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AI-ENABLED INFORMAL LEARNING IN THE WORKPLACE: EVIDENCE FROM AUSTRIAN KNOWLEDGE WORKERS

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Abstract

This work project examines how knowledge workers perceive AI as a tool for informal learning and development, and how these perceptions relate to career impact, confidence, and overreliance concerns in Italy and Austria. Using a cross-sectional online survey (N = 195), we constructed composite measures for AI-enabled informal learning, problem-solving support, confidence, overreliance ("ghost-learner" risk), and career impact. Three country-specific regressions show that learning-oriented AI use most consistently predicts perceived career benefits. Confidence is mainly learning-driven in Austria, but more problem-solving-driven in Italy. Overreliance follows the classic frequency pattern in Italy, but links to autonomy/deep integration in Austria.

Keywords

Generative AI, Organizational Behavior, Informal Learning, Knowledge Workers.

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1 Introduction *Group Part*

Digitalization and artificial intelligence (AI) are reshaping how organizations create value and how knowledge workers learn and develop in their roles. In technology-intensive sectors such as software, fintech and e-commerce, employees face fast-changing tools, tasks and skill requirements, making continuous learning central to both employability and organizational performance (van den Broek 2025). Much of this learning happens informally in everyday work rather than through formal training programs, for example via problem solving, experimentation and feedback seeking (Karhapää et al. 2025).

Recent advances in analytical and generative AI mean that many knowledge workers now use AI tools to search for information, generate text or code, and support decision-making. These tools can, in principle, create new opportunities for informal learning by offering real-time feedback, alternative solutions and personalized prompts. At the same time, scholars warn of a potential "ghost-learner" effect: if workers simply accept AI outputs without reflection, they may appear to perform better while actually learning less and becoming over-dependent on AI support. This tension raises the question of when AI functions as a meaningful learning resource and when it risks undermining learning and skill development (Rausch 2025).

This thesis investigates these issues among knowledge workers in Italy and Austria, two European countries with advanced digital sectors but different institutional and organizational contexts. Focusing on professionals in digitally intensive roles (e.g. software, data, fintech), we examine how they use AI in their daily work, how they perceive its impact on learning, career development and job quality, and under what conditions they report concerns about overreliance on AI. The study is guided by the following research question:

How is AI adoption in organizations perceived as a means of informal development and training, and how does it relate to perceived skill development and job quality across different national contexts?

To address this question, we explore four sub-questions:

1. How frequently and in what ways do knowledge workers in Italy and Austria use AI tools at work?
2. How do AI use frequency and AI-enabled learning relate to perceived problem-solving effectiveness and confidence
3. How does AI-enabled informal learning relate to perceived job quality indicators such as career impact and professional growth?
4. Under what conditions do workers report concerns about overreliance on AI, and how are these concerns associated with AI use, learning and autonomy?

Methodologically, the thesis uses a quantitative, cross-sectional survey of approximately 200 knowledge workers (approximately 100 per country). Standardized Likert-type items capture AI use, informal learning behaviours, confidence, career impact and overreliance, alongside demographic and professional background variables. Multiple linear regression models are estimated separately for Italy and Austria, using the same model specifications and variables in both countries, which allows us to compare whether the same relationships hold in Italy and Austria and where patterns diverge. The remainder of the thesis reviews the theoretical background (Chapter 2), outlines the research design and measures (Chapter 3), presents the empirical results for each country (Chapter 4 & 5), and discusses implications, limitations and directions for future research.

2 Literature Review *Group Part*

2.1 Knowledge Workers and Digital Transformation

Knowledge workers are professional whose main output is knowledge creation, interpretation, and problem solving rather than routine physical tasks (Drucker 1999). As Drucker (1999) originally articulated, knowledge workers are distinguished by their continuous need to learn and adapt because their tasks are often non-routine and require ongoing updating of domain knowledge, tools and problem-solving approaches. In contrast to many manual roles, knowledge work more often involves interpreting ambiguous information, exercising judgement, and responding to changing organizational demands. In today's digital product and service driven organizations (particularly in sectors such as software, fintech, electronics, and consulting) these workers are embedded in ecosystems of rapid technological change, heavy reliance on data, and organizational expectations of continuous innovation (Karr-Wisniewski and Lu 2010).

2.1.1 Role of AI in Knowledge Intensive Work

In knowledge-intensive work, AI is increasingly woven into everyday tasks such as analysis, writing, design, and decision support but it does not simply replace human expertise. Instead, AI systems generate suggestions, patterns and draft solutions that workers must interpret, verify and adapt to specific organizational and client context (van den Broek 2025).

AI's Limits in Complex Knowledge Work

Pettersen (2019) argues that despite rising expectations surrounding AI, current systems struggle fundamentally with the situated, relational and context depended on the nature of knowledge work because complex problem solving in fields such as consulting, professional services and digital

product development rarely relies on stables rules or universal solutions. Instead, workers integrate implied knowledge, social cues, and nuanced judgement, forms of cognition that AI cannot replicate because they draw on embodied experience, interpretation and shared practices. Pettersen (2019) concludes that AI models may assist knowledge workers but are unlikely to replace them for tasks requiring contextual reasoning. This perspective emphasizes that AI's analytical strengths does not translate into "understanding". Systems excel at bounded, well-structured tasks, but fall short when work requires improvisation, negotiation meanings, or navigating organizational politics which are core aspects of knowledge-intensive work (Pettersen 2019)

More recent studies, however, examine how AI reshapes knowledge processes inside organizations. They suggest that AI's role in knowledge-intensive work is ambivalent: it can enhance organizational knowledge processes while simultaneously introducing new constraints and risks. In line with this, Dong et al. (2024) show that AI systems contribute to knowledge creation, transfer and integration by enabling faster access to information, supporting problem solving, and providing real-time analytical feedback. However, they note that AI introduces new dependencies: organizations must develop commentary capabilities such as data governance, human-AI collaboration norms, and employee upskilling to realize these benefits. Rather than replacing expertise, AI alters how knowledge flows, enabling workers to focus on higher-order task while relying on AI for routine cognitive functions (Dong et al. 2024). Their findings suggest that AI's role is best understood as augmentative: it enhances organizational knowledge processes but also requires active human oversight quality, contextual fit and ethical use (Dong et al. 2024).

In a another study, Dell'Acqua et al. (2023) provide experimental evidence that AI's effectiveness in knowledge intensive work is highly task dependent. In a large, randomized field experiment with Boston Consulting Group, they demonstrate that generative AI (GPT-4) dramatically improved

consultants' productivity and output quality, however, only for tasks within the AI's current capability frontiers. When used for tasks outside this frontier, performance significantly decreased, as consultants tended to over-rely on AI and accept its outputs uncritically. This unevenness, what the authors call "jagged frontier", means that AI excels at some complex tasks, such as writing and structured analyses, but fails at others requiring nuanced reasoning or multi-source integration (Dell'Acqua et al. 2023).

