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The Influence of Training and Digital Culture on The Capabilities of Developer Talent: A Case Study of PT.XYZ

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Abstract

This study investigates the influence of training and digital culture on developer talent capabilities at PT. XYZ, focusing on *Chapter DEV* as part of the company's digital transformation strategy. Specifically, it examines the individual and combined effects of training and digital culture in enhancing developer capabilities. Utilizing a quantitative research design, data was collected from 185 randomly selected developers out of a total of 344 trained employees through a structured online questionnaire. Data analysis was conducted using Structural Equation Modeling–Partial Least Squares (*SEM-PLS*) with SmartPLS 4 software. The analysis included outer and inner model evaluations as well as hypothesis testing. Training was found to positively and significantly affect capability ($\beta = 0.217$; $p = 0.013$), although the influence was moderate. In contrast, digital culture exerted a stronger and more significant effect ($\beta = 0.725$; $p = 0.000$) with a large effect size ($f^2 = 0.415$). This research contributes to the literature on digital capability development within agile organizations by highlighting the pivotal role of digital culture in amplifying the impact of training. The findings suggest that, while training remains essential, a strong organizational digital culture acts as a catalyst that facilitates the absorption and application of newly acquired skills. This challenges conventional assumptions that prioritize training alone and provides practical implications for talent development strategies in digitally transforming enterprises.

Keywords: training; digital culture; developer capability; digital transformation

INTRODUCTION

In the era of rapid technological advancement, digital transformation has emerged as a cornerstone of competitive advantage across industries (Wibisono & Supoyo, 2023). Defined as the organizational shift driven by the integration of digital technologies such as artificial intelligence (AI), cloud computing, and data analytics, digital transformation fundamentally alters operational models, strategic orientations, and talent management frameworks (Vanthienen, 2019). To fully leverage these technological investments, organizations must cultivate a workforce equipped with the requisite digital competencies (Rocha et al., 2023), as digital transformation is no longer optional but essential for competitiveness and long-term sustainability in the contemporary business landscape (Loonam et al., 2018).

The telecommunications industry exemplifies this imperative, facing significant disruption from *over-the-top (OTT)* applications that have eroded traditional revenue streams. Consequently, telecom companies worldwide, including those in emerging markets, must strategically invest in new technologies, reskill their workforce, and adopt innovative business models (Fahmi et al., 2020). Within this dynamic environment, developing highly capable digital talent, particularly developers, is a critical challenge. PT. XYZ, a leading telecommunications company in Indonesia, is undergoing a strategic shift towards becoming a digital service provider, evidenced by its dedicated Digital Business Directorate and substantial focus on digital product development. A central challenge in this transition is nurturing digital talent across various skill sets, including software development, data analytics, and cloud computing (Amping et al., 2019).

Despite substantial investments in training infrastructure and the strategic expansion of learning programs, internal analytics from PT. XYZ indicate a paradoxical trend: the proportion of unique developer talent actively participating in these training initiatives has declined over time. Although the absolute volume of training sessions and total learner enrollments has increased—evidenced by a 123% rise in training programs between 2023 and 2024—this growth has not translated into broader talent engagement. Specifically, participation among individual developers decreased by 7.7%, suggesting that barriers such as scheduling conflicts, limited awareness, or insufficient alignment between training content and role-specific needs may be inhibiting more inclusive learning uptake.

Compounding this issue is the stagnation observed in technical competency outcomes. PT. XYZ utilizes a structured assessment system, including T-scores derived from standardized online testing and peer interviews, to evaluate developer proficiency. Despite minor year-over-year improvements, the majority of developers continue to cluster within the “average” competency tier, with relatively few advancing to “good” or “excellent” categories. This stagnation reflects a critical gap between training availability and its effective utilization or impact, pointing to the need for more targeted, adaptive, and performance-oriented upskilling strategies.

Beyond the technical dimension, successful digital transformation requires a dual focus on both technological and managerial capabilities. As emphasized by Gerster (2018), effective implementation depends on a shift in organizational norms and greater adaptability to change. Digital culture—reflecting how technology and the internet influence human behavior, communication, and interaction—plays a critical role in this process. When embedded within the company, digital culture supports a shift in mindset toward more effective and agile ways of working and is one of the most influential enablers of digital transformation. Clarke (2017) found that the success of digital transformation initiatives is closely linked to the maturity of an organization’s digital culture and digital capabilities.

