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Training for Industry 5.0: Evaluating Effectiveness and Mapping Emerging Competences

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Abstract

As Industry 5.0 emerges as a human-centric evolution of industrial systems, this study investigates the effectiveness of training interventions in companies aimed at supporting the transition to Industry 5.0, emphasizing human-centric and resilient skill development. Drawing from multiple case studies involving engineers and operators, the research applies both meta-analysis and meta-regression to assess the added value of experiential learning approaches such as Teaching and Learning Factories. In addition, a novel methodology combining quantitative analyses with qualitative interpretation of emerging competences is presented. Principal Component Analysis and classification frameworks are employed to identify and organize key competence clusters along technological, organizational, and social dimensions. Special attention is given to the emergence of human-centered competences such as decision empowerment, which are shown to complement traditional operational capabilities. The findings confirm that experiential training interventions enhance both self-efficacy and adaptive operational readiness, while the use of fusion techniques enables the generalization of results across heterogeneous corporate settings. This work contributes to ongoing discourse on Industry 5.0 readiness by linking training design to strategic company incentives and highlights the role of structured evaluation in informing future policy and implementation pathways.

Keywords: Industry 5.0 training; experiential learning; emerging competences; meta-analysis; human-centric manufacturing

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1. Introduction

Training is a critical component of the operationalization of Industry 5.0 [1,2], serving as the bridge between strategic intent and practical implementation. Exceeding earlier industrial paradigms, Industry 5.0 emphasizes not only technological advancement but also human-centricity, resilience, and sustainability [3]. For these values to be effectively embedded into daily operations, employees must develop both technical competences and adaptive capacities [4,5]. Training supports this by aligning workforce capabilities with new technologies and evolving organizational goals, enabling smoother integration, reduced resistance to change [6], and greater empowerment on the shop floor. In this way, training becomes a foundational mechanism through which Industry 5.0 principles move from vision to reality.

At the same time, in the context of Industry 5.0, internal incentives [7]—understood as strategic drivers within the company such as talent retention, continuity of digital transformation, and commitments to green innovation—are critical to effective operationalization. These incentives are not extrinsic rewards for employees, but rather organizational imperatives that motivate and justify the integration of advanced technologies and training initiatives. For example, companies facing high turnover rates may prioritize human-centric strategies and upskilling programs to enhance retention and resilience [8]. Similarly, firms already engaged in digitalization are more likely to see value in building on existing systems [9], and through continuous training, enabling a smoother evolution toward Industry 5.0 goals. Furthermore, sustainability ambitions (e.g., decarbonization or circular economy models) act as powerful internal incentives to adopt (new) energy-efficient technologies, requiring both technical expertise and cultural alignment. Recognizing these internal drivers allows organizations to design training and transformation initiatives that are not only technically sound, but also strategically necessary. Relevant templates [10], in general, should follow a socio-technical approach [11,12], while it is useful that they have been applied in several specific cases [13–15].

1.1. State of the Art

As industry transitions from the automation-driven paradigm of Industry 4.0 to the more inclusive and ethically grounded framework of Industry 5.0, training must evolve to meet emerging skill demands while supporting resilience and the humanization of work [16,17]. Modern training programs prioritize both technical and interpersonal competencies, ranging from digital literacy and data-informed decision-making to collaboration and creativity. This enables professionals to operate within increasingly complex, cyber-physical environments [16,18,19]. These programs are increasingly personalized, leveraging AI, IoT, and data analytics to deliver adaptive, real-time learning paths that improve retention and accelerate competence acquisition [19,20]. Additionally, immersive technologies such as mixed reality and extended reality offer scalable, practical skill development, especially for frontline workers and technicians [21]. However, significant challenges persist, including organizational resistance to technological adoption, concerns regarding data privacy, and the limited incorporation of human factors in current training ecosystems [5,8]. Addressing these gaps will require a stronger alignment between training design and the core pillars of Industry 5.0 (sustainability, resilience, and human-centricity), as well as further research into the technology readiness and implementation barriers that hinder this transformation [22].

As a matter of fact, only 17% of companies in Europe will be using AI by the end 2030 [23]. This means that Industry 4.0 is not there yet. However, Industry 5.0 is seen as complementary to it, by allowing companies to transform in a sustainable and resilient way and addressing human needs.

The successful integration of Industry 5.0 into organizational ecosystems can be analyzed through multiple layers, including the effectiveness of upskilling interventions, company-specific characteristics (such as culture, readiness, and strategy), and the overall ease of technological and human-centric transition [10]. Understanding how these elements interact is essential for assessing the viability and impact of Industry 5.0 adoption across diverse contexts. Also, it is noted that the term "intervention" functions as an external framework for monitoring the transformation of training [10]. To generalize findings beyond individual case studies, the use of meta-analytic techniques [24,25] enables the aggregation of evidence from various interventions. This fusion allows for robust conclusions that reflect trends across the broader population of companies, enhancing the reliability and scalability of insights on training efficacy and emerging competencies.

Focusing on particular professional skills, the landscape has expanded significantly to accommodate the rapidly evolving demands of green, digital, and resilient economies. General skill frameworks increasingly emphasize sustainability-related knowledge, adaptability, and transversal abilities such as collaboration, digital fluency, and problem solving. As highlighted by initiatives like ESCO and the JRC reports [26,27], the integration of green and resilience-oriented skills is becoming a central element in upskilling policies. These developments support companies, especially SMEs, in navigating transitions and ensuring workforce readiness for future societal and environmental challenges [28].

Beyond general skill taxonomies, the application of statistical methods like Principal Component Analysis (PCA) has enabled researchers to identify latent structures in professional practices and competencies. Recent studies have used PCA to empirically derive competence models across diverse domains such as nursing leadership [29], construction industry management [30], and educational assessments [31]. These works demonstrate how PCA can reveal complex patterns in self-assessed capabilities, bridging theory with practice. Moreover, earlier applications like those by Todhunter [32] show how PCA supports the understanding of digital competence acquisition, especially in fields where technological integration is essential. Together, this body of research highlights the growing role of data-driven techniques in structuring and validating competence frameworks.

Future proofing training interventions involve creating educational programs that remain relevant and effective amid evolving technological landscapes, societal needs, and organizational contexts. In the context of Industry 5.0, this means not only addressing current digital competencies but also preparing the workforce for emerging roles through adaptable, human-centric training designs. Transitioning from traditional time-based learning models to competency-based training [33] ensures that learners acquire the necessary skills and capabilities to perform effectively. Real-time assessment techniques and iterative content delivery, as used in Competency-Driven Training (CDT), have demonstrated improvements in learning outcomes without increasing the training duration. For instance, CDT has been associated with up to 18% greater competency gains over conventional models [34]. Effective training systems also need to broaden their scope to include non-traditional groups and emphasize not only knowledge transfer but also personal development and implementation strategies. Training frameworks that include system-level thinking, psychological readiness, and mentorship—such as in coach or trainer education—have shown higher long-term engagement and adaptability [35,36].

Understanding the context in which training is implemented is essential. Process evaluations help uncover why some interventions succeed while others fail by examining fidelity, participant responses, and external influences. Such evaluations contribute to designing scalable and flexible models suitable for both digital and physical training environments [37]. Additionally, aligning instructional design with future employer needs, particularly in dynamic sectors like supply chain and manufacturing, is critical for maintaining relevance and impact [37,38].

