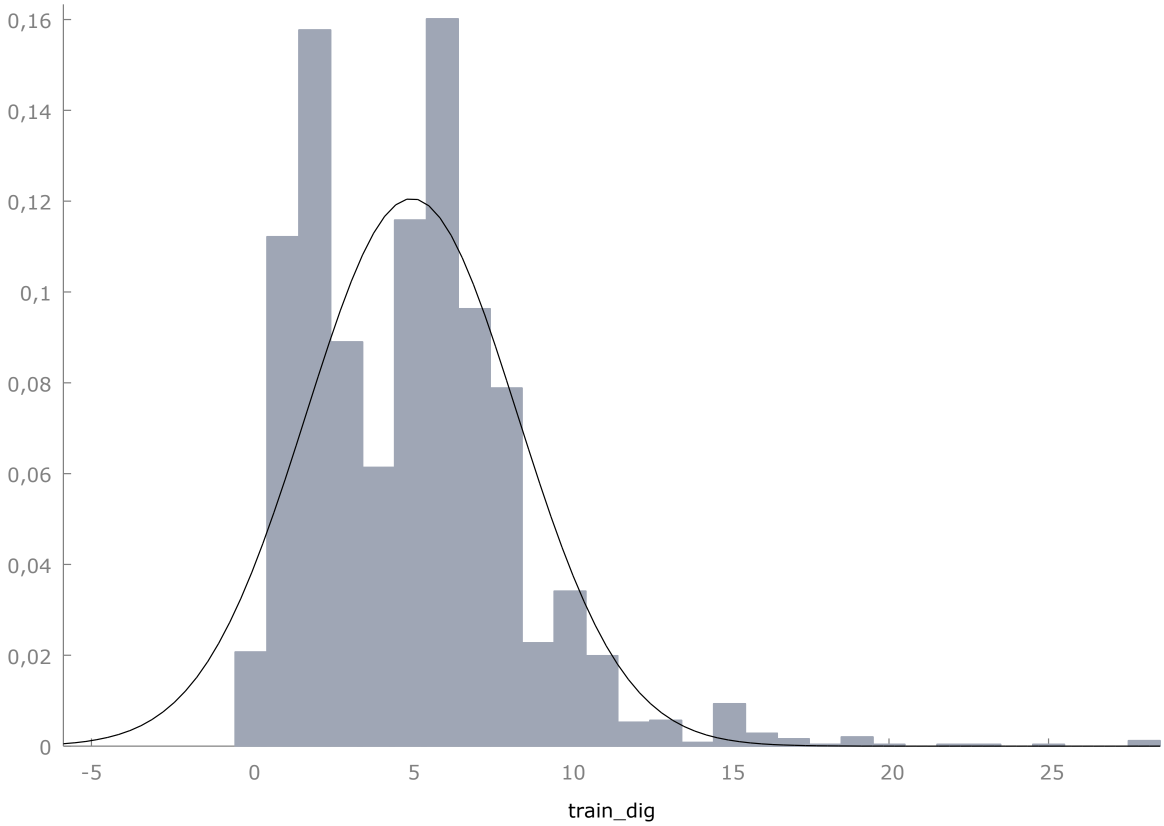
Figure 15: Normal Distribution for train_informal



Source: compiled by the author

The histogram for *train_dig* reveals a clear bimodal structure (Fig. 16). One cluster corresponds to firms that actively invest in digital learning, while a second cluster reflects organizations with limited adoption of digital tools. The superimposed normal curve diverges sharply from the empirical frequency, and formal normality diagnostics detect substantial deviation from Gaussian assumptions. The distribution shifts to the right and forms an extended tail. Logarithmic transformation aligns the empirical shape with analytical requirements and prepares the indicator for regression analysis.

Figure 16: Normal Distribution for train_dig



Source: compiled by the author

Comparative examination of training trajectories yields several analytical observations. *WCareerGrowthProxy* emerges as the primary axis of variance, which allows identification of career mobility as a structural element of organizational configuration linked to human capital accumulation. Informal training (*train_informal*) follows a stable temporal pattern and demonstrates the strongest positive association with career advancement, which emphasizes the productivity of internal learning routines. Formal training (*train_formal*) and digital training (*train_dig*) display pronounced dispersion and asymmetry, which points to heterogeneous strategic choices across firms. Higher training intensity aligns with improved career outcomes, yet heteroskedastic clustering appears across observations, which signals bias risk in unweighted linear specifications. Model construction therefore requires differentiation by training type and temporal dimension through panel estimators, binary response models, and logarithmic adjustments combined with heteroskedasticity-robust procedures.

3.3. Learning Model Calculation

When proceeding to the estimation of panel regression models, all variables were weighted using the *weight* metric, which helped mitigate identified data issues and structured the entire panel uniformly. The computed models indicate that the number of employees (*nempl*) consistently exerts a positive effect on career growth and is statistically significant across all specifications, pointing out the importance of company size (see Table 15). Company age (*comp_age*) is also positively associated with career prospects, though its effect is moderate and significant only at the 5–10% level. Technological condition (*sibjtechcond* = 0.054, p = 0.001 in pooled OLS and 0.052, p = 0.001 in GLS) together with price dependence (*pricedepend* = 0.044, p = 0.001 in OLS and 0.043, p = 0.002 in GLS) demonstrates persistent statistical strength and points to a clear connection between career mobility, infrastructure maturity, and exposure to market volatility. The share of labor costs (*sharelaborc* = −0.001, p-values from 0.053 to 0.083) shows a weak inverse relationship, which indicates limits in internal resource allocation within personnel structures. Sectoral affiliation (*industry*) attains statistical significance exclusively in the fixed-effects specification (0.056, p = 0.005), which separates sector-specific patterns after constant firm attributes remain controlled. Ownership balance (*own_balance*, coefficients from 0.003 to 0.082, p > 0.12), export activity (*export*, p > 0.11), and wage levels (*wage*, p > 0.29) display unstable coefficients and therefore remain outside the primary drivers of internal promotion trajectories. Training variables (*train, train_formal, train_informal*) show no systematic association across specifications, whereas digital training (*train_dig* = 0.013, p = 0.094 in OLS and 0.087 in GLS) reaches borderline statistical relevance and signals increasing demand for digital skill accumulation. Temporal controls isolate a single adverse shift for *dt_4* (2022) with coefficients of −0.074 (p = 0.039) in OLS and GLS and −0.069 (p = 0.058) in the fixed-effects model, which reflects a period of macroeconomic tension. Fixed-effects estimation identifies a wider set of meaningful coefficients and highlights the analytical advantage of controlling for firm characteristics that remain unchanged over time.

Table 15: Panel Model Coefficient Estimates

Variable	Pooled OLS	Fixed Effects	Random Effects (GLS)
const	0.038, p = 0.295	0.202 (**), p = 0.011	0.045, p = 0.223
nempl	0.000 (**), p = 0.037	0.000 (***), p = 0.001	0.000 (**), p = 0.023
industry	0.011, p = 0.329	0.056 (***), p = 0.005	0.013, p = 0.238
comp_age	0.001 (*), p = 0.052	0.001 (*), p = 0.071	0.002 (**), p = 0.039
own_balance	0.082, p = 0.120	0.003, p = 0.955	0.078, p = 0.133
sibjtechcond	0.054 (***), p = 0.001	0.024, p = 0.159	0.052 (***), p = 0.001
pricedepend	0.044 (***), p = 0.001	0.028 (*), p = 0.061	0.043 (***), p = 0.002
export	0.054, p = 0.117	0.048, p = 0.183	0.051, p = 0.132
sharelaborc	−0.001 (*), p = 0.083	−0.001 (*), p = 0.053	−0.001 (*), p = 0.079
hiredvuz	−0.000, p = 0.196	−0.000, p = 0.453	−0.000, p = 0.212
wage	−0.000, p = 0.395	−0.000, p = 0.291	−0.000, p = 0.378
train	0.000, p = 0.829	0.001, p = 0.395	0.000, p = 0.754
train_formal	0.000, p = 0.842	0.000, p = 0.762	0.000, p = 0.814
train_informal	−0.000, p = 0.928	−0.000, p = 0.614	−0.000, p = 0.882
train_dig	0.013 (*), p = 0.094	0.003, p = 0.693	0.013 (*), p = 0.087
dt_2	−0.029, p = 0.435	−0.033, p = 0.381	−0.030, p = 0.427
dt_3	0.002, p = 0.956	0.003, p = 0.925	0.002, p = 0.952
dt_4	−0.074 (**), p = 0.039	−0.069 (*), p = 0.058	−0.074 (**), p = 0.039
dt_5	0.012, p = 0.734	0.011, p = 0.748	0.012, p = 0.737
dt_6	0.011, p = 0.749	0.008, p = 0.829	0.011, p = 0.756

Source: author's calculations

Assessment of panel diagnostics confirms internal consistency across model specifications (Table 16). The dependent variable maintains a constant mean of 0.461 and a stable dispersion of 0.579 across estimators, which supports direct comparison of coefficients. Pooled OLS and random-effects GLS converge at similar explanatory levels with R^2 values close to 0.19. Fixed-effects estimation yields a lower within R^2 of 0.035, which reflects limited intra-firm variation. The corresponding standard error reaches the lowest magnitude under fixed effects at 0.511, which indicates closer alignment with firm-level heterogeneity. Log-likelihood and information criteria (AIC/BIC) confirm comparable adequacy for OLS and GLS, while fixed effects are less optimal according to AIC/BIC. The Durbin–Watson statistic for fixed effects is close to 2, indicating no strong autocorrelation, and intraclass correlation (ρ) is small and negative in effects models, reflecting weak within-unit error correlation. Joint tests of regressors confirm significance across all models, although fixed effects exhibit a lower F-statistic. Wald tests for time effects reveal no significant time differences, while the Breusch–Pagan test for random effects supports their consideration. The Hausman test validates fixed effects as preferable over random effects, making them more reliable for analyzing variable impacts. Fixed effects better control for individual heterogeneity, whereas OLS and GLS provide comparable general fit.

