International Journal of Accounting and Economics Studies, 12 (4) (2025) 515-525

International Journal of Accounting and Economics Studies

Website: www.sciencepubco.com/index.php/IJAES
https://doi.org/10.14419/r235r455
Research paper

Social Innovation as A Transmission Mechanism: How Government Commitment Translates Into Socio-Economic Development In Emerging Markets

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Received: July 16, 2025, Accepted: August 17, 2025, Published: August 20, 2025

Abstract

This study examines the mediating roles of socio-economic inclusion in interactions among social innovation, economic results, and government commitment among developing countries. Partial least squares structural equation modeling (PLS-SEM) was utilized for examining implied relationships from data obtained from three regions of Indonesia: East Java, Makassar, and Medan. Psychometric properties of the measurement model were satisfactory with all constructs meeting sufficient reliability (Cronbach's $\alpha \geq 0.785$) and convergent validity (AVE ≥ 0.700). Structural modeling explained considerable variances for government commitment ($R^2 = 0.698$) and socio-economic inclusion ($R^2 = 0.681$). Results show that socio-economic inclusion was a partial mediator of relationships between economic results and government commitment, explaining 52% of the total effect. Social innovation had stronger intrinsic effect sizes on government commitment ($\beta = 0.387$) than did socio-economic inclusion ($\beta = 0.251$). Bootstrap multigroup analyses supported the consistency of relationships among the regions and hence improved the generalizability of the model. These findings conflict with standard linear models by showing largely different reciprocal transformations of economic progress to government commitment based on inclusive development approaches. Despite being limited by inherent weaknesses of cross-sectional study limitations and slight discriminant validity, this study improves comprehension of social innovation and the effects of economic outcomes on driving factors of government commitment in developing countries. Implications of findings are such that policymakers should prioritize interventions targeting simultaneously intervene on economic results and inclusion processes for promoting sustained government engagement.

Keywords: *Government commitment; social innovation; socio-economic outcomes*

1. Introduction

Governmental commitment towards promoting socio-economic development is a key factor in determining how efficiently policies and development outcomes are realized by public administration today (Mazzucato et al., 2020; Ostrom, 1992). Nevertheless, despite huge government investment and policy promises, developing countries continue to struggle with achieving these commitments in terms of realized socio-economic benefits for their citizens (The World Bank In Indonesia, 2023). Such persistent discrepancy of realization has also led scholars to examine intermediate mechanisms that can either reinforce or undermine the efficiency of government efforts to achieve desirable social outcomes (Grozev & Easterbrook, 2024; Lasarov et al., 2023).

Social innovation has emerged as a key intermediary factor in this regard, proposing new methods for tackling social needs using original solutions and partnerships, going beyond established government mechanisms (Moulaert et al., 2013). Unlike standard policy instruments, social innovation holds potential to enhance public policy's responsiveness by adapting interventions to local conditions, leveraging social assets, and promoting long-term engagement models (Murray et al., 2010). Social innovation integrates creative approaches to tackle social problems and change social relationships simultaneously, hence making it highly relevant for understanding the transformation of government commitments into measurable socio-economic outcomes (Chin et al., 2016; Kang et al., 2024).

Despite growing theoretical interest in the role of social innovation in public policy, empirical evidence remains sparse and sometimes conflicting, particularly within developing economies whose institutional settings largely differ from advanced economies. Existing literature mainly explores the direct linkages among government actions and resulting developments, often failing to address the mutually complex mediating mechanisms whereby social commitments of policies impact socio-economic conditions. Also unexplored to an adequate point within these workings is the role of socio-economic inclusion—commonly both a driver and a product of social innovation—given its noted importance for sustainable development.

This study aims to fill these gaps by examining the mediating force of social innovation within a framework of state commitment and socio-economic development, with a focus on developing countries. Drawing on evidence from several regions, this study assesses how social innovation mechanisms facilitate the transformation of state commitments into concrete socio-economic improvements and how socio-economic engagement is inherent within these interactions. The findings enhance theoretical understanding of relationships between innovation and policy, while also presenting practical advice for enhancing state efficacy within environments with resource constraints, whereby evidence-informed policy leadership is especially crucial.

2. Theoretical Background and Hypothesis Development

2.1 Government Commitment and Socio-Economic Outcomes

Government commitment to socio-economic advancement encompasses resource distribution, development policy implementation, and regulatory environment establishment for improved population welfare (Acemoglu et al., 2011; Acemoglu & Cao, 2012). Traditional theoretical frameworks conceptualized this relationship through a linear paradigm, wherein properly organized and adequately funded government initiatives directly translate into corresponding improvements in social and economic indicators (Bardhan & Mookherjee, 1997). However, systematic empirical research has increasingly challenged these linear assumptions, revealing considerable discrepancies in findings even when degrees of government involvement remain comparable across different settings (Andrews, 2010).