1.2. Research Questions

This study, originating from the EU project BRIDGES 5.0 [39], contributes added value in two critical areas: first, by evaluating the efficacy of training systems within the context of Industry 5.0 job-wise, and second, by identifying emerging competences aligned with this new industrial paradigm. A core motivation for this research has been to support the development of targeted learning paths that respond to the evolving demands of human-centric and technologically integrated workplaces. Accordingly, the first research question (RQ1) investigates the feasibility of integrating Industry 5.0 principles into current training systems in companies.

In addition, with the goal of mitigating opportunity costs and ensuring that learning is immediately applicable and scalable, the study explores experiential learning methods, leading to the second research question (RQ2): Is experiential learning effective for the context of Industry 5.0?

Finally, the study aims to explore whether there is a correlation between the core pillars of Industry 5.0 and the competences fostered through training, giving rise to the third research question (RQ3): Are there identifiable emerging competences specific to Industry 5.0?

1.3. The Structure of the Paper

This paper is structured to systematically investigate the integration of Industry 5.0 principles into training systems. All sections are organized around the three central research questions (RQ1–RQ3), starting with the background information required to understand the concepts and following with the Section 3. The Sections 4 and 5 presents the findings on feasibility, training efficacy and competences, all derived from the data and taking into account technological, social, and organizational axes. Finally, the Section 6 and the outlook follow, highlighting paths for further research in aligning human-centric approaches with Industry 5.0 goals.

2. Background

This study builds on a series of documented training initiatives [13] designed to support corporate transitions toward Industry 5.0. These initiatives (referred to throughout this paper as interventions) represent structured training efforts implemented in response to company-specific motivations. In our context, intervention refers to any organized upskilling activity introduced to advance human-centric, sustainable, and resilient practices in the workplace.

The drivers behind these interventions are what we term internal incentives; that is, strategic imperatives internal to each company. Unlike employee-level rewards, internal incentives include objectives such as reducing turnover, supporting digital transformation, or achieving environmental sustainability. These organizational motivations shape how training is designed, deployed, and evaluated.

The interventions analyzed in this study have been documented in earlier work [14,15] and follow specific design and evaluation templates. These templates typically involve structured delivery, self-reporting instruments, and pre–post assessments of skill acquisition. Notable methodological features across cases include the following:

- The use of self-report surveys to capture perceived gains and engagement;
- The statistical treatment of upskilling outcomes, enabling cross-case comparison.

As illustrated in Figure 1, the concept of intervention is tightly linked with transition. Both terms are used interchangeably to describe efforts aimed at aligning training systems with Industry 5.0 values. This dual lens emphasizes not only what training is delivered, but why it is delivered, underscoring the importance of aligning educational content with broader strategic goals.

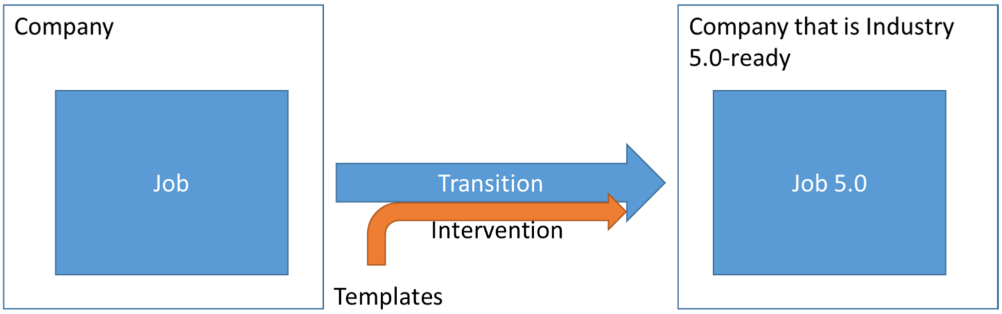

Figure 1. Schematic representation of the "intervention" term.

Finally, when assessing these interventions, we consider feasibility not just in terms of technical implementation, but as a broader concept encompassing organizational readiness, alignment with strategic direction, and measurable training outcomes. In this way, feasibility becomes a multidimensional measure of how well Industry 5.0 principles can be embedded into real-world company settings.

However, the interventions have been quite restrictive. Only Teaching Factories and Learning Factories have been utilized [40,41], not only because this has been the structure of the BRIDGES 5.0 project, but because they have been two experiential learning techniques that can help companies towards achieving internal objectives (incentives). As such, what is achieved is some sort of mitigation for the opportunity cost. Also, specific technologies that facilitate educational activities, such as Augmented and Virtual Reality can be elaborated, even though this is not pointed out in the case of companies where the current work focuses on. The main difference between Teaching and Learning Factories is that the first focus on problem solving within a company and the latter are related to hands-on learning on equipment (testbeds). They can be complementary, if needed.

3. Methodology

The case studies examined in this research include real-world implementations of training interventions across various companies and roles. They have all been previously documented.

Table 1 provides an overview of the six participating companies (C1–C6) involved in the training interventions analyzed in this study. Each case reflects a distinct industrial context, ranging from automotive robotics to electronics. The Table summarizes the sector of each company, the approach taken to workforce training or development, the initial status or challenge addressed, the main purpose of the intervention, and the key outcomes achieved. This information complements the classification provided in Table 1 and supports the interpretation of the results by clarifying the context in which each intervention was implemented.

Table 1. Overview of Participating Companies (C1–C6): Sector and Key Outcomes.

Case	Sector	Starting Point	Purpose/Focus Area	Achieved Final Result
C1	Automotive Robotics	Awareness of digital gaps	Explore and test different training methods for human-centric digital transformation	Identified skill gaps, validated co-design practices, and fostered mindset shift toward digital adoption
C2	Consumer Goods	Digitalization phase	Promote adoption of digital tools for flexible work	Improved digital mindset and willingness to adopt structured technologies
C3	Industrial Equipment	Process variability	Enhance transparency and improve internal coordination	Defined standardized workflows and boosted communication
C4	Semiconductors	Departmental restructuring	Align organizational units under a digital production strategy	Fostered collaboration and initiated roadmap development
C5	Electronics	Low automation	Investigate MES integration and operator-machine collaboration	Identified upskilling needs and initiated digital transition planning
C6	Industrial Engineering	Partial smart systems	Improve adaptability and responsiveness through real-time data	Implemented feedback loops and enhanced situational awareness

Additionally, Table 2 presents representative examples, detailing the type of training (namely traditional learning (TrL), Learning Factory (LF) [40], Teaching Factory (TF) [41]), the target group, the organizational incentive behind the transition (such as automation) and the underlying objective the training.

Table 2. A brief description of the training cases.

Company	Training Type	Target Group	Incentive	Objective
C1	Traditional learning (TrL) and partially hands-on	Engineers	Semi-automation	Belief
C1	LF	Operators	Semi-automation	Technology adoption
C1	TF	Engineers/Managers	Semi-automation	Technology redesign
C2	TF	Operators/Managers	Digitalization	Behavior
C3	TF	Operators/Managers	Digitalization	Behavior
C4	TF	Engineers/Managers	Knowledge transfer	Problem solving
C5	LF	Operators	Reduction in turnover	Full workflow
C6	TF	Operators/Managers	Digitalization and Green transformation	Behavior

In particular, the design of the cases involved a template [13] taking into consideration at minimum skills and technologies from the viewpoint of the job and strategies from the company side. However, the current work focuses on upskilling. Specific skills, either technical or soft, pertaining to the three different pillars were chosen and the evaluation framework was also used to this end. Appendix A summarizes the evaluation questions per company.

