“Cluster-driven innovation and management in healthcare under regional and socio-economic disparities”

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ARTICLE INFO	Lazat Spankulova, Alexis Belianin, Azamat Kerimbayev, Zhuldyz Asanova and Akan Nurbatsin (2026). Cluster-driven innovation and management in healthcare under regional and socio-economic disparities. *Problems and Perspectives in Management*, *24*(2), 425-437. doi:10.21511/ppm.24(2).2026.29
DOI	http://dx.doi.org/10.21511/ppm.24(2).2026.29
RELEASED ON	Thursday, 04 June 2026
RECEIVED ON	Tuesday, 03 February 2026
ACCEPTED ON	Thursday, 30 April 2026

JOURNAL	"Problems and Perspectives in Management"
ISSN PRINT	1727-7051
ISSN ONLINE	1810-5467
PUBLISHER	LLC “Consulting Publishing Company “Business Perspectives”
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
35	2	4

BUSINESS PERSPECTIVES

LLC "CPC "Business Perspectives"
Hryhorii Skovoroda lane, 10,
Sumy, 40022, Ukraine
www.businessperspectives.org

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CLUSTER-DRIVEN INNOVATION AND MANAGEMENT IN HEALTHCARE UNDER REGIONAL AND SOCIO-ECONOMIC DISPARITIES

Type of the article: Research Article

Received on: 3rd of February, 2026
Accepted on: 30th of April, 2026
Published on: 4th of June, 2026

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Abstract

The purpose of this study is to determine the socio-economic and demographic factors of intra-regional inequality in Kazakhstan and their implications for cluster-based innovation in healthcare. A hybrid approach has been used, consisting of a systematic review of 181 publications using the PRISMA 2020 protocol and econometric analysis of the 2001–2024 panel data for the districts of Kazakhstan, consisting of 3,842 observations. Fixed-effects, cluster-robust, and hierarchical mixed-effects models were employed using standardized variables of population size, fertility, mortality, migration, criminality, and investments. The results reveal that the strongest and most robust predictor of intra-regional inequality in Kazakhstan is investment in fixed capital ($\beta = 0.466$, $p < 0.01$; $\beta = 0.399$, $p < 0.01$). Population size has consistently negative effects on intra-regional inequality in Kazakhstan ($\beta = -0.240$ to -0.256, $p < 0.05$ and $p < 0.01$). In the multilevel model, fertility increases intra-regional inequality in Kazakhstan ($\beta = 0.114$, $p < 0.01$), whereas mortality and net migration decrease it ($\beta = -0.150$ and $\beta = -0.037$, $p < 0.01$). The model explained 37.1% of the variance in intra-regional inequality in Kazakhstan ($R^2 = 0.371$). The results suggest that without balanced investment and territorially differentiated policies, cluster-based innovation in healthcare can even reinforce rather than alleviate regional disparities.

Keywords healthcare innovation, regional governance, innovation clusters, spatial inequality, investment allocation, demographic determinants, health policy, innovation ecosystems

JEL Classification I18, O18, R58

Conflict of interest statement:
Author(s) reported no conflict of interest

INTRODUCTION

Territorial inequality is one of the key obstacles to the modernization of healthcare in developing and transitioning economies. In Kazakhstan, territorial inequality in investment, demographic characteristics, and institutional capacity is a key obstacle to healthcare modernization. In healthcare, territorial inequality is especially vital because it directly affects access to new technologies and qualified staff, which are essential for ensuring the quality and efficiency of healthcare systems. In this context, the idea of developing healthcare systems based on clusters is being actively discussed. The idea is to concentrate hospitals, universities, and other organizations into innovative systems and to develop innovative healthcare ecosystems. The cluster development approach is often associated with knowledge spillovers and institutional coordination and is considered more efficient for new technology transfer, especially in sectors where knowledge is essential for economic development (Porter, 1998; Cooke, 2001; Asheim & Coenen, 2005).

In healthcare, this is crucial due to the role of cooperation among various organizations, including universities and state authorities, as well as the transfer of new technologies and the development of innovations (Feldman & Zoller, 2012; Malik et al., 2017).

At the same time, the positive effects of clustering are unevenly distributed. Innovation is concentrated in regions with better infrastructure, larger markets, greater institutional density, and greater absorptive capacity (Rosenthal & Strange, 2004; Glaeser et al., 2010; Rodríguez-Pose, 2013). In healthcare services, this is particularly critical because of the need to invest in digital transformation, telemedicine services, and other services that require greater institutional preparedness in regions that enjoy better infrastructure, while peripheral regions lag in absorbing innovation (Rüth & Teuteberg, 2020).

This problem is especially relevant in Kazakhstan, where spatial heterogeneity remains high, and the modernization of the healthcare system increasingly depends on the interplay among investment allocation, demographic changes, and territorial governance. While some studies have examined regional innovation systems, healthcare transformation, and spatial disparities, these issues are rarely integrated into a single analytical framework that explains how socio-economic and demographic factors shape the territorial environment for healthcare innovation.

