Strategic Coherence and AI-Enabled Personalization: Drivers of Motivation in Corporate Learning

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Abstract: As corporations expand globally, corporate training practices evolve in parallel, raising an urgent question: how can individual development pathways be designed to better align L&D strategy with corporate goals for the benefit of both employees and the organization? Recent bibliometric work on organizational change confirms that the misalignment between strategy and learning remains a critical barrier to sustained innovation readiness. Moreover, L&D managers are not yet able to deal with the lack of time and staff engagement (42% and 41% as the main barriers, respectively). There is a large gap in the study of motivation in corporate learning: most articles consider either learning in schools or universities or the technical aspect of technology implementation in corporate learning. This study investigates four potential drivers of motivation – content personalization, environmental dynamism, AI adoption, and strategic coherence. All these factors affect staff, and some of them relate directly to personalized learning strategies. Artificial-intelligence–enabled tutors and chatbots are already tailoring learning paths in real time, mirroring patterns observed in higher-education AI diffusion. Guided by Self-Determination Theory, we formulate hypotheses linking each driver to specific dimensions of motivation. We will survey employees of large firms who have recently completed corporate training programmes with the help of an author's questionnaire. Our research closes an important gap in understanding employee motivation within corporate learning and provides a springboard for future investigations into additional motivational antecedents. Based on the findings, we will offer actionable recommendations for embedding these drivers in learning and development strategies. When applied effectively, these insights can help organizations optimize training through higher employee motivation.

Keywords: Corporate Learning, Learning and Development Management; Content Personalization, Strategic Coherence

1. Introduction

Individual learning strategies are gaining popularity. Currently, L&D managers are the main developers of individual learning strategies in organizations. Modern L&D managers face serious challenges in staff training. Nowadays, a “skill gap” could be found worldwide in modern companies (Buckley & Castro Jorge, 2024) which leads to lack of staff training (Braun et al., 2024). A less visible but equally powerful obstacle stems from employees’ informal networks that can silently block new initiatives (Aksiutin et al., 2022; Bagrationi et al., 2021, 2022). Nowadays, the effectiveness of staff in the workplace directly depends on the quality of L&D management in an organization, so the question arises of how L&D managers can improve development strategies and develop new approaches to training (Garavan, 2023).

It is worth noting that the functions of L&D managers are not only about learning functions, but also about strategic staff management (Garavan et al., 2020). Due to digital transformation, such managers should be able to react quickly to changes, adapt new technologies, and be able to anticipate labor market movements (Tewari & Pant, 2020). Change-oriented leadership behaviours have proved decisive when entire units transition to strategic autonomy (Diakova et al., 2024), underscoring the human side of L&D governance. Analytical thinking and the ability to work with data are also highly appreciated (Bhatt & Muduli, 2022).

In modern world, there are many factors that influence employee motivation in corporate training, and an L&D manager must take them all into account for training to be beneficial (Garavan et al., 2020). In addition to factors that are not directly related to learning, such as the rapidly changing external environment or organizational stocks in the company, there are technologies that can be used in training (Bisht et al., 2025). This is how L&D managers can use artificial intelligence or content personalization to increase employee motivation during the learning process (Bisht et al., 2025). Scenarios work on corporate universities further shows that content-personalisation pressures intensify as firms compete with external course providers (Zinchenko et al., 2024). Such foresight findings signal that motivation drivers cannot be decoupled from institutional learning formats.

The purpose of the study is to analyze the influence of several factors such as strategic coherence, content personalization, AI technologies, dynamic organizational abilities, etc. on different scales of staff motivation in corporate training, as well as to form recommendations for L&D managers on the implementation of technology in training strategies.

2. Literature Review

Most of the research around personalization of content and AI technologies in corporate training focuses on results and technical aspects. This study will fill a gap in the field of the impact of AI and personalization on employee motivation through the prism of Self-Determination Theory.

Some scientific articles indicate the need for new research to identify the elements of personalized learning strategies and their impact on motivation:

"Future research should consider larger and more diverse samples to further explore the impact of personalization. Additionally, long-term studies that examine the sustainability and effectiveness of personalization in adaptive learning environments would provide valuable insights." (Graf, A., 2023, P. 53)

"… future research should use a more representative sampling strategy and a longitudinal design to track improvements. Expanding the study to include other countries and academic disciplines would help explain AI's effect on intrinsic motivation." (Mohamed et al., 2025, P. 604)

Currently, the influence of AI on motivation is widely studied in various fields. The 2024 study showed that statistically, the introduction of AI into the learning process has a positive effect on student engagement. Thanks to the introduction of ChatGPT, students' motivation has increased, as they can now receive personalized feedback in the educational process (Ahmed et al., 2025). Another study analyzes the impact of AI on the motivation and academic performance of university students (Pertiwi et al., 2024). In addition to the positive association, some risks associated with a decrease in independence and the development of "cognitive laziness" in students were identified (Karamuk, 2025).