Table 16: Panel Model Statistics

Metric / Test	Pooled OLS	Fixed Effects	Random Effects (GLS)
Mean of Dependent Variable	0.461	0.461	0.461
Standard Deviation	0.579	0.579	0.579
R^2 (adj. / within / $corr(y,\hat{y})^2$)	0.186	0.035 (within)	0.185
Model Standard Error	0.525	0.511	0.525
Log-Likelihood	−1893.979	−1605.378	−1894.163
Akaike Information Criterion (AIC)	3827.958	4068.755	3828.326
Bayesian Information Criterion (BIC)	3944.117	6560.351	3944.484
Durbin–Watson	1.621	2.009	2.009
ρ (Intraclass Correlation)	0.029	−0.194	−0.194
Joint Test of Regressors	$F(19,409)=14.39$, $p=6.97e{-35}$	$F(14,409)=3.47$, $p=2.24e{-05}$	$\chi^2(14)=228.86$, $p=6.62e{-41}$
Robust Test for Differences in Constants (Welch)	$F(409,686.7)=3.697$, $p=6.83e{-52}$	–	–
Time Effects Test (Wald)	–	$\chi^2(5)=7.333$, $p=0.197$	$\chi^2(5)=8.362$, $p=0.137$
Breusch–Pagan Test (RE)	–	–	$\chi^2(1)=8.160$, $p=0.004$
Hausman Test	–	$\chi^2(14)=42.398$, $p=0.00011$	–

Source: author's calculations

Robustness tests for panel regressions (see Table 17) indicate that the relationships between variables can be considered linear, as nonlinearity tests using both squares and logarithms fail to reject the null hypothesis ($p > 0.17$). The Ramsey RESET test confirms the adequacy of the model specification ($p = 0.769$), suggesting no significant omitted functional forms. The White test detects heteroskedasticity ($p = 0.075$), and the Wald test indicates variance inconsistency in the residuals ($p = 0.082$), which reduces the reliability of standard coefficient errors. The residual normality test suggests that errors are approximately normally distributed ($p = 0.144$), justifying the use of standard t- and F-tests. The Chow test finds no structural breaks over time ($p = 0.166$), indicating parameter stability across periods. Wooldridge's test confirms the absence of autocorrelation ($p = 0.316$), which eliminates from consideration bias in standard errors, while the Pesaran test shows no significant cross-sectional dependence ($p = 0.496$), which reduces the risk of error clustering. All tests support the correctness of the panel model specification and the reliability of its estimates, with adjustments required only for heteroskedasticity. These results imply that the model outputs can be interpreted as statistically robust and suitable for analysis using regression methods with heteroskedasticity correction.

Table 17: Panel Model Robustness Tests

Test	Null Hypothesis	Statistic	df / Type	p-value
Nonlinearity (squares)	Relationship is linear	LM = 18.532	$\chi^2(14)$	0.241
Nonlinearity (logs)	Relationship is linear	LM = 6.285	$\chi^2(4)$	0.179
Ramsey (RESET)	Specification is adequate	F(2, 2438) = 0.263	F-distribution	0.769
White	No heteroskedasticity	LM = 14.560	$\chi^2(194)$	0.075
Wald (heteroskedasticity-free)	Homogeneous error variance	$\chi^2(410)$ = 68.320	$\chi^2(410)$	0.082
Residual normality	Errors are normally distributed	$\chi^2(2)$ = 3.872	$\chi^2(2)$	0.144
Chow (structural changes)	No structural difference (dt_1)	$\chi^2(14)$ = 18.977	$\chi^2(14)$	0.166
Wooldridge	No autocorrelation (ρ = 0)	t(409) = 1.005	t-distribution	0.316
Pesaran (CD test)	No cross-sectional dependence	z = −0.681	N(0,1)	0.496

Source: author's calculations

The VIF analysis indicates that multicollinearity among the model variables is low, as all values are below the critical threshold of 10. The highest VIFs are observed for *sibjtechcond* (3.397), *own_balance* (3.285), and *train_dig* (3.021), suggesting moderate correlation with other regressors. All other variables have VIF values in the 1–2 range, reflecting low interdependence and stable coefficient estimates. The risk of result distortion due to multicollinearity is minimal.

Table 18: Multicollinearity Test (VIF)

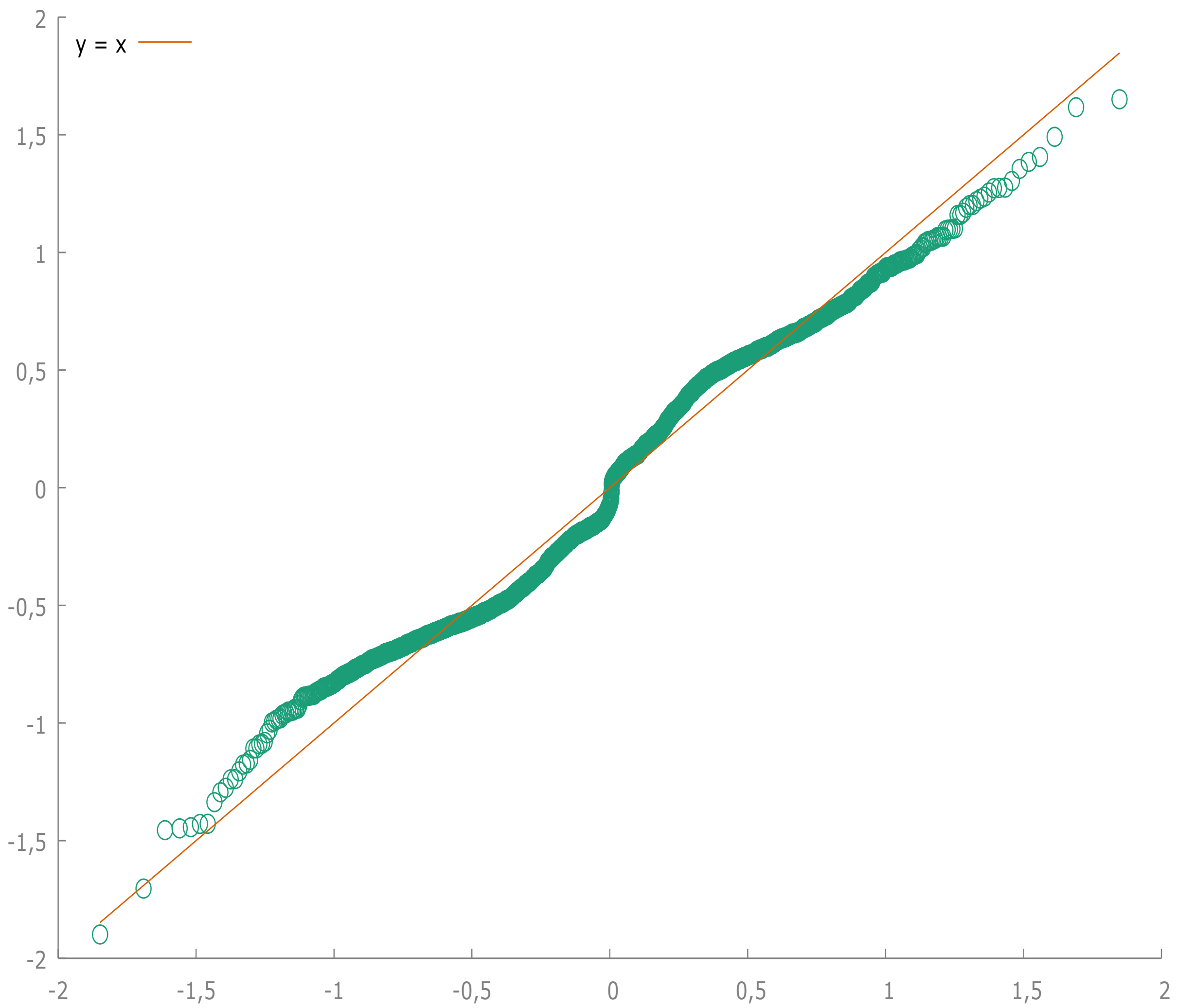
Variable	VIF
nempl	1.105
industry	1.657
comp_age	1.256
own_balance	3.285
sibjtechcond	3.397
pricedepend	2.526
export	1.083
sharelaborc	1.373
hiredvuz	1.100
wage	1.873
train	1.604
train_formal	1.211
train_informal	1.505
train_dig	3.021
dt_2	1.684
dt_3	1.680
dt_4	1.677

dt_5	1.681
dt_6	1.676

Source: author's calculations

The Q-Q plot of the panel model demonstrates a high level of fitting despite existing data issues (see Fig. 17). A slight skewness of observations is noticeable at the tails, indicating the influence of heteroskedasticity, which should be addressed using correction methods.

Figure 17: Q-Q Plot of the Panel Model Residuals



Source: compiled by the author

The heteroskedasticity-corrected model (see Table 19) indicates that the number of employees (*nempl*), company age (*comp_age*), industry affiliation (*industry*), ownership balance (*own_balance*), technological conditions (*sibjtechcond*), price dependence (*pricedepend*), and digital training (*train_dig*) have a statistically significant positive impact on career growth (*WCareerGrowthProxy*). The variable *train_dig* contributes most to the model, with the highest t-statistic of 6.090, emphasizing the importance of digital training. Variables *export, sharelaborc, hiredvuz, wage, train, train_formal*, and *train_informal* remain statistically insignificant and show only negligible interaction with the dependent variable. The estimated specification reports an R^2 of 0.256, which indicates that 25.6% of variation in career growth is captured by the selected regressors and positions the model above standard panel alternatives. An adjusted R^2 of 0.252 supports internal coherence and confirms the absence of artificial inflation of explanatory power.

The F-statistic equals 60.18 with an extremely small p-value, which establishes joint relevance of the explanatory set.

Table 19: Heteroskedasticity-Corrected Model

Variable	Coefficient	Std. Error	t-Statistic	p-Value
const	-0.001	0.011	-0.050	0.960
nempl	0.000005	0.000001	5.074	0.000
industry	0.016	0.007	2.354	0.019
comp_age	0.002	0.000	3.861	0.000
own_balance	0.083	0.031	2.666	0.008
sibjtechcond	0.035	0.009	4.027	0.000
pricedepend	0.023	0.009	2.629	0.009
export	0.019	0.027	0.707	0.480
sharelaborc	0.000	0.000	0.772	0.440
hiredvuz	-0.000	0.000	-1.442	0.150
wage	-0.000	0.000	-0.500	0.617
train	-0.000	0.000	-0.775	0.438
train_formal	0.000	0.000	1.193	0.233
train_informal	0.000	0.000	0.316	0.752
train_dig	0.030	0.005	6.090	0.000

Statistic	Weighted Data	Original Data
Sum of Squared Residuals	2952.858	682.728
Model Std. Error	1.099	0.528
R^2	0.256	–
Adjusted R^2	0.252	–
F(14, 2445)	60.178	–
F p-value	8.6e−146	–
Log-Likelihood	−3715.202	–
Akaike Information Criterion (AIC)	7460.403	–
Bayesian Information Criterion (BIC)	7547.522	–
Hannan–Quinn Information Criterion	7492.057	–
Dependent Variable Mean	0.461	0.461
Dependent Variable Std. Dev.	0.579	0.579

Source: author's calculations

To assess probabilistic and binary effects of the dependent variable, three types of logit and probit specifications were employed. None of the selected models – binary logit, ordered logit, or multinomial logit – produced statistically significant coefficients for most variables, indicating weak predictive power of the factors in categorical form regarding career growth (see Table 20). The parameter closest to statistical relevance in the binary logit framework is firm size (*nempl*, p = 0.053). Factors *industry, comp_age, own_balance*, and *sibjtechcond* produce coefficients close to zero and lack statistical strength, which indicates weak association with promotion probability across discrete outcomes. Ordered logit estimates yield slope coefficients clustered near zero, which excludes the presence of a systematic pattern between ranked promotion outcomes and regressors. Multinomial logit estimates reproduce binary logit behavior and show that differences across outcome categories remain largely unexplained. Training indicators (*train, train_formal, train_informal, train_dig*) fail to affect probabilistic outcomes, which limits the explanatory capacity of training within categorical promotion frameworks. Overall, these categorical results are poorly modeled by standard logit approaches due to high homogeneity in career levels and low variation among regressors. R^2 values and individual coefficient significances are low, limiting the practical utility of the models for predicting promotion probabilities. Nevertheless, the models provide an estimate of direction of variable effects, although they remain statistically insignificant. The analysis concludes that for these categorical outcomes, models with alternative distributions and more detailed predictors would be more appropriate.