1. LITERATURE REVIEW AND HYPOTHESES

The notion of clusters has evolved into a prominent tool for analyzing innovation dynamics and regional competitiveness. Classical approaches to innovation dynamics include insights that geographically concentrated networks of enterprises and institutions generate external economies through knowledge spillovers (Porter, 1998; Rosenthal & Strange, 2004). Innovation has been conceptualized not through a firm-level approach in territorial systems of production and innovation (Cooke, 2001; Edquist, 1997).

The Regional Innovation Systems (RIS) literature can also be seen as advancing the above view by emphasizing the institutional and organizational basis of innovation outcomes. Innovation performance is a function of the strength of interlinkages among businesses, universities, public institutions, and financial institutions, as well as territorial governance (Cooke et al., 1997; Asheim & Coenen, 2005). Analogous investment in innovation yields territorial differences in innovation outcomes, stemming from differences in institutional thickness, absorptive capacity, or the institutional complementarity of territorial policy (Asheim et al., 2019; Tödtling & Trippl, 2005). The knowledge attributes have a decisive influence on cluster dynamics. The distinction between tacit and codified knowledge highlights the role of geographical proximity in learning-intensive tasks, especially in knowledge-producing fields that require person-to-person interaction, trust, and experience (Johnson et al., 2003; Lundvall, 2016). Consequently, knowledge clusters form more easily in urbanized areas characterized by strong institutional thickness, thereby accentuating pre-existing geographical disparities (Glaeser et al., 2010; Rodríguez-Pose, 2013).

Healthcare innovation has characteristics that are particularly susceptible to the dynamics of clusters. Unlike the manufacturing industry, the healthcare industry is characterized by knowledge-intensive services, cutting-edge technology, strict regulations, and a prominent public sector role. In fact, healthcare innovation relies on an ensemble of interactions between hospitals, research institutions, medical universities, technology companies, and the public sector (Malik et al., 2017). Research on biomedical and life-science clusters shows that innovative ecosystems positively impact scientific productivity, the commercialization process, and the rate of medical technology transfer (Feldman & Zoller, 2012; Zucker et al., 2002). These tendencies are strengthened when cluster contexts promote ambidextrous organizational behavior, which can explore new technologies and exploit existing ones simultaneously (Birkinshaw & Gibson, 2004). Evidence from healthcare settings indicates that ambidexterity can enhance adaptive and innovative efforts in complex institutional settings.

http://dx.doi.org/10.21511/ppm.24(2).2026.29

At an overarching level, healthcare clusters act as an enabling platform for the convergence of digital technology, data analytics, and innovative care delivery models. The phenomenon of Health 4.0 represents the convergence of the healthcare sector and Industry 4.0, encompassing innovations such as artificial intelligence, telemedicine, and a shared digital framework (Rüth & Teuteberg, 2020; Schwab, 2016). The digital divide, understood as differences in individuals'/communities' access, skills, and use of digital technologies despite efforts to bridge the gap, is likely to reflect inequalities already present along socioeconomic and geographical divides (van Dijk, 2020). Areas that are infrastructure-constrained, have low income, and face institutional capacity constraints are at a disadvantage when trying to embrace digital healthcare innovations, thereby likely exacerbating polarization rather than reducing it, particularly in terms of regional disparities (Yusuf, 2008). Urban-rural disparities also make innovation in the healthcare sector even more challenging. New forms of urbanization and metropolitan concentration reinforce the superiority of innovation in megalopolises, while peripheral areas remain disadvantaged in this regard (Champion & Hugo, 2004; Partridge et al., 2007). This is in line with agglomeration theory, which holds that the main innovative benefits will continue to flow, in practice, to highly populated areas with diverse economic profiles (Glaeser et al., 2010). Empirical research also confirms the dependence of doctor visits on medical and socio-economic attributes, which, in turn, testifies to the existence of structural demand heterogeneity and its impact on behavior and, ultimately, the effectiveness of new service organizational models (Spankulova et al., 2021). New findings on medicine demand and the potential impact of introducing co-payments have also highlighted the role of affordability restrictions, along with behavior adjustments, in changing access and equity effects, which, in turn, are directly connected to territorially differentiated approaches to modernizing healthcare (Spankulova & Asanova, 2024).

A growing body of literature stresses the role of demographic and socioeconomic conditions in shaping healthcare innovation capacity. Consistently, large and dense populations are associated with stronger innovation outcomes, as they imply scale effects, depth in the labor market, and institutional diversity, as referenced by Rosenthal and Strange (2004) and Cooke (2001). Larger regions serve as pull factors for investment and talent, thereby increasing their status as innovation hotspots. Demographic factors such as birth, mortality, and migration rates play an indirect but important role in healthcare (Bloom et al., 2014). Demographic changes drive demand for healthcare provision, financial viability, and labor markets, hence shaping innovation incentive forces (Bloom et al., 2014). Migration rates represent a significant reallocation of talent from one region to another and are often driven by economically dynamic regions (Partridge et al., 2007). An institutional framework connects these variables, enabling regions to leverage demographic challenges and convert them into innovation drivers (Rodríguez-Pose, 2013; Kodama, 2007). Poor institutional frameworks impede regions' ability to manage their complex healthcare systems and incorporate innovation into service provision. On the other hand, inadequate institutional settings constrain the effectiveness of managing a healthcare system and the incorporation of innovation into healthcare delivery. Related literature on the role of merit good consumption underscores the importance of preference divergence in predicting the impact of policy interventions and in designing healthcare programs. Lastly, ICT/mHealth studies on performance management and social transformation, which specifically consider gender, validate the assumption that mHealth diffusion is conditioned by organizational capacity and social structure, but not by infrastructure (Spankulova et al., 2024).

