



Contents lists available at [Elora Center](#)

Lentera Negeri

Journal homepage: <https://lentera.eloracenter.org/lentera>



Social protection data governance and public trust: the mediating role of targeting fairness among generation z

Bambang Arwanto

Universitas Kutai Kartanegara, Indonesia

Article Info

Article history:

Received Aug 07th, 2026

Revised Sep 20th, 2026

Accepted Oct 06th, 2026

Keyword:

Data governance,
Public trust,
Targeting fairness,
Social protection,
Generation z

ABSTRACT

Digital social protection increasingly depends on integrated administrative data, making data governance, targeting fairness, and public trust closely connected. This sequential explanatory mixed-methods study examined whether perceived targeting fairness mediates the association between social protection data governance and public trust and used Generation Z interviews to explain the quantitative pattern. The quantitative dataset comprised 180 complete responses analyzed with PLS-SEM and 5,000 bootstrap subsamples. Because the available dataset does not retain recruitment metadata, the quantitative sample is not treated as probability-representative; a sensitivity power check nevertheless shows that $n = 180$ provides >0.99 power to detect a medium effect ($f^2 = 0.15$) with two predictors at $\alpha = 0.05$. Measurement quality was satisfactory (Cronbach's $\alpha = 0.887$ - 0.906 ; $\rho_C = 0.917$ - 0.927 ; AVE = 0.680 - 0.714 ; HTMT = 0.648 - 0.681). Data governance was strongly associated with targeting fairness ($\beta = 0.603$; $f^2 = 0.572$), while targeting fairness had a moderate association with public trust ($\beta = 0.411$; $f^2 = 0.196$) and the direct governance-trust association was smaller ($\beta = 0.339$; $f^2 = 0.133$). The indirect effect was significant ($\beta = 0.248$), indicating partial mediation. The qualitative corpus comprised 20 Generation Z informants aged 19-29 with personal or family experience of social protection services. Six themes data updating, explainable targeting, correction and appeals, privacy and security, hybrid assistance, and visible follow-up clarified why fairness is a key pathway between governance and trust. The findings suggest that integrated data systems are more likely to be trusted when citizens can understand, challenge, and correct data-driven decisions.



© 2026 The Authors.

This is an open access article under the CC BY-NC-SA license
(<https://creativecommons.org/licenses/by-nc-sa/4.0>)

Corresponding Author:

Bambang Arwanto,

bambangarwanto@unikarta.ac.id

Introduction

The digital transformation of government has shifted data from being merely an administrative output to becoming a core infrastructure that shapes how services are designed, who is recognized by public systems, and how public decisions are implemented. Digital-government success depends on the alignment of implementation capacity, information quality, service design, and citizen adoption rather than technology alone (Gil-Garcia & Flores-Zúñiga, 2020). This issue is especially consequential in social protection because errors in representation can alter access to benefits and can affect public value, accountability, and citizens' willingness to rely on state data systems (van Zoonen, 2020; MacLean & Titah, 2022).

In Indonesia, this issue has become more salient with the strengthening of One Data Indonesia, the Personal Data Protection Law, and the establishment of the National Unified Socioeconomic Data (Data Tunggal Sosial dan Ekonomi Nasional, DTSN). Presidential Regulation No. 39 of 2019 emphasizes data standards, metadata, interoperability, and reference codes; Law No. 27 of 2022 strengthens data-subject

rights; Presidential Instruction No. 4 of 2025 directs the use of a unified socioeconomic database; and Statistics Indonesia Regulation No. 6 of 2025 provides the framework for preparing and managing DTSEN (Indonesia, 2019; Indonesia, 2022; Indonesia, 2025; Badan Pusat Statistik, 2025). Recent Indonesian evidence also links transparency, digital-government quality, and organizational capacity with public trust (Priyadi, 2024; Virmandes et al., 2024; Ariansyah et al., 2026).

Data integration, however, does not automatically produce fair targeting. The social-assistance literature shows that inclusion and exclusion errors can arise from stale data, indicator selection, source-data quality, and changes in household circumstances. Indonesian evidence has long shown that targeting accuracy depends on the quality and updating of welfare registries (Sutanto et al., 2020). A Ministry of Finance presentation at the 2024 Indonesia Social Protection Technical Seminar reported that around 32% of food-assistance recipients were still located in welfare deciles 6-10, illustrating the substantive magnitude of inclusion error before the transition to a unified data architecture (Ministry of Finance of the Republic of Indonesia, 2024). International studies likewise show that data and analytical methods can improve targeting, but welfare consequences still depend on how poverty is represented and how implementation handles bias and error (Dadap-Cantal et al., 2021; Aiken et al., 2022; Smythe & Blumenstock, 2022; Dietrich et al., 2024).

