

The Effect of Digital Profiling, Talent Pool, and Dynamic Reskilling on Civil Servant Talent Management at BKPSDM Rokan Hulu Regency

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ABSTRACT

This study examines the effect of digital competency profiling, competency-based talent-pool effectiveness, and dynamic reskilling on the quality of civil-servant talent management at BKPSDM Rokan Hulu Regency, Indonesia. Evidence on these three practices comes mostly from corporate settings, and they have rarely been tested together in local government. An explanatory quantitative survey was conducted with 155 civil servants selected through proportionate stratified random sampling from 4,247 active employees. Data were collected with a structured questionnaire and analyzed using multiple linear regression in IBM SPSS Statistics 27.0. Each predictor had a positive and significant partial effect, with digital profiling showing the strongest influence. Together, the three variables explained 68.4% of the variance in talent-management quality ($R^2 = 0.684$; $F = 107.23$; $p < 0.001$). The findings extend the dynamic-capabilities and strategic talent-management perspectives to a regional bureaucracy. In practical terms, BKPSDM Rokan Hulu should first establish a reliable digital profiling system and then expand its talent-pool and reskilling programs. The study contributes by testing the three practices within one integrated model in the context of Indonesian regional civil service.

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1. INTRODUCTION

Artificial intelligence (AI), robotic process automation, and large-scale data analytics are changing how work is organized in private firms and government agencies alike. In their review, Nadkarni and Prügl [1] treat digital transformation as a change that involves both technology and the actors within an organization. The World Economic Forum [2] estimates that nearly a quarter of

current job structures will change within five years, with around 69 million new jobs created and roughly 83 million existing jobs displaced. Autor et al. [3] show that each historical wave of technological change has produced new categories of work, and this pattern is now moving faster as generative AI spreads. According to Morandini et al. [4], the shift places upskilling and reskilling at the center of organizational strategy across sectors, because the skills that make a

workforce valuable are also changing faster than before. Li [5] adds that lifelong learning should be built into an organization's strategic goals so that its workforce is prepared for Industry 4.0.

Government bureaucracies are not exempt from these changes. The OECD [6] argues that digital government reform depends on civil servants who can use data strategically and adapt quickly. A survey by Tangi et al. [7] of 491 public administrations in Italy found that a sense of urgency, a perceived need for change, and a collaborative environment drive digital government transformation, while organizational barriers and weak institutional support hold it back. Wilson and Mergel [8] also mapped the strategies that digital champions use to overcome structural and cultural barriers in digital government. These demands have pushed many public administrations toward a skills-based model, in which competence rather than tenure or rank becomes the basis for managing human resources. Meeting them requires a talent-management system that is adaptive, data-driven, and able to track competency development over time. The need is urgent for local governments that still rely on manual or fragmented personnel records.

Most of what is known about digital competency profiling, talent pools, and reskilling still comes from corporate settings in developed countries. Marler and Boudreau [9] showed that evidence-based HR analytics can meaningfully improve talent-management decisions. Margherita [10] later systematized HR analytics research topics and future directions, while Tursunbayeva et al. [11] warned of ethical risks in people analytics, among them transparency, privacy, and excessive data collection. Tambe et al. [12] described the opportunities AI opens for competency mapping and workforce forecasting, and they also noted problems of data readiness and algorithmic bias. Several systematic reviews have mapped the use of AI across HR functions [13]–[15]. Chowdhury et al. [16] stress that the value of AI in HR management can be realized only when organizations also build non-technical

resources such as employee skills and competencies, leadership, and team coordination. After reviewing practices in OECD member countries, Burtcher et al. [17] concluded that digital skills transformation succeeds only when profiling systems, talent planning, and continuous reskilling are run together rather than as separate initiatives.

