HETEROGENEOUS RELATIONSHIPS BETWEEN DIGITAL TRANSFORMATION, INNOVATION, AND INSURANCE MARKET DEVELOPMENT IN THE EU: EVIDENCE FROM QUANTILE REGRESSION AND STRUCTURAL EQUATION MODELING

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Abstract

The research objective is to assess the associations of digitalization and innovation with the development of the European Union (EU) insurance market, using a differentiated approach that captures heterogeneity across the conditional distribution of insurance market size, as well as the overall structural relationships. The panel dataset for the EU-27 Member States (MS) includes variables capturing the size of the insurance market, the level of digitalization and innovation, as well as control variables serving as proxies of socio-economic development. Therefore, to examine heterogeneity in the estimated relationships, the methodology employs pooled quantile regression models (QREG) using robust standard errors, at the lower (0.25), median (0.50), and upper (0.75) quantiles of the conditional distribution of insurance market size. In addition, structural relationships across the EU are examined using Structural Equations Modeling (SEM) with the Maximum Likelihood method and bootstrap standard errors. The results reveal the heterogeneity of the EU MS, showing that the level of development of the insurance market is associated with the degree of digitalization and innovation, in the sense that the estimated associations tend to be stronger at the higher quantiles. At a global level, innovation has positive associations with the development of the insurance market. However, digitalization shows mixed associations: internet access is positively associated with insurance penetration, while the share of the ICT sector in GDP is negatively associated with both insurance penetration and density. These findings highlight the need for strategies that consider differences in insurance market development across EU MS. Such strategies could help countries make better use of digitalization and innovation while supporting financial inclusion and socioeconomic resilience.

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Insurance market, digital transformation, innovation, socio-economic development, quantile regression, Structural Equation Modeling.

JEL Classification
C31, G22, I30, O15, O30.

Introduction

The potential of digitalization and technological innovation for the development of the insurance market is realized through facilitating access to insurance products, diversifying the range of offerings, reducing distribution costs, and expanding the policyholder base - mechanisms that can contribute to an increase in the volume of gross written premiums and the level of insurance penetration within the economy (Braun & Jia, 2025; Cosma & Rimo, 2024).

Thus, at a macroeconomic level, digitalization and technological innovation in the insurance sector can contribute to increasing market efficiency and competitiveness, as well as strengthening economic resilience in the face of systemic and emerging risks - provided that the vulnerabilities associated with new technologies are appropriately managed (European Insurance and Occupational Pensions Authority, 2026; International Association of Insurance Supervisors, 2025).

The literature highlights a growing interest in assessing the implications of digitalization and innovation for the development of the insurance sector. In this context, Bayar et al. (2023) found that the use of information and communication technologies and the development of the insurance sector influence each other in ten European Union (EU) Member States (MS). Cosma and Rimo (2024) also highlight how InsurTech is changing the insurance industry and point to the need for more research on its economic effects.

Cristea et al. (2025) also examine the relationship between digital transformation, innovation, and the performance of the European insurance market, with particular attention to the differences between life and non-life insurance. The present study builds on their findings but approaches the issue differently. Rather than comparing insurance segments, it focuses on how these relationships vary across different levels of insurance market development. More specifically, the analysis considers the lower, median, and upper quantiles of the conditional distribution of insurance market size. It also examines the overall structural relationships between digitalization, innovation, and insurance market development across EU MS. These two approaches offer different but complementary perspectives. Quantile regression helps identify variations in the relationships across the distribution, while SEM provides a broader view of how the variables are structurally related. Together, they allow for a more detailed examination of the links between digitalization, innovation, and insurance market development in the EU.

The study draws on panel data covering all 27 EU MS from 2007 to 2023. Insurance market development is measured using two indicators: insurance penetration and insurance density. The dataset also includes variables related to digitalization and innovation, alongside the Human Development Index and poverty level, which are used

to account for socio-economic conditions. Two complementary methods are employed. First, pooled quantile regression (QREG), with robust standard errors, is used to examine whether the relationships between digitalization, innovation, and insurance market development differ across the distribution. The analysis focuses on three quantiles: 0.25, 0.50, and 0.75. Second, Structural Equation Modeling (SEM) is applied to investigate the broader structural relationships among these variables across EU MS. The model is estimated using maximum likelihood, with bootstrapped standard errors based on 50 replications.

The paper is organized as follows. Section 2 reviews the relevant literature regarding digital transformation, innovation and the insurance field. Section 3 outlines the data, methodology, and research hypotheses. The empirical results are presented and discussed in Section 4. Section 5 concludes the paper by highlighting the main findings, their policy implications, the study's limitations, and possible directions for future research.

1. Review of the scientific literature

The insurance market is currently experiencing an important structural shift, driven by the convergence of digital transformation, innovation, and the reconfiguration of modern financial institutions (Didenko & Sidelnyk, 2021). While the insurance market has traditionally been defined by rigid administrative processes and relatively static risk assessment models, recent developments indicate an accelerated transition to an integrated digital ecosystem based on advanced analytics solutions, platforms, and sophisticated technologies (Nepochatenko et al., 2023; Volosovych et al., 2021). In this regard, digital transformation cannot be considered just as technology modernization, but rather as a systemic shift affecting products, processes, business models, and the competitive structure of the insurance market (Kathroju, 2025).

Kanapathipillai et al. (2024) emphasize that digitalization and innovation have become essential elements for performance and competitiveness in the insurance industry, but their effects are divergent. Institutional transformations and national market structures have a complex impact. The digital transformation of the insurance market must be understood not just as an improvement in technology, but rather as a fundamental change (Monkiewicz & Monkiewicz, 2023) in the way risk is created, assessed and traded. Digitalization is changing the insurance industry, moving it away from traditional, relatively static business models towards a more dynamic, data-driven environment. Personalization and continuous monitoring are becoming increasingly important in this process. Skaf et al. (2026) also point to the role of technology and service quality in influencing customer satisfaction and loyalty, especially during periods of crisis.