2.2 Informal Learning in Organisations

Informal learning is a critical yet historically underestimated dimension of development in the workplace. Unlike formal training programs, marked by rigid schedules, pre-defined objectives and pedagogical design (Rausch 2025), informal learning arises naturally from everyday work processes, is mainly self-directed, and happens without explicit institutional organisation (Tannenbaum and Wolfson 2022). According to Eraut's foundational conceptualization, it exists on a continuum ranging from implicit, unconscious adaptation processes to deliberative, self-regulated learning activities (Eraut 2004). This is relevant to understand how employees develop competencies in dynamic work contexts where formal training alone may result insufficient to address the rapidly changing demands of modern work environments (Decius et al. 2025).

Informal vs. Formal Learning in Organisations

Formal learning in companies refers to structured, intentional educational activities designed by the firm and typically performed outside the regular flow of daily work (for example workshops, scheduled training sessions, courses and seminars, etc.) This kind of learning stands out for clear pre-defined objectives, often led by a trainer, with outcomes that may be assessed and recognised by certificates or qualifications. In contrast, informal learning arises without a proper planning, it's

"present" in daily job tasks, and it's shaped by the learner's own need, rather than an explicit curriculum. It occurs through problem-solving, observation, social interaction, knowledge sharing, experimenting, or learning by doing, often in response to real-time challenges. While informal learning rarely ends in formal certificates, it is increasingly recognised as a major contributor to knowledge and skills building (Laubengaier et al. 2025; Sharma and Raghuvanshi 2020).

The two forms of learning are neither exclusive nor opposed, but they happen to complement, reinforce, or trigger one another (Tynjälä 2008). For instance, participation in structured training programs may lead to knowledge sharing, experimentation, or reflections; likewise, developing new skills informally on the job can create motivation for formal upskilling or create a need for getting "certified" (Wijga et al. 2025). From this, we get that formal learning is best at providing a shared solid foundation of knowledge, ensuring compliance with regulatory or organisational standards, and legitimising new practices through certifications. However, its effectiveness can easily be limited by low conversion to actual job performance unless reinforced by on-the-job practice and social learning mechanisms. Informal learning, on the other hand, is highly responsive to changing scenarios, assists personal and professional growth, and is central to innovation and problem-solving, but suffers from being less visible, less valued, and sometimes inconsistent across groups (Laubengaier et al. 2025).

Theoretical Foundations on Informal Learning: Experiential & Self-Regulated Perspectives

The theoretical foundations of informal learning draw mainly from the experiential learning theory, stating that learning happens through a cyclical process of experience, reflective observation, abstract conceptualisation, and active experimentation (Wijga et al. 2025; Kolb 1984). This perspective focus on the fact that employees do not simply acquire knowledge through passive absorption, but they actively build it through engagement with work-related challenges and

reflection on those experiences (Rausch 2025). Building on this, informal learning can be categorised by intentionality (ranging from incidental learning to intentional) and self-directed learning pursuits (Cerasoli et al. 2018).

Secondly, the self-regulated learning perspective highlights that effective informal learning requires employees to spot knowledge gaps independently, understand where to access relevant information, keep track of their learning progress, and regulate their cognitive and emotional responses throughout the whole process (Deshmukh and Mehta 2025). This self-regulatory capacity becomes a winning factor in smaller contexts where guidance and structure are low, placing greater responsibility on the individual learner to push their own development (Decius et al. 2025).

Informal Learning Typologies: Implicit, Reactive, and Deliberative

Eraut's taxonomy (Eraut 2004) distinguishes between three linked types of informal learning that continuously operate: implicit, reactive, and deliberative (Rausch 2025). Implicit learning refers to routine activities where learning goals, processes and outcomes are secondary, and where the person is not aware of their learning. These small-scale, day-to-day boosts in an individual's knowledge, skills, attitudes, or other characteristics are based on subtle feedback from the environment and are usually not perceived as proper learning by employees (Tynjälä 2008). Reactive learning, on the other hand, is intentional and comes when problems arise, that is when the matter is not routine, or the available routines are not effective in achieving the goal (Eraut 2004). Triggers for reactive learning include things such as unknown variations in otherwise familiar work tasks, or changes in well-established workflows (e.g., updated software tools with slightly new interfaces, or new product versions with unknown new features), which often lead to emotional states like confusion or surprise (Rausch et al. 2017). Deliberative learning, finally,

refers to conscious, intentional, self-monitored problem-solving and decision-making actions in which learning goals are seen as critical for achieving current or future work goals (Rausch 2025).

Contextual Influences: Organisational, Social, and Managerial Factors

The firm's context strongly influences the degree and quality of informal learning, as several environmental factors shape employees' attitude and motivation to engage in such behaviours. A culture defined by shared beliefs that value continuous development, room for experimentation, and recognition of efforts, serves as a key enabler (Ali et al. 2025). Within such cultures, employees perceive greater encouragement to seek creative problem-solving, access developmental resources, and ask for managerial support for learning initiatives (Laubengaier et al. 2025). Job characteristics also matter a lot: roles offering autonomy, task variety, and chance for social interaction provide more opportunities compared to highly repetitive positions with little room for change (Rausch 2025; Tannenbaum and Wolfson 2022). As a result, the availability of social resources (including helping colleagues willing to share knowledge, provide feedback, and serve as role models and tutors) positively affects learning outcomes, while organisational barriers such as excessive workload, time pressure, and cultures that punish mistakes can strongly inhibit employees' engagement (Kittel et al. 2021). For these reasons, companies seeking to leverage informal learning must focus on designing work environments that balance performance demands with self-development, encourage psychologically safe climates where experimentation is accepted, and ensure that learning is recognised and valued (Laubengaier et al. 2025).

2.3 AI-Enabled Informal Learning

The integration of artificial intelligence (AI) in the workplace (OECD 2024) has deeply changed how employees engage in informal learning (Nguyen and Elbanna 2025). As companies

increasingly adopt AI-powered technologies, workplace learning goes beyond traditional methodologies to include custom real-time experiences (Deshmukh and Mehta 2025).

AI Tools as Learning Resources

Modern AI tools serve as dynamic learning resources, improving employees' problem-solving skills across several dimensions (Stan et al. 2025). Analytical AI assists learning by identifying and highlighting individual user behaviour (such as errors, delays, or inefficiencies), and processing large amounts of data by automatically analysing it to find patterns, make predictions, or offer helpful insights (e.g. tools that spot anomalies in data, predict future trends based on past behaviour, or monitor performance). Thus, it identifies critical areas and variables within complex situations, allowing employees to externalise and better understand complex problems (Rausch 2025). Generative AI, on the other hand, goes further through content creation and dynamic assistance (Dubey et al. 2025): it can generate ideas, summaries, causal maps, decision trees, and simulations (this can be most useful in supporting deliberative learning, where employees intentionally find time to develop new competencies and skills). What's more, GenAI leverages AI agents based on fine-tuned Large Language Models (LLMs), offering assistance based on context that can replace basic expert consultation (Söllner et al. 2025).