While PT. XYZ has institutionalized core values like *AKHLAK* to guide corporate culture, internal evaluations reveal uneven activation of these values within the digital division, particularly in areas such as cybersecurity awareness, learning programs, and cross-functional collaboration. This suggests a disconnect between strategic cultural initiatives and their practical implementation, posing a significant hurdle to enhancing digital capabilities. Data from the Culture Monitoring System (CMS) as of December 2024 highlight uneven engagement across key *AKHLAK* dimensions. While *Amanah* achieved relatively strong scores in leader-driven initiatives such as project documentation and customer experience, core competencies such as cybersecurity, adaptivity, and collaboration received scores as low as 2.5%, 1.0%, and 1.8%, respectively.

Prior literature has thoroughly examined the significance of digital transformation and the need for robust digital capabilities (e.g., Rocha et al., 2023; Vanthienen, 2019). Furthermore, existing studies have underscored the role of training in improving individual and organizational performance (Flegl et al., 2022), as well as the pivotal influence of digital culture on transformation initiatives (Clarke, 2018; Manyika et al., 2017). Fahmi et al. (2020)

introduced a Digital Talent Capability Model, which emphasizes the foundational roles of digital literacy, organizational culture, and adaptability. However, a substantial gap remains in understanding the interplay and combined impact of formal training interventions and digital culture on the capabilities of developer talent in large telecommunications firms undergoing significant digital transformation. While the importance of both training and culture is widely acknowledged, their synergistic effects on enhancing developer capability—particularly in addressing specific developmental challenges faced by organizations such as PT. XYZ—are still insufficiently explored.

In the era of rapid digital transformation, organizations across industries are prioritizing the development of digital talent to maintain competitiveness, yet a critical gap remains in understanding how training and digital culture collectively influence developer capabilities. While existing studies highlight the individual importance of training programs and organizational culture in skill development, few explore their synergistic effects, particularly in large telecommunications firms undergoing significant digital shifts. PT. XYZ, a leading Indonesian telecom company, exemplifies this challenge, as internal data reveal declining developer participation in training programs and stagnant competency outcomes despite increased investments.

This study addresses the gap by examining the interplay between training and digital culture, offering insights into how these factors jointly shape developer talent capabilities in agile organizational structures. The research novelty lies in its focus on PT. XYZ as a case study, providing empirical evidence on the relative impact of training and digital culture within a real-world digital transformation context, where cultural enablers like collaboration and agility are often overlooked in favor of technical upskilling.

The primary objective of this research is to analyze the individual and combined effects of training and digital culture on developer capabilities at PT. XYZ, with a focus on identifying strategies to optimize talent development in a digital-first environment. By achieving this objective, the study provides practical benefits for organizations seeking to enhance their digital talent strategies, such as aligning training programs with cultural initiatives like mentorship and agile workflows to maximize engagement and competency growth. The results underscore the need for a holistic approach, where investments in training are complemented by efforts to cultivate a digital culture that encourages continuous learning and collaboration.

For PT. XYZ and similar firms, these insights can inform policies to bridge the gap between training availability and its practical application, ultimately driving higher performance and innovation in digital product development. Beyond immediate organizational benefits, the study contributes to broader discourse on human capital development in the digital age, offering a replicable framework for future research across industries and organizational models.

This study aims to bridge this research gap by investigating the influence of training and digital culture on the capabilities of developer talent at PT. XYZ. Specifically, it seeks to: (1) analyze the influence of training on the capability development of developer talent at PT. XYZ[A1]; (2) examine the impact of digital culture on the enhancement of developer talent capabilities; and (3) identify the relationship between training and digital culture in strengthening the capabilities of developer talent at PT. XYZ. By addressing these objectives, this study offers novel insights into how structured training, complemented by a supportive digital culture, can collectively enhance developer capabilities. The findings will contribute theoretically by enriching the literature on digital capability development within agile organizational structures and practically by offering actionable guidance for organizations seeking to optimize their digital talent strategies, thereby enhancing competitiveness in a technologically advanced business environment.

METHOD

This study adopted a quantitative approach, utilizing a survey methodology to examine the influence of training and digital culture on developer talent capability at PT. XYZ. Data were gathered through an online questionnaire distributed to employees in the *DEV Chapter* who had attended at least one formal training program. The research design was cross-sectional, with data collected at a single point in time and without researcher intervention.