However, these changes also bring challenges. Although digitalization can improve efficiency and support market growth, its benefits may be constrained by rigid legacy systems and growing cybersecurity risks (Lanfranchi & Grassi, 2021; Zhang, 2023; Taskin et al., 2025). From a performance perspective, Rajapathirana and Hui (2018) emphasize a positive correlation between the financial performance of insurance companies and innovation capacity; thus, market performance, growth in gross written premiums and improvement in financial indicators are all related to innovative capacity. According to the study conducted by Menhart et al. (2004), in Germany, innovation

improves organizational performance in a substantial way, with effects often moderated by firm size.

Analyses at the aggregate level of the EU suggest the existence of complex relationships; in Central and Eastern Europe (CEE), according to Stojčić (2021), innovation is positively correlated with a series of insurance market indicators. However, there are differences between countries and between insurance segments, indicating that there are different development trajectories. Therefore, the effect of innovation is not uniform, but depends on the structure and maturity of the insurance market; the same technology can have a positive impact on one economy and a negative impact on another economy. These findings indicate that the relationship between digitalization, innovation and insurance market development is not linear and depends on the level of maturity of the market in general.

Moreover, the willingness to invest in innovation varies significantly between EU MS, according to the analysis of Yin et al. (2023). This is due to differences in digital readiness and maturity of the insurance market, and disparities contribute to the asymmetric effects of digital transformation across the EU.

Cristea et al. (2025) examine the relationship between digitalization, innovation, and insurance market development in the EU, with a particular focus on the differences between life and non-life insurance. Using robust regression models and Bayesian network analysis, the authors find that both digitalization and innovation are associated with insurance market development, although these relationships vary between the two segments. Socioeconomic factors are also important, especially human development, which is closely linked to insurance penetration and density. The findings suggest that technological progress does not relate to insurance market development in the same way across all segments. Instead, these relationships appear to depend, at least partly, on the specific characteristics of life and non-life insurance markets.

These findings point to the value of further research by investigating how the relationships between digitalization, innovation, and the size of the insurance market vary, not only at the aggregate market level or across different market segments, but also along the conditional distribution of market size.

2. Research methodology

The data used were extracted from different databases for the EU countries, for the period 2007-2023. The variables employed in our research were grouped into three categories:

- *Insurance market dimension:* insurance penetration degree (*inspn*) (% of Gross Domestic Product - GDP); insurance density (*insdn*) (USD/capita);
- *Digital and innovation dimensions:* households - level of internet access (*hsic*) (% of households); individuals - internet use, for last internet use over the previous 12 months (*iiu)* (% of individuals); Information and Communication Technology (ICT) in the total sector on GDP (*shict*) (% of GDP); high-speed internet coverage (*hia*) (% of households); Global Innovation Index (*gbinn*) (scores from 0 - 100);
- *Socio-economic development:* Human Development Index (*hdi*) (scores from 0 - 1); at-risk-of-poverty rate (*pvrt*) (% of the total population).

The data source differs for each dimension addressed. Thus, for the insurance sector, data were extracted from Swiss Re Institute (2024); for those in the field of digitalization and

poverty rate, from Eurostat (European Commission, 2025); for the degree of innovation, from the World Organization of Intellectual Property (WIPO, 2025); and for the human development index, from UNDP (2025). The analysis ends in 2023, as Swiss Re insurance market data from 2024 onwards are no longer publicly available at the country level, but only at the regional level.

Table no. 1 presents the descriptive statistics for the variables included in the econometric analysis. The data reveal considerable differences across EU MS, while also showing some gaps in the dataset due to incomplete reporting for certain variables.

Table no. 1. Summary statistics of variables used in the econometric analysis, 2007-2023

Variables	Obs.	Mean	Standard deviation	Min.	Max.	Skewness	Kurtozis
inspn	434	5.307	2.909	1.09	13.6	0.602	2.423
insdn	405	2300.563	1932.048	107.2	7746	0.654	2.24
insdn lg	405	3.143	0.495	2	3.9	-0.462	2.097
hdi	453	0.883	0.041	0.773	0.962	-0.279	2.27
pvrt	450	23.171	7.169	10.8	49.3	1.117	4.139
hsic	457	77.516	16.312	18.96	99.18	-1.021	3.536
iiu	457	78.372	14.906	28.3	99.35	-0.885	3.219
shict	280	4.347	1.262	1.99	10.14	1.11	5.033
hia	297	49.044	29.814	0	100	-0.068	1.83
gbinn	294	48.547	7.421	34.7	64.2	0.241	2.061

Source: Authors' contribution in Stata 17.

The insurance market metrics reveal significant structural disparities. Insurance penetration degree (*inspn*) has an average value of 5.307, with a range of 1.09 to 13.6, indicating significant disparities in the significance of the insurance industry in EU MS economies. The positive skewness (0.602) implies that the majority of EU MS fall below the sample average, but a small number of mature markets leads the distribution to shift to the right. A similar dynamic is seen in the case of insurance density for total insurance (*insdn*), where the standard deviation (1932.05), compared to the average of 2300.56, reflects significant disparities in per capita insurance spending among EU MS. The logarithmic transformation of insurance density (*insdn_lg*) decreases dispersion and produces a slight negative skewness, demonstrating the presence of extreme values in the initial distribution and validating the logarithmic transformation in econometric analysis. The Human Development Index (*hdi*) shows relatively little variation across EU MS, with a mean of 0.883 and a standard deviation of 0.041. This suggests that human development levels are generally similar across the EU. The distribution is negatively skewed, with most observations concentrated towards higher values, reflecting the relatively high level of human development in the region. A different pattern emerges for the at-risk-of-poverty rate (*pvrt*), which varies considerably more across Member States. With a mean of 23.17 and a standard deviation of 7.17, this indicator also shows positive skewness