The role of AI learning expands remarkably also through collaboration platforms and simulation environments. These, increasingly enriched with AI features, facilitate informal workplace learning, especially in international teams and remote work scenarios. These platforms, such as Microsoft Teams with Copilot, function as integrated spaces where work communication and AI-driven support co-exist, enabling real-time access to knowledge and peer collaboration; specifically, Teams and Copilot allow workers to ask AI questions directly within team chats and documents, getting instant answers without leaving their workspace. When linked to internal

management systems, they also recommend social resources for consulting more experienced colleagues based on contextual needs.

The “AI Ghost-Learner Effect”: Process Ownership and AI Nudging

While AI offers several resources for informal workplace learning, it also bears risks that need to be carefully taken into account. On this matter, Rausch (Rausch 2025) introduces the concept of the "AI ghost-learner effect", a phenomenon according to which employees use AI-generated solutions or problem-solving strategies without their own further processing and reflection, thereby ignoring learning opportunities. This effect parallels the “AI ghostwriter effect” observed in academic contexts, where students do not consider themselves owners of AI-made texts and yet avoid publicly declaring AI authorship (Draxler et al. 2024). Applied to workplaces, the AI ghost-learner effect happens when employees use AI passively rather than actively integrating its inputs and outcomes into their own mental models. In such cases, employees may feel that 'AI can handle that', outsourcing the problem entirely, but, even more problematic, they perceive implemented solutions as their own and remain professionally responsible for them: this can create tensions due to the fact that increased performance gets misinterpreted as evidence of increased skills or even as a signal that more learning is unnecessary (mistaking task completion for skill development).

From this we get that the concept of process ownership is crucial for ensuring that AI tools facilitate learning rather than just task completion. (Rausch et al. 2015) show that, to ensure learning opportunities during problem-solving, it is key for workers to not delegate problems entirely but instead remain process owners: process ownership is kept when employees receive help in planning but implement plans themselves, receive assistance in implementation but follow and reconstruct the process on their own, or implement plans alone with feedback provided only afterwards. These forms of cooperation promote informal learning, while mere delegation and passive reliance do

not: as a result, AI-assisted platforms should ideally increase learner agency rather than replace it, letting employees maintain active engagement.

To preserve this vision, nudging, that is subtle interventions guiding individuals' behaviours without limiting choices or altering incentives (Luo et al. 2024), emerges as a promising approach to tackle detachment and ensure active contribution. Nudging learning when using AI tools includes designing a way to trigger human thinking through follow-up questions (e.g., "How does this solution compare to your initial task understanding?"), self-assessment (e.g., "Do you think your solution is coherent, accurate, and complete?"), and additional learning resources. However, AI nudging has ethical implications and some potential downsides: it may manipulate employees' behaviour without explicit consent or create pressure to adapt to predefined "correct" answers rather than encouraging genuine reflection. Additionally, it may, to some degree, formalise informal learning: to avoid this paradox, it's key to keep the balance between maintaining the spontaneous, self-directed nature of informal learning and implementing structured interventions.

Cross-Country Perspectives on AI Adoption

The use of AI technologies, including those contributing to informal workplace learning, varies a lot across national contexts, shaped by macroeconomic conditions, institutional frameworks, labour market structures, and cultural factors. (Ali et al. 2025) investigated key causes of GenAI adoption across 136 countries, using negative binomial regression models to account for data overdispersion. Their findings showcased that economic stability, robust IT infrastructure, R&D investments, and firms' investments in emerging technologies highly foster GenAI use, while, on the contrary, misaligned government policies may limit it, despite intentions to promote innovation (Ali et al. 2025). Additionally, research on macroeconomic and labour market drivers of AI adoption in the EU (Drago et al. 2025) provides more insights. A study analysing 28 European countries from 2018

to 2023 employed panel data econometric models together with machine learning approaches to identify drivers of AI adoption by large enterprises (≥250 employees). Fixed-effects and random-effects models revealed that health expenditure, GDP per capita, exports of goods and services, and inflation positively correlate with AI adoption, while domestic credit to the private sector and gross fixed capital formation exhibit unexpected negative associations in some contexts, suggesting inefficiencies or mismatches in financial and capital resource deployment. The same study found that the share of employers among total employment displays statistically significant negative effects, suggesting that employer-dominated labour markets (notably family businesses or small-medium businesses) may have reluctance to invest in AI technologies, preferring traditional business models (Hoffman & Nurski, 2021). On the contrary, self-employment has a significant positive correlation with AI adoption, increasing productivity and competitiveness. These findings suggest that AI adoption barriers are partly structural: labour markets dominated by SMEs and family businesses invest less in AI regardless of policy intentions; as a result, workers in different national contexts face different levels of access to AI tools and support for learning, shaping the conditions under which informal learning can occur.

Finally, internal factors tied with culture alongside with organisational readiness also shape AI adoption patterns. The “2025 AI at Work Report” (Globalization Partners 2025) surveyed 2,850 executives across the US, Germany, Singapore, Australia, and France, alongside 500 US HR professionals, revealing that 74% of executives view AI as crucial to company success, with 60% reporting aggressive AI use for industry innovation. However, perceptions of AI importance and adoption intensity vary across regions and firms, reflecting cultural attitudes towards technology, risk tolerance, and innovation (bsi 2024).

3 The Austrian Case *Felix Kriegler*

3.1 Digital Transformation and AI Adoption in Austria

Austria has made significant steps in digital transformation over the past decade. As of 2022, the country ranks at 10th among EU member states on the European Commission's Digital Economy and Society Index (DESI), reflecting solid performance in connectivity, digital skills, and online public services (European Commission, 2022).

At the national level, Austria formulated a comprehensive AI policy framework in 2021 with the Artificial Intelligence Mission Austria 2030 (AIM AT 2030) strategy. This strategy emphasizes broad use of AI for societal benefit, positioning Austria as an innovation hub, and securing economics competitiveness (Federal Ministry of Economy, Energy and Tourism and Federal Ministry of Innovation, Mobility and Infrastructure 2025). It aligns with EU initiatives and incorporates European values (e.g. "trustworthy AI" and human-centered approaches). Furthermore, AIM AT 2030 includes a dedicated focus on "AI in the world of work" and "qualification, education, and training", underlining that workforce development and ethical deployment in workplaces are national priorities. Implementation has been active and by late 2025 most measures under the AI strategy were reportedly underway or completed, guided by an AI implementation plan covering all ministries. Additionally, Austria is investing in digital infrastructure and research capacities (e.g. high-performance computer centers and AI research hubs), as well as launching targeted programs to cultivate AI talent (e.g. digital skills initiatives, AI school competitions, and new AI-focused professorships) (OECD 2025). These efforts indicate strong government commitment to improve AI adoption across the main sectors.