Technical accuracy therefore needs to be considered alongside perceived fairness. Citizens cannot always observe database integration, data matching, or back-end rules, but they can assess whether beneficiaries appear to match actual conditions, whether similar cases are treated consistently, and whether meaningful opportunities exist to correct errors (Afrilia, Muharam, & Nurlia, 2024). The administrative burden literature shows that learning, compliance, and psychological costs can shape citizen-state relationships (Masood & Nisar, 2021; Halling & Bækgaard, 2024). Recent experimental evidence also suggests that administrative burdens may be associated with trust and participation (Mikkelsen et al., 2025), while fairness perceptions are related to social welfare participation and to how citizens interpret allocation procedures (Shen et al., 2026).

Transparency is an important mechanism because data-driven decisions require explanations that citizens can use, rather than the mere disclosure of technical information. Digital transparency must be deliberately designed around citizen needs (Matheus et al., 2021). In algorithmic decision-making, explainability can fail when explanations do not match users' informational needs (de Bruijn et al., 2022), while experimental evidence shows that explanation type can affect perceived accuracy, fairness, and trustworthiness (Aoki et al., 2024). In social protection, transparency is therefore operational when it communicates reasons for decisions, data status, correction steps, and the boundaries of institutional authority in language that citizens can act upon.

Privacy and security cannot be separated from trust in digital social protection systems. Mutimukwe et al. (2020) show that organizational privacy assurances are associated with risk perceptions, trust, and self-disclosure. Saura et al. (2022) highlight behavioral-data and privacy concerns when governments deploy artificial intelligence analytics, while Distel et al. (2022) show that e-government risks include both technical and organizational threats. Vetrò et al. (2021) position data quality as an important component in identifying discrimination risks in automated decision-making. Bodó and Janssen (2022) further argue that maintaining trust in an increasingly technologized public sector requires institutional safeguards that extend beyond system performance alone.

Public trust is also shaped by service experience rather than arising automatically from digitalization. Aoki (2020) shows that system characteristics and contextual conditions influence trust in public-sector chatbots. Berg and Johansson (2020) demonstrate the importance of service experiences for institutional trust, while Arshad and Khurram (2020) identify transparency, responsiveness, and trust as important mechanisms in digital government interactions. Abdulkareem and Ramli (2021) link information quality, service quality, trust, and public value; Hooda et al. (2022) emphasize the central role of trust in behavioral intention and actual e-government use; and Li and Shang (2023) show that e-government use can shape trust through citizens' service experiences.

At the same time, the success of digital channels is influenced by disparities in access, literacy, and user capacity. Pérez-Morote et al. (2020) show that trust and the digital divide help explain variation in e-government use. Lee et al. (2020) identify information literacy as a factor affecting trust in government websites, while Hyytinen et al. (2022) demonstrate that behavioral interventions can increase the adoption of digital public services. Simonofski et al. (2021) show that citizens' expectations of digital government are heterogeneous, and Mesa (2023) emphasizes the role of education in the relationship between the digital

divide, e-government, and trust. Therefore, a digital design that is efficient for younger users may not necessarily be inclusive for households with different levels of digital capability.

The relevance of Generation Z lies not only in their status as digital natives but also in their role as users and digital intermediaries within families. González-Gallego and Nieto-Torrejón (2021) show that open data may be associated with younger generations' trust in democratic institutions. In Indonesia, Maulana et al. (2022) find that Generation Z and Millennials' perceptions of the trustworthiness of public-sector AI implementation are related to ability, benevolence, and integrity. The literature on AI-enabled public services also indicates that acceptance and trust are influenced by perceived fairness, uncertainty, institutional reputation, and conditions of use (Gesik & Leyer, 2022; Harrison & Luna-Reyes, 2022; Kleizen et al., 2023; Wang et al., 2024; Schmager et al., 2024). These findings provide an additional lens for understanding how younger citizens evaluate increasingly data-driven social protection services.

From an organizational perspective, sustainable digital transformation requires the capacity to maintain data quality, integrate processes, and translate innovation into public value. Chatterjee et al. (2022) emphasize that the use of AI in public services should be directed toward citizen satisfaction, while Selten and Klievink (2024) show the importance of organizational structures in managing public-sector technology adoption. van Noordt and Tangi (2024) likewise demonstrate that organizational capabilities are a prerequisite for technology to generate public value. Social protection data governance should therefore be understood as a combination of technical capabilities, institutional rules, correction mechanisms, decision communication, and inclusive service design.