Evidence from the public sector is growing, but it remains scattered. Kravariti et al. [18], in a survey of the talent pool of a government institution in Bahrain, found that developmental support from line managers mediates the relationship between talent-management practices and individual talent performance. In South Africa, Gandi and Saurombe [19] found that weak talent-management practices, including those in training and development, push talented employees out of public-sector organizations. Bilan et al. [20] reported that the digital skills of civil servants in Ukraine were still underdeveloped, particularly content-related competencies. Standardized profiling and assessment systems, in other words, are still being built outside Indonesia as well. Within Indonesia, Fauzian et al. [21] documented how the West Java Provincial Government combined digital profiling and talent mapping in one system. Sudrajat et al. [22] showed how talent management has been applied to civil-servant career development through the State Civil Apparatus Information System (SI-ASN), while noting that its competency-testing methods still need improvement. Ikhwal et al. [23] likewise observed that although digital systems such as SIASN and e-SKP, as well as regional talent pools, have been built, inconsistent data integration remains an obstacle. Pagiu et al. [24] found that digital talent management, treated as a single composite practice, significantly strengthens the competitiveness of regional government agencies ($\beta = 0.42$; $p < 0.05$).

None of these studies, however, tested digital profiling, talent-pool effectiveness, and reskilling as separately measured predictors within one causal model, and none was conducted at a regional civil service and human resource development

agency (*Badan Kepegawaian dan Pengembangan Sumber Daya Manusia*, BKPSDM). Among the literature reviewed for this study, no work has tested the three practices as distinct predictors in one model at the BKPSDM level. Empirical evidence on how they operate at BKPSDM Rokan Hulu is also unavailable, and this gap is what motivates the present study.

Indonesia's regulatory framework adds to the urgency of closing this gap. Law Number 20 of 2023 on the State Civil Apparatus mandates a stronger competency-based merit system [25]. Regulation of the Minister of Administrative and Bureaucratic Reform (PANRB) Number 3 of 2020 [26], as amended by Regulation of the Minister of PANRB Number 20 of 2025 [27], sets out a more comprehensive civil-service talent-management framework that relies on digital data. The National Civil Service Agency (*Badan Kepegawaian Negara*, BKN) [28] also positions talent management as the basis for systematic regeneration of human resources across all government institutions.

The novelty of this study lies in testing digital competency profiling, competency-based talent-pool effectiveness, and dynamic reskilling in a single hypothesis-driven model, through a quantitative survey at BKPSDM Rokan Hulu Regency. This approach also responds to the call by Thunnissen and Gallardo-Gallardo [29] and by Dries [30] for talent-management research that is more integrated and grounded in empirical data. Specifically, the study asks whether each of these factors significantly affects the quality of civil-servant talent management, and whether the three jointly affect it as bureaucracies move toward a skills-based model in the AI era. The results are expected to provide an evidence base for BKPSDM Rokan Hulu Regency, other local governments in Indonesia, and national bodies such as the Ministry of PANRB and BKN in designing civil-service talent-management systems that are more adaptive, grounded in digital data, and oriented toward continuous competency development.

2. LITERATURE REVIEW

2.1 *Dynamic Capabilities in the Public Sector*

The dynamic-capabilities framework of Teece et al. [31] offers a way to understand the gap described above. Beta et al. [32] later extended this framework to explain how public institutions build sensing, seizing, and transforming capacities in response to generative AI. The central idea is that organizations stay relevant amid rapid change because they can detect new needs, take advantage of opportunities, and reorganize their resources. In a personnel context, these three capacities map fairly easily. Digital competency profiling performs the sensing role because it detects competency gaps. A competency-based talent pool performs the seizing role because it allocates talent strategically. Dynamic reskilling performs the reconfiguring role because it adjusts competencies when job demands change.

Building such capabilities in the public sector does not happen on its own. A study by Mikalef et al. [33] of 91 municipal governments in Germany, Norway, and Finland showed that the formation of AI capabilities is shaped by perceived costs, organizational innovativeness, governmental pressure, governmental incentives, and regulatory support. Mergel et al. [34] highlight the practical challenges that public managers face when implementing AI, whereas Selten and Klievink [35] show that public organizations need to balance the separation of innovation units against their

integration into core activities. These findings suggest that sensing, seizing, and reconfiguring capacities in a bureaucracy depend heavily on institutional readiness.