In the private sector, Austrian companies are gradually embracing AI, though adoption rates still lag behind digital frontrunners in Europe (Eurostat 2025b). A recent national survey showed that 20% of Austrian enterprises were using some form of AI in 2024, which is almost double compared to the prior year of 11% in 2023, and 9% in 2021. Adoption is highly skewed by company size: half of large firms (50% of companies with 250+ employees) use AI technologies, compared to only of 18% of small businesses (10 – 49 employees) (Statistics Austria 2024b) (Statistics Austria 2023). This suggests that while many smaller firms remain in early stages of digital maturity, larger organizations are more aggressively implementing AI to optimize operations. Sector-wise, the information and communication industry is leading with around 61% of companies in this sector using AI, whereas more traditional sectors like transportation, storage, hospitality, and wholesale show lower rates of adoption. However, these industries seem to catch up as numbers have almost tripled in some sectors compared to the year prior. Common AI applications in Austrian companies include natural language generation (41%) and data analysis (34%) (Statistics Austria 2024b).

Despite growing interest, the majority of Austrian companies has not yet implemented AI. Common barriers in 2023 were often lack of in-house expertise, legal uncertainties, data quality issues, and integration difficulties with legacy systems (Statistics Austria 2023). On a positive note, Austria's innovations ecosystem provides a supportive backdrop: the country is an open, export-driven economy with a high share of knowledge-intensive industries and a robust innovation system characterized by high R&D expenditures. (Federal Ministry For Climate Action, Environment, Energy, Mobility, Innovation And Technology 2021). In fact, in 2025 Austria is considered a "strong innovator" in Europe, with an innovation performance of 114% of the EU average according to the European Innovation Scoreboard (European Commission 2025b). This innovative

climate, combined with strong R&D investment suggest that Austrian organizations have the potential to integrate advanced technologies like AI effectively.

Overall, while Austria's digital transformation is a work in progress, the combination of supportive government policies and the innovation-friendly economy has laid the groundwork for increasing AI adoption at both nation and organizational level.

3.2 Informal Learning Culture and Continuing Professional Development

Austria boats a longstanding culture of continuous learning and professional development, supported by both societal values and intuitional frameworks. Lifelong learning is widely seen as essential for career success, and participation in adult education are relatively high (European Commission 2025a). According to the latest Adult Education Survey, about 58% of Austrian adults (25 – 65 years) participated in some form of formal or non-formal education or training in 2022/2023 (Statistics Austria 2024a). This means that a majority of working-ages Austrians engaged in activities like courses, workshops, seminars, or job-related training within a 12-mont period. Although this participation rate was slightly lower five years prior, it remains significantly above levels seen a decade earlier. The data also show that engagement in further training depends on educational level: over 78% of adults with a university degree pursued continuous education, versus only 27% of those with only compulsory schooling (Statistics Austria 2024a). This highlights an ongoing challenge to broaden upskilling opportunities to lower-skilled workers. Nonetheless, the overall figures show that continuous professional development is the norm for a large segment of the Austrian workforce.

A distinctive aspect of Austria's learning culture is the emphasis on informal learning in the workplace. Surveys suggests that informal on-the-job learning is common. Notably, among

younger adults (aged 18-24) in Austria, the prevalence of reported informal learning activities has skyrocketed in the last decade: only around 29% of young adults acknowledged informal learning in 2011/12, whereas by 2022/23 this share had reached over 86%. (Statistics Austria 2024a). In other words, almost all young workers now consciously learn new things informally at work or in daily life. This dramatic increase may partly reflect greater awareness, but it also signals that the newest generation in the workforce is continuously picking up skills through channels like online resources, trial-and-error, peer mentoring, and using digital tools. Indeed, global studies have found that "learning by doing" and knowledge exchange among colleagues contribute more to workers' skill development than formal training courses in many cases (De Grip 2015).

4 Methodology *Group Part*

4.1 Research Design and Approach

This study employs a quantitative, cross-sectional survey design to investigate AI-enabled informal learning among knowledge workers in two countries. We chose a survey-based quantitative approach for its ability to gather standardized data from a broad sample efficiently, allowing statistical analysis of trends and relationships. Collecting data at a single point in time captures a snapshot of current behaviours and perceptions without requiring lengthy follow up, which is suitable given the fast evolution of AI tools. The focus is on measurable constructs (e.g. frequency of AI use, self-estimated learning outcomes, etc.) that can be quantified and compared across respondents. This design allows for objective examination of patterns and hypotheses. Furthermore, an online questionnaire format was used to reach participants in different organizations and locations with minimal cost and time as online survey are considered cost-effective and a quick method of data collection (Siva Durga Prasad Nayak and Narayan 2019).

Overall, this quantitative survey approach provides the breadth and objectivity needed to address this research question, in contrast to a qualitative design which we deemed less feasible for capturing broad usage patterns across multiples firms and countries.

4.1.1 Cross-Country Comparative Design

A distinctive feature of this research is its comparative design across Italy and Austria where we're targeting 200 knowledge workers (approx. 100 per country) in digitally intensive roles. By incorporating two national contexts, we can examine how informal learning with AI might be similar of different under various cultural and organizational environments. In cross-national comparative research, the same concepts are measured in multiple countries with the aim of getting a deeper understanding of the phenomenon (Gharawi et al. 2019). This design adds external validity and richness: it enables testing whether observed relationships hold across diverse settings, and it can reveal contextual influences on AI-enabled learning.

In this Field Lab, we chose Italy and Austria as comparable European context with high technological development, yet with potentially differing workplace cultures, digital adoption rates, and AI adoption rates within organizations (Eurostat 2025a) (European Investment Bank 2020) (European Commission 2022c). By analysing both groups side-by-side, we control for broad factors (all are knowledge workers in tech-related fields) while observing any national variations that emerge. This cross-country approach not only enhances the study's generalizability but also allows intervention of country specific factors that can be used as basis for future research (e.g. if Italian respondents report higher reliance on AI than Austrians, or vice versa, possible cultural or policy reasons can be discuss). To ensure a valid comparison, the survey was kept consistent across the two countries by presenting the questionnaire in the same language (English) and format, targeting the same industries and roles in each country (Kaminska and Lynn 2017).

4.2 Sample and Data Collection

Our research targets knowledge workers in technology-intensive organisations in Italy and Austria, mainly professionals in roles such as software engineers, business & data analysts, product managers and others within e-commerce, digital and fintech sectors. We chose this population because knowledge workers in such environments interact regularly with AI tools in their daily work, making their experiences relevant to understanding how AI supports or inhibits informal learning processes. In addition, these professionals require continuous skill development and learning, making these mechanisms key in their careers and contexts.