Stratified random sampling was employed to account for the heterogeneous nature of the population, with strata defined by developer level (basic, junior, middle, and senior). The total population consisted of 344 developers as of November 2024. Applying Slovin's formula with a 5% margin of error yielded a required minimum sample size of 185 respondents. The survey was disseminated via internal communication[A1] channels, including the company's official email and group messaging platforms. Throughout the data collection period, 185 valid responses were obtained. Initial screening confirmed that all responses met the inclusion criteria and that there were no significant outliers or missing data.

Demographic mapping of the 185 respondents was conducted using SmartPLS 4 software. Respondents were categorized based on gender, age range, work experience, developer stream, and developer level. The results showed that the respondent group was predominantly male (79%), with most individuals falling within the 20–30-year age range (62.16%). In terms of work experience, a majority of developers (51.89%) had 2–6 years of experience, while 42.16% had more than 6 years. Regarding professional roles, the largest proportions of respondents were Back End Developers (30.3%), Front End Developers (21.6%), and Software Quality Assurance (14.6%). At the professional level, junior and basic developers accounted for 54.59% and 27.57%, respectively, while only 2.16% were in senior positions.

Table 1. Respondent Demographics

Profile Classification	Category	Frequency	Percentage
Gender	Male	146	79.00%
	Female	39	21.00%
Age Range	20–30 years	115	62.16%
	31–40 years	65	35.14%
	41–50 years	5	2.70%
Work Experience	< 2 years	11	5.95%
	2 – <6 years	96	51.89%
	> 6 years	78	42.16%
Developer Stream	Back End Developer	56	30.30%
	Front End Developer	40	21.60%
	Software Quality Assurance	27	14.60%
	Mobile Developer	24	13.00%

Profile Classification	Category	Frequency	Percentage
	Others (Scrum, Architect, etc.)	38	20.50%
Developer Level	Basic	51	27.57%
	Junior	101	54.59%
	Middle	29	15.68%
	Senior	4	2.16%

Source: Primary Data (2025)

Measurement

Training was measured using indicators developed by Ganyang (2018), comprising 20 items structured into seven dimensions: *training needs analysis*, *curriculum*, *training participants*, *instructors*, *training implementation*, *training evaluation*, and *post-training follow-up*. These dimensions comprehensively assess the quality and effectiveness of training interventions received by developer talents.

Digital culture was measured using 21 items adapted from Buvat (2017), which reflect seven key attributes of a digitally oriented organizational culture: *innovation*, *data-driven decision-making*, *collaboration*, *open culture*, *digital-first mindset*, *agility and flexibility*, and *customer centricity*. These attributes are critical for organizations undergoing digital transformation and align with cultural enablers for innovation and adaptability.

Developer talent capability was assessed through a framework proposed by Kapil (2020), which includes 15 items distributed across five dimensions: *technical capability*, *experience*, *code constraints*, *bug-resistive ability*, and *learning adaptation*. These indicators were selected to capture both hard and soft skill competencies that define the performance and growth potential of software developers.

The measurement scale employed in this study was a 4-point Likert scale ranging from 1 (*Strongly Disagree*) to 4 (*Strongly Agree*). This scale was selected to capture ordinal-level responses while avoiding neutral options, thereby encouraging respondents to provide more definitive feedback. The use of a *forced-choice* format is consistent with recommended practices for Likert scale application in social science research.

RESULTS AND DISCUSSION

The data processing in this study was conducted using the Structural Equation Modelling–Partial Least Squares (SEM-PLS) method through SmartPLS 4 software. The analysis included outer and inner model evaluations as well as Hypothesis testing.

1. Outer Model

The outer model evaluation aims to confirm that the measurement model used as the standard instrument is both valid and reliable (Sugiyono, 2019). Data were gathered through questionnaires administered to respondents, then compiled and saved in CSV (Comma-Separated Values) format for further analysis. The validity and reliability results for all variables are summarized in Table 2. The findings show that all indicators for training, digital culture, and developer capability exceed the recommended SLF threshold of 0.5. Furthermore, the CR values for each dimension across all variables surpass 0.7, and the AVE values exceed 0.5. These results are consistent with Malhotra and Dash (2020), who note that AVE is a more stringent criterion than CR. Given that all CR values meet the required thresholds, the constructs can be considered to have achieved convergent validity. Overall, the findings confirm that the measurement model satisfies the criteria for both validity and reliability.