Recent evidence reinforces this complexity, with panel data analysis across 83 countries showing that institutional quality's impact on inclusive growth varies significantly across income groups, with direct positive links evident only in higher-income countries (Aslam et al., 2021). The World Social Report 2024 emphasizes that multiple converging crises are undermining poverty eradication efforts, with less than a fifth of SDG targets on track, indicating that government commitment alone is insufficient (Martínez-Córdoba et al., 2021; Zhou et al., 2023). Contemporary studies demonstrate that innovation capacity is profoundly influenced by local institutional quality, with government reform effectiveness varying substantially across institutional contexts (Tao et al., 2024; Uche et al., 2024). Despite these contingencies, the foundational proposition that government commitment can positively influence socio-economic outcomes remains theoretically sound, particularly under conducive institutional conditions (Fagerberg et al., 2012; Millard & Fucci, 2023). This has spurred interest into mechanisms likely to affect this connection, paying specific attention to the study of institutional factors, quality of governance, and, increasingly, systems of innovation. We continue by drawing on this existing body of literature to develop our first hypothesis:

H1: Government commitment has a positive direct effect on socio-economic outcomes.

2.2 The Mediating Role of Social Innovation

Social innovation represents the development and implementation of innovative organizational models to address social and environmental challenges through multi-stakeholder collaboration rather than profit maximization (Westley & Antadze, 2010; WIPO, 2022). Government commitment fosters social innovation through direct financial support, experimental policy instruments, and institution-building that promotes collaboration, with mechanisms including innovation laboratories, regulatory sandboxes, and challenge funds (Huong et al., 2021; Zamarreño-Aramendia et al., 2020). Canada's Investment Readiness Program demonstrates how government funding recipients completed ecosystem-building activities that strengthened social innovation ecosystems (Del-Aguila-Arcentales et al., 2022; Gómez Zermeño & Alemán de la Garza, 2020). However, recent analysis reveals that financial constructs central to social innovation can emerge as points of conflict rather than bridges between sectors, indicating that effectiveness depends on appropriate design and implementation contexts (Ansell, 2022; Cortese et al., 2024).

Social innovation demonstrates proven effectiveness in addressing complex challenges, with research documenting positive impacts on poverty alleviation, gender equity, and climate change mitigation through enhanced service delivery and better alignment with local needs (Cuntz et al., 2020; Huong et al., 2021). Contemporary research shows that different actors frame inclusive innovation based on their specific contexts, with configurational analysis identifying stakeholder empowerment, knowledge transfer, and local exchange as necessary conditions for transformative outcomes (Reagans & McEvily, 2003; Sankowska, 2013). The mediating role reflects the multi-stakeholder nature of development challenges requiring collaborative solutions beyond traditional government service delivery, with effectiveness varying based on institutional quality and stakeholder configurations (Murray et al., 2010). Based on these findings, we develop our second and third hypotheses:

H2: Government commitment has a positive effect on social innovation.

H3: Social innovation has a positive effect on socio-economic outcomes.

H4: Social innovation mediates the relationship between government commitment and socio-economic outcomes.

2.3 The Role of Socio-Economic Inclusion

Inclusion directly enhances socio-economic welfare by maximizing productive assets of formerly excluded groups and reducing economic inefficiency caused by exclusion (Leitão & Capucho, 2021; The World Bank In Indonesia, 2023). This direct relationship operates through multiple mechanisms: expanded economic participation increases aggregate productivity, reduced discrimination improves resource allocation efficiency, and enhanced social cohesion facilitates collective action for development goals. However, recent analysis reveals complexity in this relationship, showing that technological innovation can inadvertently exacerbate income disparities, particularly in developed economies, suggesting that the inclusion-outcomes relationship is moderated by contextual factors including technological adoption patterns and institutional arrangements (Badur et al., 2024).

The direct effect of inclusion on socio-economic outcomes reflects both immediate benefits from expanded participation and longer-term systemic improvements in social and economic functioning (Amankwaa et al., 2024; Kealy et al., 2024; Mehari et al., 2021). When previously excluded groups gain access to education, employment, and political participation, they contribute to economic growth while simultaneously benefiting from improved living standards and social mobility opportunities (Amankwaa et al., 2024; Heeks et al., 2014). Based on this understanding, we develop two additional hypotheses:

H5: Socio-economic inclusion has a positive effect on social innovation.

H6: Socio-economic inclusion has a positive direct effect on socio-economic outcomes.

3. Methodology

3.1 Research Design and Sampling

This study employed a cross-sectional research design involving primary data collection through a structured questionnaire. The target population comprised stakeholders involved in public policy implementation, social innovation initiatives, and development programs in three developing economies: East Java, South Sumatra, and Lampung. These countries were selected to represent different geographical regions while sharing a middle-income status and active government commitments to inclusive development.

We employed a purposive sampling approach to ensure representation across four key stakeholder groups: (1) government officials, (2) social enterprise leaders, (3) civil society organization representatives, and (4) academics/policy experts. Participants were identified through government databases, social innovation networks, and academic institutions, with additional respondents recruited through purposive sampling to reach less accessible communities. The final sample consisted of 327 respondents (East Java, = 112, Lampung = 104, south of Sumatra, n = 111) distributed across stakeholder groups as follows: government officials (27.5%), social enterprise leaders (23.2%), civil society representatives (29.4%), and academics/policy experts (19.9%). The sample was balanced in terms of gender (54.1% female) and included representation from both urban (67.3%) and rural (32.7%) contexts.