The theoretical framework combines procedural justice with public-value and digital-governance perspectives. Procedural justice theory argues that legitimacy is shaped not only by outcomes but also by whether procedures are consistent, unbiased, correctable, and allow meaningful voice (Lind & Tyler, 1988; Tyler, 2006). Applied to data-driven social protection, data governance constitutes the institutional process through which information is updated, integrated, protected, explained, and corrected; perceived targeting fairness represents citizens' evaluation of whether those processes produce acceptable and contestable allocation decisions; and public trust is the broader institutional evaluation that follows from both stewardship quality and experienced fairness. This framework predicts a direct governance-trust pathway and an indirect pathway through fairness, while allowing privacy, security, service experience, and prior institutional evaluations to remain additional sources of trust.

The study's novelty is threefold. Conceptually, it places perceived targeting fairness as a mediating mechanism between social-protection data governance and public trust rather than treating data integration as an endpoint. Empirically, it evaluates this mechanism with PLS-SEM while distinguishing data stewardship, targeting fairness, and trust as separate latent constructs. Methodologically, it uses a sequential explanatory mixed-methods design in which Generation Z interview themes are explicitly mapped to structural paths through a joint display. The study tests H1: data governance is positively associated with perceived targeting fairness; H2: data governance is positively associated with public trust; H3: perceived targeting fairness is positively associated with public trust; and H4: perceived targeting fairness mediates the association between data governance and public trust.

Method

This study employed a sequential explanatory mixed-methods design (QUAN→QUAL). The quantitative phase was analyzed first to estimate relationships among the three constructs and the mediation pathway. The qualitative phase was then used to explain why the observed paths may occur in citizens' service experiences. Integration was operationalized through a joint-display procedure: each statistically supported path was paired with interview themes and illustrative experiences that either explained, qualified, or delimited the quantitative pattern. This procedure is presented explicitly in Table 4 so that the mixed-methods inference can be followed rather than inferred from separate result sections.

The quantitative phase used 180 complete responses measured on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). The available analytical file does not preserve recruitment metadata or demographic variables; consequently, the sample is not described as probability-representative and no population prevalence estimates are made. As a sensitivity check for the structural model, with a maximum of two predictors for the endogenous trust construct, $n = 180$ provides approximately 0.998 statistical power to detect a medium effect ($f^2 = 0.15$) at $\alpha = 0.05$; a sample of about 68 would be sufficient for 0.80 power under the same assumptions. The model comprised three reflective constructs: Social Protection Data

Governance (X; six indicators), Perceived Targeting Fairness (M; five indicators), and Public Trust (Y; five indicators). Their substantive domains are summarized in Table 1.

Quantitative analysis was conducted using SmartPLS 4 (Ringle et al., 2024). The measurement model was evaluated using outer loadings, Cronbach's alpha, rho_A, composite reliability (rho_C), average variance extracted (AVE), and the heterotrait-monotrait ratio (HTMT). The structural model was evaluated using R^2 , f^2 , path coefficients, specific indirect effects, total effects, SRMR, NFI, and bootstrap confidence intervals. Significance was assessed with 5,000 bootstrap subsamples and a two-tailed test. Interpretation followed contemporary PLS-SEM guidance (Hair et al., 2022). Because all variables were collected within one cross-sectional questionnaire, common-method bias remains a potential threat and is treated as a limitation rather than ruled out by model fit alone.

The qualitative corpus comprised 20 semi-structured interview transcripts from Generation Z informants coded N01-N20, aged 19-29 years and residing in several Indonesian cities. For analytic inclusion, a transcript had to identify an informant within the stated age range and contain personal or family experience with social-protection services sufficient to discuss data updating, targeting, transparency, correction or complaints, privacy, digital access, trust, or service improvement. The interview guide therefore covered these domains while allowing informants to elaborate on concrete experiences. The documented analysis combined deductive coding from the three quantitative constructs with inductive coding for mechanisms that emerged from the narratives. The available research materials do not document a second independent coder; therefore, no intercoder-reliability coefficient is reported or implied.

Qualitative interpretation proceeded in four transparent steps: (1) transcript familiarization and identification of passages relevant to governance, fairness, and trust; (2) assignment of deductive construct codes alongside inductive mechanism codes; (3) consolidation of recurring mechanism codes into six themes; and (4) integration with PLS-SEM results through a path-by-theme joint display. The qualitative phase was explanatory rather than prevalence-estimating: theme frequency was not treated as population incidence, and interview evidence was used to clarify mechanisms, boundary conditions, and implementation implications of the statistical relationships.