Table 2. Validity and Reliability Test Result

Variables	Indicators	Items	SLF	CR	CA	AVE	Conclusion
Training	Training Need Analysis	P1	0.798	0.968	0.968	0.607	Valid and Reliable
		P2	0.765				Valid and Reliable
		P3	0.774				Valid and Reliable
	Training Curriculum	P4	0.807				Valid and Reliable
		P5	0.722				Valid and Reliable
		P6	0.8				Valid and Reliable
	Training Participant	P7	0.754				Valid and Reliable
		P8	0.806				Valid and Reliable
		P9	0.798				Valid and Reliable
	Training Instructor	P10	0.81				Valid and Reliable
		P11	0.784				Valid and Reliable
		P12	0.776				Valid and Reliable
	training delivery	P13	0.749				Valid and Reliable
		P14	0.806				Valid and Reliable
		P15	0.759				Valid and Reliable
	Training Evaluation	P16	0.768				Valid and Reliable
		P17	0.763				Valid and Reliable
		P18	0.79				Valid and Reliable
	Training Follow up	P19	0.747				Valid and Reliable
		P20	0.778				Valid and Reliable
		P21	0.794				Valid and Reliable
Digital Culture	Innovation	B1	0.779	0.973	0.972	0.633	Valid and Reliable
		B2	0.801				Valid and Reliable
		B3	0.764				Valid and Reliable
	Data-Driven Making	B4	0.814				Valid and Reliable
		B5	0.811				Valid and Reliable
		B6	0.823				Valid and Reliable
	collaboration	B7	0.656				Not Valid
		B8	0.765				Valid and Reliable
		B9	0.839				Valid and Reliable
	open culture	B10	0.797				Valid and Reliable
		B11	0.781				Valid and Reliable
		B12	0.801				Valid and Reliable
	Digital First Mindset	B13	0.798				Valid and Reliable
		B14	0.801				Valid and Reliable
		B15	0.796				Valid and Reliable
		B16	0.803				Valid and Reliable
	Agility and Flexibility	B17	0.804				Valid and Reliable
		B18	0.781				Valid and Reliable
		B19	0.818				Valid and Reliable
	Customer Centricity	B20	0.82				Valid and Reliable
		B21	0.823				Valid and Reliable
		B22	0.805				Valid and Reliable
Developer Capability	Technical capability	K1	0.83	0.962	0.961	0.65	Valid and Reliable
		K2	0.776				Valid and Reliable
		K3	0.786				Valid and Reliable

Variables	Indicators	Items	SLF	CR	CA	AVE	Conclusion
	Experience	K4	0.768				Valid and Reliable
		K5	0.797				Valid and Reliable
		K6	0.814				Valid and Reliable
	Bug resistive	K7	0.823				Valid and Reliable
		K8	0.811				Valid and Reliable
		K9	0.817				Valid and Reliable
	Code Constraints	K10	0.849				Valid and Reliable
		K11	0.817				Valid and Reliable
	Learning Adoption	K12	0.845				Valid and Reliable
		K13	0.764				Valid and Reliable
		K14	0.794				Valid and Reliable
		K15	0.794				Valid and Reliable

Source: Primary Data (2025)

2. Inner Model

The inner or structural model evaluation in SEM-PLS is conducted to examine the relationships among latent variables as specified in the proposed hypotheses. This model reflects the influence of the independent constructs on the dependent variable (Sarstedt et al., 2022). Its assessment involves evaluating the strength and significance of these relationships by examining the coefficient of determination (R^2) and the effect size (f^2), as well as testing statistical significance through t-values obtained via the bootstrapping procedure (Ghozali, 2016).