4.2.1 Sampling Strategy and Access

For sampling, we leveraged our professional networks to identify and gather participants matching our target population criteria. Recruitment happened primarily through direct connections in a well-known multinational electronics company in Italy and a large financial services provider in Austria, and secondarily through professional networks via LinkedIn and industry associations. This strategy ensures coherence of the sample around our target while making data collection feasible, given the practical constraints of reaching busy professionals. We are aware of the fact that this approach may introduce selection bias (respondents may be more willing to engage with AI research or more digitally oriented than the broader workers population): as a response, we offset this through intentional recruitment across diverse sectors, firms, and roles to capture meaningful variation in experiences and opinions.

Survey Development

The survey is made of 24 items structured across five sections: 1) demographic and professional background, 2) modes and frequency of AI tools usage at work (these first two addressed through

MCQ), 3) informal learning dimensions 4) sentiment on professional growth and career impact (these two assessed through the 5 Likert-scale items, tackling problem-solving effectiveness, skill development, learning support, confidence, experimentation, concerns about over-reliance, and autonomy), 5) and three non-mandatory open-ended questions allowing respondents to give specific examples and more insights. The survey was designed to require approximately 5-8 minutes to be completed, balancing comprehensiveness and time convenience. Each question was formulated to avoid ambiguous phrasing or double meanings, with differentiated response options.

4.3 Hypotheses

Based on prior research on informal learning, we expect that AI-enabled informal learning will be positively associated with perceived job quality outcomes. Specifically, we hypothesize that (H1) AI-enabled informal learning is positively related to perceived career impact, (H2) AI-enabled informal learning and perceived AI-supported problem solving are positively related to confidence in handling complex tasks; and (H3) greater reliance on AI is associated with stronger concerns about overreliance, while autonomy and active learning with AI mitigate these concerns. These hypotheses are tested separately for Italy and Austria using the same model specifications to assess common mechanisms and potential context-specific differences.

4.4 Analytical Approach

4.4.1 Power Analysis and Sample Size Justification

Before setting up the survey design, we performed a power analysis to determine the necessary sample size for detecting meaningful effects. To ensure feasibility in time-effort and network reach as well as following conventional guidelines in social sciences, we set the significance level (alpha) at 0.05 and the desired statistical power at 0.80, meaning we accept an 80% chance of detecting a

true effect. We anticipated a medium-sized effect of interested (around Cohen's d = 0.40), which falls in the mid-range of Cohen's effect size conventions. Using these parameters for a two-tailed independent-samples comparison (e.g. deleting differences between the two countries), the power analysis indicated a requirement of N = 200 participants (approx. 100 per country) (Cohen 1992).

4.4.2 Operationalization of Variables and Scale Construction

The survey items were operationalized into a set of indices reflecting the main constructs of interest. All attitudinal questions were measured on five-point Likert scales (1 = strongly disagree to 5 = strongly agree). Based on the literature on informal learning and self-regulated development at work (Decius et al. 2025; Eraut 2004; Rausch 2025), we grouped items into the following composite or single-items scales:

- **AI-enabled informal learning (AI_InformalLearning):** mean of items capturing use of AI tools to learn or improve skills, receive useful prompts for learning, and feel actively engaged in learning while using AI.
- **Problem-solving effectiveness (ProblemSolving):** items assessing the extent to which AI tools help respondents solve work-related problems more effectively.
- **Confidence / self-efficacy (Confidence):** items indicating increased confidence in handling complex or challenging tasks when using AI.
- **Overreliance concern (Overreliance):** a focused item capturing worry about relying too much on AI and not learning enough, used as an indicator of the "ghost-learner" risk.
- **Career impact (CareerImpact):** mean of items on perceived improvement in job performance, development of career-relevant skills, readiness for future changes, job satisfaction, and the long-term importance of AI for professional development.

- **Additional indicators:** single items for AI use frequency ("How often do you use AI tools in your daily work?"), autonomy with AI ("AI tools allow me to work more autonomously without needing excessive help from colleagues"), and perceived organizational support and training for AI.

For each multi-item scale, we computed respondent-level scores as the mean of the component items.

4.4.3 Regression Models

To address the core research question (how AI adoption, when used as a means of informal learning relates to perceived career impact, confidence and overreliance) we implemented a set of multiple linear regression models estimated separately for Italy and Austria. Running the same model structures per country allows us to test the theoretical relationships within each context and to compare patterns qualitatively across them.

Across both subsamples, three core models were specified:

- **Model 1: Career impact from AI-enabled informal learning**

  Dependent variable: CareerImpact.

  Key predictor: AI_InformalLearning.

  Control variables: AI use frequency and, in the Italian model, additional covariates such as education level, years of experience, and a digital-sector indicator, reflecting the more heterogeneous sector mix. This model tests whether AI-enabled informal learning predicts perceived career benefits over and above general AI adoption and basic demographics.

- **Model 2: Confidence development**

  Dependent variable: Confidence.

Predictors: ProblemSolving and AI_InformalLearning, with AI use frequency and selected controls included where theoretically appropriate. This model is grounded in self-efficacy theory, examining whether perceived problem-solving support and learning with AI are associated with greater confidence in handling complex tasks.

- **Model 3: Ghost-learner / overreliance effect**

  Dependent variable: Overreliance.

  Predictors: AI use frequency, AI_InformalLearning, and autonomy with AI, plus organisational support in the Italian analysis. This model tests the critical perspective that high frequency of AI use may be associated with increased concern about dependency, and whether active learning and process ownership mitigate (Italy) or shape (Austria) this risk.

In all models, unstandardized coefficients, standard error, t-values, p-values, and explained variance (R^2 and adjusted R^2) were reported. Statistical significance was assessed at $\alpha = 0.05$ (two-tailed). The Italian and Austrian analyses followed the same conceptual logic, although specific control variables differed sightly to reflect sample composition.

4.4.4 Software and Diagnostics

All statistical analyses were conducted using Jamovi. Prior to interpreting coefficients, examined standard regression diagnostics in each country: residual plots to check for non-linearity and heteroscedasticity, normal Q-Q plots of residuals, and basic multicollinearity indicators. No severe violations were detected that would invalidate the models.

5 Analysis of Austrian Survey Data *Felix Kriegler*

Sample characteristics

The Austrian subsample consists of 103 knowledge workers employed in a range of technology- and knowledge-intensive roles. In line with the sampling strategy, respondents predominantly work in organizations where digital technologies and data-driven processes are central to daily operations. The industry distribution shows that the largest share of participants is employed in Fintech/Financial Services (43.69%) and Software/SaaS (23.30%), followed by E-commerce/Digital Services (14.56%), Consulting (9.71%), and Electronics/Hardware (8.74%). This confirms that the Austrian sample is strongly embedded in the digital and financial technology ecosystem, where AI tools are particularly relevant for both operational tasks and knowledge work.