Investment allocation appears to be a crucial factor in determining regional innovation dynamics. The existing literature indicates that capital investment tends to flow into developed regions due to perceived predictability (Yusuf, 2008; Asheim et al., 2019). However, this pattern hinders the equitable distribution of infrastructure quality, technological advancements, or services in the healthcare sector. Hence, the necessary condition for forming clusters tends to widen the intra-regional inequality gap. Areas with major hospitals, scientific institutions, and technology companies attract more resources, leading to a cumulative advantage effect, while neighboring regions fall behind (Breschi & Malerba, 2005; Feldman & Zoller, 2012). The polarization mechanism presents a fundamental policy dilemma: how to capitalize on the cluster as an innovation driver while reducing regional disparities.

The meaning of cluster-driven innovative activities within the Kazakhstani healthcare system should be understood against the backdrop of evidence showing that outcomes are contingent on governance quality and territorial design. In the European context, the effectiveness of public systems matters because public funds contribute to high-quality outcomes, mostly when management structures are already effective (Koibichuk et al., 2022). Also, public spending on essential sectors influences the quality of life, suggesting that medical modernization should be assessed from a welfare perspective rather than focusing solely on technological performance (Vasylieva et al., 2023). Nevertheless, innovative potential remains constrained by workforce dynamics: nurses' migration plans are contingent on socio-economic and organizational factors, suggesting that clusters may contribute to territorial disparities should peripheral zones lose their human capital (Amofa-Adade & Koltai, 2024). In addition, digital and ESG-oriented modernization requires standardized metrics and governance; otherwise, uneven technological diffusion and its monitoring could be observed (Roy & Vasa, 2025). Evidence from studies on investment-sustainability finally suggests that for measurable investments, partial impacts can be achieved, underscoring the need to balance allocation and to adopt territorially differentiated policy design (Tóth et al., 2025).

In this respect, comparative studies of regional innovation systems suggest that balanced development requires deliberate policy interventions to strengthen peripheral regions through targeted investment, institutional support, and connectivity with leading clusters. In the absence of such actions, cluster-driven innovation may reinforce spatial divergence rather than enable inclusive development (Trippl et al., 2019). Challenges, as identified in the literature, are particularly exacerbated in developing and transition economies, with resource-constrained healthcare systems combined with uneven territorial development. Factors inhibiting innovativeness and development in healthcare informatics and technology include fragmented and dispersed government and financial resources, as well as inequality in human capital (Oliveira et al., 2016; Scott & Mars, 2015). Conversely, such environments also present challenges and opportunities to perform a leapfrog approach using ICT and institutional mechanisms. Healthcare and innovative cluster development in developing economies require a coordinated government approach, and investments should be linked to demographic needs (Yusuf, 2008; Zucker et al., 2002).

The literature review shows that cluster-based innovation is highly dependent on interactions among institutional coordination, investment concentration, and knowledge spillovers. On the other hand, the literature shows that healthcare innovation is highly sensitive to spatial and socioeconomic factors. This is because spatial and socioeconomic factors are crucial determinants of infrastructure availability, demographic pressure, and public sector capacity. However, the literature shows that most studies focus on cluster-based innovation, healthcare innovation, and inequality, but very little provides integrated insights into these factors.

This study aims to explore the socio-economic and demographic determinants of intra-regional inequality in Kazakhstan and their effects on cluster-based innovation and healthcare management. To achieve this aim, the following hypotheses are presented:

H1: *There is a positive association between investment in fixed capital and intra-regional inequality, given the high concentration of resources in economically advanced regions.*

H2: *There is a negative association between the size of the population and intra-regional inequality, considering the high degree of diversification in large regions.*

H3: *There is a significant association between demographic factors, including fertility, mortality, and migration, and intra-regional inequality.*

H4: *High intra-regional inequality can create unequal preconditions for the formation of healthcare innovation clusters.*

http://dx.doi.org/10.21511/ppm.24(2).2026.29

2. METHODOLOGY

The paper uses a mixed-methods design approach in which system-level evidence integration through econometric modeling leads to an understanding of the role of socio-economic-demographic fundamentals in making cluster-driven, innovative activity in healthcare viable in conditions of evident spatial inequality. The design framework remains anchored in the understanding that forming an innovative healthcare cluster goes beyond a 'technological act' to become, essentially, an issue of territorial management. Consequently, the methodology comprises two blocks. First, a systematic review using the PRISMA framework synthesizes global knowledge on innovative healthcare clusters and requirements, followed by a meta-analysis. This would enable a comprehensive understanding of worldwide knowledge on innovative healthcare clusters. Second, an econometric model estimates inequality conditions within districts, specifically in Kazakhstan, as an enabling factor for an innovative ecosystem.