As seen after examining the questions used for upskilling (in Appendix A), the selection of skills was therefore not generic but case-dependent, reflecting the specific problems and priorities that each company faced. For example, in some cases the focus was on enhancing cross-functional communication or operator autonomy, while in others the emphasis lay in integrating digital tools or improving responsiveness to variability. In this way, the Industry 5.0 pillars of people-centricity, resilience, and sustainability were not assessed in the abstract, but rather emerged through the alignment of skill development with concrete organizational challenges and strategies. This contextualization ensures that the framework captures how upskilling initiatives contribute to Industry 5.0 in practice, while maintaining a direct link between company needs, competence development, and the overarching research questions.

All the cases are regarded as pre–post studies [42], given the absence of a control group. Also, convenience sampling has been applied. As such, uncontrolled designs can be influenced by factors like maturation, regression to the mean, or historical events. They potentially overestimate intervention impact compared to controlled designs. It is noted that this fact may be acceptable in the current case, as it aligns with the study's aim of confirming practitioner perceptions. However, as seen below, this is mitigated by comparing to the traditional learning. It is noted, for the sake of completeness, that the traditional learning occurred in an attempt to emulate the concept of Learning Factory [15].

Also, as per the documentation of the cases [13–15], self-efficacy has been shown to significantly influence both employee performance and learning outcomes, acting through mediators such as motivation, engagement, and confidence in digital environments [43,44]. However, in assessing training effectiveness, it is important to recognize the methodological constraints of using standardized mean differences (SMDs) in pre–post analyses. These effect sizes can be inflated and may not fully reflect the true impact of the intervention [45]. The score used in all cases comes from a set of questions rated on a 5-point Likert scale. For each question, the difference between the post- and pre-assessment scores was calculated. These questions are then grouped either by their corresponding pillars—using average values per pillar—or combined into a single overall metric representing Industry 5.0-related upskilling.

The self-assessment of upskilling, where all the following analyses were mentioned, were based on a common scheme. In particular, the questions were grouped per pillar, depending on the nature., i.e., a question on their confidence on separating waste was used in the estimation of sustainability. Since all the responses were on a 5-Likert scale, their averages on differential assessment (post-intervention minus pre-intervention) were gathered per question along all trainees forming Q_n variables (Q_1 for question 1, Q_2 for question 2, and so on). Then, per pillar, they were grouped thematically using averages (i.e., for sustainability $S_n = \sum_{\text{relevant } n} Q_n$), or all together to form an overall Industry 5.0 metric ($I_5 = \sum_{\text{all } n} Q_n$). These metrics were treated as interval-level data, since composite scores, such as sustainability, are considered [46]. Additionally, the normality was checked (Shapiro–Walk test).

To investigate RQ1, a meta-analysis was employed as the primary methodological tool. Meta-analysis [24,25,47] enables the synthesis of findings across multiple independent studies or case implementations, allowing for the estimation of a pooled effect size. In this context, effect sizes derived from training interventions related to Industry 5.0 were aggregated (either in the form of pre–post training gains, or as independent group comparisons). The objective has been to evaluate the overall efficacy and practical feasibility of such integration. Random-effects models were used to account for variation in study designs and contexts. It is noted that only the methodology of meta-analysis is adopted, with respect to fusing different cases. However, the current work is not intended to be a meta-analysis per se.

To be able to respond to RQ1, herein, only upskilling was considered, so, the overall metrics upskilling with respect to Industry 5.0 per company were used. Per case, the question has been asked if the upskilling has been enough. To this end, a characterization was used based on specific thresholds. Also, on a global level, fusing the results from all the companies, the outcome of the meta-analysis is used to respond to RQ1.

For RQ2, a meta-regression [48] was used to explore how specific characteristics of the training interventions moderate the observed effects, particularly the presence or absence of experiential learning features. This approach allowed not only for estimating overall efficacy, but also for explaining between-study variance and guiding the design of future experiential training models aligned with Industry 5.0 goals. This method proved highly useful in estimating the impact of the method used (TF/LF/TrL) on the final outcome, thus, facilitating the respond to RQ2, since both TF and LF are experiential learning techniques.

Subsequently, to identify emerging Industry 5.0 competences (RQ3), a structured, data-driven methodology was applied across participating companies (Figure 2). For each company, survey responses related to upskilling, work practices, technology use, and organizational readiness were collected. Principal Component Analysis (PCA) [49–52] was then conducted individually for each company's dataset. This statistical technique was used to reduce dimensionality and uncover latent structures among the questionnaire items, which were then grouped into distinct components representing potential underlying competences.

Following the PCA, each component grouping was analyzed to interpret what new competence it might represent. A large language model (LLM), namely ChatGPT version GPT-4o [53]) was utilized to propose an initial semantic label for each emerging competence based on the content and coherence of the included questions. These preliminary labels were reviewed and refined in collaboration with human experts to ensure validity, contextual alignment, and clarity. The final output—validated emerging competences—was systematically documented and stored for further analysis and cross-case comparison. The procedure used for validating the competence labels is described in detail below:

- The loadings and the questions per se were given as input to ChatGPT;

- ChatGPT suggested the naming;
- Three different experts that were involved in the corresponding training were called to confirm the naming of the emerging competence. Their background was mixed, meaning that there were two from academia and one from the company.

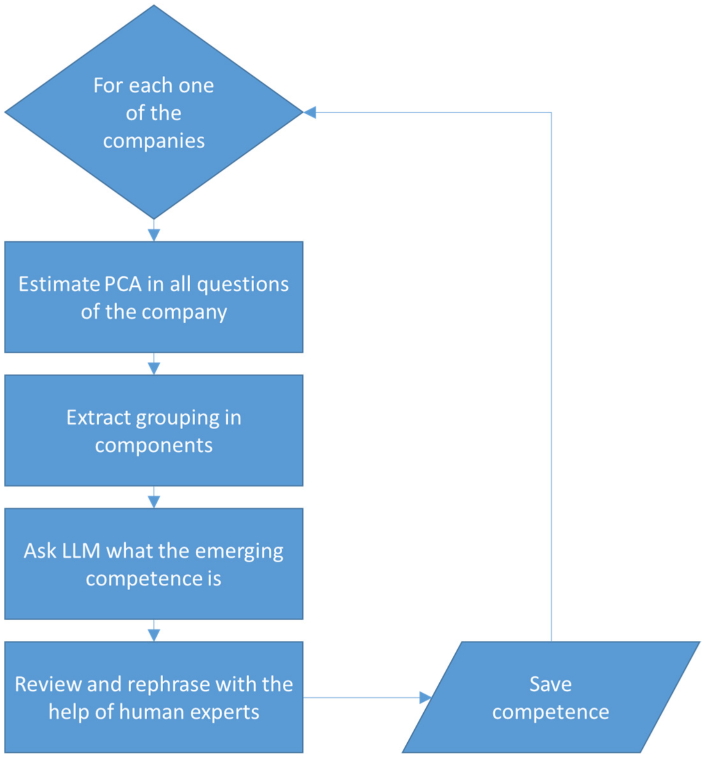

Figure 2. The method for extracting emerging competences from grouping of upskilling-related questions.

4. Results and Discussion on Upskilling Effectiveness (RQ1 and RQ2)

4.1. Raw Data per Industry 5.0 Pillar

Table 3 provides a visual summary of how upskilling in different companies (C1 to C6) has aligned with key Industry 5.0 pillars. Each row represents a company, while each column corresponds to one of the pillars—such as human-centricity, resilience, or sustainability. The metrics are defined as the mean values of the implicated questions, as per the original designs.

Table 3. Upskilling results per pillar and per training intervention. The scale refers to differential Likert scale (post–pre).