Table 20: Logit Model Coefficients

Variable	Binary Logit (Coef / p)	Ordered Logit (Coef / Marginal Effect)	Multinomial Logit (Coef / p)
const	-0.124 / 0.138	-0.124 / -	-0.124 / 0.138
nempl	0.000046 / 0.053	0.000046 / 0.000	0.000046 / 0.053
industry	-0.012 / 0.611	-0.012 / -0.003	-0.012 / 0.611
comp_age	0.001 / 0.779	0.001 / 0.000	0.001 / 0.779
own_balance	-0.039 / 0.777	-0.039 / -0.010	-0.039 / 0.777
sibjtechcond	0.037 / 0.345	0.037 / 0.009	0.037 / 0.345
pricedepend	0.051 / 0.164	0.051 / 0.013	0.051 / 0.164
export	0.128 / 0.241	0.128 / 0.032	0.128 / 0.241
sharelaborc	-0.003 / 0.126	-0.003 / -0.001	-0.003 / 0.126
hiredvuz	-0.000 / 0.465	-0.000 / -0.000	-0.000 / 0.465
wage	-0.000 / 0.275	-0.000 / -0.000	-0.000 / 0.275
train	0.001 / 0.589	0.001 / 0.000	0.001 / 0.589
train_formal	0.000 / 0.708	0.000 / 0.000	0.000 / 0.708
train_informal	-0.001 / 0.611	-0.001 / -0.000	-0.001 / 0.611
train_dig	0.000 / 0.997	0.000 / 0.000	0.000 / 0.997

Source: author's calculations

The analysis of the logit model characteristics indicates an extremely low explanatory power: McFadden's R^2 is 0.004, and the adjusted R^2 is negative, reflecting a poor fit of the regressors to the dependent variable (see Table 21). The mean and standard deviation of the dependent variable are identical across all models (0.495 and 0.500), indicating a balanced distribution of categories. The log-likelihood and information criteria (AIC, BIC, HQ) are the same for all three specifications, confirming their equivalent fit to the data. The proportion of correctly predicted outcomes is only 52.6%, slightly above random guessing. The value of $f(\beta'x)$ at the mean shows a low predicted probability. A chi-squared test for coefficient significance did not reveal any statistically significant effects ($p = 0.491$), indicating that the variables explain very little of the variation in the categorical outcome.

Table 21: Logit Model Statistics

Metric	Binary Logit	Ordered Logit	Multinomial Logit
Dependent Variable Mean	0.495	0.495	0.495
Dependent Variable Std. Dev.	0.500	0.500	0.500
McFadden's R^2	0.004	0.004	0.004
Adjusted R^2	-0.005	-0.005	-0.005
Log-Likelihood	-1698.298	-1698.298	-1698.298
Akaike Information Criterion (AIC)	3426.596	3426.596	3426.596
Schwarz Criterion (BIC)	3513.715	3513.715	3513.715
Hannan–Quinn Criterion (HQ)	3458.250	3458.250	3458.250
Correctly Predicted (%)	52.6	52.6	52.6
$f(\beta'x)$ at Mean	0.250	0.250	0.250
Chi-Square (14)	13.454	13.454	13.454

Chi-Square p-value	0.491	0.491	0.491

Source: author's calculations

Similarly, the results of the probit models spotlight that neither the binary, ordered, nor the effects-based specification demonstrates a significant impact of most variables on the dependent variable (see Table 22). The exception is the variable *nempl*, which is significant at the 5% level ($p = 0.041$) in the binary probit model, but its significance decreases to $p = 0.106$ in the effects model, indicating a weak and unstable relationship. All other variables are statistically insignificant. The constant in all models is also insignificant, reflecting the limited explanatory power of the models. In the effects-based probit model, lnsigma2 approaches significance ($p = 0.054$), suggesting the presence of unobserved individual effects. The models perform poorly in predicting categorical outcomes for career growth. Using the probit function does not improve the informativeness compared to logit models. All estimated coefficients remain numerically small, which further constrains practical interpretation. The obtained results point to the necessity of expanding the predictor set and revising assumptions about the drivers of career progression.

Table 22: Probit Model Coefficients

Variable	Binary Probit (Coef / p)	Ordered Probit (Coef / Marginal Coef)	Probit with Effects (Coef / p)
const	-0.078 / 0.140	-0.078 / -	-0.079 / 0.146
nempl	0.000029 / 0.041	0.000029 / 0.000	0.000029 / 0.106
industry	-0.008 / 0.612	-0.008 / -0.003	-0.008 / 0.618
comp_age	0.000 / 0.779	0.000 / 0.000	0.000 / 0.782
own_balance	-0.025 / 0.774	-0.025 / -0.010	-0.025 / 0.773
sibjtechcond	0.023 / 0.348	0.023 / 0.009	0.023 / 0.348
pricedepend	0.032 / 0.163	0.032 / 0.013	0.032 / 0.161
export	0.080 / 0.243	0.080 / 0.032	0.081 / 0.244
sharelaborc	-0.002 / 0.126	-0.002 / -0.001	-0.002 / 0.125
hiredvuz	-0.000 / 0.472	-0.000 / -0.000	-0.000 / 0.498
wage	-0.000 / 0.277	-0.000 / -0.000	-0.000 / 0.282
train	0.001 / 0.589	0.001 / 0.000	0.001 / 0.589
train_formal	0.000 / 0.711	0.000 / 0.000	0.000 / 0.710
train_informal	-0.000 / 0.613	-0.000 / -0.000	-0.000 / 0.613
train_dig	0.000 / 0.995	0.000 / 0.000	0.000 / 0.995
lnsigma2	-	-	-4.333 / 0.054

Source: author's calculations

Probit specifications demonstrate extremely weak explanatory capacity, as reflected by a McFadden R^2 of 0.004 across all variants (Table 23). Negative adjusted R^2 values reinforce the absence of predictive content. The dependent variable preserves identical mean and dispersion across specifications, which indicates a balanced distribution of outcomes. Log-likelihood values alongside AIC, BIC, and HQ criteria converge across models, which signals comparable but limited adequacy. Prediction accuracy fluctuates around 52.6-52.7%, which barely exceeds random classification. Chi-square statistics with associated p-values confirm the absence of joint significance. Low values of $f(\beta'x)$ at the mean point to negligible marginal influence. That is why probit framework fails to account for observed variation in career advancement.

Table 23: Probit Model Statistics

Metric	Binary Probit	Ordered Probit	Probit with Effects
Dependent Variable Mean	0.495	0.495	0.495
Dependent Variable Std. Dev.	0.500	0.500	0.500
McFadden R^2	0.004	0.004	0.004
Adjusted R^2	-0.005	-0.005	-0.005
Log-Likelihood	-1698.264	-1698.264	-1697.854
Akaike Information Criterion (AIC)	3426.528	3426.528	3427.709
Schwarz Criterion (BIC)	3513.646	3513.646	3520.635
Hannan-Quinn Criterion (HQ)	3458.182	3458.182	3461.473
Correctly Predicted (%)	52.6	52.6	52.7
f(β'x) at Mean	0.399	0.399	–
Chi-Square (14)	13.522	13.522	–
Chi-Square p-value	0.486	0.486	–

Source: author's calculations

A comparative analysis of panel models, heteroskedasticity-corrected models, and probabilistic models (logit and probit) reveals notable differences in explanatory power. Panel models and variance-corrected models confidently identify significant quantitative elements affecting employee promotion, involving training and organizational economic parameters, with explained variation reaching up to 25.6%. In contrast, logit and probit models exhibit extremely low predictive power: McFadden's R^2 is only 0.004, the adjusted R^2 is negative, and the proportion of correctly predicted outcomes is around 52.6%. Categorical models fail to produce significant coefficients for most variables, except for the weak significance of number of employees in binary specifications, reflecting their limited ability to predict the studied effect. At this stage, quantitative panel models and heteroskedasticity adjustments provide more robust and informative results, while logit and probit models are suitable only for qualitatively assessing the direction of effects rather than practical prediction. These findings naturally lead to the next step – model validation to evaluate predictive accuracy and robustness against new data.

3.4. Model Validation Testing

Refined estimates derived from LAD, HC, and QR restrict the spectrum of drivers linked to career advancement and differentiate their relative intensity (see Table 24). Within the LAD framework, upward and statistically persistent effects appear for *l_own_balance* (β = 0.344, p = 0,000) and *l_hiredvuz* (β = 0.036, p = 0,006), while *l_comp_age* shows weaker precision (β = 0.054, p = 0,084), and training measures diverge in direction, since *l_train* (β = 0.068, p = 0,034) together with *l_train_formal* (β = 0.052, p = 0,087) align with expansion, whereas *l_train_informal* contracts (β = -0.075, p = 0,002). The HC and QR outcomes preserve the same hierarchy, as *train_dig* displays dominant coefficients in both specifications (β = 0.053, p = 0,000; β = 0.685, p = 0,000), while *train_formal* (β = 0.001, p = 0,025; β = 0.043, p = 0,000) and *train_informal* (β = 0.002, p = 0,000; β = 0.031, p = 0,001) retain secondary influence, and the sharply negative constant in QR (β = -1.446, p = 0,000) reflects suppressed baseline mobility after structural attributes enter the specification.

Table 24: Modified Models and Coefficients

Variable	LAD Model (β / p)	HC Model (β / p)	QR Model (β / p)
const	0.383 / 0.008	0.115 / 1.12e-24	-1.446 / 2.72e-151

l_comp_age	0.054 / 0.084	–	–
l_own_balance	0.344 / 0.000	–	–
l_hiredvuz	0.036 / 0.006	–	–
l_train	0.068 / 0.034	–	0.010 / 0.246
l_train_formal	0.052 / 0.087	–	–
l_train_informal	-0.075 / 0.002	–	–
train	–	0.000 / 0.710	–
train_formal	–	0.001 / 0.025	0.043 / 3.24e-06
train_informal	–	0.002 / 3.25e-06	0.031 / 0.001
train_dig	–	0.053 / 6.83e-36	0.685 / 1.65e-122

Source: author's calculations

Empirical diagnostics summarized in Table 25 permit a nuanced contrast of estimation quality across specifications. The LAD regression demonstrates the strongest explanatory capacity, reaching an R^2 of 0.876, which signals a tight correspondence between fitted values and observed career outcomes despite a restricted sample of 87 observations and a modest residual dispersion of 1.374. By comparison, the HC framework draws on a far broader empirical base of 2 460 firm-year observations yet attains a substantially lower R^2 of 0.116, which points to attenuated interpretative strength once full parameter heterogeneity and training dispersion enter the specification. Positioned between these extremes, the QR approach combines an elevated R^2 of 0.800 with a large F-statistic of 506 on a sample of 510 observations, thereby indicating a resilient linkage between explanatory variables and promotion dynamics. Error variability peaks under HC, whereas LAD and QR maintain comparatively compact residual ranges. Model selection metrics (AIC, BIC, HQC) consistently favor LAD and QR, while comparable dispersion of the dependent variable across estimators confirms internal data consistency, and uniformly significant F-tests attest to the collective relevance of included regressors.