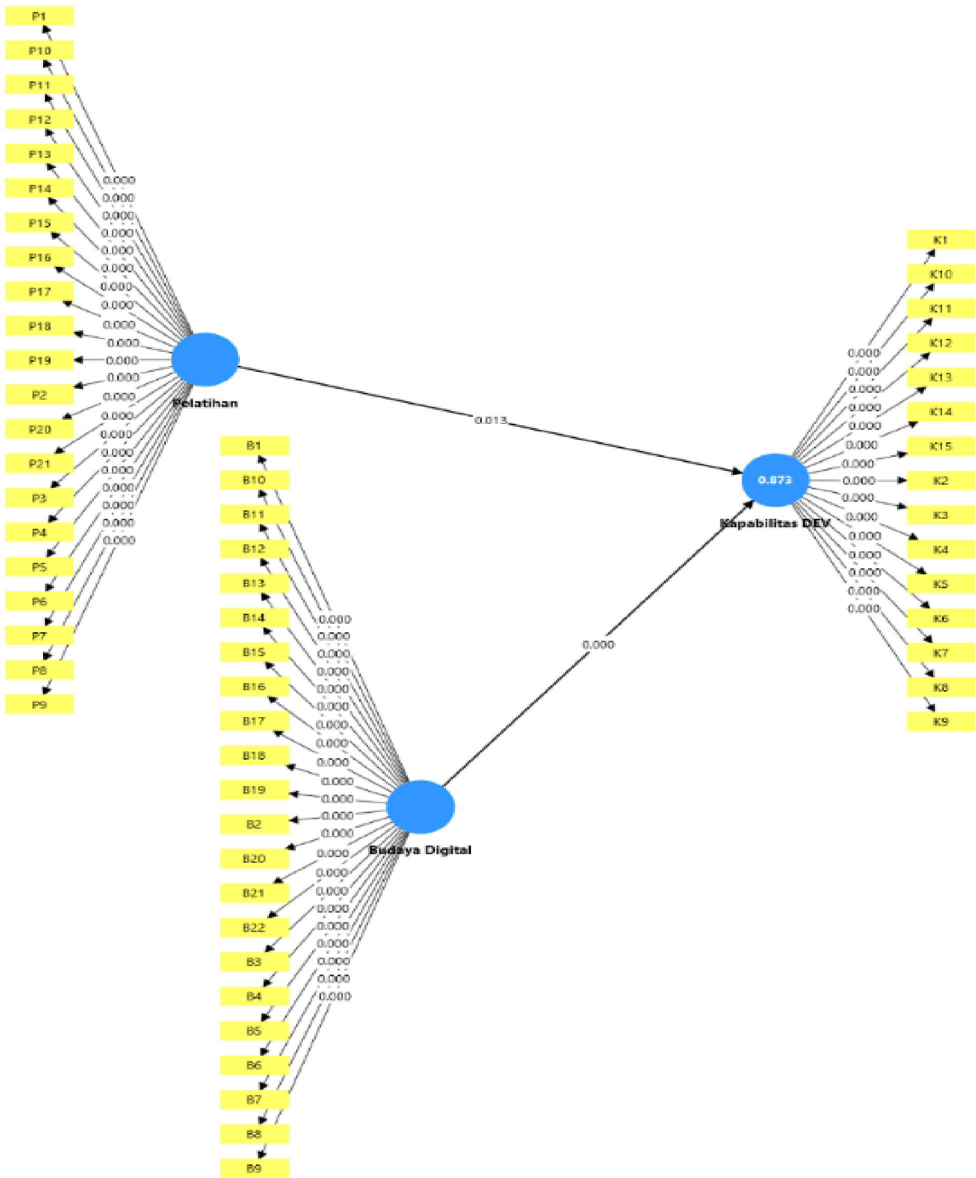

Fig. 1.T-value from structural model
Source: Primary Data (2025)

The coefficient of determination (R^2) reflects the proportion of variance in the dependent variable that is accounted for by the independent variables. Based on the criteria suggested by Hair et al. (2022), R^2 values of ≥ 0.75, ≥ 0.50, and ≥ 0.25 indicate strong, moderate, and weak explanatory power, respectively. In contrast, Ghozali (2021) recommends alternative thresholds, with $R^2 \geq 0.67$ considered strong, approximately 0.33 as moderate, and approximately 0.19 as weak. In general, a higher R^2 value implies greater predictive accuracy of the model, although its practical significance depends on the specific research context. The results of the R-square and adjusted R-square analyses obtained using SmartPLS 4 are presented in the table below:

Table 3. Coefficient of Determination (R^2)

Construct	R-square	R-square adjusted
Developer Capability	0.873	0.871

Source: Primary Data (2025)

The R-square value of 0.873 implies that 87.3% of the variance in Developer Capability is accounted for by the independent variables. According to the criteria proposed by Hair et al. (2022) and Ghozali (2021), this result falls into the strong category, indicating that the model exhibits very good explanatory power. The adjusted R-square value of 0.871 further confirms the model's robustness, even after adjusting for the number of predictors and the sample size. Furthermore, the F-square (f^2) statistic was calculated to evaluate the relative contribution of each independent variable to the R^2 of the dependent variable. Following the thresholds recommended by Hair et al. (2022) and Ghozali (2021), f^2 values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively. These criteria help to assess the relative importance of each independent variable in predicting the dependent construct. The results of the f^2 analysis, conducted using SmartPLS 4, are presented in the following table.