Company	Sustainability	Resilience	Human Centricity
C1 TrL	0.207	0.27	0.22
C1 LF	1.397	1.375	0.816
C1 TF	0.533	0.467	0.433
C2	0.95	1.75	1.625
C3	0.571	0.851	0.786
C4	0.567	0.1	0.268
C5	1.21	1.45	1.23
C6	1.83	1.4	1.67

Also, Figure 3 reveals the correlation coefficient (Pearson coefficient) between the pillars' related upskilling, pointing out the minimum and the maximum values across companies. The non-zero correlation coefficient can be considered as the driver behind the search for new competences (RQ3), since this is an indication for other potential groupings of questions in upskilling evaluation.

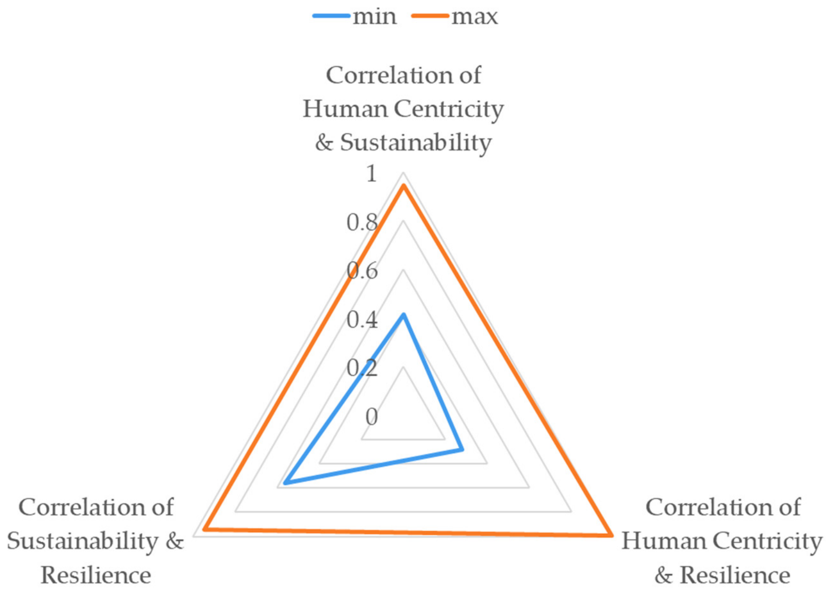

Figure 3. Minimum and maximum Pearson correlation coefficient across companies per pair of pillars.

4.2. Results on Overall Industry 5.0 Metric (RQ1)

With upskilling being a statistical measure, thresholds of reference have been utilized in terms of minimally important difference (MID). The exact numerical value of 0.5 is used as the "reference" threshold [54] for absolute numbers in upskilling's differential assessment. This method is complemented with another metric using a standardized effect size measure, namely Cohen's d [55,56]. Table 4 mentions these values.

Table 4. Upskilling results per pillar and per training intervention.

Company	Industry 5.0 Overall Metric	Verbal Characterization of Upskilling Impact Based on Cohen's d of the Overall Metric
C1 TrL	Small (0.207)	Small (0.27)
C1 LF	Medium (0.938)	Large (2.56)
C1 TF	Medium (0.633)	Large (1.93)
C2	Large (1.45)	Extremely Large (3.26)
C3	Medium (0.735)	Large (0.75)
C4	Marginal (0.357)	Medium (0.6)
C5	Medium (1.359)	Large (1.99)
C6	Large (2.13)	Extremely Large (6.17)

It is evident that per case, the integration of Industry 5.0 can be considered successful in all the cases where both the overall Industry 5.0 metric I_5 and the corresponding Cohen's d are not small. The C1 TrL case, which employed traditional learning, is considered not successful; however, it can be used as a reference for the others.

Also, on a global level, exploiting the meta-analysis, the forest plot of Figure 4 illustrates the outcomes of a meta-analysis performed across multiple training interventions from different companies (C1 to C6) and instructional formats (e.g., traditional learning, LF, TF). Each row represents the mean effectiveness score (post-intervention–pre-intervention), along with corresponding standard deviations and confidence intervals. Since the studies follow a pre–post design without control groups, the mean values themselves serve as the effect sizes. A metric that takes into account all the upskilling-focused questions in terms of an average has been used to this end.

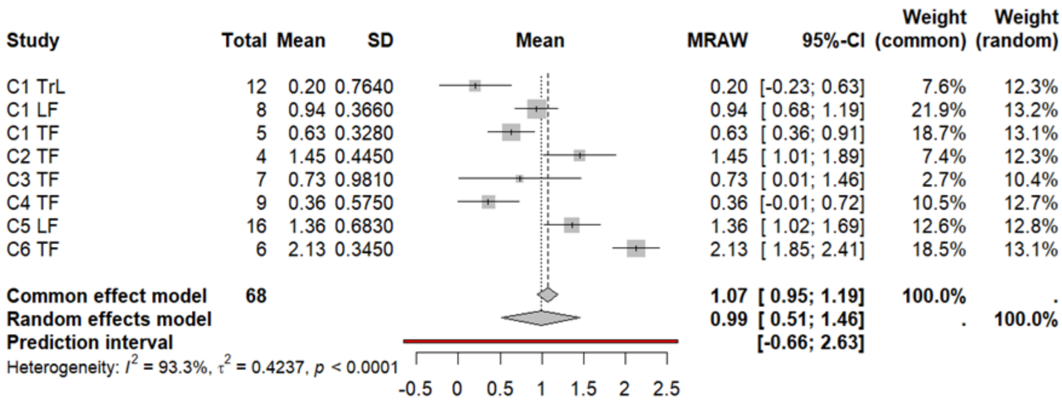

Figure 4. Meta-analysis (mean values) for overall Industry 5.0 metric: the forest plot.

The meta-analysis aggregates these results using both common and random-effects models (Figure 4). Given the high heterogeneity (I^2 = 93.3% is the percentage due to intrinsic heterogeneity), the random-effects model is preferred for interpretation. The resulting overall effect estimate under the random model is 0.99 [95% CI: 0.51, 1.46], with a prediction interval ranging from −0.66 to 2.63. This interval acknowledges potential variability in future implementation contexts, underscoring the importance of situational factors in upskilling outcomes. This could be interpreted as follows: **Overall, the Industry 5.0-related upskilling is feasible; however, it is case dependent, and it should be treated as such.** As such, RQ1 can be answered in a positive way.

The number of trainees per case was relatively small (e.g., up to 16 in the largest group). As a result, mean and standard deviation values may be influenced by individual responses, particularly in cases such as C1 TrL, where dispersion is high. These data should therefore be interpreted as indicative trends rather than statistically representative distributions. However, the meta-analytic approach mitigates this limitation by weighting results according to their precision, so that more stable estimates contribute more to the overall effect than noisy, small-sample groups. Similar challenges are documented in other domains where small samples are common, such as rare disease studies or training interventions. In these contexts, meta-analysis has been shown to provide meaningful synthesis while requiring careful interpretation of wide confidence intervals [57,58].

Also, given the funnel diagram (Figure 5), it might be worth exploring subgroup analyses or meta-regression (RQ2) to explain variability, especially due to training type (TF, LF, traditional learning).