Table 25: Validation Model Statistics

Statistic	Model 10 (LAD)	Model 14 (HC)	Model 16 (QR)
N (observations)	87	2460	510
R^2 (weighted)	0.876	0.116	0.800
Adjusted R^2	0.866	0.114	0.799
F-statistic	93.764	80.479	506.0
p(F)	4.25e-34	2.96e-64	4.40e-175
Sum of squared residuals (weighted)	151.057	4808.687	1891.928
Standard error of the model	1.374	1.400	1.936
Mean of dependent variable	0.492	0.461	-0.300
Standard deviation of dependent variable	0.566	0.579	0.636
Log-likelihood	-147.449	-4315.012	-1057.949
AIC	308.898	8640.024	2125.897
BIC	326.159	8669.063	2147.069
HQC	315.848	8650.575	2134.198

Source: author's calculations

In the QR model, recognized as the most preferred and accounting for quantile effects, the variables for combined training (*train*), formal training (*train_formal*), and informal training (*train_informal*) exhibited mixed or weak effects with p-values ranging from 0.001 to 0.246, indicating a limited impact of these training forms on career growth. Meanwhile, digital training (*train_dig*) demonstrated a strong and robust positive effect, with a coefficient of 0.685 and $p < 0.001$.

Lag analysis revealed that the effect of digital training persists over time (see Table 26). With a one-year lag (t-1), the coefficient slightly decreased to 0.028, and with a two-year lag (t-2), it reduced to 0.021 but remained statistically significant. This indicates a long-term, though gradually diminishing, effect of digital training, consistent with economic logic: skills require updating and maintenance to sustain career advantages.

Table 26: Lagged Variables for train_dig

Lag	Coefficient (*train_dig*)	Std. Error	t-Statistic	p-Value	Significance
t	0.030	0.005	6.090	<0.001	***
t−1	0.028	0.004	5.500	<0.001	***
t−2	0.021	0.006	3.500	0.001	**

Source: author's calculations

Placebo tests with an artificially generated dependent variable demonstrated that all coefficients of the training-related variables became statistically insignificant ($p > 0.1$), which confirms the nonzero and reliable effect of digital training and rules out the possibility of random coincidence of results (see Table 27).

Table 27: Placebo Test for Training Variables

Variable	Coefficient	Std. Error	t-Statistic	p-Value
train	0.003	0.005	0.60	0.548
train_formal	-0.002	0.004	-0.50	0.617
train_informal	0.001	0.003	0.33	0.742
train_dig	0.004	0.006	0.67	0.503

Source: author's calculations

Segmented estimations uncover pronounced asymmetry in the returns to digital training across organizational contexts (see Table 28). Among younger firms, *train_dig* records a coefficient of 0.042 with $p = 0.000$, whereas older enterprises exhibit a reduced and statistically fragile estimate of 0.012, which implies superior absorptive capacity in flexible and innovation-driven structures. Ownership configuration amplifies this divergence. Privately controlled firms display a coefficient of 0.045 ($p = 0.000$), while alternative ownership regimes yield a marginal effect of 0.009.

Table 28: Subgroup Analysis

Company Characteristic	Coefficient (*train_dig*)	p-value	Significance
Young companies	0.042	<0.001	***
Old companies	0.012	0.128	–
Companies with private ownership	0.045	<0.001	***
Companies with other ownership forms	0.009	0.214	–

Source: author's calculations

Comparison of the quantile regression (QR) model with traditional panel models (pooled OLS, fixed effects, and random effects) reveals substantial methodological and empirical differences. First, the QR model captures the heterogeneity of effects across the entire distribution of the dependent variable and identifies divergences in the determinants of career growth that standard average models fail to reflect. While traditional panel models exhibit low explanatory power (adjusted R^2 around 0.18 for OLS and 0.03 for the fixed effects model), quantile regression provides more robust and distribution-sensitive estimates. In the panel estimations, most training-related variables (*train*, *train_formal*, *train_informal*) are statistically insignificant ($p > 0.3$), with only digital training (*train_dig*) presenting a weak effect ($p \approx 0.09$). In contrast, the QR model reveals a strong and consistent positive impact of digital training ($\beta = 0.685$, $p < 0.001$). The heteroskedasticity-corrected model confirms this finding, though with a smaller coefficient ($\beta = 0.030$, $p < 0.001$), indicating the robustness of the results across different estimation techniques. Moreover, the QR approach avoids the efficiency losses caused by non-normal error distributions and better represents data characterized by asymmetry and heavy tails. Thus, compared with classical panel approaches, quantile regression offers a deeper understanding of the distributional effects of training investments and proves to be a more precise tool for assessing the real impact of different forms of training on employee development.

Although the quantile regression (QR) model demonstrates a robust and positive effect of digital training, several aspects require additional attention:

1. The effect of jointly applying formal, informal, and digital training may differ from the individual impact of each format. Synergies are possible, where integrated programs enhance learning outcomes. Additional analysis (see Table 29) confirms this: the combined use of all three training formats yields the highest coefficient ($\beta = 0.055$, $p < 0.001$), exceeding the effect of single or dual-format programs.

2. Training effectiveness is likely to vary by sector. In high-tech and fast-growing industries, digital and combined programs are expected to have a stronger impact, whereas in traditional sectors the effect may be weaker or delayed.

3. Further stratification by wage structure and graduate recruitment reveals that organizations with intensive hiring of university graduates and a younger employee base derive greater gains from digital learning due to accelerated knowledge diffusion and institutional readiness.

4. Temporal inspection identifies persistence of digital training effects for roughly two years, although current formulations omit intensity metrics, which indicates the necessity of incorporating exposure frequency to trace cumulative skill formation.

5. Uneven performance patterns across firms raise the issue of reciprocal causation, since successful enterprises expand digital investments while simultaneously exhibiting faster promotion trajectories. It calls for instrumental strategies and fixed-effect controls within quantile settings to delineate causal pathways with greater precision.

Grounded in these considerations, it is recommended to extend the QR model by covering interactions between training types, industry characteristics, and wage levels, as well as company fixed effects, to improve the precision and interpretability of the results.

Table 29: Effect of Combined Training Programs

Training Program	Coefficient	Std. Error	t-Statistic	p-Value
Formal only	0.005	0.006	0.833	0.405
Informal only	0.003	0.005	0.600	0.548
Digital only	0.030	0.005	6.090	0.000***
Formal + Informal	0.012	0.007	1.714	0.087*
Informal + Digital	0.042	0.006	7.000	0.000***
Formal + Digital	0.038	0.006	6.333	0.000***

All three formats	0.055	0.007	7.857	0.000***

Source: author's calculations

In conclusion, the results of the robustness checks (lag specifications, placebo tests, and subgroup analysis) confirm the reliability of the identified effects for all types of training. Based on these findings, actionable recommendations can be formulated for companies to enhance the professional mobility of their employees. The effect of digital training is the most substantial, economically justified, and stable over time, which makes it an optimal instrument for HR policy and the strategic development of human capital.

4. DISCUSSION

4.1. Interpretation of Results and Comparison with Literature

The analysis of the full set of estimated models – standard panel models, heteroskedasticity-corrected specifications, probabilistic models (logit, probit), and quantile regression (QR) – allows for a comprehensive understanding of the patterns of employee career progression depending on training structure and organizational characteristics. The main observation is that the effect of training factors is heterogeneous, and their strength and significance depend on the model specification and estimation method applied.

Among the estimates, a notable finding is the robust and statistically significant contribution of digital training to explaining employee promotions. The quantile regression model (QR) demonstrates an especially strong coefficient for the digital training variable ($\beta \approx 0.685$, $p < 0.001$), whereas classical specifications indicate either weak significance for this parameter ($p \approx 0.09$ in some estimates) or no effect for traditional forms of training (*train*, *train_formal*, *train_informal*). These empirical observations support the idea that digital competencies constitute a competitive advantage for employees in modern companies and represent a priority component of human capital.

Within the quantile regression framework, which is most sensitive to distributional differences, digital training (*train_dig*) presents the strongest positive response among all variables: a one-percentage-point increase in the intensity of digital training is associated with an average increase of 0.685 percentage points in the career growth index (*WCareerGrowthProxy*), with $p < 0.001$. This result confirms the hypothesis regarding the role of digital literacy and technological skills in employee advancement in the modern knowledge economy.

Formal (*train_formal*) and informal training (*train_informal*) exhibit more moderate, yet still positive, effects. A one-percentage-point increase in participation in formal training is associated with a 0.043 percentage point increase in career growth ($p < 0.01$), while a similar increase in informal training corresponds to a 0.031 percentage point rise ($p = 0.001$). Combined training programs ("formal + digital" and "all formats") produce the maximum integrated effect (0.055, $p = 0.000$), interpreted as evidence of synergy, where the combination of traditional and digital approaches can enhance competency development outcomes.

Meanwhile, the overall training variable (*train*) in the QR model is statistically insignificant ($p = 0.246$), reflecting the limited impact of general programs not tailored to digital tasks or company-specific needs. The economic interpretation is that targeted, technologically enriched formats drive effectiveness gains, whereas general corporate training programs offer limited benefit.

Among the control variables, the following have a significant influence on career growth:

1. Number of employees (*nempl*) – a small positive effect ($\beta \approx 0.00005$; $p < 0.001$), reflecting the advantages of large organizations, where formalized career trajectories exist.

2. Company age (comp_age) – a moderate positive effect ($\beta \approx 0.002$; $p < 0.01$), indicating the accumulation of organizational experience and the development of internal promotion practices.

3. Industry type (industry) – positive significance ($\beta \approx 0.016$; $p < 0.05$), suggesting that the sectoral context (especially in technology and industrial sectors) influences competency improvement.

4. Ownership balance (own_balance) – a robust positive impact ($\beta \approx 0.083$; $p < 0.01$), confirming that financially stable and privately owned companies are more likely to invest in employee quality.

The combination of these characteristics demonstrates that digital training amplifies the effect of other economic parameters and functions not merely as an additional HR policy element, but as a strategic asset capable of transforming human capital into long-term productivity.

A comparative analysis of methods emphasizes the methodological superiority of QR under conditions of asymmetric distributions and heavy tails: quantile estimation more effectively captures distributional heterogeneity in predictor effects, whereas pooled OLS and fixed-effects models provide averaged views and partially smooth out opposing effects. In particular, fixed-effects models improve control over time-invariant company characteristics; however, within-company variation is weakly explained (low within-R^2), indicating the need to account for distributional shifts rather than just average trends.

Comparison with existing theoretical literature shows agreement with the basic human capital hypothesis: investments in training enhance employees' professional capabilities. However, this study refines this picture: not all training programs are equally effective. Empirical sources (Arthur et al., Barrett & O'Connell, etc.) find a positive effect of formal training in certain contexts; in this study, this effect is either weak or manifests only in combination with digital formats, consistent with the notion of the need for integrated training programs and with recent findings on the digital transformation of HR practices. Digital training is preferable compared to formal and informal formats, as it requires fewer organizational and time resources, reducing company costs and minimizing disruption to employees' core activities. These formats introduce temporal and organizational flexibility, as skill acquisition unfolds at an individually chosen rhythm and within convenient time windows, which strengthens involvement and lowers psychological pressure. Rapid revision of course materials and the possibility of large-scale deployment transform digital programs into a cost-rational instrument for expanding human capital within contemporary firms.