Before interpreting the statistical results, the operationalization of the constructs must be clarified so that numerical findings remain connected to the substantive meaning of each variable. Table 1 summarizes the constructs, number of indicators, and measurement focus, providing a bridge between the conceptual definitions and the indicators subsequently evaluated in the SmartPLS outer model.

Table 1. Constructs and Measurement Focus

Construct	Indicators	Measurement focus
Social Protection Data Governance (X)	6	Updating, integration, transparency, security, correction, accountability
Perceived Targeting Fairness (M)	5	Targeting accuracy, consistency, nondiscrimination, appeal/correction, alignment with actual conditions
Public Trust (Y)	5	Responsibility, reliability, public interest, data sharing, complaint response

Source: Research instrument and SmartPLS workbook, processed in 2026.

Results and Discussions

The evaluation begins with the measurement model. Figure 1 presents the PLS Algorithm output from the SEM-PLS workbook, displaying outer loadings, path coefficients, and R-squared values before the significance of the inner model is assessed.

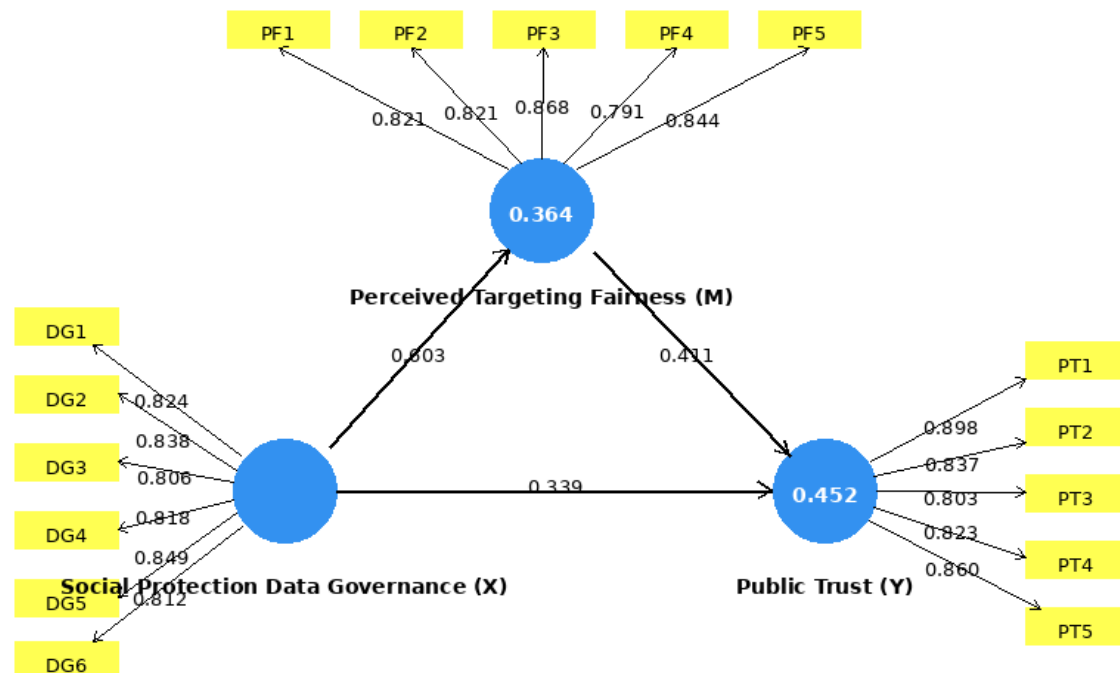


Figure 1. Outer Model (PLS Algorithm) SEM-PLS

Source: SmartPLS PLS Algorithm output from the research workbook, 2026.

Figure 1 shows that all outer loadings exceeded 0.70, ranging from 0.806 to 0.849 for Data Governance, 0.791 to 0.868 for Perceived Targeting Fairness, and 0.803 to 0.898 for Public Trust. Within the Data Governance construct, DG5 had the highest loading (0.849), whereas DG3 had the lowest (0.806). This pattern does not imply that DG5 has the largest causal effect; rather, it indicates that the data-correction mechanism is a particularly strong representation of the governance construct in the analyzed sample. Substantively, this finding is consistent with the interviews, in which the ability to correct data was repeatedly identified as a basic condition for considering the system accountable.