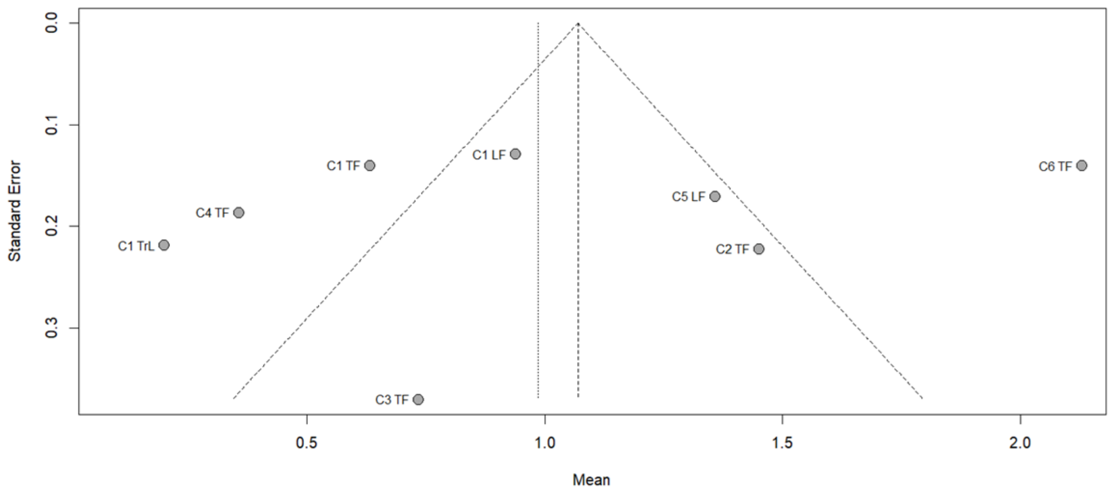

Figure 5. Meta-analysis (mean values) for overall Industry 5.0 metric: the funnel plot.

Regarding medians-based meta-analysis, the majority of studies show positive effect estimates, meaning that the interventions (likely training or upskilling programs) resulted in favorable outcomes. Even though exact measures may vary, the central tendency across studies is above 1.0, with the random-effects summary estimate at 1.18 [0.74, 1.61], suggesting overall benefit. There is moderate heterogeneity, as implied in the wide confidence intervals for some studies and their spread across the plot.

4.3. Results as a Function of Training Method (RQ2)

As a natural continuation, to assess the relative effectiveness of different training interventions under the framework of Industry 5.0, a network meta-regression was conducted. This establishes the relevance of RQ2 and allows us to evaluate whether experiential learning is useful for integrating Industry 5.0. The dependent variable in this model was the standardized effect size reflecting training impact across studies. The model included four binary (dummy-coded) independent variables (also known as moderators–Table 5), representing key characteristics of the training interventions.

- TF (Teaching Factory): coded as 1 when the intervention was implemented in a teaching factory context—typically characterized by collaboration between academia and industry, with a focus on real-world production scenarios.
- LF (Learning Factory): coded as 1 when the intervention took place in a learning factory environment—usually emphasizing hands-on experiential learning in simulated or semi-real production setups.
- psych: coded as 1 when the intervention included behavioral or psychological components, such as reflective learning, motivational aspects, or mindset development.

Table 5. Moderators (independent variables) used in meta-regression and their values per intervention.

Company	TF Variable	LF Variable	Psych (Psychological/Behavioral Component)
C1 TrL	0	0	0
C1 LF	0	1	0
C1 TF	1	0	0
C2	1	0	1
C3	1	0	1
C4	1	0	0
C5	0	1	0
C6	1	0	1

It is noted that size is not a relevant factor. However, these variables were modeled to investigate which configurations are associated with greater training efficacy. The model allowed us to isolate and evaluate the contribution of each approach while accounting for variability across studies (Table 6).

Table 6. Coefficients (estimates) used in meta-regression and their values.

Factor	Estimate	Confidence Interval Lower Limit
intercept	0.2	<0
TF	0.3652	<0
LF	0.8319	<0
psych	0.9214	>0 (marginally)

The mixed-effects model revealed no significant residual heterogeneity ($\tau^2 = 0$, $I^2 = 0\%$), indicating that the between-study variation was well explained by sampling variance or the moderators included. The intercept corresponds to the estimated effect size of training programs that did not include TF, LF, or psychological framing. These basic interventions still resulted in a small positive gain in competences. Psychological interventions had a significant positive effect, suggesting that behavioral and motivational framing plays a crucial role in enhancing the impact of training in Industry 5.0 settings. Learning Factory (LF) methods demonstrated a positive effect, indicating a promising direction that may require more power to detect effects. Teaching Factory (TF) was also associated with a promising direction.

Since the intercept is not negligible, a validation with a network meta-analysis [59] is conducted in Appendix B as well, confirming the tendencies appearing here. Both analyses confirm positively RQ2.

5. Results and Discussion on the Competences (RQ3)

Building on the previous analysis of overall training effectiveness and the role of intervention types, the next phase of this study delves deeper into the qualitative dimension of upskilling, specifically the nature and structure of the competences fostered by these interventions. Thus, RQ3 is relevant here. While Section 4 demonstrated that Industry 5.0-aligned training can produce measurable gains, Section 5 shifts focus to what those gains represent in terms of emerging human, technological, and organizational capabilities. By applying Principal Component Analysis (PCA), this section uncovers the latent (or "emerging") competences embedded in employee responses and offers a structured interpretation of how these align with the core pillars of Industry 5.0.

5.1. Identifying Capabilities

To distill the underlying dimensions of competence within the survey data, Principal Component Analysis (PCA) was conducted across each case study. The results are summarized below, where each component captures a latent pattern of operator responses. For clarity and interpretability, only items with the strongest factor loadings are highlighted, indicating the most influential questions contributing to each component. Only principal components with eigenvalues above 1 (or other threshold) are shown. Table 7 justifies the use of PCA in a Likert scale.

Table 7. Criteria [60] for using PCA in various cases.

Factor	Barlett Success	KMO Success
C1 LF	Yes	
C2		Yes
C3	Yes	
C4		
C4 excluding last question from the questionnaire		Yes, but marginally
C5	Yes	
C6	Yes	

5.1.1. The Competences in the Company C1

Herein, the first three principal components (PC) are shown in Table 8, which includes the engaged questions, as well as the loadings. An attempt for naming is also made, with the help of the aforementioned large language model (ChatGPT).

Depending on the engagement of the skills, shown as rows in the table, different competences arise. For instance, the competence "Self-efficacy and Openness to Technological Change" is derived from the combination of skills "Awareness", "Feeling prepared for change", "Anticipated role change", "Perceived adaptability", and "Job satisfaction through tech"

Regarding the three competences extracted in terms of principal components, the first factor reflects a self-efficacy and adaptability mindset—how confident and ready the operator feels in adapting to the new technology. The second one represents a positive valuation of the technology's benefits—especially regarding workload and quality improvements. The last factor represents a sustainability and operational awareness competence, relating to responsible, efficient, and safe use of technology.

Table 8. Fuzzy (qualitative) engagement of principal components in the case of C1 and the respective naming of the emerging competences.

Original Question	PC 1 Engagement	PC 2 Engagement	PC 3 Engagement
Awareness	Low		
Impact on physical work		High	
Perceived quality improvement		High	
Feeling prepared for change	Medium	Low	
Anticipated role change	High		
Training importance			
Perceived adaptability	Medium	Low	
Job satisfaction through tech	Medium		
Energy efficiency			High
Material waste			High
Safety			Low
Maintainability			High
Continuity			High
Competence name	Self-efficacy and openness to technological change	positive perceptions and value attribution	Sustainability and efficiency awareness

5.1.2. The Competences in the Companies C2–C6

Herein, for the sake of space, the results of the PCA-based analysis for the rest of the cases are summarized in a tabular form. Table 9 summarizes these outcomes.