(1.117) and relatively high kurtosis (4.139), pointing to a distribution with some unusually high values and notable differences in poverty levels across countries.
Digitalization and innovation indicators also vary across the EU, although the patterns are not the same for all variables. Internet access (*hsic*) and internet use (*iiu*), for example, both have negatively skewed distributions, with values of -1.021 and -0.885, respectively. This suggests that higher levels of internet access and use are more common among Member States, while a smaller number of observations are concentrated towards the lower end of the distribution. In contrast, ICT in the total sector on GDP (*shict*) indicates strong positive skewness (1.11) and high kurtosis (5.033), revealing a concentration of values at low levels and the existence of a small group of high-performing countries, reflecting the uneven development of the digital labour market.
High-speed internet coverage (*hia*) demonstrates a substantial range (0-100) and a skewness close to zero, suggesting a relatively balanced dispersion, but high variability (standard deviation 29.81), indicating significant differences in the degree of digitalization of public services and access to technology. Similarly, the Global Innovation Index (*gbinn*) shows moderate variation across EU MS, with a mean of 48.55 and a standard deviation of 7.42, which suggests that innovation performance differs between EU countries.
Before estimating econometric models, an essential preliminary step is to test the multicollinearity of the variables. In this regard, the *Variance Inflation Factor (VIF)* and *the tolerance index (TOL)* were calculated by estimating auxiliary Ordinary Least Squares (OLS) regressions for each variable in relation to the other variables in the model.
The results in table no. 2, performed separately for both dependent variables used in the models (*inspn* and *insdn*, respectively*)*, indicate that the internet use variable *(iiu)* records the highest VIF values among all the variables analyzed: VIF= 10.77 (TOL=0.092) in the case of the model with insurance penetration degree (*inspn)* as dependent variable, and VIF=12.03 (TOL=0.083) in the case of the model with insurance density (*insdn_lg*) as dependent variable. The indicative thresholds used in the specialized econometric literature indicate that VIF values exceeding 10 are commonly used as an indicative threshold for identifying potential multicollinearity problems, rather than as a strict statistical criterion (O'Brien, 2007). These results suggest potential multicollinearity, particularly between internet use (*iiu)* and household internet access (*hsic*), and support the decision to reconsider the inclusion of both variables in the models.

Table no. 2. Results of the multicollinearity test for the independent variables included in the models (*inspn* and *insdn_lg* as dependent variables)

Variables	**VIF**	**1/VIF (TOL)**	**Variable**	**VIF**	**1/VIF (TOL)**
Dependent variable*: inspn*			**Dependent variable: *insdn_lg***		
iiu	10.77	0.092867	*iiu*	12.03	0.083156
hsic	9.37	0.106745	*hsic*	10.65	0.093857
hdi	6.51	0.153525	*hdi*	6.85	0.145957
gbinn	4.39	0.227995	*gbinn*	4.57	0.218955
pvrt	3.04	0.329219	*pvrt*	2.97	0.336879

shict	1.86	0.536389	*shict*	1.85	0.541322
hia	1.62	0.618835	*hia*	1.71	0.584777
Mean VIF: 5.36			**Mean VIF: 5.80**		

Source: Authors' contribution in Stata 17.

Based on these results, the internet use variable *(iiu)* was eliminated from the dataset used in econometric models, following the standard approach to multicollinearity remediation. The choice to remove the *iiu* variable is justified both by the higher values of the VIF and TOL recorded and by conceptual considerations. After eliminating the internet use indicator (*iiu)*, the VIF and TOL calculation for the reduced set of variables was resumed. The results presented in table no. 3 show a significant decrease in multicollinearity indicators.

Table no. 3 shows that the Human Development Index (*hdi)* has the highest VIF values in the remaining dataset (6.51 and 6.85, respectively), but below the accepted critical threshold. The other variables record VIF values between 1.46 and 4.83, with corresponding tolerances above the threshold of 0.10, indicating the absence of significant multicollinearity problems.

Tabelul no. 3. Results of the multicollinearity test for the independent variables included in the models (*inspn* and *insdn_lg* as dependent variables) after eliminating the internet use indicator (*iiu*)

Variables	**VIF**	**1/VIF (TOL)**	**Variable**	**VIF**	**1/VIF (TOL)**
Dependent variable*: inspn*			**Dependent variable: *insdn_lg***		
hdi	6.51	0.153537	*hdi*	6.85	0.146079
hsic	4.56	0.219071	*hsic*	4.83	0.207207
gbinn	3.94	0.253984	*gbinn*	4.23	0.236663
pvrt	2.80	0.356534	*pvrt*	2.71	0.368472
shict	1.84	0.543183	*shict*	1.85	0.541905
hia	1.46	0.682890	*hia*	1.68	0.596136
Mean VIF: 3.52			**Mean VIF: 3.69**		

Source: Authors' contribution in Stata 17.

The methodology used in this study aims to provide a better understanding of how digital transformation, innovation, and living standards are related to insurance market development. To achieve this, two econometric models have been employed: *the pooled quantile regression model (QREG*) for the levels 0.25, 0.5 and 0.75, representing the lower, median, and upper segments of the conditional distribution; and *Structural Equations Modeling (SEM),* using Maximum Likelihood method with bootstrap standard error (50 replications).

To capture the heterogeneous relationships between digital transformation, innovation, socio-economic conditions and insurance market development, this study was performed using a *pooled quantile regression model (QREG), using robust standard errors* to

account for potential heteroscedasticity (robust vce), following the approach proposed by Koenker and Bassett (1978). This allows the relationships between independent variables and insurance market development to vary across the conditional distribution of the dependent variable.

This approach is justified by the literature, which reveals that the level of economic and institutional development (Beck & Webb, 2003; Arena, 2008; Lee et. al., 2016) is reflected in the heterogeneous nature of the determinants of insurance market development. In particular, digitalization and innovation may generate more pronounced associations with insurance dimension in advanced economies, while traditional socio-economic factors may dominate in emerging economies.

Two separate models are estimated, using insurance penetration (*inspn*) and the logarithm of insurance density (*insdn_lg*) as dependent variables. Robust standard errors are employed to account for potential heteroskedasticity.

Given the longitudinal structure of the dataset, the QREG estimates are interpreted as *pooled conditional associations*, without explicitly controlling for unobserved country-specific effects. This limitation is considered when interpreting the empirical findings.