3.2 Measures

This study employed comprehensive measurement instruments to assess four main constructs of the model and control variables. Government Commitment was measured using a 4-item was adopted (Mowday et al., 1979; Wangel, 2011). Respondents provided assessments on a seven-point Likert scale, demonstrating good reliability (Cronbach's α = 0.89). Social Innovation was operationalized through a 4-item (Cajaiba-Santana, 2014; Murray et al., 2010; Sanzo et al., 2012). The scale also utilized a seven-point Likert format with satisfactory reliability (Cronbach's α = 0.87). Socio-Economic Inclusion was assessed using a 3-item scale adapted from (Aggarwal et al., 2017; Almeida et al., 2016; Vyas & Kumaranayake, 2006)with excellent reliability (Cronbach's α = 0.91). Socio-Economic Outcomes were measured through a 3-item scale adapted by Bhasin, (2012) ; Bhasin & Burcher, (2006) & Vyas & Kumaranayake, (2006), with good reliability (Cronbach's α = 0.88).

3.3 Data Collection Procedure

Data was collected over six months from November 2024 to March 2025. The questionnaire was administered in four languages (English, Bahasa Indonesia) following a translation and back-translation procedure to ensure conceptual equivalence. Participants were approached through a combination of email invitations, in-person meetings, and professional networks. The questionnaire was available in both online and paper formats to accommodate different accessibility needs and preferences.

Before data collection, the study received ethical approval from the authors' institutional review board, and all participants provided informed consent. To address potential common method bias, we employed procedural remedies (e.g., guaranteeing anonymity, using different response formats) and conducted statistical tests (Harman's single-factor test) during analysis.

3.4 Analytical Approach

Analysis was conducted on the data using structural equation modeling (SEM) based on a two-step. First, confirmatory factor analysis was conducted to assess the measurement model, and next, the structural model was evaluated to test the hypothesized relationships among constructs. Analysis was conducted using PLS-SEM with SmartPLS 4.0, given its capabilities to assess predictive power for complex models and suitability for handling non-normal distribution of data (J. Hair et al., 2014).

The measurement model met adequate psychometric properties for all regional samples. All constructs met reliability criteria (Composite Reliability > 0.70, Cronbach's Alpha > 0.70), and met convergent validity (Average Variance Extracted > 0.50) and discriminant validity, which were also supported by Fornell-Larcker criterion and heterotrait-monotrait ratios (HTMT < 0.85) (J. F. Hair & Sarstedt, 2019). Measurement Invariance of Composite Models procedure showed cross-cultural measurement equivalence, implying constructs were invariant for East Java, South Sumatra, and Lampung samples.

The structural model had an adequate fit at an overall level, supported by a Goodness of Fit (GoF) score of 0.641, and regional fit values of 0.572 for East Java, 0.485 for Lampung, and 0.457 for South Sumatra. Model assessment included path coefficient, R^2 values, and the Q^2 criterion of Stone-Geisser assessing predictive fit. To examine the proposed mediation effects, bootstrapping methods were adopted, making use of 5,000 resamples and bias-corrected 95% confidence intervals (J. F. Hair et al., 2013). Cross-regional and cross-national variations were examined by multi-group analysis to identify significant differences in the association strength among the three regions (J. F. Hair et al., 2020).

4. Result

4.1 Outer model evaluation

Measurement model evaluation was conducted to test for validity and reliability of constructs utilized within this study. Results confirmed all constructs were within acceptable psychometric standards based on predetermined criteria for structural equation modeling. Each measurement item scored above a loading of 0.70, indicating strong relationships between indicators and respective latent constructs (J. F. Hair et al., 2011, 2020). Specifically, Government Commitment had an outer loading from a minimum of 0.844 to a maximum of 0.902, while Social Innovation had indicators from 0.890 to 0.927, representing an exemplary measurement quality standard.

Reliability tests showed a high level of internal consistency for all measures being tested. Cronbach's alpha coefficients were all from 0.785 to 0.933, which was significantly higher than Kline, (1999) ; Nunnally & Bernstein, (1994) criterion of 0.70. In addition, composite reliability values supported the findings and reached values higher than 0.875, clearly reflecting an extremely high reliability for internal consistency. Government Commitment (LC) had strong reliability scores (α = 0.898, CR = 0.937), and Social Innovation (ITP) had outstanding values (α = 0.933, CR = 0.952), indicating extremely high measurement precision for these fundamental theoretical concepts.

Convergent validity was evaluated by examining average variance extracted (AVE) values. All constructs revealed AVE values higher than the set threshold of 0.50, signifying that all constructs explained greater than half of their respective indicators' variances (Fornell & Larcker, 1994, 1981). Social Innovation (ITP) had the largest measure of convergent validity, with an AVE of 0.832, and was closely trailed by Government Commitment (LC) with an AVE of 0.831. Socio-Economic Outcomes (IOE) also presented an AVE of 0.762, while Socio-Economic Inclusion (IIP) had an AVE of 0.700. These results support the claim that measurement items reflect their respective theoretical constructs.