Table 9. Emerging competences from companies C2–C6.

Case	Engaged Skills (Through Principal Components' Loadings)	Name of the Emerging Competence
C2	Strategic understanding, operational capability, understanding of disengagement (negative loading)	Human-Centric Transformation Readiness
C3	Disengagement causes, human-centric criteria and practices, tech implementation knowledge, integration of human-centricity with performance	Human-Centric Knowledge and Organizational Readiness
C3	Reducing waste, environmental sustainability via optimization	Confidence in Sustainable Optimization
C4	Problem solving, shared control, project multitasking	Operational Confidence
C4	Solving problems, project multitasking	Decision Empowerment
C5	Company principles, Lean methodology, security standards, production documentation, ERP use, communication	Company Standards and Procedures
C5	ESD safety, hazardous waste sorting, component orientation, manufacturing execution system (MES) use	Core Operational Competence
C5	General waste sorting, working across different areas, communication	Adaptability and Practical Skills
C6	Problem solving, human–machine collaboration, multitasking/project switching	Adaptive Operational Readiness
C6	Problem solving, human–machine collaboration, Multitasking/project switching, spatial/functional adaptability across work areas	Cross-Functional Readiness

Regarding C2, the competence seems to capture an optimistic, empowered orientation toward human-centric transformation, combining confidence, knowledge and conceptual clarity. The negative loading on Q1 might suggest that those who are more knowledgeable/confident are less focused on—or less aware of—causes of disengagement.

For C3, the first competence reflects organizational awareness, conceptual knowledge, and readiness for human-centric transformation, while the second one reflects practical self-confidence in applying digital tools toward sustainability outcomes.

The first component of C4 appears to represent a competence around operational agility—the ability to multitask, handle complexity, and act decisively within flexible production environments. The strong negative loading for shared control might imply a perceived trade-off or tension between human autonomy and automation. On the other hand, the second component captures confidence in organizational support structures, including interfaces, tools, and empowerment mechanisms.

For C5, the first competence reflects a psychosocial competence related to engagement and organizational satisfaction, suggesting that employees who find fulfillment in the new setup may value organizational alignment more than task juggling or complexity. At the same time, the second factor seems to represent a "Core Operational Competence", involving understanding of the company's structured practices, quality processes, and team-based communication.

Finally, regarding C6, the first component reflects a broad sense of functional readiness and cognitive flexibility; these three cluster very tightly, suggesting a cohesive latent competence, named as "Adaptive Operational Readiness". The second component primarily captures a cognitive and role-flexibility competence, especially around problem solving, collaborative control, and multitasking. Physical or spatial flexibility appears only partially related and may be influenced by other unmeasured factors (e.g., experience, familiarity with departments, comfort zone). It can be named as Cross-Functional Readiness.

So far, regarding RQ3, it is evident already that there are various emerging competences that can be derived from these training sessions, even though these are case-dependent. These have been derived from grouping the skills that have been relevant in terms of maximum variance per company. The PCA proved to be useful in this grouping, while the LLM has been crucial in naming the competences.

5.2. Characterization of Emerging Competences

In continuation, the aforementioned components were thematically grouped with the assistance of a generic-purpose LLM (ChatGPT in particular), which facilitated semantic clustering based on latent meaning and contextual similarity. The experts did not participate in this, as they were biased to some extent, since they had participated in the design and implementation of the case study. The objective had been to discover new patterns, not existing ones.

The resulting clusters were validated and interpreted as derived competences, such as Operational Confidence and Generating Ideas. These were subsequently positioned within a three-dimensional conceptual space defined by (i) human-centricity, (ii) resilience, and (iii) sustainability, as illustrated in Figure 6. Human-centricity and resilience were mapped on orthogonal axes, while sustainability was encoded using a color gradient. This visualization supports the identification of strategic training priorities and highlights the multidimensional relevance of each competence to the goals of Industry 5.0.

Additionally, Table 10 presents an analytical classification of identified competence components based on their functional orientation across three dimensions: Work System, Technology, and Social. Each derived competence component (e.g., Decision Empowerment, Operational Confidence) is mapped according to its primary relevance to these operational domains. The Work System dimension captures competences that relate to organizational procedures, role clarity, and process optimization. The Technology dimension refers to competences linked to digitalization, automation, and technical adaptability. The Social dimension emphasizes interpersonal, emotional, and collaborative skills essential for human-centric and resilient workplaces. This classification is grounded in the co-evolving socio-technical systems framework articulated by Parker et al. [61], which underscores the importance of balancing technological and social subsystems within high-quality future work. By situating competence components along these axes, the table serves as a strategic tool to inform training design, workforce development, and organizational transformation in the context of Industry 5.0.

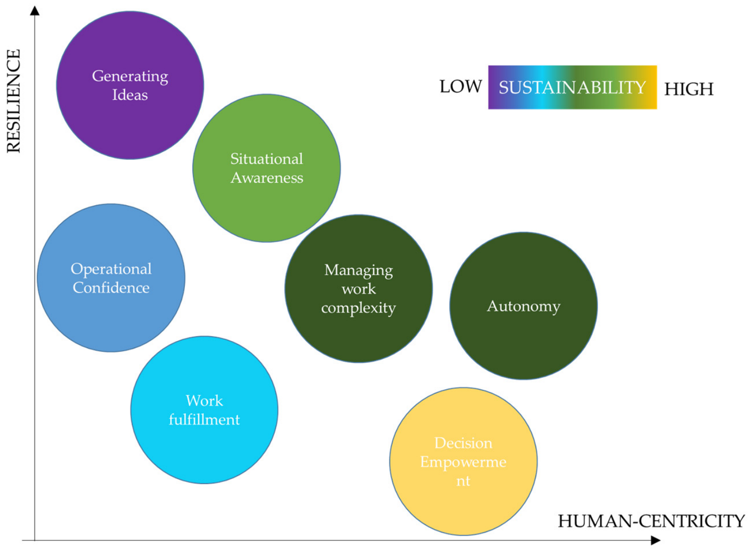

Figure 6. Derived competences and their characterization in terms of Industry 5.0 pillars.

Table 10. Emerging competences classification in a socio-technical frame of reference.

Competence	Work System	Technology	Social
Company Standards and Procedures	X	X	
Process and Safety Control	X	X	
Self-efficacy and Openness to Technological Change		X	X
Positive Perceptions and Value Attribution			X
Sustainability and Efficiency Awareness	X	X	X
Human-Centric Transformation Readiness	X	X	X
Human-Centric Knowledge and Organizational Readiness	X	X	X
Confidence in Sustainable Optimization		X	
Adaptive Operational Readiness	X	X	
Cross-Functional Readiness	X		X
Operational Confidence	X	X	
Decision Empowerment		X	X
Organizational Systems Fluency	X	X	
Operational Safety and Agility	X		X

As a note to the presented classification of Figure 6, it is important to highlight that the grouping of most terms into emerging competences was conceptually coherent and consistently supported by thematic overlap in the underlying PCA components, as reviewed by the experts. However, an additional competence (or even ability), “Empathy”, also came up. Empathy has been excluded from both the diagram of Figure 5 and Table 10. This concept had a less straightforward semantic and structural alignment, and the reviewers could not link it directly to the original skills in the questionnaires. To address this ambiguity, ChatGPT was employed to assist in the interpretation and explain why empathy was included in the emerging competences. As a result, a high-level conceptual explanation was synthesized by ChatGPT (Figure 7), highlighting common traits such as perspective-taking, understanding team needs, and cross-functional emotional communication. This aggregation of insights from merging diverse data points across companies helped justify

"Empathy" as a legitimate emergent competence, grounded in multi-source behavioral signals rather than a single-question mapping. This approach ensures interpretive rigor, particularly in cases where human-centric traits are embedded across multiple latent variables. Herein, different competences from different companies indeed can be used to justify the existence of empathy, as long as data from different companies can be used, forming an ecosystem (or a network) of skills.