Within the Perceived Targeting Fairness construct, PF3 had the highest loading (0.868), followed by PF5 (0.844), while PF4 had a loading of 0.791. These are psychometric results: they show how strongly each item represents the latent fairness construct in this sample, not that one fairness dimension causes trust more strongly than another. Substantively, the item content is consistent with procedural-justice theory, which emphasizes consistency, neutrality, correctability, and opportunities for voice as bases for judging procedures (Lind & Tyler, 1988; Tyler, 2006). Contemporary welfare research similarly shows that fairness perceptions and administrative burdens shape how citizens evaluate access to social programs (Halling & Bækgaard, 2024; Shen et al., 2026).

Within the Public Trust construct, PT1 had the highest loading (0.898), while PT3 had a loading of 0.803. Thus, confidence that the government manages social protection data responsibly is the most prominent representation of trust. This finding is consistent with the digital government literature, which treats trust as an evaluation of service quality, reliability, responsiveness, and institutional integrity rather than merely an attitude toward technology (Abdulkareem & Ramli, 2021; Hooda et al., 2022; Li & Shang, 2023). In the context of social data, citizens assess not only whether the system works but also whether institutions can legitimately be entrusted with collecting, matching, and using sensitive data.

Indicator consistency is also reflected in the reliability and convergent validity measures. Cronbach's alpha ranged from 0.887 to 0.906, rho_A from 0.892 to 0.907, rho_C from 0.917 to 0.927, and AVE from 0.680 to 0.714. All values fall within ranges that support internal reliability and convergent validity. HTMT values also ranged from 0.648 to 0.681, indicating adequate empirical separation among the three constructs. This is important because data governance, fairness, and trust are conceptually related; adequate discriminant validity shows that respondents still distinguish the quality of data management, evaluations of procedural and outcome fairness, and trust in institutions as separate constructs.

To ensure that interpretation of Figure 1 does not rely solely on reading arrows and loadings, reliability, validity, and descriptive measures are presented numerically. Table 2 summarizes the mean, standard

deviation, reliability, AVE, and loading ranges, allowing the quality of the measurement model to be assessed more transparently before the structural relationships are discussed.

Table 2. Measurement Model Evaluation

Construct	Mean	SD	Cronbach α	ρ_A	ρ_C	AVE	Loading
Data Governance	3.266	0.975	0.906	0.907	0.927	0.680	0.806-0.849
Targeting Fairness	3.154	0.967	0.887	0.892	0.917	0.688	0.791-0.868
Public Trust	3.197	0.978	0.899	0.905	0.926	0.714	0.803-0.898

Source: SmartPLS 4 analysis results, 2026.

The construct means ranged from 3.154 to 3.266, with standard deviations of approximately 0.97. Descriptively, these scores indicate sufficient response variation to differentiate respondents' evaluations; however, they should not be interpreted as national indices because the quantitative data did not include a population-weighting design. The inferential focus of this study is therefore the relationships among constructs. An R-squared value of 0.364 for Perceived Targeting Fairness indicates that Data Governance explains 36.4% of the variance in fairness, while an R-squared value of 0.452 for Public Trust indicates that Data Governance and Targeting Fairness jointly explain 45.2% of the variance in trust. In behavioral and public administration research, this degree of explanatory power is substantively meaningful because trust is also influenced by historical experience, institutional reputation, political context, the quality of other public services, and individual characteristics that fall outside the model.

The f^2 values add practical meaning beyond statistical significance. Data Governance $\rightarrow$ Targeting Fairness produced $f^2 = 0.572$, conventionally a large effect; Targeting Fairness $\rightarrow$ Public Trust produced $f^2 = 0.196$, a medium effect; and the direct Data Governance $\rightarrow$ Public Trust path produced $f^2 = 0.133$, a small-to-moderate effect (Hair et al., 2022). Thus, the model's most substantial contribution is the governance-fairness link, while trust is formed through both fairness and a smaller direct stewardship pathway. Model fit was also acceptable (SRMR = 0.049; NFI = 0.917). These indicators support interpretation of the specified model but do not establish causal direction in a cross-sectional design. Once the measurement model was established as adequate, the analysis proceeded to the inner model. Figure 2 presents the t-statistics from bootstrapping with 5,000 subsamples to assess the significance of the loadings and structural paths.