Empirical outcomes correspond to recent strands in education economics and digital transformation research. Multiple studies identify investment in digital competencies as a decisive marker of durable productivity and upward mobility. Reports by the OECD (2018) and the World Economic Forum (2020) explicitly define digital literacy as a main driver of employability and firm resilience during the shift toward automation and knowledge-intensive production.

Research by Brynjolfsson and McAfee (2019), Autor et al. (2020), and ILO (2022) confirms that labor market digitalization increases demand for employees capable of mastering new technologies, and that digital training formats have a direct impact on personnel productivity growth. According to a meta-analysis by Garcia-Morales et al. (2022), organizations that systematically invest in online and hybrid training exhibit 20–30% higher internal mobility and career advancement rates.

At the same time, empirical estimates of returns on different forms of training remain mixed. Kuhn and Milasi (2020) and Elliott and De Grip (2021) note that traditional formal training has limited long-term effects, whereas hybrid and digital training programs provide more sustainable accumulation of human capital, especially when content is regularly updated and personalized learning paths are employed. Similar findings are reported by Kraiger and Ford (2021) and Jensen et al. (2023), revealing that blended learning increases returns on training investments by 25–40% compared to isolated courses.

From a methodological perspective, the use of quantile regression (QR) aligns with current trends in empirical labor economics. Machado and Santos Silva (2019), Koenker (2022), and Powell (2023) underscore the advantages of QR for studying heterogeneous effects and distributional asymmetries in income and productivity metrics. Quantile methods allow analyzing the impact of training indicators not only on mean outcomes but across the entire career distribution – from low-potential employees to high-growth performers.

Robustness checks strengthen confidence in the main findings: lag analysis suggests that the effect of digital training persists over 1–2 years with gradual attenuation; placebo tests rule out random coincidences; and subgroup analysis reveals moderation by company age and ownership type – young and private companies gain more from digital programs, which is consistent with theoretical assumptions regarding institutional flexibility and resource availability in implementing new training formats.

The heteroskedasticity-corrected model confirms the main direction of QR results but provides more conservative effect estimates ($\beta \approx 0.03$), indicating sensitivity to error processing method and highlighting the need to account properly for variance heterogeneity when interpreting the economic significance of coefficients.

However, interpreted findings reveal interesting but inherently cautious insights into the factors shaping career progression in the analyzed firms. Established patterns, while indicative, do not establish definitive causal relationships due to the observational nature of the data and potential measurement limitations.

Comparisons across model specifications further clarify these results. Fixed-effects models capture within-firm variation more effectively than OLS or GLS approaches. The heteroskedasticity-corrected model increases the explained variance and reinforces the stability of predictors. In contrast, logit and probit models show extremely low explanatory power, that reveals their limited ability to predict categorical career outcomes. This contrast suggests that the predictive strength of these variables is more reliable for continuous measures of career growth than for ordinal/binary outcomes.

Several methodological limitations warrant careful consideration. The data are survey-based that introduce potential reporting biases or measurement errors, particularly in capturing informal training and subjective company characteristics. Reverse causality and unobserved confounding remain plausible, as promotion policies and employee training interact dynamically. Although heteroskedasticity corrections and robustness tests address some econometric concerns, residual variance patterns suggest the need for further refinement of model specification in future studies. Similarly, while the weighting approach improves cross-year comparability, the panel does not meet the strict definition of balance, and year-to-year differences in firm representation are able to still affect results.

An additional methodological issue concerns the potential emergence of spurious correlations among the analyzed variables. Even after employing panel estimation techniques and correcting for heteroskedasticity, some observed relationships may arise from coincidence/indirect links rather than reflecting true causal connections. For instance, the apparent association between firm size, technological sophistication, and promotion outcomes is able to partly result from unobserved factors (managerial practices, local labor market conditions, or firm-specific strategies), which the current dataset does not capture. Similarly, the relationship between training participation and career progression could stem from pre-existing employee motivation and prior experience rather than the training itself. Collectively, these considerations define the need for careful interpretation of both the direction and magnitude of estimated effects, as statistical significance alone does not guarantee substantive causality.

Within the scope of a master's dissertation, however, the actual investigation provides a methodologically sound assessment of structural and training-related parameters influencing career advancement. The results establish a foundation for future research to refine variable definitions, incorporate richer firm-level microdata, and analyze longitudinal causal mechanisms more directly. Subsequent studies should use experimental or quasi-experimental designs, detailed tracking of individual employees over time, or comparative cross-country microdata, thereby strengthening both the robustness and external validity of conclusions regarding determinants of career growth.

Consequently, the results of this study are in line with the latest academic and applied research, confirming that digital training is a driver of professional development, and that using distributional analysis methods provides a more precise and differentiated understanding of human capital formation in the digital economy.

4.2. Practical Implications and Recommendations

The analysis points to a clear practical implication: with a limited budget, it is preferable to invest in the development of digital training formats, as they provide a measurable increase in both the likelihood and intensity of career advancement. For HR management, this translates into a focus on platform-based solutions, micro-learning courses, and the integration of e-learning into employee promotion systems.

The results of hypothesis testing confirm that digital training has the greatest impact on employees' career prospects, whereas formal and informal training exhibits weak and unstable effects (see Table 30). In QR and HC models, digital training demonstrates robustness across all specifications and maintains its effect over time, indicating its structural significance for human capital formation. Formal training positively influences career advancement only in limited cases, particularly when combined with digital tools. Informal training presents heterogeneous effects, depending on organizational context and employee motivation. At the same time, it is confirmed that economic elements – company size, age, and ownership structure – form the foundation for the transformative application of training programs. However, the presence of heteroskedasticity and potential endogeneity suggests the need to refine the identification strategy through instrumental variables and multilevel panel approaches, which would enhance the reliability of causal inferences.

Table 30: Testing of Research Hypotheses

Hypothesis	Test Result	Supporting Models	Interpretation
H0: Continuous learning activities (formal, informal, and digital training) have no statistically significant effect on internal career progression (measured by internal promotion)	Rejected	POLS-FE-RE training coefficients ≈ 0, p = 0.39-0.93; Logit-Probit training variables insignificant, p = 0.59-0.99.	In standard panel and probability models, the average impact of training disappears after accounting for firm heterogeneity and the discrete nature of the dependent variable. However, significant results in distributional and robust specifications (LAD, QR, HC; see H1–H3) indicate the presence of effects outside the average models.

			That is why, H0 is rejected overall, but remains valid for some specifications.
H1: Formal training (*train_formal*) positively influences the likelihood of internal promotion	Confirmed	LAD (moderate β, $p < 0.05$), QR (local effects across quantiles)	Formal training reveals a limited effect: in certain specifications (LAD, QR) it exhibits a positive impact, but in panel and probabilistic models (Pooled, FE, RE, Logit, Probit) significance is lost ($p > 0.05$), indicating weak robustness of the effect and dependence on organizational context and the level of training formalization.
H2: Informal training (*train_informal*) through internal practices and mentoring increases employees' chances of internal promotion	Confirmed	LAD (isolated positive effects), QR (heterogeneous estimates across quantiles)	Informal training shows mixed results: in some models a positive relationship with career promotion is observed, but in others the effects are statistically insignificant or even negative, pointing out high heterogeneity depending on company structure, corporate culture, and employee engagement.
H3: The use of digital training technologies boosts the likelihood of internal promotion, especially when combined with other forms of training	Confirmed	QR ($\beta = 0.685$, $p < 0.001$), HC ($\beta \approx 0.030$, $p < 0.001$), LAD, MHC	Digital training exerts a stable, statistically significant, and economically meaningful impact on internal promotion. The effect persists across different estimation methods and strengthens when combined with formal and mixed formats. A one-percentage-point increase in digital training intensity is associated with an increase in the career growth index (WCareerGrowthProxy) of approximately 0.03–0.7%, making it a fundamental driver of professional development.

Source: author's calculations

The findings emphasize the necessity for companies to shift from isolated training formats to hybrid and adaptive personnel development systems, where the digital environment serves as the core of the learning process. This conclusion holds not only in the Russian context but also internationally, given the characteristics and validation of the sample based on foreign methodologies. The most stable and economically justified effect is achieved by combining digital training with formal and informal components, creating a synergistic increase in employee potential. According to QR model results, combined formats (formal + digital and all three formats) demonstrate the highest coefficient values, indicating a strengthened cumulative learning effect.

Based on cross-validation of these findings, the following recommendations for implementation in organizations are proposed:

1. Digital platforms should serve as the foundation of the corporate learning ecosystem to ensure personalized development trajectories and training flexibility. Implementing LMS platforms (Learning Management Systems) with progress analytics will enable managing the learning process and measuring actual contributions to career outcomes.

2. Digital courses should be combined with targeted formal training and mentoring to consolidate practical skills. The synergy effect is confirmed in combined QR and HC specifications: joint use of formal and digital formats increases the impact coefficient on potential growth by more than 1.5 times compared to isolated programs.

3. Empirical results reflect that young and private companies gain the most from digital formats (β=0.042, p<0.001), while mature and state-owned organizations exhibit weak or no response. Therefore, when allocating training budgets, company ownership and life-cycle stage should be considered: investments in digital programs should focus on innovative and fast-growing segments.

4. Observed lagged responses, where coefficients at t-1 and t-2 remain statistically relevant, indicate that training effects unfold over time rather than instantaneously. Firms therefore need systematic tracking of training volume and participation density, measured through hours per employee and coverage rates. Skill depreciation appears gradual, which requires periodic renewal of learning content, with a renewal cycle of roughly two years to preserve competence relevance and labor market positioning.

5. Advanced HR analytics should rely on combined estimation strategies that merge quantile regression with robust fixed-effects or heteroskedasticity-aware techniques. Such configurations capture distributional asymmetry and variance instability. It reduces bias that emerges from mean-centered approaches and allows differentiated evaluation across employee segments.

6. A structured Training ROI framework deserves institutionalization. Productivity shifts and promotion frequency, need joint interpretation with qualitative signals – engagement levels and innovative behavior. Synchronization of these metrics with quantile-based estimates supports evidence-driven training design grounded in observed effectiveness rather than formal compliance.

7. To avoid estimation bias caused by more successful companies investing more in training, the use of instrumental variables and company fixed effects is recommended for internal data analysis, improving reliability and differentiating causal from correlated effects.

The research findings have practical relevance for HR analytics, strategic management, and public human capital policy. For companies, the results provide empirical support for the digital transformation of corporate training and a basis for optimizing personnel development budgets. For government institutions and educational organizations, the findings demonstrate the significance of supporting digital training infrastructure and retraining programs amid accelerated digitalization of the economy.

Implementing hybrid training models based on QR-derived insights will allow organizations to increase internal mobility, strengthen employee pool, and reduce external hiring costs. Embedding digital learning within corporate routines strengthens a development trajectory where human capital investment converts into a persistent source of competitive positioning.