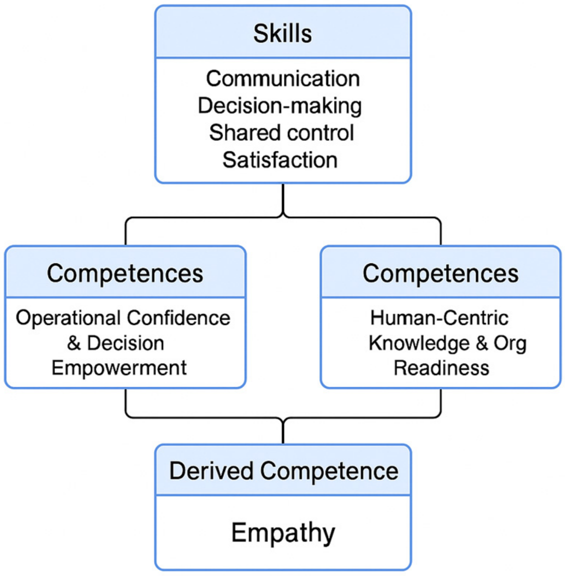

Figure 7. Concepts diagram explaining the generation of empathy as a derived competence (generated by LLMs [53]).

5.3. Non-Linear Approach

To complement the linear dimensionality reduction and provide a richer representation of complex relationships among competences, a non-linear Principal Component Analysis (PCA) [62] was conducted. This method allowed the discovery of latent constructs that may not align linearly with observed variables but still reflect meaningful structures in the data.

Figure 8 presents an example of optimal scaling applied to a Likert-type question. In this transformation, the original ordinal responses are rescaled non-linearly based on their contribution to the underlying component. The resulting curve shows that the response levels do not contribute equally or linearly to the variance; instead, there is a sharp decline in contribution after a certain threshold. This reveals complex relationships—such as plateauing effects or sudden drops in perceived competence—that linear PCA would fail to capture. Such patterns support the use of non-linear PCA in identifying more nuanced and emergent competences in Industry 5.0 contexts.

With this approach, additional emergent competences were identified. The first one, noted Organizational Systems Fluency, captures the ability to understand, navigate, and apply structured organizational mechanisms such as documentation, regulatory standards, and process tools. This competence reflects a high-level integration of procedural literacy and system-wide awareness necessary in complex, compliance-heavy industrial settings.

The second one, Operational Safety and Agility, reflects hands-on readiness to act safely, responsively, and adaptively under dynamic working conditions. It encapsulates competences related to environmental awareness, physical dexterity, and adherence to safety protocols.

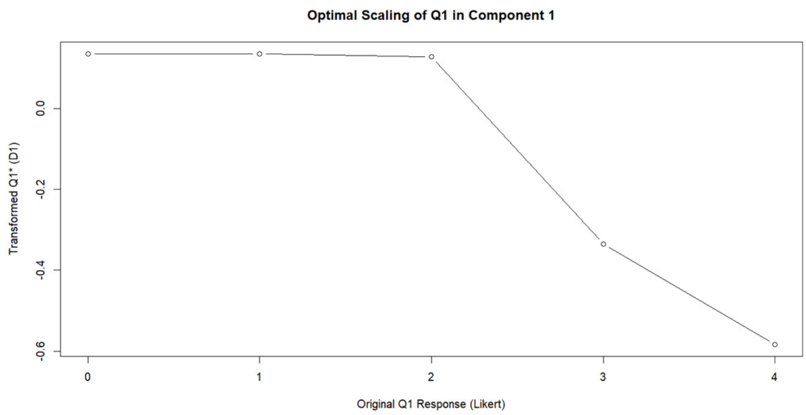

Figure 8. Transformation of a Principal Component within the framework of non-linear PCA (from original to transformed).

6. Conclusions and Future Outlook

In summation, the integration of Industry 5.0 values into training sessions was investigated. More specifically, there have been three research questions: the feasibility of such integration (RQ1), the suitability of experiential learning methods (RQ2), and the identification of emerging competences aligned with Industry 5.0 (RQ3). Through a combination of quantitative synthesis and competence mapping, several key conclusions can be drawn.

First, with respect to RQ1, the elaboration of the results confirms that integrating Industry 5.0 within trainings is feasible. The meta-analysis of training interventions demonstrated overall positive effects across various indicators of effectiveness. These include improved knowledge acquisition, behavioral shifts toward more autonomous work practices, and increased capacity for dealing with technological and organizational change.

The limitations of this meta-analysis, as clearly dictated by the corresponding prediction interval is that, each time, the internal incentives of the companies, interpreted as need for technology and desired skills, affect the methodology and render the integration of Industry 5.0 a case-dependent subject. Nevertheless, by weighting results across diverse cases, the overall Industry 5.0 metric can be considered a reliable trend indicator, offering cautious generalization beyond individual enterprises while still requiring context-sensitive interpretation.

Secondly, with respect to the second research question (RQ2), the study explored whether experiential learning approaches (Learning Factories (LF) and Teaching Factories (TF) in particular) are useful towards achieving Industry 5.0. The results of the meta-regression provide robust evidence in favor of these methods. Specifically, interventions that included, among others, psychological or behavioral elements had a greater impact on trainees.

The restrictions here have to do with the fact that the techniques used are limited. Also, experiential learning techniques combinations (i.e., existence of both TF, LF and gamification) as well as taking into account specific education-related technologies, such as Augmented Reality, need to be studied individually.

Finally, regarding the third research question, with a data-driven analysis, emergent competences were identified. These include, for example, Empathy and Operational Agility. These newly defined competences reflect the shifting expectations of employees in the Industry 5.0 paradigm, where emotional intelligence, quick adaptation to operational changes, and collaborative problem solving become more and more relevant.

Once again, the case-dependent character of the outcome is verified. That is because each company has different needs, as aforementioned, and this impacts all steps of such interventions, namely the design, the evaluation and the results.

The effectiveness of these training interventions must be considered in a multifold way. Technological and social skills, as well as the mentality change, contributed to broader organizational improvements. In fact, the training systems studied did not only deliver content, but they also helped in cultural change.

Also, in general, the methodological framework and findings presented herein offer a foundation for evidence-based policy development, supporting the scalable implementation of human-centric and strategically aligned training systems under the Industry 5.0 paradigm. However, the templates of both the interventions' design and evaluation need to be updated, i.e., with education-related technologies. This exceeds, however, the purposes of the current work.

In the near future, various critical developments seem to be necessary to enhance the value and scalability of Industry 5.0-aligned training. First, standardized assessment instruments (with respect to both formative and summative evaluation) towards determining the precise magnitude of training outcomes could be employed. Second, the interaction of various stakeholders, such as public–private partnerships, vocational education, training centers, and authorities is expected to boost the transformation in all types of companies.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A Trainee Questionnaires per Company

Table A1 summarizes the questionnaires per case and the classification of the questions per Industry 5.0 pillar. It is noted that in the case where the characterization is "General", the questions have to do with the company itself and/or the technologies applied. Also, in the case of C6, the questions are of mixed type, as the questions are pertaining to more than one topic., i.e., the problem-solving capacity is related to environmental topics-related optimization.