The canonical form of models is given by equation (1):

$$Q_\tau(Y_{it} \mid X_{it}) = \beta_0(\tau) + \beta_1(\tau)hdi_{it} + \beta_2(\tau)pvrt_{it} + \beta_3(\tau)hsic_{it} + \beta_4(\tau)shict_{it} + \beta_5(\tau)hia_{it} + \beta_6(\tau)gbinn_{it} \quad (1)$$

where:

i = 1, ..., N denotes the country;

t = year; $Q_\tau(Y_{it} \mid X_{it})$ - conditional quantile of the dependent variable Y_{it}, $\tau \in \{0.25, 0.50, 0.75\}$;

Y_{it} – dependent variable, namely insurance penetration (*inspn*) or the logarithm of insurance density (*insdn_lg*);

X_{it} – vector of independent variables (*hdi, pvrt, hsic, shict, hia, and gbinn*);

$\beta_0(\tau)$ - the intercept specific to the τ quantile;

$\beta_k(\tau)$ for k = 1, …, 6 denotes regression coefficients associated with explanatory variable X_{it} at quantile τ.

To capture the relationships between digital transformation, innovation, socio-economic determinants and insurance market development across EU MS, the study further employs *Structural Equation Modeling (SEM)*, estimated using Maximum Likelihood (ML) method, with bootstrap standard error (50 replications). This approach has its origins in the path analysis proposed by Wright (1960) and in the following developments of Structural Equation Models (Bollen, 1989), being later extended to integrate generalized linear modeling frameworks by Rabe-Hesketh et al. (2004).

Two separate models were built, corresponding to insurance penetration (*inspn*) and insurance density (*insdn_lg*). Each model includes all remained explanatory variables, with direct paths linking the selected indicators to the corresponding dependent variable. The model specifications are illustrated in figures no. 1 and no. 2.

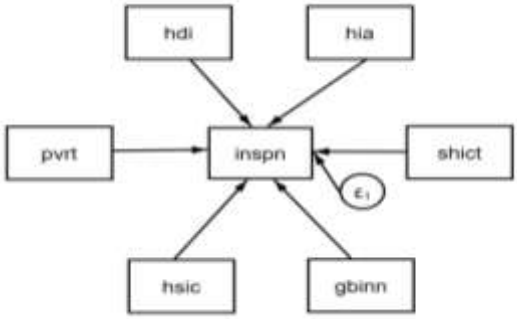

Figure no. 1. General configuration of SEM for insurance penetration
Source: Authors' contribution in Stata 17.

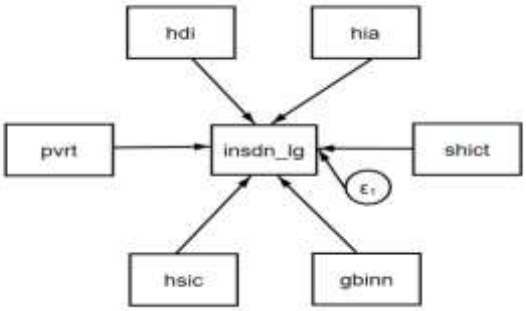

Figure no. 2. General configuration of SEM for insurance density
Source: Authors' contribution in Stata 17.

Together with quantile regression, which examines how these associations vary across the conditional distribution of insurance market development, SEM provides a complementary perspective on the relationships investigated in this study.
Based on the proposed methodological framework, the following research hypotheses are examined:

- *H1: Digital transformation is positively associated with insurance market development, as reflected in higher levels of insurance penetration and insurance density.*
- *H2: Innovation is positively associated with insurance market development, in terms of both insurance penetration and insurance density.*
- *H3: Higher levels of socio-economic development are positively associated with insurance penetration and insurance density, whereas poverty risk is expected to exhibit a negative relationship with both indicators.*

- *H4: Digital transformation, innovation, and socio-economic conditions jointly contribute to explaining variations in insurance penetration and insurance density across EU MS.*
- *H5: The relationships between digital transformation, innovation, socio-economic conditions, and insurance market development differ across the lower, median, and upper conditional quantiles of insurance penetration and insurance density*.

3. Results and Discussion

3.1. Results for pooled quantile regression with robust standard errors

The results of the pooled quantile regression models, estimated with robust standard errors, are reported in tables no. 4 and no. 5 for insurance penetration and insurance density, respectively.

Looking first at insurance penetration, table no. 4 shows a positive and statistically significant relationship with the Human Development Index (*hdi*) at the lower quantiles. This relationship becomes weaker as we move towards the upper end of the conditional distribution, a pattern also illustrated in figure no. 3. At the upper quantile, the coefficient is still positive (1.425), but it is no longer statistically significant. This suggests that human development may be less closely linked to insurance penetration at higher quantiles, where other institutional and structural factors could play a greater role (Outreville, 1996).

Table no. 4 also shows a positive relationship between the at-risk-of-poverty rate (*pvrt*) and insurance penetration across all three quantiles, although the coefficient is statistically significant only at the lower quantile ($p< 0.05$). One possible explanation is the role of institutional support and insurance schemes designed to address socio-economic vulnerabilities, as discussed by Dror and Jacquier (1999). Figure no. 3 provides a clearer picture of how this relationship varies across the distribution. The estimated coefficients change only slightly between the lower and median quantiles, before increasing at upper one. However, the association at the upper quantile remains statistically insignificant.