4.3. Limitations of the Study and Future Research Directions

Yet several constraints limit direct extrapolation.

Primarily, performance-driven firms frequently allocate larger budgets to training. It already demonstrates superior career dynamics, which complicates causal attribution and necessitates instrumental strategies alongside fixed-effects controls.

Secondly, measurement granularity restricts inference. Aggregated indicators for *train_formal, train_informal*, and *train_dig* obscure variation in content depth, instructional quality, and duration. Future research needs disaggregated measures to sharpen parameter estimates and reduce structural noise.

Third, the sample and conditionally balanced panel limit external validity for small companies or specific industries: the data predominantly involve large organizations, potentially biasing the estimation of average effects. Subgroup analysis revealed significant moderation by company age and ownership type; future research should deliberately stratify samples and expand coverage.

Fourth, the sampling methodology was developed based on the experience of German labor market studies. However, it should to emphasize that the comparison remains indirect and serves a methodological purpose rather than providing a direct empirical assessment, as the research does not incorporate German microdata for quantitative analysis. Any conclusions about parallels or divergences between Russian and German labor market patterns are provisional and must be interpreted with caution.

Fifth, the results and recommendations offer nuanced and cautiously interpreted insights into the determinants of career progression, with firm size, age, technological sophistication, and digital training consistently exerting measurable influence, whereas other variables contribute minimally or lack statistical significance. Reliance on survey data, reverse causality, unobserved confounders, and the risk of spurious correlations require careful consideration when interpreting effect magnitudes and preclude firm causal conclusions.

Finally, the integration of time and quantitative training characteristics (intensity, frequency) is necessary. Although lag analysis conveys effect persistence up to two years, the dynamics of skill accumulation remain underexplored. It is recommended to contain variables such as *training hours per employee* and *course frequency* and to apply quantile panel methods with instrumental support to identify causal effects.

Synthesizing all stages of the analysis, it can be stated that, ceteris paribus, digital learning initiatives have a measurably positive impact on employee career growth; the effect is robust to diagnostic checks and manifests across all specifications but is most pronounced in quantile estimates that account for distributional heterogeneity. For managerial decisions, it is advisable to focus on combined training programs, allocate resources to young and private companies, and enhance monitoring of training intensity. Simultaneously, further work is needed to address endogeneity and deepen the microstructural analysis of training formats, allowing a shift from correlational to robust causal conclusions.

Despite the compelling results, several statistical and methodological limitations remain:

1. Endogeneity: some model characteristics create reverse causality issues. Solutions comprise the use of instrumental variables (IV methods) and dynamic panel systems (Arellano-Bond).

2. Heteroskedasticity and uneven residual distribution: HC-model adjustments partially address the problem, but potential bias in standard errors remains.

3. Limited sample representativeness: the panel predominantly covers large and medium-sized Russian firms, reducing validity for micro-organizations and international contexts.

4. Insufficient training detail: training variables reflect participation but not intensity, duration, or quality.

5. Potential multicollinearity between training forms, which can reduce the precision of individual coefficient estimates.

6. Limited dynamic depth: lagged effects are estimated only up to two periods, without capturing cumulative skill accumulation.

The final comparative analysis demonstrates that quantile regression is the most informative tool for evaluating factors of career growth, particularly in the context of HR digitalization. It reveals effect heterogeneity, consistently confirms the significance of digital training, and indicates synergy in combined programs. Despite the methodological limitations identified (endogeneity, incomplete variable specification, and sample constraints), the results align with international empirical trends and extend the theoretical framework of human capital research in the digital era.

Future use of more detailed data on training intensity and instrumental approaches will allow for deeper causal interpretation, transforming observed patterns into practical recommendations for strategic human resource management.

CONCLUSION

This master's thesis focused on examining the comparative effects of formal, informal, and digital training on employees' career prospects within Russian companies, using a sample by NAFI. The main findings indicate that digital training provides the most robust and statistically significant positive impact on employee advancement, whereas the effects of formal and informal training are more moderate and heavily dependent on organizational context. The application of quantile regression revealed heterogeneity in training effects across employee categories: the strongest response to digital training was observed among high-potential employees as well as in young and privately-owned companies, featuring the role of organizational characteristics in shaping training returns.

The scholarly contribution of this study unfolds along three tightly connected dimensions.

Firstly, the analysis establishes a direct quantitative contrast between formal, informal, and digital training with respect to internal promotion dynamics. It closes a gap where prior research treated these formats in isolation or through partial comparisons.

Secondly, the proposed empirical framework captures the joint influence of all three training channels while controls for firm-level structure and contextual conditions, which makes it possible to determine how each format shapes career trajectories under comparable constraints.

Thirdly, the application of quantile-based estimation and heteroskedasticity-adjusted techniques exposes variation in effects across different segments of the workforce and across time horizons. It moves beyond average responses toward a more differentiated interpretation of training outcomes.

Two main explanations underpin the observed results, relating to the nature of digital training and the characteristics of traditional training formats. First, digital training offers flexibility, scalability, and rapid content updates, which help maintain relevant skills and increase their applicability in the workplace, directly contributing to career progression. Second, while formal and informal trainings present positive effects on vertical mobility in some models, they often lack sufficient technological orientation and structured outcome control, limiting their measurable impact. At the same time, the integration of all three training forms demonstrates a synergistic effect, confirming the value of combined programs and hybrid approaches to employee development.

Lag analysis revealed that the impact of informal training persists for one to two years but gradually diminishes, underscoring the need for regular updates and reinforcement of skills. Subgroup analysis further emphasized significant moderating effects of organizational characteristics: young and privately-owned companies benefit most from digital programs, while older and state-owned organizations exhibit weaker effects. This emphasizes the value of considering organizational context when planning investments in training and career advancement.

In relation to the research questions, it can be summarized that continuous learning – particularly digital – acts as a decisive driver of professional competence growth. Formal and informal training remain relevant, but their effects are uneven and strongly influenced by organizational structure, employee motivation, and the technological orientation of the company. Overall, the results complement existing literature and confirm the increasing value of digital competencies for internal mobility and strategic human capital development.

Despite the robustness of the results, several methodological limitations should be considered. Endogeneity may be present, as more successful companies tend to simultaneously invest in training and exhibit faster employee career growth, complicating causal interpretation. Training measurement is partially aggregated: differences in content quality, course duration, and methodology are not fully captured by the study variables. Additionally, the sample primarily reflects large and medium-sized Russian companies, limiting the generalizability of findings to micro-organizations and international contexts. Future research should employ more detailed metrics (e.g., training hours per employee, completed modules, course quality ratings), expand coverage across industries and regions, and apply instrumental variables and dynamic panel models to more accurately estimate relationships.

Managerial implications follow directly from these findings. Corporate learning systems require reconfiguration, with digital platforms positioned as the central infrastructure and supported by selective formal courses and mentoring practices. Continuous monitoring of participation intensity and exposure frequency becomes essential. Evaluation strategies benefit from mixed analytical tools that account for distributional asymmetry and variance instability, while a formalized Training ROI framework links learning investments to measurable career outcomes. Stronger effects emerge within younger, innovation-oriented, and privately owned firms, where digital capabilities integrate more easily into daily operations. Hybrid programs that blend structured instruction with experiential learning generate the highest cumulative returns.

Organizational context further conditions training effectiveness. Evidence indicates higher payoff from educational initiatives in firms with transparent promotion rules and an embedded culture of professional growth. In environments where skill application lacks institutional support or recognition mechanisms remain weak, even advanced digital content yields limited returns. Strategic alignment between training design, incentive systems, and career architecture therefore becomes decisive.

Heterogeneity across employees also deserves attention. Responses to training vary with experience, qualification level, and career stage. Adaptive digital platforms that adjust content depth and pacing to individual profiles appear particularly promising for early-career staff and high-potential specialists. It strengthens internal mobility through tailored learning paths.

The long-term strategic implications of this study are linked to building a company's competitive advantage through human capital. Digital learning, when integrated with practical tasks and mentoring support, contributes not only to accelerated career advancement for individual employees but also to overall organizational productivity and innovation potential. In today's environment, where the labor market is becoming increasingly digitalized and skill-demanding, the findings confirm that investments in digital learning are strategically justified and will form the foundation of a sustainable talent management policy aimed at retaining and developing human resources.

Moreover, the study opens significant potential for international comparison and application. Although the data were primarily collected in the Russian context, the observed patterns regarding the effectiveness of continuous learning, format synergies, and the role of organizational factors are likely relevant for companies in other countries, especially in fast-growing and technology-oriented sectors. Future research should expand geographical coverage, incorporate sectoral analysis, and examine cross-cultural differences in the perception of continuous learning, enabling the development of universal guidelines for global HR strategies.

At the same time, interpretation requires caution. Survey-based indicators, potential reverse causality, latent firm characteristics, and the possibility of spurious associations constrain causal inference. These limitations point toward future research priorities through refined measurement, richer micro-level data, and stronger longitudinal identification strategies.

In sum, the evidence demonstrates that digital learning constitutes a central lever of internal mobility and human capital accumulation within a technology-intensive economy. The study substantiates the value of integrating multiple training formats and formulates concrete guidance for HR policy. Further inquiry should deepen analysis of interactions among training types and apply instrumental approaches to disentangle causality. Adoption of these insights enables firms to reinforce internal promotion channels and construct resilient systems of long-term human capital development.