Table 4. effect size (f^2)

	Digital Culture	Developer Capability	Training
Digital Culture		0.415	
Developer Capability			
Training		0.037	

Source: Primary Data (2025)

The F-square (f^2) value is used to assess the relative contribution of each independent variable to the R^2 of the dependent construct, in this case, Developer Capability. The results indicate that digital culture has a substantial effect on developer capability, with an f^2 value of 0.415, exceeding the 0.35 threshold (Hair et al., 2022; Ghozali, 2021). This reflects its significant contribution to the R^2 value of 0.873. In contrast, training shows only a small effect, with an f^2 value of 0.037, suggesting a relatively low contribution to developer capability compared to digital culture.

3. Hypothesis Testing

In PLS hypothesis testing, the t-statistic is compared with the t-table value, and the p-value is used to determine significance (Hair et al., 2022). A p-value < 0.05 indicates a significant effect, while a p-value > 0.05 means the variable has no significant effect. Meanwhile, the path coefficient shows whether the variable has a positive or negative influence (Hair et al., 2022). The hypothesis testing was conducted using the bootstrapping technique, and the results are presented in the following figure:

Table 5. Path coefficient dan T-statistic

	Path Coefficient	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Conclusion
Training -> Dev Capability	0.217	0.22	0.087	2.491	0.013	H1 accepted significant
Digital Culture -> Dev Capability	0.725	0.723	0.083	8.785	0,000	H2 accepted significant

Source: Primary Data (2025)

The path coefficient of 0.725 for the influence of Digital Culture on Developer Capability reflects a strong and positive effect. This suggests that enhancements in the organization's digital culture including the adoption of digital work practices, collaborative platforms, and online communication have a substantial impact on strengthening developer capabilities. In contrast, the path coefficient of 0.217 for the effect of Training on Developer Capability, although positive and significant, is relatively moderate. This indicates that while training contributes meaningfully to the improvement of developer capabilities, its effect is less pronounced compared to the role of digital culture. Together, these findings highlight the critical role of fostering a digital-first environment within the organization, while also acknowledging the supportive role that training plays in building developer talent.

Based on Table 5, the results show that the t-statistic for the effect of Training on Developer Capability is 2.491, while for Digital Culture it is 8.785. These values exceed the t-table threshold of 1.978, indicating that both hypotheses are accepted. The p-value for the relationship between Training and Developer Capability is 0.013, and for Digital Culture it is 0.000, which confirms that both independent variables have a statistically significant effect. The hypothesis testing results can be summarized as follows:

a. H1: The Influence of Training on Developer Capability

The hypothesis testing results indicate that training has a significant and positive effect on developer capability, with a path coefficient of 0.217, a t-statistic of 2.491, and a p-value of 0.013. Given that the t-value exceeds the critical threshold of 1.978 and the p-value is below 0.05, Hypothesis H1 is supported. These findings suggest that training contributes meaningfully to the enhancement of developer capabilities. Although the corresponding effect size is relatively modest, training remains a vital factor in fostering skill development and improving developer performance.

b. H2: The Influence of Digital Culture on Developer Capability

The quantitative analysis indicates that digital culture has a strong and positive effect on developer capability, with a path coefficient of 0.725. This implies that improvements in digital culture substantially enhance the skills and performance of developers within the organization. In contrast, the path coefficient for training was 0.217, suggesting a positive yet more moderate influence. While training supports developer development, its overall impact appears considerably weaker in comparison to the role of digital culture.

Discussion

1. Developer Capability Analysis

The quantitative analysis indicates that digital culture has a strong and positive effect on developer capability, with a path coefficient of 0.725. This implies that improvements in digital culture substantially enhance the skills and performance of developers within the organization. In contrast, the path coefficient for training was 0.217, suggesting a positive yet more moderate influence. While training supports developer development, its overall impact appears considerably weaker in comparison to the role of digital culture.