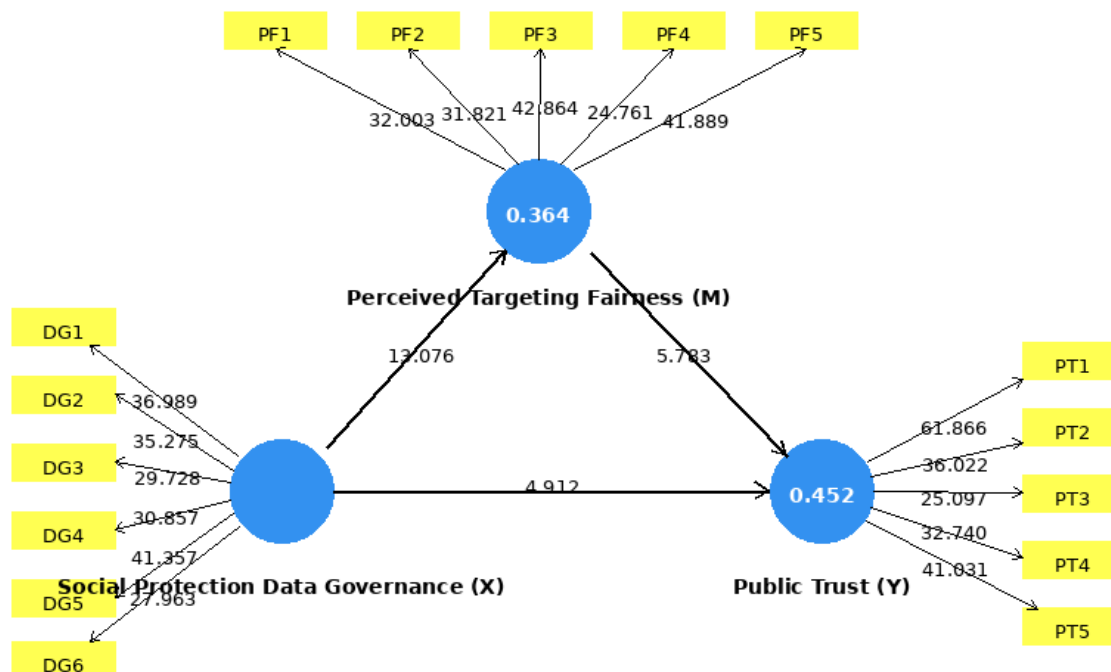


Figure 2. Inner Model (Bootstrapping) SEM-PLS

Source: SmartPLS bootstrapping output (5,000 subsamples), 2026.

Figure 2 shows indicator t-statistics ranging from 24.761 to 61.866, well above the 1.96 threshold for a two-tailed test at the 5% significance level. The Data Governance $\rightarrow$ Perceived Targeting Fairness path yielded $t = 13.076$; Data Governance $\rightarrow$ Public Trust yielded $t = 4.912$; and Perceived Targeting Fairness $\rightarrow$ Public Trust yielded $t = 5.783$. Thus, the measurement model and all three direct paths received strong

statistical support. Interpretation, however, should not stop at significance: the substantial differences in path coefficients show that governance is most strongly associated with fairness, while trust is formed through a combination of the direct path and the path mediated by fairness.

H1 was supported, with $\beta = 0.603$ ($t = 13.076$; $p < 0.001$; 95% CI = 0.508-0.688). This coefficient indicates that the more positively respondents evaluated data updating, integration, transparency, security, correction, and accountability, the more positively they perceived targeting as accurate, consistent, nondiscriminatory, and correctable. This relationship is coherent with the targeting literature: accurate data can improve identification, but allocation quality is also strongly influenced by bias, exclusion and inclusion errors, and the system's ability to reflect changes in household circumstances (Sutanto et al., 2020; Aiken et al., 2022; Smythe & Blumenstock, 2022; Dietrich et al., 2024).

H2 was supported, with $\beta = 0.339$ ($t = 4.912$; $p < 0.001$; 95% CI = 0.201-0.475). This direct effect is important because it shows that governance has legitimacy value that is not entirely dependent on targeting outcomes. Citizens may trust institutions because data are managed securely, purposes of use are explained, official channels provide consistent information, and agencies can be held accountable. This mechanism is consistent with studies of privacy assurances and the technologized public sector, which identify organizational assurances, risk control, and institutional safeguards as foundations of trust (Mutimukwe et al., 2020; Bodó & Janssen, 2022; Saura et al., 2022).

H3 was supported, with $\beta = 0.411$ ($t = 5.783$; $p < 0.001$; 95% CI = 0.268-0.548). This coefficient shows that fairness is not a normative variable detached from trust but a concrete evaluative mechanism. When citizens perceive that criteria are applied consistently, decisions reflect actual conditions, discriminatory treatment is avoided, and decisions can be challenged through correction mechanisms, institutional trust increases. The explainability and digital transparency literature provides a consistent explanation: digital decisions are more readily accepted when citizens receive information that helps them understand the reasons, procedures, and opportunities for contestability (Matheus et al., 2021; de Bruijn et al., 2022; Grimmelikhuijsen, 2023; Aoki et al., 2024).