Job roles are similarly concentrated in knowledge-intensive functions. The most frequently reported roles include Software Engineer/Developer (19.42%), IT Support/Operations (14.56%), Digital Operations/Marketing (13.59%), UX/UI Designer (10.68%), Product/Project Manager (10.68%), and Data Scientist/Analyst (9.71%). Smaller proportions of respondents work as Business Analysts (5.83%), Consultants (1.94%), or in more specialized positions. Overall, this distribution indicates that the Austrian subsample is composed mainly of digital professionals and technical experts who are likely to encounter AI in their everyday work and who have substantial autonomy in how they approach problem solving and learning on the job.

In terms of **professional experience**, most respondents occupy early- to mid-career stages. Almost two-fifths report 4-6 years of experience in their current field (38.83%), while just over a quarter have 7-10 years of experience (26.21%). A further 18.45% have 1-3 years of experience, whereas only 3.88% are in their first year and 12.62% report more than 10 years of experience. This suggests that the majority of the Austrian respondents have already accumulated several years of professional practice yet are still in phases of active skill development and role evolution which can be an important context for examining informal learning and continuous upskilling with AI.

The **educational profile** of the sample reflects its knowledge-intensive character. A clear majority hold a Master's degree (62.14%), and a further 33.98% have a Bachelor's degree. Only 2.91% report a PhD, and 0.97% indicate high school as their highest completed level of education. This underscores that the sample is highly educated and well aligned with the definition of knowledge workers used in this study. Taken together, the industry, role, experience, and education distributions indicate that the Austrian subsample represents a highly skilled, digitally embedded segment of the workforce, for whom AI-enabled informal learning is both relevant and plausible in day-to-day work contexts.

Descriptive statistics of AI-related learning constructs

Table 1 reports the descriptive statistics for the composite scales used in the Austrian subsample (N = 103). Overall, respondents reported relatively positive experiences with AI as a learning and development tool. AI_InformalLearning_AT (mean of items on using AI to learn/improve skills, receiving useful prompts, and feeling actively engaged in learning) showed a mean of 3.54 (SD = 0.74) on a 5-point scale, slightly above the neutral midpoint. This suggests that, on average, Austrian knowledge workers perceive AI as a moderately important resource for informal learning, with some variation between individuals.

Perceived problem-solving support was even stronger. The ProblemSolving_AT scale had the highest mean of all constructs at 4.06 (SD = 0.80), indicating clear agreement that AI tools help respondents solve work-related problems more effectively. In contrast, Confidence_AT showed a somewhat lower mean of 3.34 (SD = 1.04), suggesting that while many respondents feel more confident when using AI, this perception is less unanimous and more heterogeneous than views on problem-solving effectiveness.

Concerns about Rausch' (2025) ghost-learner effect appear relatively modest on average. The Overreliance_AT item had a mean of 2.59 (SD = 1.12), below the scale midpoint, implying that respondents tend to disagree or remain ambivalent with the statement that they rely too much on AI and do not learn enough themselves. However, the relatively high standard deviation indicates that some individuals do experience substantial concern about overreliance, even if this is not the dominant pattern in the sample.

Finally, the CareerImpact_AT composite (mean of perceived effects of AI on job performance, skill development, future preparedness, job satisfaction and professional development) showed a mean of 3.93 (SD = 0.71). This reflects a generally positive assessment of AI's impact on job quality and career prospects among Austrian respondents. Taken together, these descriptives suggest that Austrian knowledge workers in the sample typically view AI as useful for problem solving and career development, moderately supportive of informal learning and confidence, and only somewhat associated with perceived overreliance.

Descriptives

	AI_InformalLearning_AT	ProblemSolving_AT	Confidence_AT	Overreliance_AT	CareerImpact_AT
N	103	103	103	103	103
Missing	0	0	0	0	0
Mean	3.54	4.06	3.34	2.59	3.93
Median	3.67	4	4	3	4.00
Standard deviation	0.740	0.802	1.04	1.12	0.706
Minimum	1.67	2	1	1	2.00
Maximum	4.67	5	5	5	5.00

Table 1: descriptive statistics for AI-related learning constructs in the Austrian subsample (N=103)

Model 1: Does AI-enabled informal learning predict career impact (job quality)?

To examine whether AI-enabled informal learning is associated with perceived career impact among Austrian knowledge workers, a linear regression analysis was conducted with CareerImpact_AT as dependent variable and AI_InformalLearning_AT and AI_Use_Frequency_num as predictors. The overall model was statistically significant and

explained a substantial share of variance in perceived career impact (R^2 = .34, adjusted R^2 = .33, N = 103).

Both predictors were positively and significantly related to career impact. AI_InformalLearning_AT showed a strong positive association (Estimate = 0.37, SE = 0.09, t = 4.19, p < .001), indicating that respondents who more strongly experience AI as a tool for learning (e.g. acquiring new skills, receiving useful prompts, feeling actively engaged in learning) also report higher perceived benefits of AI for their job performance, skills, future readiness, satisfaction and professional development. AI_Use_Frequency_num was likewise a significant positive predictor (Estimate = 0.28, SE = 0.09, t = 3.03, p = .003), suggesting that more frequent use of AI in daily work is associated with greater perceived career impact, even when controlling for the learning dimension. Taken together, these results indicate that in the Austrian subsample, AI is perceived as having a more positive effect on job quality and career outcomes when it is both used regularly and experienced as a genuine learning resource, rather than as a purely instrumental tool.

Model Fit Measures

Model	R^2	Adjusted R^2
1	0.343	0.330

Note. Models estimated using sample size of N=103

Model Coefficients - CareerImpact_AT

Predictor	Estimate	SE	t	p
Intercept	1.453	0.3588	4.05	<.001
AI_InformalLearning_AT	0.373	0.0892	4.19	<.001
AI_Use_Frequency_num	0.280	0.0923	3.03	0.003

Table 2: linear regression – career impact

Model 2: AI-supported problem solving and learning as predictors of confidence

To examine whether AI-supported problem solving and AI-enabled informal learning are associated with confidence in handling complex tasks, a linear regression was estimated with Confidence_AT as the dependent variable and ProblemSolving_AT, AI_InformalLearning_AT, and AI_Use_Frequencey_num as predictors (N=103). The model explained around 30% of the variance in confidence (R^2 = .301), indicating a moderate overall effect.