Table no. 4. QREG results, dependent variable insurance penetration degree (*inspn*), 2007-2023

Variables	(1) 0.25	(2) 0.5	(3) 0.75
hdi	20.81***	23.86*	1.425
	(5.154)	(9.879)	(6.957)
pvrt	0.0340*	0.0258	0.0562
	(0.0166)	(0.0247)	(0.0382)
hsic	0.0252*	0.00550	0.0694*
	(0.0119)	(0.0216)	(0.0344)
shict	0.114	-0.0691	-0.525***
	(0.0706)	(0.153)	(0.101)
hia	-0.00276	0.00371	-0.00113
	(0.00338)	(0.00596)	(0.00736)

gbinn	0.122*** (0.0228)	0.180** (0.0538)	0.402*** (0.0483)
_cons	-24.04*** (3.902)	-26.36*** (7.377)	-19.37*** (5.343)
N	170	170	170
Pseudo-R^2	0.4371	0.4792	0.5153

*Note: Standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$*
Source: Authors' contribution in Stata 17

A somewhat different pattern emerges for internet access (*hsic*). Its relationship with insurance penetration is positive and statistically significant at both the lower and upper quantiles, while at the median, the coefficient is smaller and no longer statistically significant. The stronger association observed at the upper quantile may indicate that internet access is more closely linked to insurance penetration in markets where penetration levels are already relatively high. This pattern is also illustrated in figure no. 3 and is consistent with Eling and Lehmann (2018), who highlight the role of digital transformation in improving access to insurance services.

The share of the ICT sector in GDP (*shict*) also shows an interesting pattern across quantiles. Its association with insurance penetration is not statistically significant at lower or median quantiles, but becomes negative and highly significant at higher one ($p<0.001$). This suggests that a larger ICT sector is associated with lower insurance penetration at the upper quantile. One possible explanation is that a higher ICT share may reflect economies with productive structures more focused on digital services, in line with the broader discussion of ICT-driven structural change by Carlsson (2004).

As shown in table no. 4, high-speed internet coverage (*hia*) is not statistically significantly associated with insurance penetration at any of the three quantiles, suggesting that its relationship with insurance market development remains unclear.

The Global Innovation Index (*gbinn*) is positively and statistically significantly associated with insurance penetration across all three quantiles. The coefficients increase from 0.122 at lower quantile to 0.180 at median and 0.402 at upper one, suggesting a stronger relationship between innovation and insurance penetration at higher quantiles. This pattern is also illustrated in figure no. 3, highlighting the growing importance of innovation in insurance markets with higher penetration levels.

The Pseudo-R^2 values increase across quantiles, suggesting a better model fit at higher levels of insurance penetration.

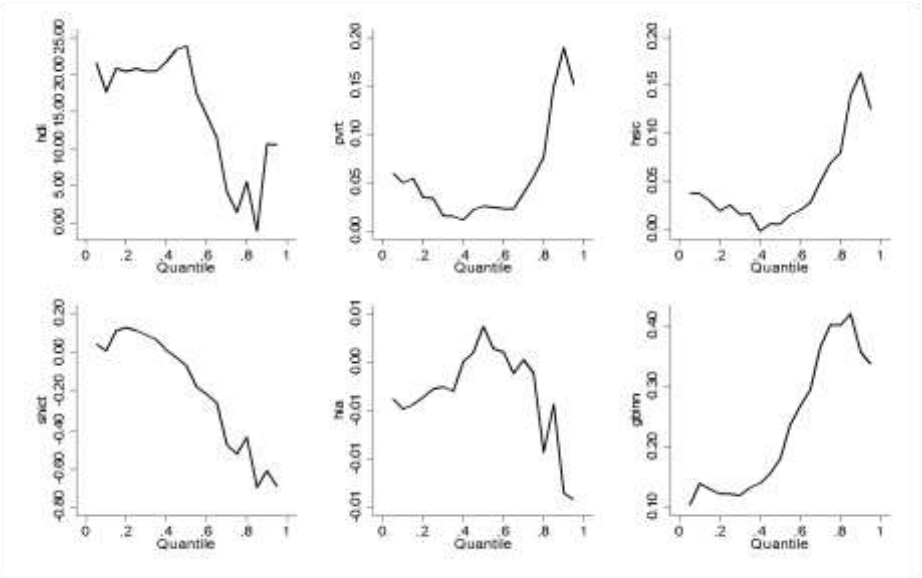

Figure no. 3. Graphical representation of variation in QREG coefficients across the distribution of insurance penetration (*inspn*), 2007-2023
Source: Authors' contribution in Stata 17.

The results of the first quantile regression model, estimated for total insurance penetration (*inspn*) at the lower, median, and upper quantiles, provide different levels of support for the research hypotheses.

Hypothesis H1. *Digital transformation is positively associated with insurance market development, as reflected in higher levels of insurance penetration and insurance density* is partially supported. Internet access (*hsic*) shows a positive and significant association at the lower and upper quantiles, while high-speed internet coverage (*hia*) is not statistically significant. The share of the ICT sector in GDP (*shict*) also shows a significant negative association at the upper quantile. Hypothesis H2. *Innovation is positively associated with insurance market development, in terms of both insurance penetration and insurance density* is supported at all three quantiles. The Global Innovation Index (*gbinn*) has a positive and significant association with insurance penetration, which becomes stronger at higher quantiles. Hypothesis H3. *Higher levels of socio-economic development are positively associated with insurance penetration and insurance density, whereas poverty risk is expected to exhibit a negative relationship with both indicators, which* is partially supported. The Human Development Index (*hdi*) is positively and significantly associated with insurance penetration at the lower quantiles. However, the at-risk-of-poverty rate (*pvrt*) shows a positive and significant association only at the lower level, which is opposite to the expected negative relationship. Finally, Hypothesis H5. *The relationships between digital transformation, innovation, socio-economic conditions, and insurance market development differ across the lower, median, and upper conditional quantiles of insurance penetration and insurance density* is

supported by the variation in the estimated coefficients. However, further statistical testing is needed to confirm whether these differences are significant.

Table no. 5 presents the results of the second quantile regression model, which uses the logarithm of total insurance density (*insdn_lg*) as the dependent variable. The model is estimated at the lower, median, and upper quantiles. The Pseudo-R^2 values are relatively high across all three quantiles, with the highest value recorded at the median, suggesting a better model fit at this point of the distribution.