2.2 *Strategic Talent Management*

The dynamic-capabilities lens is complemented by the strategic talent-management tradition developed by Collings and Mellahi [36] and by Cappelli and Keller [37]. These authors emphasize identifying key positions, building strong talent pools, and staying responsive to changes in organizational needs. Meyers and van Woerkom [38] add that an organization's talent philosophy, whether inclusive or exclusive, shapes how its talent pool is designed. Thunnissen and Gallardo-Gallardo [29] recommend an approach that views the organizational context as a whole. Dries [30], for her part, argues that talent-management research needs to move from conceptual discussion toward rigorous empirical testing; this call has largely gone unanswered in the Indonesian bureaucratic context. In their critical review, Kwon and Jang [39] also question the "war for talent" framing that colors much of the talent-management literature.

2.3 *UTAUT as a Supporting Lens*

This study also draws, to a limited extent, on the unified theory of acceptance and use of technology (UTAUT) [40]. The theory explains technology adoption through performance expectancy, effort expectancy, social influence, and facilitating conditions. Because UTAUT speaks most directly to how civil servants accept a digital tool, it is used here only as a lens for

interpreting their responses to the digital profiling system. It is not treated as a separate construct and carries no hypothesis of its own. This choice is consistent with Venkatesh [41], who set out a research agenda on the adoption and use of AI tools grounded in UTAUT.

2.4 *Research Hypotheses*

Building on the dynamic-capabilities and strategic talent-management foundations above, this study proposes that digital competency profiling has a positive and significant effect on the quality of civil-servant talent management (H1). Competency-based talent-pool effectiveness is also expected to have a positive and significant effect on that quality (H2), as is dynamic reskilling (H3). In addition, the three variables are expected to have a joint positive and significant effect on the quality of civil-servant talent management (H4).

3. METHODS

This study used an explanatory quantitative survey design, chosen because it allows causal relationships among variables to be formulated and tested systematically. The research model consists of three independent variables, namely digital competency profiling (X1), competency-based talent-pool effectiveness (X2), and dynamic reskilling (X3), and one dependent variable, the quality of civil-servant talent management (Y). The research subjects were civil servants managed by BKPSDM Rokan Hulu Regency. The design follows directly from the integrated model built on strategic talent-management theory and dynamic-capabilities theory, with UTAUT as a supporting theory.

The population comprised all civil servants administratively registered with BKPSDM Rokan Hulu Regency, the agency

responsible for managing civil-service human resources in the Rokan Hulu Regency Government. At the time of data collection, the population numbered 4,247 active civil servants. Sample size was calculated with the Slovin formula, $n = N / (1 + Ne^2)$, with $N = 4,247$ and a margin of error of 8%. This yielded a minimum sample of about 151 respondents ($4,247 / [1 + 4,247 \times 0.08^2] \approx 150.7$, rounded up). The target was then raised slightly to 155 civil servants to allow for invalid or incomplete responses and to keep all four position strata represented (implementing staff, functional officials, administrators, and senior executives). Respondents were selected by proportionate stratified random sampling, and their distribution across strata is reported together with the respondent profile in Table 2.

Table 1 summarizes how each variable was operationalized. Digital competency profiling (X1) is defined as the systematic mapping of civil-servant competencies through a standardized digital platform. Competency-based talent-pool effectiveness (X2) refers to the organization's capacity to manage and place high-potential civil servants on the basis of competence. Dynamic reskilling (X3) is adaptive and continuous competency development in response to technological change. The quality of civil-servant talent management (Y) reflects the organization's overall success in identifying, developing, and retaining talent. All four variables were measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