The systematic review and meta-analysis were fully performed in accordance with the PRISMA 2020 guidelines. The literature search was conducted across Scopus, Web of Science, and PubMed. It was further enhanced by targeted searches on Google Scholar, international organization publications, and national statistical and policy publications. The keywords were defined within a framework of three concepts:

(1) healthcare innovation and transformations (digital health, telemedicine, e-health, Health 4.0, healthcare technologies);

(2) cluster and ecosystem concepts (innovation cluster, healthcare cluster, regional innovation system, ecosystem approach); and

(3) concepts regarding spatial inequality and determinants (spatial inequality, fertility rate, mortality rate, migration rate, investment, human capital, and its regional development, specifically within the context of Kazakhstan).

The literature selection and screening completed standard PRISMA phases (identification, screening, eligibility, inclusion) with a result set of 181 peer-reviewed literature in a final corpus with a focus on recurring mechanisms (institutional coordination, links between university, industry, and government, readiness to support digitization, finance mechanisms, and human capital) and harvested patterns useful in developing country settings. Table 1 presents descriptive statistics for the key variables.

The choice of panel data analysis is motivated by the fact that the underlying factors in the formation and development of innovative medicine clusters begin to take shape within a territorial space characterized by strong disparities in income levels, demographic structures, and investment activity. The panel data analysis allows one to reveal the factors influencing these three aspects, the interregional difference, and thus the territorial opportunities and constraints for innovation adaptation and diffusion in the healthcare arena. In this case, three different models were used to approximate and validate the analysis results. These models include a linear model with regional fixed effects, a linear model with standard errors clustered at the

Table 1. Descriptive statistics

vars	n	mean	Sd	Median	min	max
Avwage	4299	94338.73	87563.69	68029.00	6229.00	798192.00
Difwage	4299	0.00	32774.69	–2640.00	–173708.80	390236.57
PopK	4344	73.85	96.17	40.48	1.60	935.70
GFRpK	4286	18.36	6.04	17.03	1.34	39.48
GMRpK	4264	9.52	3.18	9.19	0.88	23.82
Migrsal	4276	–388.30	1090.37	–284.00	–12005.00	16448.00
Crimes	3947	788.79	1744.75	254.00	10.00	23332.00
fcinvM	4311	21630.45	40727.78	6489.00	407233.00	407232.80

Note: Avwage = average monthly wage in the district (KZT); Difwage = deviation of district average wage from the corresponding regional average wage; PopK = population size (thousand persons); GFRpK = general fertility rate per 1,000 population; GMRpK = general mortality rate per 1,000 population; Migrsal = net migration balance; Crimes = number of registered crimes; fcinvM = investment in fixed capital (million KZT).

district level, and a linear model with random intercepts at both the regional and district levels.

This paper utilizes the econometric approach based on a district-level panel dataset for Kazakhstan covering 2001–2024 to estimate the socio-economic determinants of intra-regional inequality. The idea is that inequality within regions might be explained by the polarization of resources and institutional capacities across territories, affecting their potential to host and sustain healthcare innovation clusters. The dependent variable, a difwage, denotes the deviation of the district average wage from the corresponding regional average and can be interpreted as an indicator of intra-regional economic divergence and unequal development capacity. Explanatory variables capture demographic pressure and mobility (population size PopK; fertility rate GFRpK; mortality rate GMRpK; net migration Migrsal), investment intensity (investment in fixed capital fcinvM), and an additional structural control (crime rate Crimes), enabling a check of whether broader social conditions alter inequality patterns. To ensure comparability across variables measured in different units and allow coefficient interpretation as standardized effects, all continuous variables were transformed into *z*-scores:

$$z_{it} = \frac{x_{it} - \bar{x}}{s_x}, \tag{1}$$

where x_{it} is the observed value for district *i* in year *t*, $\bar{x}$ is the sample mean, and s_x is the sample standard deviation.

The baseline specification was estimated using a regional fixed-effects model, which controls for time-invariant heterogeneity across regions (e.g., historical specialization, institutional quality, inherited infrastructure) and isolates within-region variation across districts over time. Year fixed effects were also included to account for common macroeconomic shocks, national reforms, and countrywide policy cycles. The model is written as:

$$\begin{aligned} y_{it} &= \alpha + \beta_1 PopK_{it} + \beta_2 Migrsal_{it} \\ &+ \beta_3 GFRpK_{it} + \beta_4 GMRpK_{it} + \beta_5 Crimes_{it} \\ &+ \beta_6 fcinvM_{it} + \mu_r + \tau_t + \varepsilon_{it}, \end{aligned} \tag{2}$$

where y_{it} denotes standardized intra-regional inequality, μ_r captures region fixed effects, τ_t captures year fixed effects, and ε_{it} is the idiosyncratic error term.