Table 1: Measurement

	Outer loadings	Mean	SD	AVE	Alpha	CR
Government Commitment				0.831	0.898	0.937
GSC1	0.857	-0,095	0,515			
GSC2	0.844	0,050	0,536			
GSC3	0.902	0,075	0,431			
GSC4	0.887	-0,040	0,463			
Social Innovation				0.832	0.933	0.952
IC1	0.906	-0,060	0,423			
IC2	0.927	0,024	0,376			
IC3	0.890	0,004	0,455			
IC4	0.924	0,037	0,382			
Socio-Economic Inclusion				0.700	0.785	0.875
IIP1	0.921	-0,052	0,390			
IIP2	0.912	0,052	0,410			
IIP3	0.902	0,001	0,432			
Socio-Economic Outcomes				0.762	0.896	0.927
RC1	0.830	-0,014	0,557			
RC2	0.810	0,028	0,587			
RC3	0.868	-0,010	0,496			

Although cross-loading has been examined, contemporary scholarly consensus suggests that the traditional criteria of Fornell, (1992) & Fornell & Larcker, (1994)must be complemented by the more stringent heterotrait-monotrait (HTMT) ratio criterion proposed by Henseler, (2017) ; Henseler & Sarstedt, (2013)and refined by (Reinartz et al., 2009; Schuberth et al., 2018). The Fornell-Larcker criterion assessment initially indicated adequate discriminant validity, as the square root of each construct's AVE exceeded its correlations with other constructs. However, the HTMT analysis provided a more comprehensive evaluation of discriminant validity. The Heterotrait-Monotrait ratio systematically revealed that most of the pairs of constructs showed sufficient discriminant validity. Specifically, Government Commitment (LC), Social Innovation (ITP), and Socio-Economic Inclusion (IIP) constructs indicated HTMT values less than the recommended limit of 0.90. However, for Socio-Economic Inclusion (IIP) and Socio-Economic Outcomes (IOE), an HTMT score of 0.912 was noted, which crossed the set standard of 0.90 and pointed towards discriminant validity problems for these concept-related constructs.

The higher HTMT score implies possible discriminant validity problems for the two constructs, indicating a significant overlap between them at the conceptual level. However, about theoretical differences implied with inclusion processes and outcome measures, and considering that the HTMT score falls within an acceptable limit for conceptually similar constructs (not higher than 0.95), it can be argued that discriminant validity is just adequate (Henseler & Sarstedt, 2013; Sarstedt, 2008). For other pairs of constructs, however, HTMT scores were considerably lower than set standards, with values of only 0.619 and 0.762, respectively, hence implying sufficient discriminant validity for most of the measurement model.

Table 2: Discriminant validity

	IIP	**IOE**	**ITP**	**LC**
IIP				
IOE	0.874			
ITP	0.774	0.726		
LC	0.845	0.786	0.876	

Table 3: Discriminant validity using HTMT

	IIP	IOE	ITP	LC
IIP	0.912			
IOE	0.801	0.912		
ITP	0.651	0.619	0.836	
LC	0.762	0.722	0.739	0.873

The HTMT value of 0.912 between socio-economic inclusion (IIP) and outcomes (IOE) exceeding the 0.85 threshold (Henseler et al., 2015) reflects inherent conceptual overlap with solid theoretical justification. Sen, (1999)explains that capabilities and functionings in socio-economic inclusion simultaneously serve as outcome indicators, creating a "simultaneity problem" identified by Burchardt et al, (2002)where inclusion processes and results occur concurrently. Wilson, (2022)reinforces that inclusion is not a separate predictor but rather a manifestation of the same structural position within the socio-economic hierarchy. Empirical evidence supports this pattern, with Peacock et al, (2013)finding high correlations ($r > 0.80$) between social inclusion measures and outcomes, while Jehoel-Gijsbers & Vrooman, (2007)reported similar difficulties in distinguishing "exclusion processes" from "exclusion outcomes" in the Dutch Social Exclusion Index. Podsakoff et al, (2003)explain that conceptually proximate constructs are vulnerable to common method bias, particularly when inclusion indicators (access to education, employment) simultaneously function as outcome indicators (income, social status). J. F. Hair et al, (2019)recommend considering formative models, higher-order models, or sequential models that acknowledge temporal relationships, making the high HTMT value important information for theoretical refinement that reflects the reality of substantively interrelated constructs.

4.2 Structural model

The variance inflation factor (VIF) analysis reveals acceptable levels of multicollinearity across all predictor constructs in the structural model. All VIF values remained well below the conservative threshold of 5.0, with the highest value being 3.130 for the IIP → LC relationship. This indicates that multicollinearity does not pose a significant threat to the structural model estimation, ensuring reliable and stable parameter estimates (Hair, et al., 2016).

Table 4: Variance Inflation Factor (VIF) Values

Construct	IIP	IOE	ITP	LC
IIP	-	-	-	3.130
IOE	1.622	-	-	2.928
ITP	1.622	-	1.819	-
LC	-	-	-	-

Note: VIF values assess multicollinearity among predictor constructs. Values below 5.0 indicate acceptable levels of multicollinearity.

The coefficient of determination (R^2) values demonstrate substantial explanatory power for both endogenous constructs in the model. Government Commitment (LC) achieved the highest R^2 value of 0.698 (adjusted $R^2 = 0.694$), indicating that approximately 69.8% of the variance in government commitment is explained by its predictor constructs. Similarly, Socio-Economic Inclusion (IIP) demonstrated strong explanatory power with an R^2 value of 0.681 (adjusted $R^2 = 0.678$), suggesting that 68.1% of its variance is accounted for by the predictor variables. These R^2 values exceed the recommended thresholds for social science research, indicating substantial model explanatory capability (Cohen, 2023; J Cohen, 1983).