Table 1. Operationalization of Research Variables

Variable	Operational Definition	Indicators	Scale	Source
Digital Competency Profiling (X1)	Mapping of civil-servant competencies through a standardized digital system	Competency data accuracy, platform accessibility, system integration, periodic data updating	Likert 1–5	Tambe et al. [12]; Venkatesh et al. [40]
Talent-Pool Effectiveness (X2)	Dynamic, competency-based management of high-talent civil servants	Talent identification, HR mobilization, talent retention, fit between position and competency	Likert 1–5	Collings and Mellahi [36]
Dynamic Reskilling (X3)	Adaptive competency development in response to technological disruption	Program relevance, training frequency, learning transfer, impact evaluation	Likert 1–5	Burtscher et al. [17]; World Economic Forum [2]
Quality of Civil-Servant Talent Management (Y)	Organizational success in identifying, developing, and retaining talent	Effectiveness of talent recruitment, continuous development, retention, strategic alignment	Likert 1–5	Collings and Mellahi [36]; Kravariti et al. [18]

Source: *Synthesis of Previous Studies (2025)*

The questionnaire contained 46 items: 12 for digital competency profiling, 10 for talent-pool effectiveness, 11 for dynamic reskilling, and 13 for talent-management quality. Content validity was established through a review by three experts in human resource management and public administration. Empirical validity was tested with corrected item-total correlations, which had to exceed 0.30, and reliability was tested with Cronbach's alpha against a minimum of 0.70.

Data were collected between January and May 2025 at BKPSDM Rokan Hulu Regency. The questionnaire was distributed in print and online (Google Forms) to respondents drawn from the sample list of each position stratum. Enumerators accompanied respondents while they filled it in, checked responses for completeness, and screened out inconsistent answer patterns. Responses that were incomplete or indicated systematic bias were removed and replaced

by reserve respondents from the same stratum.

Data were analyzed with multiple linear regression, $Y = \alpha + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \varepsilon$, to test both the partial and the simultaneous effects of the independent variables. In this equation, Y is the quality of civil-servant talent management, α is the constant, β_1 to β_3 are the regression coefficients, X_1 to X_3 are the independent variables, and ε is the error term. Before the hypotheses were tested, classical assumption tests were run for normality (Kolmogorov-Smirnov, criterion $p > 0.05$), multicollinearity ($VIF < 10$ and tolerance > 0.10), heteroscedasticity (Glejser test, criterion $p > 0.05$), and autocorrelation (Durbin-Watson). Overall model fit was assessed with the F test (criterion F-count $>$ F-table and $p < 0.05$) together with the coefficient of determination (R^2). Partial hypotheses were tested with the t test at the 5% significance level. All analyses were performed in IBM SPSS Statistics version 27.0.

4. RESULTS AND DISCUSSION

4.1 Respondent Characteristics

All 155 questionnaires distributed through proportionate stratified random sampling were returned and judged suitable for analysis, giving a response rate of 100%. Table 2 presents the respondent profile. Most respondents were male (89; 57.4%). By position group, implementing staff formed the largest group (72; 46.5%), followed by functional officials (48; 31.0%), administrators (23; 14.8%), and senior executives (12; 7.7%). In terms of education, holders of a bachelor's degree were the most numerous (98; 63.2%), followed by master's degree holders (31; 20.0%), diploma (D3) holders (18; 11.6%), and senior high school graduates or equivalent (8; 5.2%). By length of service, civil servants with 11–20 years of service formed the largest group (67; 43.2%), followed by those with 1–10 years (58; 37.4%) and more than 20 years (30; 19.4%). This composition indicates that the position strata of civil servants at BKPSDM Rokan Hulu Regency are adequately represented.