To improve inference and address violations of classical assumptions, two robustness methods were pursued. First, re-estimation of the model using district-clustered standard errors better addresses potential issues arising from correlated errors in domains likely characterized by path-dependent socioeconomic evolution over time. Second, estimation via a hierarchical linear model with random intercepts allows a structured assessment of whether measures of demographic dynamics become significant when controlling for a variance-component decomposition accounting for between-region and within-region variation at the second level.

3. RESULTS

The results section presents the empirical results of the two analytical parts of the study in a non-interpretative manner. Firstly, the results of the systematic review and meta-analysis, presented in a PRISMA 2020-compliant manner, are highlighted to outline the major enabling factors for cluster-driven innovation in healthcare, based on the final sample of 181 peer-reviewed analyses. Secondly, the results of the econometric analysis for the period of 2001–2024 in the Kazakhstani districts are presented, in which the descriptive statistics for the dataset as well as the results of three model specifications (the Regional Fixed-Effects model, OLS model with District-Clustered Errors, and the Hierarchical Mixed-Effects model) are further highlighted clearly. The econometric results are reported in terms of the *z*-transformations of the variables to allow direct comparisons; in addition, goodness-of-fit statistics will be reported to visualize the statistical significance of the results. Table 2 presents the results of Regression Model 1 (regional fixed-effects OLS regression).

The results show that approximately 37% of regional disparities are explained by both district-level demographic and economic attributes, in addition to regional fixed effects. The variable with the highest and most significant effect on regional

http://dx.doi.org/10.21511/ppm.24(2).2026.29

Table 2. Regression results for Model 1 (OLS with regional fixed effects with dependent variable scale(adifwage))

Variable	Coefficient	Std. Error
Regional fixed effects (oblast)		
Aktobe	0.014	(0.062)
Akmola	–0.141**	(0.058)
Almaty	–0.003	(0.069)
East Kazakhstan	0.116*	(0.068)
Zhambyl	–0.146*	(0.076)
Zhetysu	–0.253*	(0.131)
West Kazakhstan	0.594***	(0.061)
Karagandy	0.045	(0.062)
Kostanay	–0.031	(0.057)
Kyzylorda	–0.226***	(0.074)
Mangystau	0.859***	(0.085)
Pavlodar	0.070	(0.060)
North Kazakhstan	–0.228***	(0.061)
Turkestan	0.046	(0.075)
Ulytau	0.266***	(0.084)
Socioeconomic controls (standardized)		
Population size (*scale(PopK)*)	–0.240***	(0.025)
Net migration balance (*scale(Migrsal)*)	–0.014	(0.013)
General fertility rate (*scale(GFRpK)*)	0.027	(0.022)
General mortality rate (*scale(GMRpK)*)	–0.037**	(0.017)
Crime rate (*scale(crimes)*)	0.002	(0.021)
Fixed capital investment (*scale(fcinvM)*)	0.466***	(0.014)
Constant	–0.080*	(0.046)
Model statistics		
Observations	3,842	
R^2 / Adjusted R^2	0.371 / 0.368	
Residual Std. Error (df)	0.668 (3,820)	
F-statistic (df)	107.38*** (21; 3,820)	

Note: Standard errors in parentheses. Continuous variables are standardized (mean = 0, SD = 1). Regional fixed effects included. * p < 0.10, ** p < 0.05, *** p < 0.01.

disparities, according to its positive and large coefficient value β = 0.466 (p < 0.01), is fcinvM, which stands for investments in fixed capital. This implies that higher investment levels intensify disparities in a region because resources and investments are currently unevenly distributed, with a focus mainly on established and most attractive localities.

By contrast, the variable PopK (Population Size) shows a counterintuitive relationship, with a strong negative coefficient (β = –0.240), p < 0.01, suggesting that larger districts are less likely to differ from the regional mean. Such a relationship might be reasonably explained in the context of economic diversification and institutions by the fact that large districts usually have more advanced infrastructure and are more directly incorporated into the regional economy. They possess characteristics that increase their resistance to variations and qualify them to form innovation ecosystems based on clusters.

Other variables in the fixed-effects model reflect a more complex reality. The small but significant negative impact of GMRpK (mortality rate) with a coefficient of β = –0.037 (p < .05) indicates that a higher mortality rate tends to prevail in less-developed regions, where the total income level tends to stay low; therefore, differences tend not to be extreme in terms of the regional average compared to more-developed nations. The presence of regions like these does not imply a similar level of development; rather, a specific type of "bottom-tier" inequality tends to prevail in less-developed regions. Fertility rates (GFRpK) and migration (Migrsal) do not reach conventional levels of statistical significance in the model because the main

Table 3. Regression results for Model 2 (OLS with clustered standard errors)

Variable (standardized)	Coefficient	Clustered Std. Error
Population size (scale(PopK))	−0.240**	(0.113)
Net migration balance (scale(Migrsal))	−0.014	(0.028)
General fertility rate (scale(GFRpK))	0.027	(0.039)
General mortality rate (scale(GMRpK))	−0.037	(0.037)
Crime rate (scale(crimes))	0.002	(0.052)
Fixed capital investment (scale(fcinvM))	0.466***	(0.135)
Model statistics		
Observations	3,842	
R^2 / Adjusted R^2	0.371 / 0.368	
Residual Std. Error (df)	0.668 (3,820)	

Note: Cluster-robust standard errors reported in parentheses. All explanatory variables are standardized (mean = 0, SD = 1). * p < 0.10, ** p < 0.05, *** p < 0.01.

determinants are investment behaviors and population size, among others.