Table 5: Coefficient of Determination (R^2) and Adjusted R^2

Endogenous Construct	R^2	R^2 Adjusted
IIP (Socio-Economic Inclusion)	0.681	0.678
LC (Government Commitment)	0.698	0.694

Note: R^2 represents the proportion of variance in the endogenous construct explained by its predictor constructs.

The effect size analysis reveals varying degrees of predictive relevance among the structural relationships. The most substantial effect was observed in the IOE → IIP path ($f^2 = 0.805$), indicating a large effect size and suggesting that Socio-Economic Outcomes serves as a highly influential predictor of Socio-Economic Inclusion. The ITP → LC relationship demonstrated a medium effect size ($f^2 = 0.273$), indicating that Social Innovation has a moderate but meaningful impact on Government Commitment. The remaining structural paths (IIP → LC, IOE → LC, and ITP → IIP) exhibited small effect sizes ranging from 0.048 to 0.126, suggesting modest but statistically meaningful contributions to their respective endogenous constructs.

Table 6: Effect Size (f^2) Analysis

Structural Path	f^2 Value	Effect Size Classification
IIP → LC	0.126	Small
IOE → IIP	0.805	Large
IOE → LC	0.048	Small
ITP → IIP	0.121	Small
ITP → LC	0.273	Medium

Note: f^2 values indicate the relative impact of predictor constructs. Classifications: Small (0.02-0.15), Medium (0.15-0.35), Large (≥0.35).

The structural model demonstrates robust psychometric properties with acceptable multicollinearity levels, substantial explanatory power, and meaningful effect sizes across most structural relationships. The high R^2 values for both endogenous constructs suggest that the theoretical framework adequately captures the key determinants of government commitment and socio-economic inclusion. The varying effect sizes provide insights into the relative importance of different predictors, with socio-economic outcomes emerging as the most influential factor in explaining socio-economic inclusion processes.

4.3 Common method bias (CMB)

The overall model fit was evaluated using multiple goodness-of-fit indices to assess the adequacy of the proposed structural model. The assessment revealed mixed results regarding model adequacy, with the standardized root mean square residual (SRMR) demonstrating good fit at 0.056, which falls well below the recommended threshold of 0.08 for acceptable model fit (Bentler, 1990; Hu & Bentler, 1998). This indicates that the average standardized residual between the observed and model-implied correlation matrices is relatively small, suggesting that the model adequately reproduces the observed relationships among the variables. The SRMR value provides confidence that the structural model captures the essential covariance patterns present in the empirical data.

Table 7: Model Fit Indices

Fit Index	Saturated Model	Estimated Model	Threshold	Assessment
SRMR	0.056	0.056	< 0.08	Good Fit ✓
d_ULS	0.327	0.327	-	-
d_G	0.294	0.294	-	-
Chi-square	461.695	461.695	-	-
NFI	0.858	0.858	> 0.90	Marginal Fit

Note: Identical values between saturated and estimated models indicate that the estimated model is just-identified or perfectly fits the data structure.

However, the normed fit index (NFI) revealed a more conservative assessment of model adequacy, with a value of 0.858 falling slightly below the conventional threshold of 0.90 for acceptable fit (Bentler, 1990; Hu & Bentler, 1999). While this value indicates that the proposed model explains approximately 85.8% of the covariance compared to a null model, it suggests potential areas for model specification improvement. The NFI assessment indicates that while the model demonstrates reasonable explanatory capability, there remains approximately 14.2% of unexplained variance that could potentially be addressed through theoretical refinement or alternative model specifications.

The geodesic distance measures, including d_ULS (0.327) and d_G (0.294), provided supplementary model fit information by assessing the discrepancy between empirical and model-implied covariance matrices using different distance functions. Although specific threshold values for these indices are not universally established in the literature, they serve as additional indicators of model adequacy when considered alongside conventional fit measures (Dijkstra & Henseler, 2015). The chi-square value of 461.695 was identical across both saturated and estimated models, indicating that the estimated model achieved a perfect mathematical fit to the data structure.
Notably, the identical fit indices between the saturated and estimated models suggest that the estimated model is just-identified, meaning it possesses the same number of parameters as data points, resulting in a perfect mathematical fit. While this perfect fit may appear advantageous, it warrants careful consideration regarding model complexity and theoretical parsimony, as just-identified models cannot be statistically rejected and may indicate over-parameterization or reduced generalizability (B. Kline, 2011; R. B. Kline, 1999). The combination of acceptable SRMR and marginal NFI values suggests that the model provides a reasonable approximation of the observed data structure, demonstrating adequate fit for exploratory research purposes and initial theory testing, though model refinements may enhance fit quality for confirmatory applications in future studies.