The results show that AI_InformalLearning_AT was a strong and statistically significant predictor of confidence (Estimate = 0.63, SE = 0.14, t = 4.39, p < .001). This suggests that Austrian respondents who more strongly experience AI as a learning tool (using it to develop skills, receive useful prompts, and feel actively engaged in learning) also report substantially higher confidence in dealing with complex tasks at work. In contrast, ProblemSolving_AT showed only a marginal effect (Estimate = 0.25, SE = 0.14, t = 1.71, p = 0.09), indicating that perceiving AI as helpful for problem solving alone is not a consistently strong predictor of confidence once the learning dimension is taken into account. Finally, AI_Use_Frequency_num was not a significant predictor of confidence (Estimate = -0.04, SE = 0.16, t = -0.27, p = .785), implying that merely using AI more often does not translate to greater self-efficacy when controlling for perceived learning and problem-solving support. Overall, these findings suggest that for Austrian knowledge workers, confidence is driven primarily by the extent to which AI use is experienced as genuine learning, rather than by frequency of use or problem-solving support alone.

Model Fit Measures

Model	R	R^2
1	0.549	0.301

Note. Models estimated using sample size of N=103

Model Coefficients - Confidence_AT

Predictor	Estimate	SE	t	p
Intercept	0.2972	0.563	0.528	0.599
ProblemSolving_AT	0.2456	0.144	1.711	0.090
AI_InformalLearning_AT	0.6295	0.143	4.393	<.001
AI_Use_Frequency_num	-0.0437	0.160	-0.273	0.785

Table 3: linear regression - confidence

Model 3: Predictors of overreliance concerns (ghost-learner effect)

To explore when AI use is associated with concerns about overreliance, a linear regression was conducted with Overreliance_AT ("I rely too much on AI tools and worry that I am not learning as much as I should") as the depended variable, and AI_Use_Frequency_num, AI_InformalLearning_AT, and Autonomy_AI as predictors (N = 103). The model explained a

substantial portion of variance in overreliance concerns (R^2 = .35), indicating that these variables together account for around one third of the individual differences in perceived overreliance.

Contrary to a simple "more use = more overreliance" expectation, AI_Use_Frequency_num was not a significant predictor of overreliance (Estimate = 0.18, SE = 0.15, t = 1.2, p = .235). This suggests that, in the Austrian subsample, merely using AI more often does not by itself translate into stronger worries about depending too much on it. Instead, overreliance concerns were significantly associated with AI_InformalLearning_AT and Autonomy_AI. Respondents who reported higher levels of AI-enabled informal learning showed higher overreliance concerns (Estimate = 0.37, SE = 0.14, t = 2.57, p = 0.12), and those who felt that AI tools allow them to work more autonomously also reported higher perceived overreliance (Estimate = 0.43, SE = 0.09, t = 4.84, p < .001).

Model Fit Measures

Model	R	R^2
1	0.592	0.351

Note. Models estimated using sample size of N=103

Model Coefficients - Overreliance_AT

Predictor	Estimate	SE	t	p
Intercept	-0.850	0.5792	-1.47	0.146
AI_Use_Frequency_num	0.175	0.1464	1.20	0.235
AI_InformalLearning_AT	0.370	0.1441	2.57	0.012
Autonomy_AI	0.429	0.0886	4.84	<.001

Table 4: linear regression - ghost learner effect

These patterns indicate that in Austria, worries about becoming too dependent on AI are not concentrated among casual users, but rather those who engage more intensively with AI as a learning and autonomy-enhancing tool. One interpretation is that workers who actively integrate AI into their learning and enjoy greater autonomy with AI also become more aware of the potential risk of letting the tool take over too much of cognitive work. In other words, overreliance concerns may reflect a form of critical self-awareness among advanced users, rather than a simple function of use frequency alone.

Main findings for Austrian knowledge workers

The Austrian analysis examined how AI-enabled informal learning relates to perceived career impact, confidence and overreliance concerns among 103 knowledge workers in predominantly digital and financial services sectors. The descriptive results already suggest a generally positive but differentiated view of AI. Respondents clearly perceive AI as helpful for problem solving and career development (ProblemSolving and CareerImpact means around 4 on a 5-point scale), while their ratings of AI-enabled informal learning and confidence are more moderate, and overreliance concerns remain below the midpoint but with considerable variation.

Across the three regression models, several robust patterns emerge:

- **AI-enabled informal learning and AI use frequency both predict career impact.** In Model 1, AI_InformalLearning_AT and AI_Use_Frequency_num together explained around one third of the variance in CareerImpact_AT ($R^2 \approx .34$). Both coefficients were positive and statically significant: employees who feel they genuinely learn with AI and those who use it more frequently tent to perceive stronger positive effects on job performance, skill development, future preparedness and professional development.
- **Confidence depends more on learning quality than on frequency.** In Model 2 ($R^2 \approx .30$), AI_InformalLearning_AT was a strong positive predictor of Confidence_AT, while ProblemSolving_AT showed only a marginal effect and AI_Use_Frequency_num was not significant. This indicates that confidence in handling complex tasks is driven mainly by whether workers experience AI as a meaningful learning resource, rather than simply by using AI often.
- **Overreliance concerns are linked to learning and autonomy, not frequency.** In Model 3 ($R^2 \approx .35$), AI_Use_Frequency_num was not a significant predictor of Overreliance_AT. Instead, both AI_InformalLearning_AT and Autonomy_AI had positive and significant

coefficients: those who report higher learning with AI and greater autonomy when using AI also report stronger worries about relying too much on it.

Taken together the Austrian, findings portray AI as a powerful development tool whose positive effects on career outcomes and confidence are strongest when workers integrate it into their learning processes. At the same time, heightened learning and autonomy with AI can coincide with an increased awareness of the risk of overreliance.

AI-enabled informal learning and self-regulated development

The results align closely with the theoretical perspective on informal learning and self-regulated development discussed in the literature review. Informal learning is understood as learning that emerges in and through work rather than via formal training programs, often through problem solving, experimentation, social interaction and reflection (Eraut 2004). Experimental and self-regulated learning theories empathize that employees learn most effectively when they actively engage with challenges, reflect on experiences and regulate their own learning strategies (Decius et al. 2025).

The Austrian evidence that AI is used for informal learning predicts both career impact and confidence supports this view. Workers who use AI not merely as a shortcut but as a support for skill development, useful prompts and active engagement appear to transform AI into a genuine learning environment. This fits Eraut's idea of deliberative informal learning, where employees deliberately use tools and situations to pursue learning goals within work tasks. It also reinforces research showing that trial-and-error experimentation, feedback seeking and reflection are core mechanisms of effective informal learning (Eraut 2004).

The fact that the frequency of AI use alone is insufficient to predict confidence, and only one of several drivers of career impact, also resonates with the broader learning literature. It suggests that quantity of use is less important than quality of engagement (that is, whether employees remain cognitively engaged, reflective and in control when using AI). This nuance mirrors the Italian findings, where informal learning emerged as the dominant driver of career impact, and frequency played a much smaller role.