To assess the strength of the coefficients, a model with district-level cluster-robust standard errors has been used. The results of regression Model 2, an OLS model with clustered standard errors, are presented in Table 3.

Model 2 reinforces the supposition that investment concentration is the most potent determinant of the standardized adjusted wage differential. The fixed capital investment variable exhibits a very strong, highly significant positive effect, β = 0.466 ($p < 0.01$), indicating that districts characterized by higher investment intensities exhibit correspondingly higher wage differentials once these are standardized. On the other hand, population size exerts a negative effect on wage differentials, β = −0.240 ($p < 0.05$), indicating that larger districts display comparatively lower inequality in the examined wage structure. All remaining demographic and social indicators (net migration balance, fertility, mortality, and crime) cannot achieve their conventional levels of significance with clustered standard errors, thus implying their overall impact is relatively weaker and less robust than those exerted by the investment and population variables for the explanation of wage differentiation at the district level. Figure 1 presents graphically the estimated coefficients arising from the model.

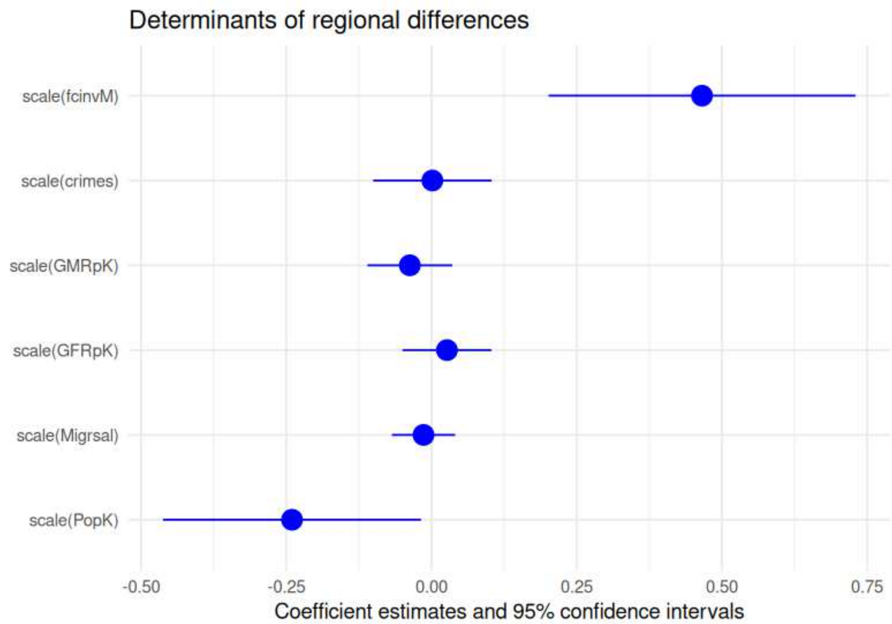

Figure 1. Coefficient estimates and 95% confidence intervals for Model 2 (OLS with clustered standard errors)

http://dx.doi.org/10.21511/ppm.24(2).2026.29

This specification accounts for the correlation of district-level characteristics within the same region, reflecting the influence of shared regional policies, infrastructure, and institutional environments. It is reassuring that most coefficient estimates stay largely constant, indicating the robustness of the core effects. As expected, standard errors inflate, leading some demographic variables to lose statistical significance. Importantly, the main findings are preserved: investment remains highly significant with β = 0.466*** (p < 0.01), while the negative impact of population size remains statistically significant with β = –0.240* (p < 0.05). All these results confirm that the observed relationships are robust and not driven by the specific structure of the error terms.

Because the data are nested, a multilevel mixed-effects model was used to provide a complete analysis that accounts for the nested structure. This approach, meanwhile, allowed for simultaneous assessment of factors at both the regional and district levels. Table 4 shows regression results for Model 3.