Content personalization technologies can include comprehensive user data collection, student profile formation, adaptive recommendation systems, and more. As a rule, all these technologies are integrated into one system: for example, a repository of educational facilities with a built-in adaptation mechanism that creates customized content based on experience (Su et al., 2011). There are also systems that, along with personalization, use elements of ontology and machine learning to account for a larger number of learner parameters (Raj & Renumol, 2022). In corporate training, the introduction of personalization significantly increases the comfort of employees, as it allows them to be flexible: to adjust the convenient time and method of presentation of the material. The combination of content relevance and individual development of point competencies significantly increases the effectiveness of training in an organization (Chunaev & Shikov, 2018).

In addition to AI and personalization of content in training, many studies identify other factors that could potentially be related to employee motivation in corporate training. For example, such a factor as "dynamic and contextual changes" is singled out as promising in the context of corporate training: *"Consideration of the dynamic and contextual influences on trainees provides an avenue for future research aimed at explaining transfer motivation in constantly changing workplaces."* (Gegenfurtner et al., 2009, P. 412)

Another additional factor is the strategic orientation and resources of the organization. The latest research notes: *"Future research should explore the optimal strategies used by industries that have successfully implemented training and development initiatives."* (Lee, Z., 2025, P. 2)

Thus, there are a few factors that could potentially be related to employee motivation in corporate training. Within this article the roles of these factors will be evaluated, thereby filling the existing gap in research by offering a fundamentally new approach based on the Self-Determination Theory (SDT) (Deci & Ryan, 2012).

3. Methodology

SDT was chosen as the methodological framework for the study. This theory primarily focuses on factors influencing employee expectations. SDT is already actively used as a basis for assessing employee motivation (Gagné, M. et al., 2015), as well as in the context of personalized learning strategies (Alamri, H. A., 2019). Due to its use in some studies related to learning, it can be argued that SDT has established itself as a theory that meets the business context, so its use in work is quite relevant.

At the first stage of the work, potential factors that can influence employee motivation in corporate training were found and selected. The scientific literature was studied and the factors for which the connection with motivation is still poorly understood were selected.

To collect data as part of the analysis of the role of factors influencing motivation for corporate training within the framework of the company's strategy, an author's questionnaire was developed to combine existing methods to assess the impact of factors on motivation in corporate training. The questionnaire includes the following factors with subscales, which are represented on Figure 1.

Factor / Scale	Sub-scale	Reference
Strategic Coherence	Vertical fit Horizontal fit Learning alignment	Based on Lusiani & Langley, 2019
Strategic Orientation	Exploration Exploitation Contextual ambidexterity	Based on Lubatkin et al., 2006
Environmental Dynamism	Speed Unpredictability	Based on Green et al., 2008
Slack Resources	Financial resources Operational resources Human resources Time resources	Adapted based on Nohria & Gulati, 1996 and Voss et al., 2008
Dynamic Capabilities	Sensing Seizing Transforming	Based on Kump et al., 2019
Key Financial Indicators	Cash Flow ROE Gross margin Operational income Net profit margin ROI	Covin et al., 1990 Gupta and Govindarajan, 1984
Content Personalization	Differences in learning styles and preferences Consideration of knowledge levels and competence gaps Automatic or intelligent routing of learning Flexibility in content generation (dynamic resource assembly) Content customization based on feedback	Su et al., 2011 Raj & Renumol, 2021 Garrido & Morales, 2014 Türker et al., 2006
AI	Automatic student profile building and individual assistance based on student behavior The dependence of "personalized" systems on average models Adaptive learning using ITS Personalized retrieval practice based on AI tutors Using AI to automatically create personalized microlearning	Schiaffino et al., 2008 Holmes et al, 2019 Ma et al., 2014 Baillifard et al., 2023
WPI Motivation Scale	Intrinsic motivation Extrinsic motivation Job satisfaction Complexity of the work Focus on the external environment Compensation for work	Amabile at al., 1994

Figure 1: Scales and sub-scales for the author's questionnaire, the Likert scale (1-7) was employed.