Table 2. Respondent Characteristics (n = 155)

Characteristic	Category	Frequency (n)	Percentage (%)
Gender	Male	89	57.4
	Female	66	42.6
Position Group	Implementing staff	72	46.5
	Functional official	48	31.0
	Administrator	23	14.8
	Senior executive	12	7.7
	Senior high school or equivalent	8	5.2
	Diploma III (D3)	18	11.6
Education	Bachelor's degree (S1)	98	63.2
	Master's degree (S2)	31	20.0
	1–10 years	58	37.4
Length of Service	11–20 years	67	43.2
	> 20 years	30	19.4

Source: Processed Data (2025)

4.2 Descriptive Statistics, Validity, and Reliability of the Instrument

As Table 3 shows, the mean scores of all four variables fall in the good category, ranging from 3.634 to 3.891 on the five-point

scale. Talent-management quality (Y) had the highest mean (3.891), and dynamic reskilling the lowest (3.634), which suggests that reskilling practice still lags behind the other three dimensions. All 46 items met the corrected item-total correlation criterion.

Cronbach's alpha values ranged from 0.854 to 0.891, well above the 0.70 threshold, so the

internal-consistency reliability of the instrument is high.

Table 3. Descriptive Statistics, Validity, and Reliability of the Instrument

Variable	N	Mean	SD	Category	Valid Items	Cronbach's α
Digital Competency Profiling (X1)	155	3.847	0.612	Good	12/12	0.872
Talent-Pool Effectiveness (X2)	155	3.712	0.594	Good	10/10	0.854
Dynamic Reskilling (X3)	155	3.634	0.581	Good	11/11	0.869
Quality of Civil-Servant Talent Management (Y)	155	3.891	0.637	Good	13/13	0.891

Source: Processed Data (2025)

4.3 Classical Assumption Tests

The classical assumption tests summarized in Table 4 support the suitability of the regression model. The Kolmogorov-Smirnov test produced $Z = 1.147$ with a two-tailed asymptotic significance of 0.112 ($p > 0.05$), meaning that the residuals are normally distributed. VIF values for the three predictors ranged from 1.779 to 1.873, far below the limit of 10, and tolerance values

were above 0.10, so no multicollinearity was found. The Glejser test gave significance values between 0.214 and 0.460 (all $p > 0.05$), indicating no heteroscedasticity. The Durbin-Watson statistic of 1.947 lies within the acceptable range of 1.788 to 2.212, so autocorrelation is not present. With these assumptions met, the regression estimates satisfy the Gauss-Markov conditions for the best linear unbiased estimator (BLUE).

Table 4. Results of the Classical Assumption Tests

Assumption Test	Value per Variable (X1 / X2 / X3)	Criterion	Conclusion
Residual normality (Kolmogorov-Smirnov)	$Z = 1.147$; Sig. = 0.112	Sig. > 0.05	Normally distributed
Multicollinearity (Tolerance / VIF)	0.547/1.828; 0.534/1.873; 0.562/1.779	VIF < 10; Tol > 0.10	Not present
Heteroscedasticity (Glejser test, t / Sig.)	1.247/0.214; -0.983/0.327; 0.741/0.460	Sig. > 0.05	Not present
Autocorrelation (Durbin-Watson)	DW = 1.947	$1.788 < DW < 2.212$	Not present

Source: SPSS Output (2025)

4.4 Hypothesis Testing

The regression analysis in Table 5 yields the equation $\hat{Y} = 0.312 + 0.429X_1 + 0.363X_2 + 0.315X_3$. The constant is not statistically significant ($t = 1.668$; $p = 0.097$), which is common and does not affect the interpretation of the predictor coefficients. All three independent variables have a positive and significant partial effect on talent-management quality at the 5% level. Digital competency profiling is the strongest predictor ($\beta = 0.412$; $t = 6.703$; $p < 0.001$),

followed by talent-pool effectiveness ($\beta = 0.338$; $t = 5.418$; $p < 0.001$) and dynamic reskilling ($\beta = 0.287$; $t = 4.632$; $p < 0.001$). H1, H2, and H3 are therefore accepted. The simultaneous test also supports H4 ($F = 107.23$; $p < 0.001$). The multiple correlation of $R = 0.827$ and $R^2 = 0.684$ (adjusted $R^2 = 0.677$; SEE = 0.3621) shows that the three predictors jointly explain 68.4% of the variance in talent-management quality, while the remaining 31.6% is explained by factors outside the model.