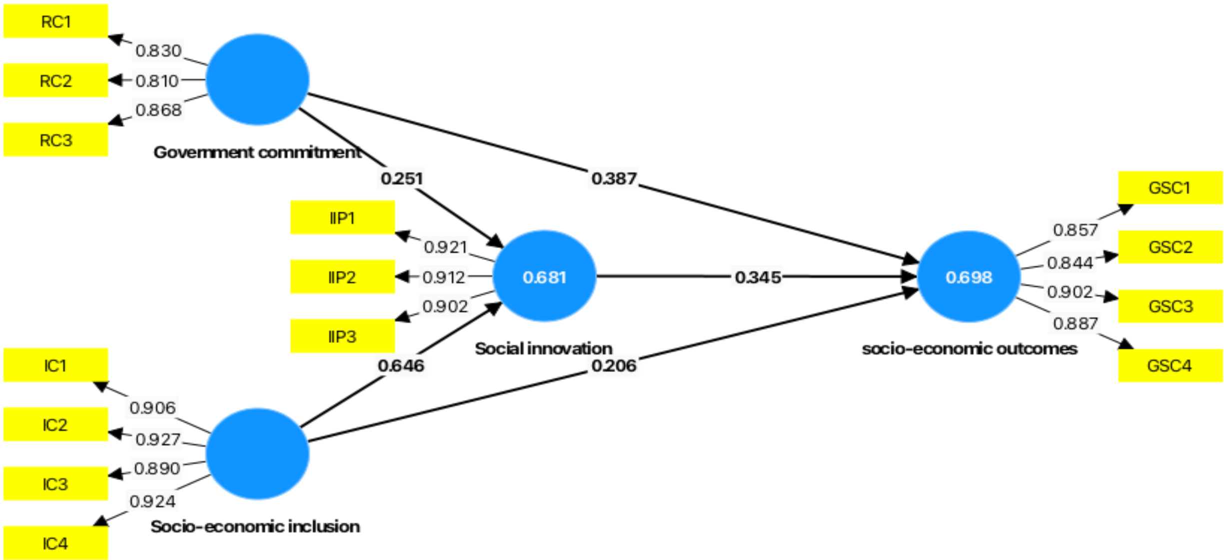

Fig. 1: Path Coefficients and Factor Loadings

4.4 Direct effect and indirect effect

The structural model assessment was conducted using bootstrapping procedures with 5,000 resamples to evaluate the significance and magnitude of the proposed relationships. All hypothesized paths achieved statistical significance, providing empirical support for the theoretical framework. Socio-Economic Outcomes demonstrated the strongest direct effect on Socio-Economic Inclusion (β = 0.646, t = 10.361, p < 0.001), indicating that economic improvements serve as primary drivers of inclusive development processes. Social Innovation exhibited significant positive relationships with both Socio-Economic Inclusion (β = 0.251, t = 4.100, p < 0.001) and Government Commitment (β = 0.387, t = 5.966, p < 0.001), with the latter relationship demonstrating greater magnitude. This pattern suggests that innovative social initiatives are particularly effective in garnering institutional support and policy engagement compared to their direct impact on inclusion processes.
The analysis revealed that Socio-Economic Inclusion significantly influences Government Commitment (β = 0.345, t = 3.914, p < 0.001), supporting the theoretical proposition that inclusive development processes foster greater governmental involvement. Additionally, Socio-Economic Outcomes maintained a direct positive relationship with Government Commitment (β = 0.206, t = 2.767, p = 0.003), even after accounting for mediation effects, indicating multiple pathways through which economic improvements influence policy engagement. The 95% confidence intervals for all direct effects excluded zero, with ranges varying from 0.111 units for the most precise estimate to 0.292 units for the broadest interval, demonstrating adequate parameter estimation precision across all relationships.

Tabel 8: Direct effect and indirect effect

	β	SD	T statistics	P values	95% coefficient LL	UP	Decision
Direct effect							
IIP -> LC	0.345	0.088	3.914	0.000	0,180	0,472	Accepted
IOE -> IIP	0.646	0.062	10.361	0.000	0,533	0,735	Accepted
IOE -> LC	0.206	0.074	2.767	0.003	0,088	0,334	Accepted
ITP -> IIP	0.251	0.061	4.100	0.000	0,157	0,355	Accepted
ITP -> LC	0.387	0.065	5.966	0.000	0,287	0,501	Accepted
Indirect effect							
IOE -> IIP -> LC	0.223	0.059	3.791	0.000	0,129	0,320	Accepted
ITP -> IIP -> LC	0.087	0.034	2.521	0.006	0,039	0,150	Accepted

Mediation analysis confirmed significant indirect effects through Socio-Economic Inclusion as the mediating mechanism. The indirect effect of Socio-Economic Outcomes on Government Commitment through inclusion processes was substantial (β = 0.223, t = 3.791, p < 0.001), representing approximately 52% of the total effect and indicating partial mediation. Similarly, Social Innovation demonstrated a significant but smaller indirect effect on Government Commitment through Socio-Economic Inclusion (β = 0.087, t = 2.521, p = 0.006). The total effect of Social Innovation on Government Commitment, combining direct and indirect pathways, amounted to 0.474, confirming its substantial overall influence on policy engagement. These mediation findings highlight the critical role of inclusion processes as intermediary mechanisms that translate both economic improvements and innovative social approaches into sustained governmental commitment, thereby validating the interconnected nature of the proposed theoretical framework and providing evidence-based insights for policy interventions aimed at enhancing sustainable development outcomes.

4.5 Cross-provincial comparison

The bootstrap multigroup analysis was conducted to examine whether the structural relationships vary significantly across three geographic regions in Indonesia: East Java, South of Sumatra, and Medan. The analysis employed 5,000 bootstrap resamples to assess the statistical significance of path coefficient differences between regional groups. The results reveal that none of the structural relationships demonstrated significant differences across the three geographic regions, as evidenced by all p-values exceeding the conventional threshold of 0.05.