At the second stage of the work, a survey was conducted among 72 employees of companies in various fields (from IT to retail, Table 1 summarizes the key demographic characteristics of the sample) who have been/are undergoing corporate training over the past year. To compile the questionnaire, the author's questionnaire was compiled, which included factors of AI, content personalization, etc., as well as an adapted questionnaire "Diagnostics of internal and external staff motivation" by T. Amabile (WPI). To confirm the reliability of the questionnaire, the Cronbach's Alpha was calculated and evaluated for each scale.

Table 1: Summary of Participant Demographics (N = 72)

Characteristic	Distribution
Gender	55.6% Female (N = 40); 44.4% Male (N = 32)
Age Group	51.4% aged 18–25; 29.2% aged 26–35; 16.7% aged 36–45; 2.8% aged 46–55
Education Level	University-educated (Bachelor's or higher)
Industry	~26% IT; 24% Banking/Finance; 14% Retail; 8% FMCG; 4% Telecom; 3% Consulting; 3% Manufacturing; 3% Education; 19% other industries (various)
Company Size	Predominantly large enterprises (most > 250 employees; many in well-known large firms)
Training Type	Varied corporate training programs in the last year (technical courses, management training, etc.)

To evaluate the adequacy of the sample size (N=72), a post-hoc power analysis was conducted. This analysis indicated that our sample of 72 participants provides approximately 99,6% power to detect a medium effect size ($f^2 \approx 0.429$) at the $\alpha = 0.05$ significance level. In other words, the study has a high power to detect moderate-sized effects in the data. This indicates that the sample size is sufficient for the initial analysis, as it eliminates the possibility of a type II error due to insufficient sample size. We therefore consider the statistical power acceptable for the scope of this research.

Further, to assess the quality of the data and identify key relationships, a correlation and then regression analysis was performed, which allowed us to evaluate the relationships between variables based on a mathematical model. To identify additional relationships, mediation (intermediary variables) and moderation (variable amplifiers) were analyzed. All models are built using the Jamovi app.

In the final part, recommendations are formed based on the results of the study based on the literature. In addition to the recommendations, an algorithm for the implementation of artificial intelligence technologies in corporate training of companies was proposed, as well as the area of further research was identified.

4. Results

In order to assess how certain factors affect motivation, we will build a linear regression. It will allow us to find out which scales have the strongest influence and to what extent this influence is statistically significant. To assess the strength of the influence, we calculate a standard estimate (β-coefficient), and for statistical significance, a p–value and a 95% confidence interval.

As a result of the regression analysis, the strongest and most statistically significant predictors were identified, which are shown on Figure 2.

Dependent Variable	Predictor	p-value	Stand. Estimate	95% Confidence Interval	
				Lower	Upper
INTR	DC Sensing	0.001	0.6718	0.2742	1.0693
EXTR	ED	0.010	0.4251	0.107	0.743
EXTR	AI Retrieval	0.116	0.5021	-0.129	1.133
ORIENT	ED	0.004	0.4572	0.1577	0.757
ORIENT	AI Retrieval	0.064	0.5595	-0.0343	1.153
COMPLEX	DC Sensing	<.001	0.77926	0.3399	1.2186
COMPLEX	AI Profile	0.050	0.48045	9.88e-4	0.9599

Figure 2: The strongest predictors in the constructed linear regression

Notably, the effect sizes of these key predictors were substantial. Several factors exhibited high β-coefficients (exceeding 0.5), indicating not just statistical significance but also a practically significant impact on motivation outcomes. For instance, the dynamic capability of sensing new opportunities had β ≈ 0.67 in predicting intrinsic motivation – a magnitude that qualifies as a large effect in behavioral research terms. Such a large standardized coefficient suggests that improvements in this predictor variable would translate into meaningful, real-world increases in employees' motivation, rather than trivial changes. Overall, the regression results imply that the identified drivers (e.g., environmental dynamism, dynamic capabilities, etc.) are not only statistically reliable but also practically important influences on corporate learning motivation.

AI Retrieval has high values of the β coefficient, but it is not very significant, so it is impossible to say for sure how accurate this factor is as a predictor for external motivation and orientation to the external environment.

Next analysis will be the analysis of mediation (mediation effects). This analysis answers the question "through which variable does a factor influence a certain component of motivation". In other words, an intermediate variable is identified through which the influence is enhanced/weakened. The Bootstrap method (1000 samples) was chosen as the SE – standard errors estimation method. 1000 random samples will be taken from the data, which is quite relevant for analyzing a relatively small sample without assuming a normal distribution. The relationships will also be evaluated by the value of the coefficient of influence (>0.3 is considered high), and the statistical significance by the p-value and 95% confidence interval. The results of the analysis are shown on Figure 3.