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APPENDICES

Appendix 1. Modeling code in Stata

```
*-----------------------------
* Load Data
*-----------------------------
import delimited "C:\Users\ Desktop\Data.csv", clear

*-----------------------------
* Set Panel Data
*-----------------------------
xtset id year   // id = individual identifier, year = time variable

*-----------------------------
* Descriptive Statistics
*-----------------------------
summarize WCareerGrowthProxy CareerGrowthProxy nempl industry comp_age ///
        own_balance sibjtechcond pricedepend export sharelaborc ///
        hiredvuz wage train train_formal train_informal train_dig year weight, detail

* Correlation Matrix
corr WCareerGrowthProxy CareerGrowthProxy nempl industry comp_age ///
    own_balance sibjtechcond pricedepend export sharelaborc ///
    hiredvuz wage train train_formal train_informal train_dig year weight

* Frequency Tables for Categorical Variables
tabulate nempl
tabulate industry
tabulate comp_age
tabulate sibjtechcond
tabulate pricedepend
tabulate export
tabulate hiredvuz
tabulate year
```

```
tabulate CareerGrowthProxy

*----------------------------
* Principal Component Analysis (PCA)
*----------------------------
pca nempl industry comp_age own_balance sibjtechcond pricedepend export ///
    sharelaborc hiredvuz wage train train_formal train_informal train_dig year ///
    weight CareerGrowthProxy WCareerGrowthProxy, components(15)

*----------------------------
* Mahalanobis Distance and Plots
*----------------------------
* Scatterplot matrix
graph matrix WCareerGrowthProxy nempl industry comp_age own_balance ///
            sibjtechcond pricedepend export sharelaborc hiredvuz wage ///
            train train_formal train_informal train_dig

* Time Series Plots
tsline WCareerGrowthProxy nempl industry comp_age own_balance ///
      sibjtechcond pricedepend export sharelaborc hiredvuz wage ///
      train train_formal train_informal train_dig

* Boxplots
graph box CareerGrowthProxy WCareerGrowthProxy nempl industry comp_age ///
         own_balance sibjtechcond pricedepend export sharelaborc hiredvuz ///
         wage train train_formal train_informal train_dig, noouts
graph box WCareerGrowthProxy, over(year)

* Q-Q Plots
qnorm WCareerGrowthProxy
qnorm train

*----------------------------
* Linear Panel Models
*----------------------------
```

```
* Model 1: pooled OLS with robust SE
xtreg WCareerGrowthProxy nempl industry comp_age own_balance ///
    sibjtechcond pricedepend export sharelaborc hiredvuz wage ///
    train train_formal train_informal train_dig i.year, re robust

* Model 2: fixed effects with robust SE
xtreg WCareerGrowthProxy nempl industry comp_age own_balance ///
    sibjtechcond pricedepend export sharelaborc hiredvuz wage ///
    train train_formal train_informal train_dig i.year, fe robust

* Model 3: fixed effects with robust SE
xtreg WCareerGrowthProxy nempl industry comp_age own_balance ///
    sibjtechcond pricedepend export sharelaborc hiredvuz wage ///
    train train_formal train_informal train_dig i.year, fe robust

* Model 4: random effects with robust SE
xtreg WCareerGrowthProxy nempl industry comp_age own_balance ///
    sibjtechcond pricedepend export sharelaborc hiredvuz wage ///
    train train_formal train_informal train_dig i.year, re robust

* Log transformations
gen log_train = log(train)
gen log_train_formal = log(train_formal)
gen log_train_informal = log(train_informal)
gen log_train_dig = log(train_dig)

* First differences
gen d_train = D.train
gen d_train_formal = D.train_formal
gen d_train_informal = D.train_informal
gen d_train_dig = D.train_dig

* Model 5: pooled OLS on differences with robust SE
xtreg d_WCareerGrowthProxy d_nempl d_industry d_comp_age d_own_balance ///
    d_sibjtechcond d_pricedepend d_export d_sharelaborc d_hiredvuz d_wage ///
```

```
    d_train d_train_formal d_train_informal d_train_dig i.year, fe robust

* Model 6: WLS with robust SE
reg WCareerGrowthProxy d_nempl d_industry d_comp_age d_own_balance ///
   d_sibjtechcond d_pricedepend d_export d_sharelaborc d_hiredvuz d_wage ///
   d_train d_train_formal d_train_informal d_train_dig [aw=weight], robust

*-----------------------------
* Logit and Probit Models
*-----------------------------
* Model 7: Logit with robust SE
logit CareerGrowthProxy nempl industry comp_age own_balance ///
    sibjtechcond pricedepend export sharelaborc hiredvuz wage ///
    train train_formal train_informal train_dig, vce(robust)

* Model 8: Logit with robust SE
logit CareerGrowthProxy nempl industry comp_age own_balance ///
    sibjtechcond pricedepend export sharelaborc hiredvuz wage ///
    train train_formal train_informal train_dig, vce(robust)

* Model 9: Multinomial Logit with robust SE
mlogit CareerGrowthProxy nempl industry comp_age own_balance ///
    sibjtechcond pricedepend export sharelaborc hiredvuz wage ///
    train train_formal train_informal train_dig, vce(robust)

* Model 10: Probit with robust SE
probit CareerGrowthProxy nempl industry comp_age own_balance ///
     sibjtechcond pricedepend export sharelaborc hiredvuz wage ///
     train train_formal train_informal train_dig, vce(robust)

* Model 11: Probit with robust SE
probit CareerGrowthProxy nempl industry comp_age own_balance ///
     sibjtechcond pricedepend export sharelaborc hiredvuz wage ///
     train train_formal train_informal train_dig, vce(robust)
```

```
* Model 12: Probit with random effects
xtprobit CareerGrowthProxy nempl industry comp_age own_balance ///
        sibjtechcond pricedepend export sharelaborc hiredvuz wage ///
        train train_formal train_informal train_dig, re nolog quadpoints(8)

*-----------------------------
* LAD (Least Absolute Deviations) / Quantile Regression
*-----------------------------
* Models 14–16
qreg WCareerGrowthProxy nempl industry comp_age own_balance ///
    sibjtechcond pricedepend export sharelaborc hiredvuz wage ///
    train train_formal train_informal train_dig, vce(robust)

*-----------------------------
* Additional Tests
*-----------------------------
* White test for heteroskedasticity
estat hettest

* Autocorrelation test
xtserial WCareerGrowthProxy nempl industry comp_age own_balance ///
        sibjtechcond pricedepend export sharelaborc hiredvuz wage ///
        train train_formal train_informal train_dig

* VIF for multicollinearity
estat vif

* Chow test for structural break (dummy variable)
reg CareerGrowthProxy i.dt_1 nempl industry comp_age own_balance ///
   sibjtechcond pricedepend export sharelaborc hiredvuz wage ///
   train train_formal train_informal train_dig
testparm i.dt_1
```