The ghost-learner effect and the Austrian pattern

The ghost-learner concept developed by Rausch (2025) warns that employees may become "invisible learners" when they outsource too much of the cognitive work to AI without reflection, thereby improving short-term performance but missing opportunities. In the Italian analysis, as conducted by my colleague, this was reflected empirically by Model 3: higher AI-enabled informal learning predicted lower overreliance concern, while higher usage frequency predicted higher overreliance concern, suggesting that active learning offset the ghost-learner risk. The Austrian pattern, however, is more inconclusive on this matter. Overreliance on AI is not significantly associated with frequency but instead increases with both AI informal learning and autonomy. Rather than contradicting the ghost-learner concept, this may point to a different mechanism. Austrian workers who deeply integrate AI into their learning processes and enjoy higher autonomy might also be those most aware of the potential downside: they recognize that AI can become a cognitive crutch and thus report higher concern about relying too much on it. Overreliance concern here may therefore indicate critical self-awareness among advanced users, not passive dependency.

This pattern can be interpreted in light of the Austrian context and sample composition. The Austrian subsample is heavily concentrated in Fintech/Financial Services and Software/Saas sectors where decision quality, risk management and regulatory compliance are particularly

important. In such environments highly autonomous professionals who use AI intensively for learning and problem solving may be especially sensitive to questions of accountability, skill erosion and long-term capability.

Limitations

This study has several limitations. First, the Austrian sample is relatively small (N = 103) and highly selective: respondents are mostly highly educated knowledge workers in fintech, software and other digital services. The results therefore cannot be generalized to a wider Austrian labor market or to more traditional sectors. Second, the cross-sectional survey design does not allow causal claims: it is unclear whether AI-enabled informal learning leads to better career outcomes and confidence, nor does it prove that already successful and confident workers are more likely to engage in AI-based learning. Third, all constructs are measured via self-report Likert items, which may be affected by recall bias, social desirability and limited awareness of one's own learning processes (Jebb et al. 2021).

Conclusion of the Austrian context

This study examined how Austrian knowledge workers in highly digitalized sectors perceive AI as means of informal learning and how this relates to career outcomes, confidence and concerns about overreliance. The analysis focused on 103 professionals working mainly in Fintech/Financial Services, Software/Saas and related digital services. The findings show that AI is clearly more than a "productivity tool" for this group. Respondents report that AI helps them solve work problems, supports their development and has a generally positive impact on job performance, skills, future readiness, satisfaction and professional development. The regression models underline that these positive career-related perceptions are strongest when AI is used as an informal learning resource:

AI-enabled informal learning and, to a lesser extent, the frequency of AI use together explain a substantial share of the variance in perceived career impact. Similarly, confidence in handling complex tasks is driven primarily by the extent to which workers feel they are genuinely learning with AI, rather than simply using it often or seeing it as helpful for problem solving in isolation.

At the same time, the Austrian results highlight an important tension. Overreliance concerns are not primarily linked to use frequency but are higher among those who report stronger AI-enabled learning and autonomy. This suggests that more advanced and autonomous AI users are also more aware of the risk of letting AI take over too much of the cognitive work. Rather than contradicting the idea of the "ghost learner", this pattern indicates that the risk of dependency is most visible to those who integrate AI deeply into their workflows, and that reflection on this risk is part of the responsible professional practice. Overall, the Austrian evidence supports the view that AI can function as a meaningful extension of informal learning processes in knowledge work, but only when workers remain actively engaged and in control.

6 Comparative Findings Analysis *Group Part*

While Italy and Austria differ in macroeconomic and institutional context the core question is whether these structural differences translate into different mechanisms of AI-enabled informal learning. The results of the three parallel regression models in each country allow a direct comparison of how AI-driven informal learning influences key outcomes across contexts.

6.1 Model 1: Career Impact

In both countries, AI-enabled informal learning significantly predicted perceived career impact. In Italy, the effect of informal learning on career impact was strong and statistically significant, while AI use frequency was only marginal. This suggests that in the Italian context, simply using AI more

often does not automatically translate into perceived career benefits unless workers experience AI as supporting learning and skill development. Austria shows a partially different pattern: while informal learning remains a strong predictor, AI use frequency also contributed significantly to career impact. A plausible interpretation is that Austria's higher digital maturity and more structured environment may allow frequent AI use to more consistently accumulate into perceived performance and development gains, whereas in Italy frequency without purposeful learning is less likely to be beneficial. Importantly, the cross-country comparison still supports the theoretical claim that AI is most valuable as a learning resource when it is used in a reflective, development-oriented way, not merely as a productivity shortcut.

6.2 Model 2: Confidence

In Austria, confidence was driven primarily by AI-enabled informal learning, while frequency of AI use was not significant and perceived problem-solving support was only marginal. This indicates that confidence in handling complex tasks develops mainly when workers feel they are actively learning with AI, rather than simply using AI frequently. Italy shows a slightly different emphasis: problem-solving support from AI played a larger role in predicting confidence, and frequency had a modest effect. This difference is consistent with self-efficacy theory: confidence grows through mastery experiences, and in the Italian setting, where organisational AI support is perceived as weaker, successful AI-assisted problem solving may be a more important source of mastery than continuous learning routines. Nonetheless, across both contexts, the key implication remains aligned with the theoretical framework: AI builds self-efficacy in knowledge work when it supports meaningful learning and competence development, not when it substitutes for cognitive engagement.

6.3 Model 3: Overreliance and Ghost-Learner Effect

In Italy, the pattern aligns closely with the theoretical expectation: higher AI use frequency increased overreliance concern, while AI-enabled informal learning reduced it. This supports the idea of Rausch' (2025) ghost-learner effect. Austria shows a different configuration: frequency did not predict overreliance concern, while both autonomy with AI and informal learning were positively associated with concern. Rather than contradicting the ghost-learner concept, this may indicate that Austrian users are more critically aware of dependency risks even when they learn actively. In other words, in Austria overreliance concern may reflect reflective monitoring among advanced users, whereas in Italy it appears more tied to frequency-driven dependency without sufficient learning. In both contexts, however, the model reinforces the theoretical importance of process ownership: concerns about "leaning on AI" are most meaningful when workers perceive a shift in control, judgment, or learning responsibility toward the system.

6.4 Conclusion

Overall, the comparative analysis supports the thesis' theoretical argument. Across both Italy and Austria, AI-enabled informal learning consistently predicts career-related benefits and is central to confidence development, confirming that informal learning mechanisms remain fundamental even as AI reshapes workflows. At the same time, national context appears to shape how secondary factors operate: Austria's environment may allow frequent AI use to translate more directly into career impact, while Italy's weaker perceived organisational support makes individual problem-solving success more central for confidence. Finally, the overreliance results suggest that ghost-learner dynamics can manifest differently: as dependency driven by high usage without learning (Italy) or as critical awareness among autonomous users (Austria).

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