				95% Confidence Interval		
Dependent Variable	Predictor	Mediator	Estimate	Lower	Upper	p-value
COMPLEX	Vertical fit	INTR	0.4542	0.252	0.726	<.001
COMPLEX	Horizontal fit	INTR	0.515	0.2849	0.7712	<.001
COMPLEX	Exploitation	INTR	0.431	0.1979	0.7544	0.002
COMPLEX	DC Sensing	INTR	0.5253	0.343	0.706	<.001
COMPLEX	DC Seizing	INTR	0.329	0.192	0.497	<.001
SAT	DC Sensing	INTR	0.3806	0.247	0.5388	<.001

Figure 3: The strongest mediators in the constructed model

The last analysis that will be conducted is a moderation analysis. The so-called conditional variables that strengthen/weaken the connection will be identified here. In this analysis, the same standard error estimation method (Bootstrap (1000 samples)) will be used, and connections will be evaluated by the value of the interaction coefficient. Its essence is to assess how much influence of some factors on motivation changes when the moderator's level increases by 1 standard deviation. Let's assume that a value >0.2 indicates a strong moderation, and values >0.15 indicate a moderately strong one. The results are shown on Figure 4.

				95% Confidence Interval		
Dependent Variable	Predictor	Moderator	Estimate	Lower	Upper	p-value
EXTR	Exploration	CP Plan	0.2057	0.11571	0.340	<.001
ORIENT	Exploration	CP Plan	0.2473	0.1239	0.412	<.001
SAT	ED	AI Model	0.1655	0.02724	0.294	0.014
ORIENT	DC Transformation	CP Know	0.1516	0.0421	0.292	0.013
ORIENT	Exploitation	CP Plan	0.1590	0.0504	0.270	0.004
ORIENT	Exploration	CP Know	0.1774	0.0544	0.434	0.068
ORIENT	Exploration	CP Feedback	0.1749	0.0100	0.4372	0.099
INTR	ED	CP Feedback	0.1534	-0.01932	0.262	0.025

Figure 4: The strongest moderators in the constructed model

It is worth noting that in all relationships (both strong and moderate), the values of the interaction coefficient are higher than the beta coefficient of direct influence which highlights that all the dedicated moderators strengthen the existing connections.

To summarize, it can be claimed that the presence of content personalization enhances the influence of many factors on many “motivation” scales (mainly related to external motivation). Intrinsic motivation serves as an excellent mediator for many factors (strategic coherence, exploitation orientation, and dynamic abilities). In other words, in the presence of these factors, employees in the organization are motivated to learn (intrinsic motivation), and work tasks are perceived as more complex (COMPLEX), or work pleasure increases (SAT). In general, the dynamism of the environment, the dynamic abilities of the organization, and several artificial intelligence technologies showed the strongest direct links to different components of motivation.

As a result, the scientific novelty of the work was reduced to the formation of a chain of strategic coherence (consistency and ambidextrity), dynamic capabilities of the company and AI/personalization technologies. Such a chain seems to be critically important to transfer employee motivation from the "need" category to the "want" mode. Thus, a synthesis of strategic and technological drivers of motivation is obtained, which makes it possible to expand the theory of SDT and transfer it to the L&D context. This paper closes a gap in recent research (Graf 2023), as it provides real data on the impact of technology on employee motivation, rather than on dry educational outcomes.

5. Discussion and Conclusion

Based on the results of the analysis and modern scientific research, a few recommendations can be proposed to increase employee motivation for corporate training.

To maximize impact, companies should ensure strategic coherence of their training programs. Empirical research underscores that learning initiatives that are tightly integrated with business strategy tend to be significantly more effective than ad hoc or disconnected efforts (Garavan, 2007; Tannenbaum et al., 2010). L&D managers should closely link training programs to the company's business strategy and current objectives. According to Garavan (2020) corporate personnel development programs today often lack correlation with strategic goals, which reduces their effectiveness. For instance, research highlights that aligning learning initiatives with key strategic competencies remains a persistent challenge for many organizations and is cited as a critical success factor for improving learning transfer and organizational performance (Blume et al., 2010; Salas et al., 2012).