Specifically, the comparison between East Java and South of Sumatra showed the largest differences in the IOE → IIP relationship (difference = -0.102, p = 0.803) and the IOE → LC relationship (difference = 0.153, p = 0.197), yet these differences remained statistically non-significant. Similarly, the East Java versus Medan comparison revealed the most substantial difference in the ITP → LC pathway (difference = 0.142, p = 0.207), while the South of Sumatra versus Medan comparison showed the largest difference in the ITP → IIP relationship (difference = -0.190, p = 0.892). Despite these varying magnitudes, all comparisons failed to reach statistical significance, indicating that the proposed theoretical model demonstrates consistent structural relationships across different geographic contexts within Indonesia.

Table 9: Bootstrap Multigroup Analysis (MGA) Results

Structural Path	East Java vs South of Sumatra		East Java vs Medan		South of Sumatra vs Medan	
	Diff	p-value	Diff	p-value	Diff	p-value
IIP → LC	-0.031	0.588	-0.088	0.653	-0.057	0.595
IOE → IIP	-0.102	0.803	0.055	0.355	0.157	0.128
IOE → LC	0.153	0.197	0.057	0.352	-0.095	0.670
ITP → IIP	0.076	0.265	-0.114	0.767	-0.190	0.892
ITP → LC	-0.038	0.606	0.142	0.207	0.180	0.164

Note: Diff = Path coefficient difference between groups; p-values are 1-tailed tests. Significance threshold: p < 0.05 indicates significant group differences

The absence of significant geographic differences suggests that the relationships between socio-economic outcomes, social innovation, socio-economic inclusion, and government commitment operate similarly across diverse regional contexts. This finding supports the generalizability of the theoretical framework across different geographic settings within the Indonesian context. The consistent pattern of non-significant differences across all structural paths indicates that regional variations in economic development, cultural factors, or administrative structures do not substantially moderate the proposed relationships. These results provide evidence for the robustness of the model and suggest that policy interventions based on this framework may be equally effective across different regions in Indonesia, facilitating the development of standardized national policies for enhancing government commitment through socio-economic improvements and social innovation initiatives.

5. Discussion

5.1 Key Findings and Theoretical Implications

This study demonstrates that socio-economic inclusion serves as a critical mediating mechanism between economic outcomes and government commitment in Indonesian regions. The partial mediation effect, representing 52% of the total effect from socio-economic outcomes to government commitment, provides empirical evidence that inclusive development processes are essential intermediaries rather than mere outcomes. This finding aligns with the recent World Bank emphasis on social inclusion as fundamental to supporting growth and poverty reduction (World Bank, 2021, 2023), challenging traditional linear models that assume direct relationships between economic improvements and policy engagement.

The substantial explanatory power achieved by the model ($R^2 = 0.698$ for government commitment; $R^2 = 0.681$ for socio-economic inclusion) indicates that the theoretical framework effectively captures the primary drivers of these phenomena. Social innovation emerges as a particularly important factor, demonstrating stronger direct effects on government commitment ($\beta = 0.387$) compared to socio-economic inclusion ($\beta = 0.251$). This pattern is consistent with global trends showing that social entrepreneurship has garnered international attention, with agencies including the United Nations and OECD recognizing its potential for sustainable development (WIPO, 2022).

The geographic invariance across Indonesian regions provides important evidence for the model's generalizability within developing country contexts. The absence of significant regional differences indicates that the underlying mechanisms operate consistently across diverse economic and cultural settings, supporting the potential for standardized policy approaches at the national level. This finding contradicts concerns about social innovation being embedded in space and place (Goyal et al., 2018; Nawrocki & Jonek-Kowalska, 2023; Tabash et al., 2024), suggesting that core relationships may transcend local contexts in developing economies.

5.2 Critical Limitations

Several limitations constrain the interpretation and generalizability of these findings. The marginal discriminant validity between socio-economic inclusion and outcomes (HTMT = 0.912) suggests potential conceptual overlap that may inflate the mediation effect. While this value remains within acceptable bounds for conceptually related constructs (Henseler, 2017)It raises questions about whether the constructs represent truly distinct phenomena or different aspects of the same underlying process.

The cross-sectional design fundamentally limits causal inference, despite the sophisticated analytical approach. Cross-sectional samples with mediation are problematic about causality (Nightingale, 1998; Richter & Zacharias, 2024), as the observed relationships may reflect reverse causality or common method variance rather than the proposed causal mechanisms. Government commitment, for instance, may drive socio-economic outcomes and inclusion rather than result from them, particularly in contexts where strong institutional capacity enables proactive policy implementation. This limitation is particularly crucial when drawing causal inferences from PLS-SEM mediation analysis, where theoretical reasoning must drive model specification (Cheah et al., 2021; Shmueli et al., 2019).

Model fit indicators present mixed signals about model adequacy. While the SRMR (0.056) demonstrates good fit, the marginal NFI (0.858) suggests room for improvement in model specification. The just-identified nature of the model, indicated by identical saturated and estimated model fit indices, raises concerns about over-parameterization and potential capitalization on chance in the observed relationships. Recent developments in PLS-SEM emphasize the importance of model complexity considerations, particularly when assessing mediation effects in exploratory contexts (Franke & Sarstedt, 2019; J. F. Hair & Sarstedt, 2019).