2. The Influence of Training on Developer Capability

Training plays a pivotal role in equipping developers with both technical and adaptive skills needed for digital transformation. The statistical results (path coefficient = 0.217; t-statistic =

2.491; p-value = 0.013) confirm that training has a significant positive effect on developer capability. Although the effect size is moderate, training remains a strategic component of talent development. Descriptive analysis reveals strong respondent agreement on the benefits of training, especially in enhancing skills related to technology, reusability, and automation—core areas emphasized by the Chapter DEV leadership. These findings align with Rudhaliawan (2013), who highlighted the importance of training in developing job-relevant expertise, and Juliadi (2023), who noted that digital-era training supports both technical competencies and adaptability.

In addition, literature suggests that structured and ongoing training supports high-quality digital project outcomes. Assyne et al. (2022) emphasized that well-trained developers are essential for delivering innovative digital solutions, while André et al., (2011) found that effective talent management through training can significantly improve team performance and project results. Although training's effect was found to be moderate in this study, its contribution to sustainable competence and organizational competitiveness remains critical.

3. The Influence of Digital Culture on Developer Capability

The study also found that the presence of a strong digital culture at PT.XYZ driven by strategic initiatives such as the "Take Leap" program and the "Culture Activation" campaign plays a fundamental role in building developer capability. These initiatives, particularly the "Talent" pillar and the activation of culture agents, translate corporate values into daily behavior and promote a culture that supports transformation goals. Van Der Bel (2018) supports this view, stating that digital culture enhances collaboration, engagement, and performance through technology integration in daily work processes.

The path coefficient of 0.725 (t-statistic = 8.785; p-value = 0.000) and an effect size (f^2) of 0.415 confirm that digital culture has a strong and statistically significant impact on developer capability. Descriptive data further supports this finding, showing that the use of digital platforms for collaboration, communication, and workflow management leads to greater efficiency, adaptability, and innovation among developers. These findings are supported by literature. Manyika et al. (2017) identified digital culture as a key driver of workforce transformation. Frank et al. (2019) argued that digital culture fosters innovation and agility. Shin et al. (2023) further emphasized that when paired with Agile and DevOps approaches, digital culture enhances efficiency, teamwork, and the quality of digital products. Thus, digital culture not only improves individual developer capability but also acts as a strategic enabler of long-term organizational relevance and competitiveness.

The results suggest that while both training and digital culture are significant, digital culture plays a more dominant role in shaping developer capabilities. Digital culture serves as the contextual foundation that enables the effective absorption and application of knowledge gained from training. Without this cultural support, training programs may not deliver their full potential. This finding emphasizes the need for a holistic approach in digital talent development, where training investments are aligned with and supported by a strong, adaptive, and innovation-driven digital culture.

CONCLUSION

This study concludes that both training and digital culture significantly influence the capability of developer talent at PT. XYZ, reinforcing their importance in driving human capital development in the digital era. Training was found to have a positive and statistically significant impact on developer capability ($\beta = 0.217$; $p = 0.013$), though with a moderate effect size. This indicates that, while beneficial, its impact may be limited if not supported by other organizational factors. In contrast, digital culture demonstrated a much stronger effect ($\beta = 0.725$; $p = 0.000$; $f^2 = 0.415$), highlighting its central role in fostering an environment conducive to innovation, adaptability, and the effective application of technological skills. These results suggest that digital culture not only directly enhances capability but also serves as a catalyst that amplifies the benefits of training. Organizations, therefore, should not rely on training in isolation but must adopt a more holistic approach that integrates cultural transformation as a foundation for talent development.

Practically, PT. XYZ is advised to strengthen post-training support mechanisms such as coaching, mentoring, and periodic performance reviews to ensure that learning is effectively translated into daily work practices. Optimizing training implementation through improved scheduling, updated materials, and qualified facilitators is also essential. Moreover, to keep pace with technological change, strategies such as microlearning and internal knowledge-sharing among developers should be promoted. Reinforcing digital culture—particularly in areas such as agility and customer-centricity—through responsive feedback systems and a strong user-focused mindset will further accelerate capability development.

Theoretically, this research contributes to the literature by positioning digital culture as a dominant factor, offering a new perspective that challenges conventional approaches which[A1] emphasize training alone. However, the study is limited to a single organization and focuses on developer roles within an *agile* structure. Future research could explore this relationship across different industries, organizational models, or with additional moderating variables such as leadership style or digital maturity levels.

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