Secondly, it is essential to develop the dynamic capabilities of the organization and establish the culture of continuous learning. The results of the study showed that the internal motivation of employees is significantly influenced by the company's ability to discover and master new opportunities (DC Sensing) (β=0.67, $p<0.01$). This, to foster improvement, L&D managers should implement practices that stimulate organizational learning and innovation. These may include knowledge-sharing initiatives, internal innovation hackathons, and cross-functional research projects targeting emerging technologies and best practices (Eisenhardt & Martin, 2000). Empirical studies have shown that organizations encouraging knowledge exchange and employee-driven innovation benefit from increased organizational learning and individual motivation (Vera & Crossan, 2004). This resonates with the bibliometric trend that forward-looking universities – and by analogy, corporate universities – leverage AI to shorten the path from insight to skill (Gordienko & Bagrationi, 2024).

Finally, organizations should personalize the training content to meet the needs of employees. Although in our study, indicators of personalization did not become unambiguous predictors of motivation, numerous studies have noted the positive effect of an individualized approach (Su et al., 2011; Chunaev & Shikov, 2018). . Adaptive learning systems that customize content based on learner profiles have been shown to improve engagement, satisfaction, and learning outcomes (Mirari, 2022).

Research has also shown that artificial intelligence technologies have significant potential to increase motivation and learning effectiveness (Zawacki-Richter et al., 2019). Based on the analysis of literature and practical recommendations of experts, it is possible to identify the stages of the implementation of AI initiatives in the education and development system:

Firstly, it is critical to ensure that the deployment of AI tools aligns with the organization’s strategic priorities and addresses specific skill gaps (Khaustova & Riabokin, 2024). By focusing on business goals (reducing training time, increasing sales through knowledge, etc.), L&D managers ensure the semantic value of the project and receive management support. At the same stage, the following resources are evaluated: financial (budget for

software/development), technical (infrastructure, data for training algorithms) and human (competences of the L&D and IT teams).

Secondly, a suitable AI solution should be selected and tested through a controlled pilot project with a small group of employees. The pilot project allows you to collect feedback, test the effectiveness of the tool and identify potential problems on a small scale. It is critically important at this stage to actively involve employees and managers themselves in the process: explain to them the advantages of the new approach, conduct training on using the AI tool, and address questions and concerns (Bond et al., 2021).

Thirdly, upon demonstrating positive pilot outcomes, the AI tool can be scaled to larger cohorts and integrated with existing learning ecosystems such as Learning Management Systems (LMS) and Human Resource Information Systems (HRIS).

Finally, post-implementation, systematic evaluation should compare pre- and post-AI integration metrics (e.g., learning engagement rates, skill acquisition benchmarks) to assess effectiveness (Baker et al., 2019). Based on the evaluation of the results, a decision is made to correct the strategy: it may be necessary to expand the functionality (for example, add a gamification module to increase motivation), or vice versa, to abandon some functions if they turn out to be unclaimed. It is important that the introduction of AI is not a one–time project, but an ongoing process: technologies are developing rapidly, and L&D managers should monitor new opportunities (for example, generative models for content creation, VR/AR for immersive learning) and test them on a separate group before scaling (Roll & Wylie, 2016; Zawacki-Richter et al., 2019).

Beyond practical recommendations, our findings also help expand Self-Determination Theory (SDT) into the corporate learning field. According to SDT, motivation improves when people feel competent, connected to others, and free to make their own choices (Deci & Ryan, 2012). Our results show that organizational factors — such as how well training aligns with company strategy — can support these needs. For example, when training clearly reflects strategic goals, employees are more likely to see it as meaningful and valuable, which in turn boosts their intrinsic motivation.

We also found that combining strategic elements (like strategic coherence) with personalized, AI-based learning tools helps shift motivation from “I have to learn” toward “I want to learn.” This transition from extrinsic to intrinsic motivation reflects a deeper internalization of learning goals — something SDT highlights as crucial. One example is the strong effect of the company’s ability to sense new opportunities, which showed a high positive link with intrinsic motivation. While personalization alone wasn’t the strongest predictor, it still plays a supporting role by giving learners more control — which helps meet their need for autonomy.

Overall, this study shows that SDT can be applied not only at the individual level but also in organizational settings, where strategic and technological factors shape motivation in meaningful ways.

Finally, the effect sizes we observed were not just statistically significant — they were large enough to matter in practice. Some predictors had beta values around 0.6–0.7, which suggests that acting on these drivers can lead to real improvements in employee motivation. This gives L&D professionals a strong evidence base for investing in strategic coherence when designing training programs.

Ethical Declarations

Ethical clearance was not required for the research

AI Declarations

AI (ChatGPT o3) was used to enhance language quality

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