These questionnaires represent the instruments used to gather data from trainees in each company. They form the empirical basis for measuring upskilling, with Table A1 showing how the resulting questions were classified against the Industry 5.0 pillars. The overarching research questions (RQ1–RQ3) are addressed at a higher analytical level, using the evaluation framework to interpret the data rather than being identical to the questionnaires themselves.

Table A1. The upskilling questionnaires.

Case	Question	Characterization
C1	How informed are you about the technology subject of the course? How much do you think that the use of a robotic welding solution will have on your role as an operator, considering that the machine will do physical work? How much do you think that the implementation of this technology can improve the quality of the welding operations?	General
C1	How much do you feel prepared to deal with the introduction of this new, bombastic welding technology in your role as an operator? How much do you expect that your role as an operator will change with the introduction of modern technology for robotic welding? How important is it for you to have adequate training to manage and supervise the activity of the technological solution? How much do you think you have the skills necessary to adapt to the new role that the use of this modern technology for welding involves? How much do you think that collaboration with this modern technology will make your job more satisfying?	Human Centricity

Table A1. *Cont.*

Case	Question	Characterization
C1	How important is it to you that the welding technology is efficient from an energy perspective? How much do you think the use of a technological solution can help reduce material waste during welding, considering a change in the working process? How important is it for you that the robotic welding technology contributes to creating a safer work environment?	Sustainability
C1	How much do you think that the introduction of a technology for robotic welding can make the production process more robust in the face of unexpected events (e.g. lack of qualified personnel, ergonomic problems, . . .)? How important is it to you that the technological solution is designed to be easy to use, maintain, and repairable in case of problems? How much do you think this technology can improve the continuity of welding operations?	Resilience
C2 and C3	Do you have an idea about why people disengage in the company? Do you have an idea of what criteria to use as a guide for implementing human-centric initiatives? Do you know the organisational practices that can help develop a more human-centric organisation? Do you feel you have more knowledge about HOW to digitise/implement a modern technology?	Human Centricity
C2 and C3	Do you know how to improve organisational flexibility (performance) while achieving a more human-centric organisation?	Resilience
C2 and C3	Once digitised, do you feel confident using production optimisation to improve environmental sustainability? Do you feel confident using production optimisation to improve waste reduction?	Sustainability
C4	Do you feel confident in solving problems during the manufacturing process? Do you feel confident in using shared control between human and machine?	Human Centricity
C4	Do you feel confident in working on multiple projects simultaneously? Do you feel confident in working in different areas of the company?	Resilience
C4	Do you rate the new organisation setup more fulfilling than before? Do you feel that the organisation setup helps you in making your decision-making process better (communication interface, hardware/software tools, empowerment?	Sustainability
C5	I am familiar with 3 main values of the Company I know what is "Y" information system and how to use it in practice	General
C5	I know how to behave in the workplace in compliance with ESD safety I understand how to identify the direction of an electronic component I feel confident when working in different working areas (operations) in the company I feel confident when communicating problems to other team members/supervisors	Human Centricity
C5	I understand the principles of lean methodology (5S principles) I know how to sort hazardous production waste I feel confident and I know how to sort waste in my daily routine	Sustainability
C5	I know what is "X" information system and how to use it in practice I know "IT security standards" in the company and understand their importance I understand the meaning and importance of production documentation (product assembly instruction)	Resilience
C6	Do you feel confident in solving problems during the manufacturing process?	Sustainability, Human Centricity
C6	Do you feel confident in using shared control between human and machine?	Resilience, Human Centricity
C6	Do you feel confident in working in different project at the same time?	Resilience, Human Centricity
C6	Do you feel confident in working in different working areas in the company?	Resilience, Human Centricity

Appendix B Network Meta-Analysis

To further evaluate the added value of experiential learning in Industry 5.0-aligned training environments, an additional meta-analytical approach was employed. Despite the heterogeneity of the individual studies, they were structured into a connected network of comparisons, as shown in the diagram (Figure A1). Here, various training settings—including Teaching Factories (TF), Learning Factories (LF), and digital/experiential methods like TrL (traditional learning)—were treated as interventions to enable indirect and direct comparisons. Although these studies are based on different case scenarios and organizations, they are modeled as comparable. This approach allows for the aggregation of evidence on learning effectiveness across diverse implementations, offering a systematic way to assess whether experiential modalities provide a significant advantage over other formats. This concept of "dummy study" was established earlier in the literature [15]. The network setup (Figure A1, left) thus ensures that even in the absence of traditional control groups, the interconnected structure supports valid inference and the exploration of consistent patterns.

Next, to evaluate the overall effectiveness of experiential learning methods, the various interventions were grouped according to their methodological framework—specifically Learning Factory (LF) and Teaching Factory (TF)—and compared against a common reference category, namely the traditional learning approach. As illustrated in the network diagram (Figure A1, right), multiple studies provided comparisons to the reference, with two studies comparing LF to TrL and 5 studies comparing TF to TrL.

The corresponding forest plot of Figure A2 summarizes the meta-analytic findings, indicating a mean difference (MD) of 0.94 [95% CI: 0.14, 1.73] for LF and 0.82 [95% CI: 0.28, 1.36] for TF relative to TrL. These statistically significant results suggest that both LF and TF formats yield superior upskilling outcomes compared to traditional TrL interventions. This provides robust evidence supporting the integration of experiential learning models in Industry 5.0-aligned training strategies.

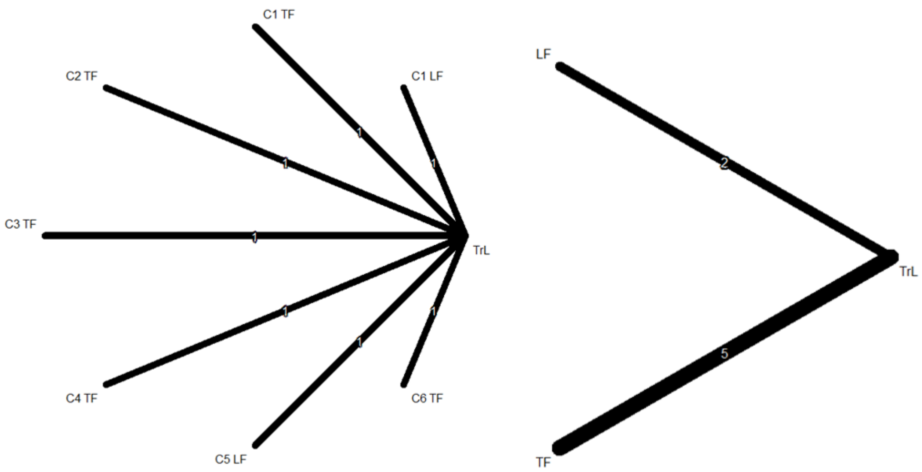

Figure A1. Network graphs used in network meta-analysis: comparing everything to TrL in terms of a one 7-arm study (**left**) and a grouping (**right**).

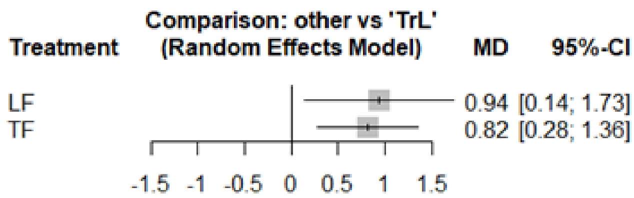

Figure A2. Network meta-analysis results: impact of LF and TF compared to TrL.

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