To facilitate interpretation of the effect sizes, confidence intervals, and hypothesis decisions shown in Figure 2, the path estimates are summarized in Table 3. The table is necessary because hypothesis decisions are based not only on t-statistics but also on the direction of the coefficients and bootstrap confidence intervals that do not cross zero.

Table 3. Structural Model Hypothesis Testing

Hyp.	Relationship	β	t	p	95% CI	Decision
H1	Data Governance → Targeting Fairness	0.603	13.076	<0.001	0.508-0.688	Supported
H2	Data Governance → Public Trust	0.339	4.912	<0.001	0.201-0.475	Supported
H3	Targeting Fairness → Public Trust	0.411	5.783	<0.001	0.268-0.548	Supported
H4	Data Governance → Targeting Fairness → Public Trust	0.248	5.347	<0.001	0.160-0.344	Partial mediation

Source: SmartPLS 4 bootstrapping output (5,000 subsamples), 2026.

The indirect effect of Data Governance → Targeting Fairness → Public Trust was $\beta = 0.248$ ($t = 5.347$; $p < 0.001$; 95% CI = 0.160-0.344), while the direct X → Y effect remained significant. The total X → Y effect was 0.587. This pattern indicates partial mediation: data governance builds trust through two channels that operate simultaneously. The first is institutional, reflecting citizens' assessments of whether data are secure, transparent, consistent, and accountable. The second is evaluative-distributive, reflecting whether the use of those data produces fair targeting decisions. The indirect effect represented approximately 42% of the total effect, indicating that fairness is a substantial mechanism without eliminating the direct role of governance.

This mediation mechanism helps explain why government digitalization does not always produce a linear increase in trust. A system may be technically efficient yet still be perceived as problematic if citizens do not understand the reasons for decisions or cannot correct inaccurate data. Conversely, a decision that disadvantages an individual may still be regarded as legitimate when criteria are considered consistent, the process can be explained, and a meaningful appeals mechanism is available. This pattern is consistent with literature showing that trust in e-government is influenced by information quality, service experience,

transparency, and responsiveness (Berg & Johansson, 2020; Arshad & Khurram, 2020; Hooda et al., 2022; Li & Shang, 2023).

The findings also provide additional insight into administrative burden. Repeated corrections, the need to move between service channels, or the absence of complaint-status information do more than increase time costs; such experiences may signal that the system lacks the capacity to recognize or correct errors. Administrative burden and fairness may therefore interact in shaping trust. This finding is consistent with Halling and Bækgaard (2024), Mikkelsen et al. (2025), and Shen et al. (2026), who position procedural experiences as part of citizens' responses to public programs.

The qualitative phase clarifies how these statistical relationships appear in Generation Z experiences. The first theme is data accuracy and updating. N01 reported that the family's address had remained recorded at a previous residence, while N03 stated that changes in household composition were not immediately reflected in service data. These experiences show that data may be accurate at one point in time yet become unrepresentative when household circumstances change. This finding gives substantive meaning to the $X \rightarrow M$ path: fairness is difficult to sustain when databases are insufficiently responsive to socioeconomic change.

The second theme concerns decision transparency. Informants did not ask for complex technical formulas; instead, they wanted simple explanations of why a person was placed in a particular category, what data were used, which elements required updating, and what steps were available when an outcome did not match actual conditions. N01 emphasized that without an explanation, even a substantively valid decision can easily be perceived as arbitrary. This pattern is consistent with digital transparency and explainability research: information becomes valuable when it helps citizens understand a decision and the actions they can take after receiving it (Matheus et al., 2021; de Bruijn et al., 2022; Aoki et al., 2024).

The third theme concerns correction and appeals. N01 stated, "A system does not have to be error-free, but it must provide a real way to correct errors." N03 described being redirected between service points without receiving a complaint tracking number, while N20 observed that citizens felt more reassured when they received a ticket number, a contactable officer, and an explanation of the processing stages. Here, contestability serves as a governance-fairness-trust bridge: a system that acknowledges the possibility of error and provides a recovery pathway may be more trustworthy than a system that claims precision but offers no correction mechanism.