Table 5. Results of Multiple Linear Regression, t-Test, and F-Test

Variable / Model Statistic	B	Std. Error	Beta (β)	t / F	Sig.	Decision
Constant (α)	0.312	0.187	-	1.668	0.097	-
X1: Digital Competency Profiling	0.429	0.064	0.412	6.703	< 0.001	H1 accepted
X2: Talent-Pool Effectiveness	0.363	0.067	0.338	5.418	< 0.001	H2 accepted
X3: Dynamic Reskilling	0.315	0.068	0.287	4.632	< 0.001	H3 accepted
R = 0.827; R ² = 0.684; Adj. R ² = 0.677; SEE = 0.3621	-	-	-	107.23	< 0.001	H4 accepted

Source: SPSS output (2025). Note: SPSS displays significance values below 0.001 as 0.000 because of rounding to three decimals. For consistency with the abstract and the text, these values are reported as < 0.001.

4.5 Effect of Digital Competency Profiling on Talent-Management Quality

Digital competency profiling emerged as the most dominant predictor. This pattern is consistent with the view of Tambe et al. [12] that integrating digital competency data helps public organizations identify competency gaps more precisely and closer to real time. At BKPSDM Rokan Hulu Regency, a standardized digital profiling system appears to serve as an evidence base for talent-management decisions. Such a system addresses the data-integration problems that Ikhwal et al. [23] identified in the Indonesian public sector, and it supports the dynamic-capabilities view [31] that an organization's ability to sense and respond to changing competency needs is a source of advantage.

4.6 Effect of Talent-Pool Effectiveness on Talent-Management Quality

Talent-pool effectiveness ranked second among the predictors. This finding is consistent with the argument of Collings and Mellahi [36] that identifying key positions and developing talent pools aligned with organizational strategy improves talent-management outcomes. Building talent pools on the basis of competence, rather than seniority or rank, marks a real shift toward a skills-based bureaucracy. This direction is in line with the OECD [6] push to modernize public-sector personnel systems through measurable and transparent competency-based practices. The result also agrees with

Kravariti et al. [18], who showed a link between talent-management practices and talent performance in the public sector.

4.7 Effect of Dynamic Reskilling on Talent-Management Quality

Although its coefficient is the smallest of the three predictors, dynamic reskilling still makes a significant contribution. This is understandable, since reskilling programs in the region are still at an early stage and need further institutional support. From the UTAUT perspective [40], the extent to which civil servants are willing to take part in such programs depends on the performance expectancy, effort expectancy, and social influence they perceive. These factors can be strengthened through incentive design and internal communication. Program content also matters. Jaiswal et al. [42] found that employee readiness for AI requires data analysis skills, digital literacy, complex cognitive abilities, decision-making, and a willingness to keep learning. The significance of reskilling at this early stage also fits the World Economic Forum [2] projection that most job competencies will change within the next five years.

4.8 Joint Effect and Comparison with Previous Studies

The three predictors can also be read as complementary parts of one capability-development cycle. Digital profiling performs the sensing function by revealing competency gaps, the talent pool performs the seizing function by placing civil servants in the

opportunities identified, and dynamic reskilling performs the reconfiguring function by continually updating competencies as demands change. This reading fits the large share of variance that the model explains jointly ($R^2 = 0.684$). Even so, the additive regression design used here cannot show whether the three variables interact synergistically, so that their combined effect exceeds the sum of their individual effects. Testing that possibility would require an interaction or non-linear specification, which is beyond the scope of this study; it is therefore noted as a direction for further research rather than drawn as a conclusion.