Model 3 yields strong evidence that economic and demographic variables interact in shaping standardized adjusted wage differentials across districts. Fixed investments in capital again prove to be a strong positive determinant (β = 0.399, p < 0.01), supporting the hypothesis that investment-driven districts have wages systematically higher than those of others, even after removing group-specific variation by subtracting random intercepts. Conversely, population size and net migration balance prove significant and negative (β = –0.256 and –0.037, p < 0.01), implying that larger and migrating-in districts have a systematically lower wage structure inequality in the modeled system. Lastly, demographic processes exhibit asymmetric interactions: fertility rate positively affects wage differentials (β = 0.114, p < 0.01), whereas mortality rate exhibits a considerable negative effect (β = –0.150, p < 0.01), implying that areas characterized by a stronger population regeneration process tend to have a possibly larger labor stratification, although the former seems to be negatively associated with wage differentials. Crime rates remain statistically insignificant, suggesting a limited direct relationship with wage differentials after controlling for the multilevel structure and key socioeconomic covariates. The estimated coefficients from the model are presented graphically in Figure 2.

The effects are further aggravated when focusing on the multilevel model. The investment variable maintains a positive effect, though with a less significant coefficient (β = 0.399, p < 0.01), implying that part of this inequality is attributed to interprovincial disparities. The significance of the PopK variable further increases (β = –0.256, p < 0.01), highlighting not only its impact on inequality differences but also its structural roles within regions in leveling income inequality and activating innovative capacity. In addition, multilevel modeling indicates that the effects are significant for fertility rates (β = 0.114, p < 0.01) and mortality rates (β = –0.150, p < 0.01). This outcome indicates the pressure on the socio-economic structure im-

Table 4. Regression results for Model 3 (hierarchical linear mixed model, random intercepts)

Variable (standardized)	Coefficient	Std. Error
Population size (scale(PopK))	−0.256***	(0.036)
Net migration balance (scale(Migrsal))	−0.037***	(0.012)
General fertility rate (scale(GFRpK))	0.114***	(0.021)
General mortality rate (scale(GMRpK))	−0.150***	(0.020)
Crime rate (scale(crimes))	0.017	(0.019)
Fixed capital investment (scale(fcinvM))	0.399***	(0.014)
Constant	−0.038	(0.072)
Model statistics		
Observations	3,842	
Log Likelihood	−3,235.816	
AIC	6,491.631	
BIC	6,554.169	

Note: Random-intercept mixed-effects model estimated with standardized predictors (mean = 0, SD = 1). Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

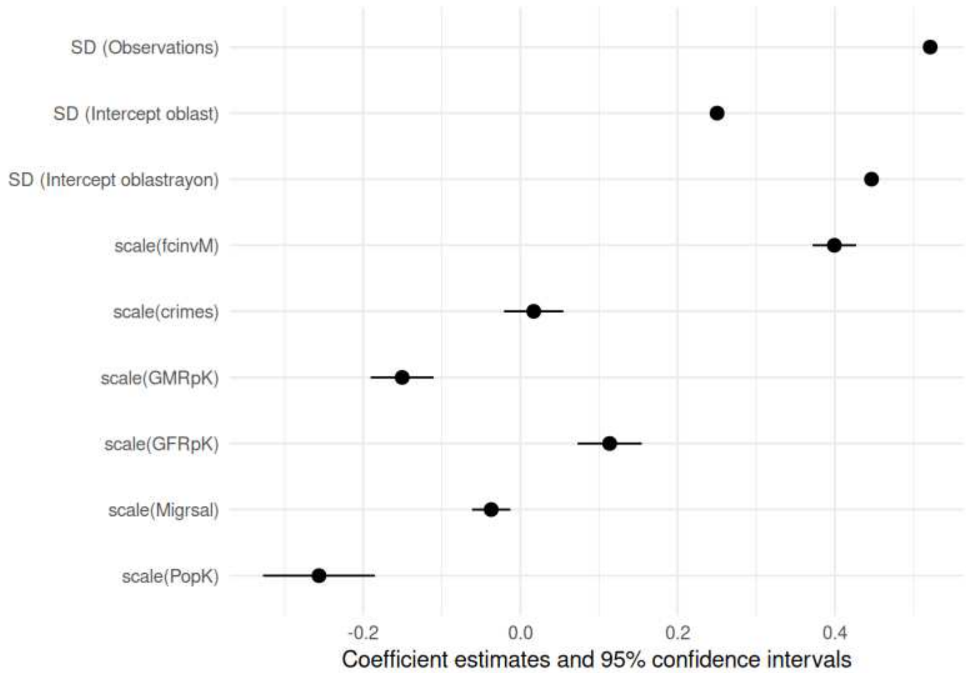

Figure 2. Coefficient estimates and 95% confidence intervals for Model 3 (hierarchical linear mixed model)

plied by demography: that is, high fertility rates imply high pressure on limited resources, and high rates imply low social welfare standards in districts with limited economic prospects. Net migration rates further gain significance ($\beta = -0.037$, $p < 0.01$), indicating that population migration decreases inequality, acting as an innovative redistributive channel from less developed to developed regions through human capital.