Turning to insurance density, the Human Development Index (*hdi*) shows a positive and statistically significant association at all three quantiles ($p < 0.001$). This contrasts with the results for insurance penetration, where the relationship is no longer statistically significant at the upper quantile. However, the strength of the association with insurance density appears to decline as we move across the distribution. The estimated coefficient decreases from 7.919 at the lower quantile to 6.472 at the median, reaching 5.076 at the upper quantile. Although the relationship remains statistically significant, the smaller coefficients at higher quantiles may point to a gradual saturation of insurance demand in more developed markets. Figure no. 4 illustrates this pattern, which is also broadly in line with the findings of Beck and Webb (2003) regarding the importance of income and human development for insurance market development.

The at-risk-of-poverty rate (*pvrt*) has a negative association with insurance density at all three quantiles, although none of the estimated coefficients is statistically significant. This differs from the positive coefficients reported for insurance penetration in table no. 4. One possible explanation lies in what the two indicators actually measure. Insurance penetration expresses premiums as a share of GDP, whereas insurance density measures premiums per capita and may be more closely related to the financial resources available to individuals for purchasing insurance. Still, given the lack of statistical significance, these results do not provide sufficient evidence of a relationship between poverty and insurance density.

Table no. 5. QREG results, dependent variable insurance density (*insdn_lg*), 2007-2023

Variables	**(1)** **0.25**	**(2)** **0.5**	**(3)** **0.75**
hdi	7.919***	6.472***	5.076***
	(1.095)	(0.861)	(1.074)
pvrt	-0.00592	-0.00125	-0.00161
	(0.00329)	(0.00383)	(0.00352)
hsic	-0.00557	0.000916	-0.000887
	(0.00288)	(0.00378)	(0.00447)
shict	0.0160	-0.0292*	-0.0468*
	(0.0180)	(0.0130)	(0.0219)
hia	-0.000216	0.000256	0.00106
	(0.000680)	(0.000743)	(0.000865)

gbinn	0.0206*** (0.00492)	0.0321*** (0.00401)	0.0384*** (0.00462)
_cons	-4.581*** (0.786)	-4.191*** (0.641)	-2.949*** (0.701)
N	152	152	152
Pseudo-R^2	0.6774	0.7024	0.6431

*Note: Standard errors in parentheses, * p < 0.05, ** p < 0.01, *** p < 0.001*
Source: Authors' contribution in Stata 17.

A different pattern can be observed for the share of the ICT sector in GDP (*shict*). The coefficients are negative and statistically significant at the median and upper quantiles, but not at the lower quantile. As figure no. 4 shows, the negative association becomes more pronounced towards the upper end of the distribution. This is broadly consistent with the results for insurance penetration and suggests that a larger ICT sector is not necessarily associated with higher insurance spending per capita, particularly in markets with relatively high insurance density. Changes in the structure of digital economies and the increasing availability of alternative risk management solutions may offer a possible explanation, as discussed by Song et al. (2022). By comparison, neither internet access (*hsic*) nor high-speed internet coverage (*hia*) shows a statistically significant association with insurance density at any of the three quantiles.

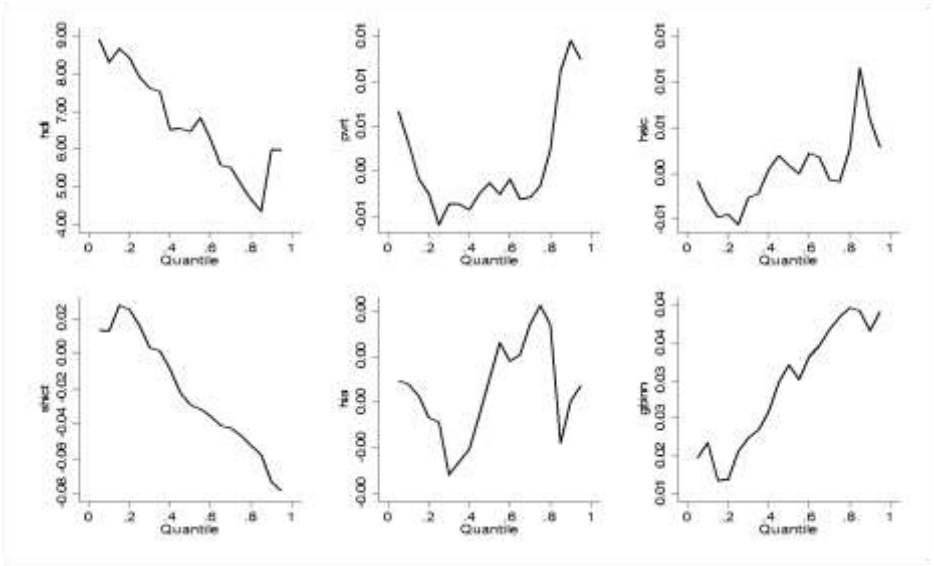

Figure no. 4. Graphical representation of variation in QREG coefficients across the distribution of insurance penetration (*insdn_lg*), 2007-2023
Source: Authors' contribution in Stata 17.

The Global Innovation Index (*gbinn*) is positively and statistically significantly associated

with insurance density across all three quantiles ($p < 0.001$). The coefficients increase from 0.0206 at the lower quantile to 0.0321 at the median and 0.0384 at the upper quantile, suggesting a stronger relationship between innovation and insurance density at higher quantiles. This may reflect the role of innovation in developing more diverse insurance products, improving distribution channels, and strengthening risk management practices (Tan, 2001).

The results of the second quantile regression model, estimated for total insurance density (*insdn_lg*) at the lower, median, and upper quantiles, also provide different levels of support for the research hypotheses.