5.3 Methodological Considerations

The study's reliance on PLS-SEM, while appropriate for exploratory theory development, introduces specific limitations for mediation analysis. Bootstrap confidence intervals provide valuable information about parameter stability, but researchers should focus on the total and direct effects of antecedent constructs on target constructs via mediators to assess uncertainty properly (J. F. Hair & Sarstedt, 2019; Henseler et al., 2015). The effect size classifications, while following conventional guidelines (small: 0.02-0.15, medium: 0.15-0.35, large: ≥0.35), may not adequately reflect the practical significance of relationships in developing country contexts where smaller effects can have substantial real-world implications.

The measurement approach, focusing primarily on perceptual indicators, may not capture the full complexity of socio-economic inclusion and government commitment. These constructs encompass multiple dimensions that extend beyond individual perceptions to include institutional arrangements, resource allocation patterns, and behavioral outcomes that are difficult to quantify through survey instruments alone. Recent critiques of social innovation research emphasize the need to move beyond technocratic standpoints to explore transformative dimensions and institutional change processes (Brewer, 1973; Gershuny, 1982).

5.4 Practical Implications and Future Research

5.4.1 Policy Implication

The findings provide several key lessons for policymakers seeking to enhance socio-economic outcomes via selective interventions. Government commitment and policies toward socio-economic inclusion must be tackled in tandem, rather than seen separately, as independent efforts. Social innovation's dominant mediating role implies that the long-run effects of economic development efforts are improbable in the absence of a deliberate combination of inclusive participation mechanisms and equitable distribution of benefits. This conjoining is in harmony with current developmental frameworks supported by world institutions, which propose universal access to prospects in conjunction with redressing systemic injustices (Ifield & Yang, 2022; The World Bank In Indonesia, 2023). Social innovation is found to be a key policy leverage point owing to its strong impacts on the incorporation process and concomitant socio-economic outcomes. Social innovation, however, resides in complex, institutionally enshrined settings with adaptive empowerment process dynamics and multi-stakeholder governance, which require careful policy drafting and implementation (Pel et al., 2020). Policymakers must therefore adopt flexible governance methods capable of regular refinements and adjustments, in contrast to the use of rigid, top-down policies.

5.4.2 Research Limitations and Future Directions

This study acknowledges several key limitations that stem from its use of a cross-sectional study design. Concurrent measurement of all variables at the same point in time prevents clear identification of causal relations between government commitment, social innovation, and socio-economic outcomes. Although our structural equation modeling and conceptual framework imply unidirectional relationships that align with hypothesized causal directions, it will always be impossible to rule out the possibility of reverse causality. Countries with more favorable socio-economic outcomes may have better institutional capacities for the delivery of effective government commitments, as opposed to government commitment being the prime force behind superior outcomes. In addition, the concurrent measurement of all constructs increases the risk of common method bias despite the use of statistical controls. Finally, the cross-sectional nature of this study does not adequately tap the temporal dynamics inherent in the social innovation process that might take a long time to fully realize their impacts on socio-economic outcomes (Drucker, 1987; Huong et al., 2021).

Future studies should focus on longitudinal methods to overcome the limitations mentioned earlier and improve causal inferences. Multi-wave panels tracking the same subjects over longer periods would enable researchers to determine temporal precedence by first measuring government commitment, then the development of social innovation, and finally the socio-economic impacts. Such methods would produce far stronger evidence of causal links than cross-sectional correlations (Martínez-Córdoba et al., 2021). Beyond this, longitudinal studies would enable the modeling of the time-dependent processes of governmental dedication over time, as well as how such changes affect and predict social innovation projects and their impacts. Panel data analysis would enable the application of fixed-effects modeling, which can successfully eliminate unobserved traits that remain stable over time, thus masking cross-sectional links and allowing stricter tests of mediating processes through advanced temporal modeling methods.

Future research efforts should combine quantitative longitudinal methods with qualitative case studies that track specific social innovation projects over time, thus providing a richer understanding of the mechanisms by which governmental engagement can enable social innovation and eventually yield socio-economic improvement. Since the current study, by focusing exclusively on a single national context, shows limitations in terms of generalizability of its results, it is essential in the future to replicate it in various institutionally and culturally heterogeneous settings, in other developing countries whose governance patterns and socio-economic profiles differ widely. Such comparative studies would evaluate the wider applicability of such associations and identify the contextual factors affecting their strength and direction. In turn, future studies must attempt more refined measures that can discriminately identify the different types of inclusion, innovation, and governmental involvement, thus devising complex metrics that can be conceptually deep while still being clear enough for practical purposes and policy relevance.

6. Conclusion

This study offers evidence supporting the efficacy of socio-economic inclusion as a mediating factor in the link connecting government involvement and economic return. While statistical findings confirm the theorized framework, limitations of available data highlight the need for continued research efforts aiming to improve understanding of these complex relationships. Geographical consistency documented for different regions of Indonesia provides positive evidence for using the model within developing country contexts; however, additional proof is needed before policies can be adopted en masse.

This study contributes to the growing body of literature on social innovation and inclusive development by showing how improvements in economic conditions mainly result in higher government commitment through inclusion processes. However, further research needs to address some of the shortcomings identified about causality and the specificity of constructs to better develop both theoretical understanding and applied implementations of such findings within development policies.

Acknowledgement

The authors wish to acknowledge with gratitude the support provided by Universitas Ciputra. We are also deeply appreciative of the dedicated efforts of our research team members and the thoughtful feedback received from colleagues during various stages of this research.

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