The empirical results generally support the proposed hypotheses. H1, which stated that investment in fixed capital positively influences intra-regional inequality, is accepted, as fixed capital investment demonstrated a strong and statistically significant positive effect across all model specifications. H2 is also accepted because population size showed a stable negative relationship with intra-regional inequality, indicating that larger districts tend to have more balanced socio-economic structures. H3 is accepted since demographic factors, including fertility, mortality, and migration, became statistically significant in the multilevel model, confirming their important role in shaping territorial inequality patterns. Finally, H4 is accepted because the findings indicate that high intra-regional inequality creates uneven territorial conditions for the development of healthcare innovation clusters, thereby reinforcing disparities in innovation capacity and healthcare modernisation potential across regions of Kazakhstan.

4. DISCUSSION

The results indicate that investment in fixed capital is the most stable positive predictor of intra-regional inequality across all model specifications. This result may imply that fixed capital is concentrated in already relatively more favorable districts, thus reinforcing asymmetric territorial development rather than compensating for it. In terms of healthcare modernization, this may imply that cluster-driven innovation is more likely to occur in territories with more favorable economic and institutional foundations. This result is in line with various studies on regional innovation systems and asymmetric development in terms of innovation clusters and unevenness in cluster development across different territories, which have emphasized that innovation resources often concentrate in spatially favored territories and thus yield “cumulative development effects” rather than “balanced modernization” (Asheim et al., 2019; Breschi & Malerba, 2005; Feldman & Zoller, 2012; Yusuf, 2008).

http://dx.doi.org/10.21511/ppm.24(2).2026.29

The population size also reveals a stable negative relationship with intra-regional inequality. This implies that more populated districts tend to be more balanced than their regional averages. This may be because more populous regions tend to have more developed and diversified economic bases and greater institutional density. This can be important for the adoption and implementation of innovation in healthcare and for the conditions for cluster formation. This finding is consistent with agglomeration and regional development theories that emphasize the potential for knowledge transfer and the diffusion of innovation in more populated regions (Cooke, 2001; Glaeser et al., 2010; Rosenthal & Strange, 2004).

The results for demographic variables show a more complex picture. Fertility, mortality, and migration variables become statistically significant in the hierarchical model, suggesting that their effects depend on the multilevel territorial structure. Higher fertility is associated with greater inequality, which may indicate greater strain on social and healthcare systems in less-affluent districts. Mortality is negatively related to inequality, suggesting that less affluent districts generally lag behind in development. However, this lag is not differentiated across these districts. Net migration is negatively related to inequality in the multilevel model, suggesting that population mobility may help to redistribute human potential to more prosperous districts. Overall, these results align with previous studies suggesting that demographic variables influence healthcare needs and development potential in regions, albeit in a more nuanced way than investment and population size (Bloom et al., 2014; Partridge et al., 2007; Rodríguez-Pose, 2013).

The results suggest that cluster-driven innovation in healthcare is shaped by pre-existing territorial inequality. Formation of healthcare innovation clusters depends on coordination, financing, and mutual interaction between hospitals, universities, businesses, and the government. This process occurs within a spatially unequal environment. In the case of Kazakhstan, this implies that regions with high levels of investment concentration, population, and favorable socioeconomic conditions are more likely to be suitable for the creation of healthcare innovation clusters. In contrast, peripheral regions may be left out of the modernization process. In this regard, cluster policy in healthcare should not be viewed solely as a mechanism for efficiency and modernization; rather, it should be seen as a means of territorially differentiated governance that can help reduce inequality rather than perpetuate it (Malik et al., 2017; Oliveira et al., 2016; Rüth & Teuteberg, 2020).

The study contributes to this body of literature by linking the concept of healthcare clusters to structural determinants of intra-regional inequality in a transitioning economy. However, it is important to note that this study has limitations. Firstly, this study uses wage differentials as a proxy for territorial inequality, which is a function of development asymmetry but does not directly measure healthcare innovation performance per se. Moreover, this study does not include direct measures of healthcare infrastructure, digitalization, and institutional quality at the district level in its empirical model.

CONCLUSION

This study aimed to identify the socio-economic and demographic determinants of intra-regional inequality in Kazakhstan and evaluate the conditions for the development of cluster-based innovation and management in the country's healthcare sector.

The paper found that the most significant and stable positive factor for intra-regional inequality in Kazakhstan is investment in fixed capital, reflecting the allocation of resources in the most advanced districts. Meanwhile, the effect of the population size is negative and stable, reflecting the integration of the largest areas within the regional system. The demographic factors also show differentiated effects: fertility rates increase inequality, whereas mortality and net migration reduce it, although the latter effect becomes significant only in the multilevel model.

The conditions for the development of innovation and management in Kazakhstan's healthcare sector, driven by the cluster approach, are characterized by structural inequality. The development of the country's healthcare sector, driven by the cluster approach, will not reduce inequality, and the lack of balance in investment allocation and in the development of specific approaches for peripheral regions will only increase inequality.

AUTHOR CONTRIBUTIONS

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ACKNOWLEDGMENT

This paper was carried out within the framework of the following grant projects funded by the Science Committee of the Ministry of Science and Higher Education of the Republic of Kazakhstan: IRN AP26198345 "Reducing socio-economic inequality in the regions of Kazakhstan through investment in and improvement of the organization ofthe healthcare system".

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