Hypothesis H1. *Digital transformation is positively associated with insurance market development, as reflected in higher levels of insurance penetration and insurance density* is not supported by this model. Internet access (*hsic*) and high-speed internet coverage (*hia*) are not statistically significant, while the share of the ICT sector in GDP (*shict*) shows a significant negative association at the median and upper quantiles. Hypothesis H2. *Innovation is positively associated with insurance market development, in terms of both insurance penetration and insurance density* is supported across all three quantiles. The Global Innovation Index (*gbinn*) shows a positive and significant association with insurance density, which becomes stronger at higher quantiles. Hypothesis H3. *Higher levels of socio-economic development are positively associated with insurance penetration and insurance density, whereas poverty risk is expected to exhibit a negative relationship with both indicators, which* is partially supported. The Human Development Index (*HDI*) is positively and significantly associated with insurance density at all three quantiles, although the relationship becomes weaker at higher quantiles. The at-risk-of-poverty rate (*pvrt*) shows the expected negative association, but it is not statistically significant. Finally, Hypothesis H5. *The relationships between digital transformation, innovation, socio-economic conditions, and insurance market development differ across the lower, median, and upper conditional quantiles of insurance penetration and insurance density* is supported by the differences observed across quantiles. Innovation has a stronger positive association with insurance density at higher quantiles, while the association with human development becomes weaker and that with the ICT sector becomes more negative. These results suggest that the relationships vary across the distribution of insurance density.

4.1. Results for Structural Equations Modeling (SEM)

The results of the Structural Equation Modeling (SEM) analysis for insurance penetration and insurance density are presented in table no. 6, while the corresponding path diagrams are shown in figures no. 5 and no. 6, respectively.

The SEM results show that both models are statistically significant, as confirmed by the Wald tests for insurance penetration and insurance density (Appendix, table no. A1). The coefficients of determination (CD) indicate that the models explain approximately 68.5% and 87.8% of the variation in insurance penetration and insurance density, respectively (Appendix, table no. A2). Overall, the Wald tests support the joint statistical significance of the explanatory variables in both models. The overall Cronbach's Alpha values indicate

relatively high internal consistency among the variables considered (Appendix, table no. A3).

As shown in figure no. 5 and table no. 6, the share of the ICT sector in GDP (*shict*) has a negative and statistically significant association with insurance penetration (β=-0.343, p<0.001). This result is consistent with the negative relationship observed at the upper quantile in the quantile regression analysis (table no. 4). Internet access (*hsic*) shows a positive and statistically significant association with insurance penetration (β=0.0453, p<0.05). This result is in line with the quantile regression findings, which also show positive and statistically significant coefficients at the lower and upper quantiles.

The Global Innovation Index (*gbinn*) is positively and significantly associated with insurance penetration (β = 0.275, p < 0.001). A similar pattern emerges from the quantile regression analysis in table no. 4, where the relationship between innovation and insurance penetration remains positive and statistically significant across all three quantiles.

Table no. 6. Results of SEM with ML bootstrap standard error

Variables	**(1)** ***inspn***	**(2)** ***insdn_lg***
hdi	11.21 (6.608)	6.091*** (0.774)
pvrt	0.0442 (0.0244)	0.00131 (0.00413)
hia	-0.000258 (0.00435)	0.0000802 (0.000643)
shict	-0.343*** (0.0991)	-0.0371* (0.0150)
hsic	0.0453* (0.0204)	0.00232 (0.00389)
gbinn	0.275*** (0.0341)	0.0327*** (0.00354)
_cons	-21.60*** (4.697)	-4.011*** (0.619)
var(e.inspn)	2.398*** (0.300)	
var(e.insdn_lg)		0.0301*** (0.00338)
N	170	152

Note: Standard errors in parentheses. * *p < 0.05,* ** *p < 0.01,* *** *p < 0.001*
Source: Authors' contribution in Stata 17.

Figure no. 5 illustrates the SEM model for insurance penetration (*inspn*), showing the direct relationships between the dependent variable and the six explanatory variables.

The results are less conclusive for the Human Development Index (*hdi),* the at-risk-of-poverty rate (*pvrt*), and high-speed internet coverage (*hia*), as none of these variables reaches statistical significance in the SEM model.

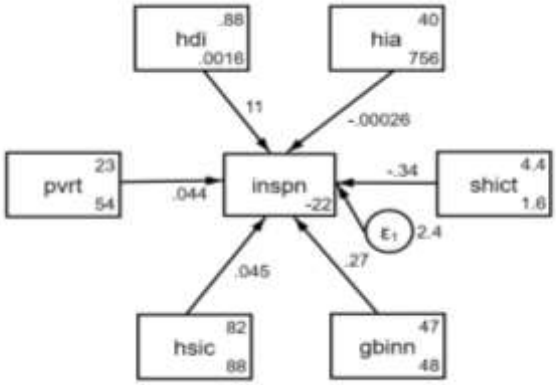

Figure no. 5. Path diagram for SEM, dependent variable insurance penetration (*inspn*), 2007-2023
Source: Authors' contribution in Stata 17.

Figure no. 6 presents the SEM model for insurance density (*insdn_lg*), estimated using the same explanatory variables as those included in the insurance penetration model. The corresponding coefficients and their statistical significance are reported in table no. 6, providing a basis for comparing the relationships identified for the two measures of insurance market development.

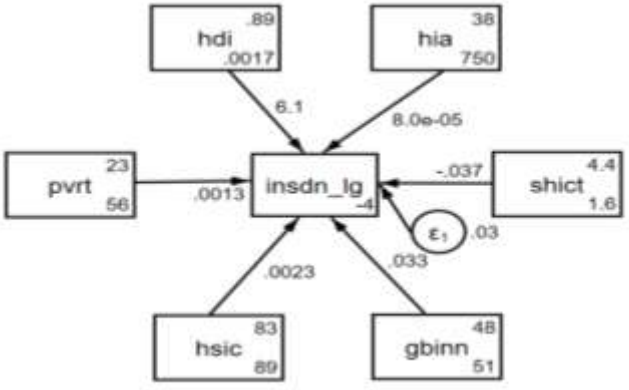

Figure no. 6. Path diagram for SEM, dependent variable insurance density (*insdn_lg*), 2007-2023
Source: Authors' contribution in Stata 17.

The Human Development Index (*hdi*) is positively and statistically significantly associated with insurance density ($\beta = 6.091$, $p < 0.001$). This finding is in line with the quantile regression results, where the relationship remains significant across all three quantiles, suggesting that socio-economic development is closely linked to insurance spending per capita. It also supports the broader argument made by Beck and Webb (2003) regarding the role of socio-economic conditions in shaping insurance demand.