Compared with the findings of Cappelli and Keller [37] on the benefits of talent pipelines in corporate settings, the present results show that a similar logic also holds in Indonesian public bureaucracy. The difference is that implementation is more complicated, owing to rigid personnel regulations and an organizational culture that still emphasizes seniority. The size of the digital profiling coefficient is also in line with the UTAUT argument of Venkatesh et al. [40] that perceived usefulness and ease of use strongly affect technology adoption. Civil servants who see digital profiling as accurate and useful appear more willing to support a broader competency-based talent ecosystem. Compared with Tambe et al. [12], who studied technology corporations in the United States, the direction of the effect of HR analytics on the quality of HR management is consistent across contexts, although its magnitude differs. That difference in magnitude is most likely related to the institutional setting. In theoretical terms, this study carries the concept of dynamic capabilities [31], originally developed for competitive corporate environments, into public management. Public organizations do not operate on market logic, yet they still need sensing, seizing, and reconfiguring mechanisms to stay relevant amid technological disruption. The unexplained 31.6% of variance is probably related to factors such as organizational culture, transformational leadership, IT infrastructure, and personnel regulations.

Even so, the overall explanatory power of the model is large by the benchmarks commonly used in the social sciences [43].

4.9 Policy Implications

These findings have fairly direct policy implications. BKPSDM Rokan Hulu Regency, as well as other regional personnel agencies in Indonesia, would likely gain more from talent-management reform designed as one system than from reform carried out program by program. Investing in one component while neglecting the others is unlikely to produce optimal results. The order of the coefficients suggests a possible sequence: first, build a digital competency profiling infrastructure as the data foundation; second, develop a talent-pool system on top of that data; and third, design reskilling programs that address the gaps revealed by the profiling system. At the national level, BKN could consider a common standard for digital competency profiling that regional agencies can adapt. The current fragmentation risks producing data that are incompatible across agencies, which in turn hinders the mobility of civil servants between regions.

5. CONCLUSION

In the sample studied, digital competency profiling had the largest positive and significant effect on the quality of civil-servant talent management at BKPSDM Rokan Hulu Regency ($\beta = 0.412$; $t = 6.703$; $p < 0.001$), followed by competency-based talent-pool effectiveness ($\beta = 0.338$; $t = 5.418$; $p < 0.001$) and dynamic reskilling ($\beta = 0.287$; $t = 4.632$; $p < 0.001$). Together, the three variables explained 68.4% of the variance in talent-management quality ($F = 107.23$; $p < 0.001$; $R^2 = 0.684$). Because the design is cross-sectional and relies on respondents' self-reported perceptions, these results are better read as evidence consistent with the dynamic-capabilities and strategic talent-management perspectives in this sample than as proof of a broader causal chain. With that caveat, the findings point to the following picture. An accurate, up-to-date, and transparent competency database serves as the foundation

of a skills-based bureaucracy. Competency-based talent pools improve the fit between civil servants and strategic positions, while continuous reskilling helps prevent the erosion of competencies caused by AI disruption. The three appear to work best when run as one interconnected system rather than as separate initiatives. These conclusions should be read alongside several limitations. The cross-sectional design captures a single point in time and cannot trace how talent management develops. Self-reported questionnaire data also leave room for subjectivity or social desirability bias. In addition, the focus on BKPSDM Rokan Hulu Regency limits generalization to agencies with different fiscal, geographic, or cultural conditions.

Future studies could address these limitations through a longitudinal design over three to five years, comparative studies across agencies, and structural equation modeling or hierarchical linear models that can test moderating variables, such as transformational leadership and civil

servants' baseline digital literacy, as well as interaction effects among the three predictors examined here. In practical terms, the Ministry of PANRB and BKN are advised to accelerate the development of a national competency taxonomy that is more flexible and responsive to developments in AI, and to establish a public-sector skills observatory as a reference for regional digital profiling efforts. For BKPSDM Rokan Hulu Regency, the relatively low dynamic reskilling score (mean 3.634) points to the need for training content that is more closely tied to actual tasks, more personalized digital literacy mentoring for civil servants over 45 years of age, and formal recognition of new competencies in the Employee Performance Targets (*Sasaran Kinerja Pegawai*, SKP).

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