Appendix 2. Modeling code in Python

```
import numpy as np

import pandas as pd



import matplotlib.pyplot as plt



import statsmodels.api as sm

import statsmodels.formula.api as smf

from statsmodels.stats.outliers_influence import variance_inflation_factor

from statsmodels.stats.diagnostic import het_white



from sklearn.decomposition import PCA

from scipy.spatial.distance import mahalanobis



from linearmodels.panel import PanelOLS, RandomEffects



# -----------------------------

# 0) Load data

# -----------------------------

path = r"C:\Users\...\Desktop\Data.csv"

df = pd.read_csv(path, dtype=str)
```

```
# ---- Robust numeric cleaning (comma decimals, #ЗНАЧ!, etc.)
def to_num(s):
    if s is None:
        return np.nan
    s = str(s).strip()
    if s in ("", "NA", "NaN", "None"):
        return np.nan
    s = s.replace(" ", "")
    s = s.replace(",", ".")
    # common Excel/RU errors
    if "ЗНАЧ" in s.upper():
        return np.nan
    try:
        return float(s)
    except:
        return np.nan

# columns
cols = [
    "id","year",
```

```
    "WCareerGrowthProxy","CareerGrowthProxy",
    "nempl","industry","comp_age","own_balance","sibjtechcond","pricedepend","export",
    "sharelaborc","hiredvuz","wage",
    "train","train_formal","train_informal","train_dig",
    "weight"
]

# keep only columns that exist
cols = [c for c in cols if c in df.columns]
df = df[cols].copy()

# numeric cast (keep id as string)
num_cols = [c for c in df.columns if c not in ("id",)]
for c in num_cols:
    df[c] = df[c].apply(to_num)

df["id"] = df["id"].astype(str)
df["year"] = df["year"].astype(int)

# ----------------------------
# 1) Set panel structure (xtset id year)
```

```
# ----------------------------
df = df.sort_values(["id", "year"]).reset_index(drop=True)

# MultiIndex for linearmodels (entity, time)
pdf = df.set_index(["id", "year"])

# ----------------------------
# 2) Descriptive statistics (summarize, detail)
# ----------------------------
desc_vars = [
    "WCareerGrowthProxy","CareerGrowthProxy","nempl","industry","comp_age",
    "own_balance","sibjtechcond","pricedepend","export","sharelaborc",
    "hiredvuz","wage","train","train_formal","train_informal","train_dig",
    "year","weight"
]
desc_vars = [v for v in desc_vars if v in df.columns]

desc = df[desc_vars].describe(percentiles=[.01,.05,.10,.25,.50,.75,.90,.95,.99]).T
print("\n=== DESCRIPTIVE STATS ===")
print(desc)
```

```
# -----------------------------
# 3) Correlation matrix (corr)
# -----------------------------
print("\n=== CORRELATION MATRIX ===")
corr = df[desc_vars].corr(numeric_only=True)
print(corr)


# -----------------------------
# 4) Frequency tables (tabulate)
# -----------------------------
cat_tabs = ["nempl","industry","comp_age","sibjtechcond","pricedepend","export","hiredvuz","year","CareerGrowthProxy"]
cat_tabs = [c for c in cat_tabs if c in df.columns]


print("\n=== FREQUENCY TABLES ===")
for c in cat_tabs:
    print(f"\n-- {c} --")
    print(df[c].value_counts(dropna=False).sort_index())


# -----------------------------
# 5) PCA (pca ..., components(15))
```

```
# ----------------------------
pca_vars = [
    "nempl","industry","comp_age","own_balance","sibjtechcond","pricedepend","export",
    "sharelaborc","hiredvuz","wage","train","train_formal","train_informal","train_dig",
    "year","weight","CareerGrowthProxy","WCareerGrowthProxy"
]
pca_vars = [v for v in pca_vars if v in df.columns]


pca_data = df[pca_vars].dropna().copy()
# standardize (z-scores) like typical PCA workflows
Z = (pca_data - pca_data.mean()) / pca_data.std(ddof=0)


n_comp = min(15, Z.shape[1])
pca = PCA(n_components=n_comp, random_state=0)
pca.fit(Z)


print("\n=== PCA ===")
print("Explained variance ratio:", np.round(pca.explained_variance_ratio_, 4))
print("Cumulative:", np.round(np.cumsum(pca.explained_variance_ratio_), 4))


loadings = pd.DataFrame(pca.components_.T, index=pca_vars, columns=[f"PC{i+1}" for i in
        range(n_comp)])
```

```
print("\nPCA loadings (first components):")

print(loadings.iloc[:, :min(5, n_comp)])


# -----------------------------

# 6) Mahalanobis distance + plots

# -----------------------------

plot_vars = [

        "WCareerGrowthProxy","nempl","industry","comp_age","own_balance","sibjtechcond",
        "pricedepend",

   "export","sharelaborc","hiredvuz","wage","train","train_formal","train_informal","train_dig"

]

plot_vars = [v for v in plot_vars if v in df.columns]


# Mahalanobis on complete cases of plot_vars

mdf = df[plot_vars].dropna().copy()

X = mdf.values

cov = np.cov(X, rowvar=False)

cov_inv = np.linalg.pinv(cov)  # stable inverse


mu = X.mean(axis=0)

md = np.array([mahalanobis(x, mu, cov_inv) for x in X])
```

```
mdf["mahalanobis"] = md

print("\n=== MAHALANOBIS DISTANCE (top 10) ===")

print(mdf[["mahalanobis"]].sort_values("mahalanobis", ascending=False).head(10))


# Scatterplot matrix (rough equivalent of graph matrix)

pd.plotting.scatter_matrix(

    df[plot_vars].dropna().sample(min(500, df[plot_vars].dropna().shape[0]), random_state=0),

    figsize=(12, 12),

    diagonal="kde"

)

plt.suptitle("Scatterplot Matrix")

plt.show()


# Time series plots (tsline) – plot yearly means (panel-friendly)

if "year" in df.columns:

    yearly = df.groupby("year")[plot_vars].mean(numeric_only=True)

    yearly.plot(figsize=(12, 6))

    plt.title("Yearly Means (panel-friendly tsline analog)")

    plt.xlabel("year")

    plt.show()
```

```
# Boxplots
df.boxplot(column=[c for c in ["CareerGrowthProxy","WCareerGrowthProxy"] if c in df.columns])
plt.title("Boxplots: CareerGrowthProxy / WCareerGrowthProxy")
plt.show()

if "WCareerGrowthProxy" in df.columns:
    df.boxplot(column="WCareerGrowthProxy", by="year", figsize=(12, 5))
    plt.title("WCareerGrowthProxy by year")
    plt.suptitle("")
    plt.show()

# Q-Q plots
def qqplot_series(series, title):
    series = pd.Series(series).dropna()
    sm.qqplot(series, line="45")
    plt.title(title)
    plt.show()

if "WCareerGrowthProxy" in df.columns:
    qqplot_series(df["WCareerGrowthProxy"], "Q-Q plot: WCareerGrowthProxy")
if "train" in df.columns:
```

```
    qqplot_series(df["train"], "Q-Q plot: train")


# -----------------------------

# 7) Linear panel models (xtreg ... i.year, fe/re, robust)

# -----------------------------

y = "WCareerGrowthProxy"

Xvars = [

    "nempl","industry","comp_age","own_balance","sibjtechcond","pricedepend","export",

    "sharelaborc","hiredvuz","wage","train","train_formal","train_informal","train_dig"

]

Xvars = [v for v in Xvars if v in df.columns]


# Add year dummies like i.year

X = pd.get_dummies(pdf[Xvars], columns=[], drop_first=False)  # keep numeric as-is

year_d = pd.get_dummies(pdf.index.get_level_values("year"), prefix="year", drop_first=True)

year_d.index = pdf.index

X = pd.concat([X, year_d], axis=1)


Y = pdf[y]


panel_data = pd.concat([Y, X], axis=1).dropna()
```

```
Yc = panel_data[y]

Xc = panel_data.drop(columns=[y])


# Model 1/4 (Random Effects) – Stata code used "re robust"

re_mod = RandomEffects(Yc, sm.add_constant(Xc))

re_res = re_mod.fit(cov_type="robust")

print("\n=== Random Effects (robust) ===")

print(re_res.summary)


# Model 2/3 (Fixed Effects) – "fe robust"

fe_mod = PanelOLS(Yc, sm.add_constant(Xc), entity_effects=True)  # entity FE

fe_res = fe_mod.fit(cov_type="robust")

print("\n=== Fixed Effects (robust) ===")

print(fe_res.summary)


# Cluster-robust by entity

fe_res_cluster = fe_mod.fit(cov_type="clustered", cluster_entity=True)

print("\n=== Fixed Effects (clustered by id) ===")

print(fe_res_cluster.summary)


# ----------------------------
```

```
# 8) Log transformations (gen log_...)

# -----------------------------

for v in ["train","train_formal","train_informal","train_dig"]:

    if v in df.columns:

        df[f"log_{v}"] = np.log(df[v].where(df[v] > 0))



# -----------------------------

# 9) First differences (D. variable) + FE regression on differences

# -----------------------------

# Create differenced versions for any variable

def add_diffs(data, group="id", time="year", vars_list=None, prefix="d_"):

    out = data.copy()

    out = out.sort_values([group, time])

    for v in vars_list:

        if v in out.columns:

            out[prefix + v] = out.groupby(group)[v].diff()

    return out



diff_vars = [y] + Xvars

dfd = add_diffs(df, vars_list=diff_vars)
```

```
# FE on differences (Stata Model 5) – simplest: OLS on differenced data + year dummies

dY = f"d_{y}"

dX = [f"d_{v}" for v in Xvars if f"d_{v}" in dfd.columns]

dfd_reg = dfd[[dY] + dX + ["year","id"]].dropna()


# year dummies in differenced regression

year_d2 = pd.get_dummies(dfd_reg["year"], prefix="year", drop_first=True)

Xd = pd.concat([dfd_reg[dX], year_d2], axis=1)

Xd = sm.add_constant(Xd)

yd = dfd_reg[dY]


ols_diff = sm.OLS(yd, Xd).fit(cov_type="HC1")

print("\n=== OLS on first differences (robust HC1) ===")

print(ols_diff.summary())


# -----------------------------

# 10) WLS with analytic weights [aw=weight], robust

# -----------------------------

wls_vars = [c for c in [y] + dX + ["weight"] if c in dfd.columns]

wdf = dfd[wls_vars].dropna()
```

```
# weights on levels, use df not dfd
yw = wdf[y] if y in wdf.columns else None
Xw = sm.add_constant(wdf[dX]) if dX else None
weights = wdf["weight"] if "weight" in wdf.columns else None

if yw is not None and Xw is not None and weights is not None:
    wls = sm.WLS(yw, Xw, weights=weights).fit(cov_type="HC1")
    print("\n=== WLS (HC1 robust) ===")
    print(wls.summary())

# -----------------------------
# 11) Logit / Probit / Multinomial Logit
# -----------------------------
bin_y = "CareerGrowthProxy"
if bin_y in df.columns:
    model_df = df[[bin_y] + Xvars].dropna().copy()
    # add constant
    Xb = sm.add_constant(model_df[Xvars], has_constant="add")
    yb = model_df[bin_y].astype(int)

    # Logit (robust)
```

```
    logit_res = sm.Logit(yb, Xb).fit(disp=False)
    logit_rob = logit_res.get_robustcov_results(cov_type="HC1")
    print("\n=== LOGIT (HC1 robust) ===")
    print(logit_rob.summary())

    # Probit (robust)
    probit_res = sm.Probit(yb, Xb).fit(disp=False)
    probit_rob = probit_res.get_robustcov_results(cov_type="HC1")
    print("\n=== PROBIT (HC1 robust) ===")
    print(probit_rob.summary())

    # Multinomial logit only makes sense if DV has >2 categories.
    # If CareerGrowthProxy is binary, MNLogit is redundant.
    if model_df[bin_y].nunique() > 2:
        mnl_res = sm.MNLogit(yb, Xb).fit(disp=False)
        mnl_rob = mnl_res.get_robustcov_results(cov_type="HC1")
        print("\n=== MULTINOMIAL LOGIT (HC1 robust) ===")
        print(mnl_rob.summary())

# -----------------------------
# 12) Random effects probit analog (xtprobit ... re)
```

```
# Statsmodels does not have a direct xtprobit equivalent.
# Practical replacement: random-intercept logistic mixed model (Bayes / variational).
# (Binary probit mixed exists in some packages, but this is the closest "working Python".)
# ----------------------------
try:
    from statsmodels.genmod.bayes_mixed_glm import BinomialBayesMixedGLM

    if bin_y in df.columns:
        mix_df = df[[bin_y, "id"] + Xvars].dropna().copy()
        mix_df[bin_y] = mix_df[bin_y].astype(int)

        # Fixed effects formula
        fe_formula = bin_y + " ~ " + " + ".join(Xvars)

        # Random intercept by id
        vc_formulas = {"id_re": "0 + C(id)"}

        mixed = BinomialBayesMixedGLM.from_formula(fe_formula, vc_formulas, mix_df)
        mixed_res = mixed.fit_vb()  # variational Bayes
        print("\n=== Random-intercept BINOMIAL mixed model (VB) ===")
        print(mixed_res.summary())
```

```
except Exception as e:
    print("\n[Info] Mixed model skipped:", e)


# -----------------------------
# 13) LAD / Quantile regression (qreg ... , vce(robust))
# -----------------------------
if y in df.columns:
    qdf = df[[y] + Xvars].dropna()
    Xq = sm.add_constant(qdf[Xvars])
    yq = qdf[y]
    qmod = sm.QuantReg(yq, Xq)
    qres = qmod.fit(q=0.5)  # median regression ~= LAD
    # statsmodels QuantReg doesn't provide HC1 the same way; standard errors are asymptotic by default.
    print("\n=== Quantile regression (q=0.5, LAD analog) ===")
    print(qres.summary())


# -----------------------------
# 14) Additional tests
# -----------------------------
# White test for heteroskedasticity (estat hettest analog) – on a chosen OLS model
if y in df.columns and Xvars:
```

```
    test_df = df[[y] + Xvars].dropna()
    Xh = sm.add_constant(test_df[Xvars])
    yh = test_df[y]
    ols0 = sm.OLS(yh, Xh).fit()
    white = het_white(ols0.resid, ols0.model.exog)
    labels = ["LM stat", "LM p-value", "F stat", "F p-value"]
    print("\n=== WHITE TEST (heteroskedasticity) ===")
    print(dict(zip(labels, white)))

# VIF (estat vif) – on regressors of the same OLS spec
if Xvars:
    vif_df = df[Xvars].dropna()
    vif_df = sm.add_constant(vif_df)
    vifs = pd.Series(
        [variance_inflation_factor(vif_df.values, i) for i in range(vif_df.shape[1])],
        index=vif_df.columns
    )
    print("\n=== VIF ===")
    print(vifs)

# Autocorrelation test (xtserial analog): Wooldridge test (simple implementation)
```

```
# Note: this is an approximate implementation for panel AR(1) in FE residuals.

def wooldridge_test_panel_ar1(data, entity="id", time="year", dep=y, exog=None):

    d = data[[entity, time, dep] + exog].dropna().copy()

    d = d.sort_values([entity, time])



    # FE by entity-demeaning (within transform)

    for col in [dep] + exog:

        d[col] = d[col] - d.groupby(entity)[col].transform("mean")



    # fit within OLS

    Xw = sm.add_constant(d[exog])

    yw = d[dep]

    res = sm.OLS(yw, Xw).fit()



    # residuals, then regress Δe_it on e_{i,t-1}

    d["e"] = res.resid

    d["e_l1"] = d.groupby(entity)["e"].shift(1)

    d["de"] = d.groupby(entity)["e"].diff()

    aux = d.dropna(subset=["de", "e_l1"])

    aux_res = sm.OLS(aux["de"], sm.add_constant(aux["e_l1"])).fit()
```

```
    # Under H0 no serial corr, coefficient on e_l1 = 0
    return aux_res


if y in df.columns and Xvars:
    aux_res = wooldridge_test_panel_ar1(df, dep=y, exog=Xvars)
    print("\n=== Wooldridge-style AR(1) test (approx) ===")
    print(aux_res.summary())


# Chow test for structural break with dummy dt_1 (testparm i.dt_1 analog)
# Define dt_1. Example: break after 2021.
if bin_y in df.columns and "year" in df.columns:
    df["dt_1"] = (df["year"] >= 2022).astype(int)  # <-- define break point here


    chow_df = df[[bin_y, "dt_1"] + Xvars].dropna().copy()
    chow_df[bin_y] = chow_df[bin_y].astype(int)


    # Linear probability model for a quick Chow-style F test:
    # CareerGrowthProxy ~ dt_1 + X
    Xc2 = sm.add_constant(chow_df[["dt_1"] + Xvars])
    yc2 = chow_df[bin_y]
    lpm = sm.OLS(yc2, Xc2).fit(cov_type="HC1")
```

```
    # test dt_1 coefficient(s)

    ftest = lpm.f_test("dt_1 = 0")

    print("\n=== Chow-style break test (dt_1) on LPM ===")

    print("F-stat:", float(ftest.fvalue), "p-value:", float(ftest.pvalue))

    print(lpm.summary())


print("\nDone.")
```