A different relationship is observed for the share of the ICT sector in GDP (*shict*), which has a negative and statistically significant coefficient (β=-0.0371, $p<0.05$). This result follows a similar pattern to that found in the quantile regression analysis, where negative and significant associations were also identified at the median and upper quantiles.

The Global Innovation Index (*gbinn*) is also positively and statistically significantly associated with insurance density (β=0.0327, $p<0.001$). This confirms the consistent positive relationship between innovation and both indicators of insurance market development.

In contrast, the at-risk-of-poverty rate (*pvrt*), internet access (*hsic*), and high-speed internet coverage (*hia*) are not statistically significant in the SEM model.

The SEM results provide different levels of support for the research hypotheses.

Hypothesis H1. *Digital transformation is positively associated with insurance market development, as reflected in higher levels of insurance penetration and insurance density* is partially supported. Internet access (*hsic*) is positively and significantly associated with insurance penetration, but not with insurance density. In contrast, the share of the ICT sector in GDP (*shict*) shows a significant negative association with both indicators, while high-speed internet coverage (*hia*) is not statistically significant. Hypothesis H2. *Innovation is positively associated with insurance market development, in terms of both insurance penetration and insurance density*, is supported. The Global Innovation Index (*gbinn*) is positively and statistically significantly associated with both insurance penetration and insurance density, confirming the consistent role of innovation in insurance market development. Hypothesis H3. *Higher levels of socio-economic development are positively associated with insurance penetration and insurance density, whereas poverty risk is expected to exhibit a negative relationship with both indicators*, is partially supported. The Human Development Index (*hdi*) shows a positive and significant association with insurance density, but not with insurance penetration. The at-risk-of-poverty rate (*pvrt*) is not statistically significant in either model. Hypothesis H4. *Digital transformation, innovation, and socio-economic conditions jointly contribute to explaining variations in insurance penetration and insurance density across EU MS* is supported by the overall significance of both SEM models, as indicated by the Wald tests ($p<0.001$). These results suggest that the explanatory variables jointly contribute to explaining variations in insurance penetration and insurance density across EU MS.

Conclusions

This study examined the relationships between digital transformation, innovation, socio-economic conditions, and insurance market development in the 27 EU MS during 2007-2023, using quantile regression and Structural Equation Modeling (SEM).

The results show that innovation has the most consistent positive relationship with

insurance market development, for both insurance penetration and insurance density. Digital transformation shows mixed results. Internet access is positively associated with insurance penetration, while the share of the ICT sector in GDP is negatively associated with both insurance indicators. Human development appears to be particularly relevant for insurance density, whereas the relationship between poverty risk and insurance market development is less clear.

The quantile regression results also reveal differences across the conditional distribution. Innovation tends to show a stronger positive association at higher quantiles, while the coefficients for human development generally decrease. These patterns suggest that the factors associated with insurance market development are not equally relevant at all levels of insurance penetration and density, and that their relationships may change as insurance markets develop.

The findings also have implications for policymakers and insurance companies. Encouraging innovation and improving access to digital services may help create more favorable conditions for insurance market development. At the same time, insurers need to consider the different financial circumstances and needs of consumers when designing their products, particularly in terms of affordability and accessibility. The results suggest, however, that expanding digital infrastructure alone may not be sufficient to support the development of insurance markets.

Several *limitations* should be considered when interpreting these findings. The analysis covers the period 2007-2023, and the number of available observations is constrained by gaps in the data. Moreover, although the econometric methods provide evidence of statistical associations, they do not establish causal relationships or fully capture the specific characteristics of individual EU MS. *Future studies* could examine these differences more closely, particularly between countries at different stages of economic and digital development. A broader set of explanatory variables, including institutional and regulatory factors, may also help explain why insurance markets develop differently across the EU.

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APPENDIX

Table no. A1. Wald tests for equations

Variables	**Chi²**	**df**	***p*-value**
observed			
inspn	506.58	6	0.0000
insdn_lg	1185.20	6	0.0000

Source: Authors' contribution in Stata 17.

Table no. A2. Goodness-of-fit statistics

Tests	***inspn***	***insdn_lg***
Likelihood ratio		
„Model vs. saturated" chi²_ms	0.000 chi²_ms (0)	0.000 chi²_ms (0)
p > chi²	0.000	0.000
„Baseline vs. saturated" chi²_bs	196.177 chi²_bs (6)	319.720 chi²_bs (6)
p > chi²	0.000	0.000
Population error		
„RMSEA (Root mean squared error of approximation)"	0.000	0.000
90% CI, lower bound	0.000	0.000
upper bound	0.000	0.000
pclose (Probability RMSEA <= 0.05)	1.000	1.000
Information criteria		
„AIC (Akaike's information criterion)"	5111.647	3920.690
„BIC (Bayesian information criterion)"	5136.734	3944.881
Baseline comparison		
„CFI (Comparative fit index)"	1.000	1.000
„TLI (Tucker–Lewis index)"	1.000	1.000
Size of residuals		
"SRMR (Standardized root mean squared residual)"	0.000	0.000
„CD (Coefficient of determination)"	0.685	0.878

Source: Authors' contribution in Stata 17.

Table no. A3. Cronbach' alfa coefficients for the SEM models

Items	*inspn*		*insdn_lg*	
	Item–test Correlation	**Alpha**	**Item–test Correlation**	**Alpha**
inspn/ insdn_lg	0.7241	0.8081	0.8318	0.8081
hdi	0.8641	0.7685	0.8777	0.7947
pvrt	0.7848	0.7942	0.7939	0.8202
hsic	0.8123	0.7801	0.8274	0.8060
shict	0.4672	0.8464	0.4532	0.8698
hia	0.4227	0.8557	0.4325	0.8758
gbinn	0.8085	0.7956	0.8039	0.8239
Test scale		**0.8334**		**0.8528**

Source: Authors' contribution in Stata 17.