The fourth theme is privacy and security. N02 generally trusted official channels but refused to send identity-document photographs through personal accounts or unverified phone numbers. N03 questioned which agencies retained copies of documents, while N20 emphasized anti-fraud education. These attitudes show that digital literacy is not equivalent to an unconditional willingness to disclose information. Willingness to provide data is conditional on clear purposes, legitimate channels, access limitations, and protection against misuse. This finding reinforces the direct $X \rightarrow Y$ mechanism and is consistent with Mutimukwe et al. (2020), Saura et al. (2022), Distel et al. (2022), and Wang et al. (2024).

The fifth theme is the role of Generation Z as digital brokers within families. N05 often helped a grandmother who struggled to use digital services and argued that "the biggest barrier is not the internet, but service design that assumes everyone can understand digital instructions." N01 similarly noted that the respondent's mother still preferred asking an officer directly even though the respondent personally found digital services easy to use. This pattern shows that the digital divide is not limited to internet connectivity but also includes interface design, the ability to interpret service status, and the availability of human support. This finding is consistent with Pérez-Morote et al. (2020), Lee et al. (2020), Mesa (2023), and Coles-Kemp et al. (2020), who emphasize the multidimensional nature of digital access.

The sixth theme is follow-up visibility. Informants wanted notifications when data were received, verified, rejected, or required supplementation; a history of data changes; ticket numbers; estimated verification stages; and consistent information across channels. N02 specifically recommended official notifications for every status change. Such visibility reduces information asymmetry between the system and citizens while transforming accountability from an abstract principle into an observable service experience. From a public value perspective, this design can strengthen satisfaction, predictability, and trust because citizens know who is processing a case, its current status, and when follow-up can be expected (MacLean & Titah, 2022; Simonofski et al., 2021).

To make mixed-methods integration explicit, the interview themes need to be mapped back onto the quantitative paths that were tested. Table 4 combines quantitative evidence with informants' experiences to

show that the PLS-SEM results and interview narratives are not separate findings but mutually explanatory evidence at the level of underlying mechanisms.

Table 4. Integration of Quantitative Findings and Generation Z Interview Evidence

Interview theme	Main finding	Link to the model
Accuracy and updating	Data should reflect changes in citizens' actual circumstances.	Explains the strength of the $X \rightarrow M$ path
Targeting transparency	Decision rationales should be simple, relevant, and easy to understand.	Strengthens the $M \rightarrow Y$ mechanism
Correction and appeals	Errors should be correctable, traceable, and accompanied by process certainty.	Contestability as a foundation of fairness and trust
Privacy and security	Purpose, official channels, limits of use, and authorized access should be clear.	Explains the direct $X \rightarrow Y$ path
Hybrid services	Generation Z may assist family members, but service access should not depend on younger intermediaries.	Implications for inclusive governance
Follow-up visibility	Notifications, tracking, and process-status information improve predictability.	Connects governance, fairness, and trust

Source: Integration of SmartPLS outputs and interview analysis of N01-N20, 2026.

The integrated findings show that fairness functions as a normative interface between data infrastructure that is largely invisible to citizens and the policy outcomes they experience. Citizens do not directly observe deduplication, interoperability, APIs, or quality-assurance processes. What they observe is whether household status reflects actual conditions, whether decisions can be explained, and whether the system responds when data are challenged. Back-end quality therefore acquires public meaning only when it is translated into fairness that citizens can experience. This finding extends the argument of Dietrich et al. (2024): data problems are not only statistical errors but also concern the social distribution of the consequences of those errors.

Partial mediation also prevents an oversimplified interpretation in which all trust must be built through fairness. The interviews show that privacy, security, consistency across official channels, and the institution's capacity to safeguard data are independent objects of trust. This is consistent with Bodó and Janssen (2022), Harrison and Luna-Reyes (2022), and Kleizen et al. (2023), who emphasize that trustworthy technology requires institutional arrangements and that short-term ethical signals are not always sufficient to create trust. In social protection, institutions must demonstrate reliability through consistent operational practice rather than policy declarations alone.

The Generation Z findings also reveal a paradox of digital inclusion. Younger people can provide additional capacity within households by helping family members navigate online channels, but a system's dependence on such informal intermediaries can obscure exclusion risks. Services may appear easy to younger respondents while older family members continue to require human assistance. In other words, successful digitalization is not synonymous with digital-only service provision. The literature on inclusive digital welfare and the digital divide supports multi-channel designs that combine digital efficiency with human assistance for users who need support (Coles-Kemp et al., 2020; Pérez-Morote et al., 2020; Mesa, 2023; Townley & Koop, 2024).

From a generational perspective, the findings do not assume that Generation Z is inherently more trusting of technology. Instead, extensive digital experience may make younger users more sensitive to status consistency, channel security, explanations of data use, and process traceability. This is consistent with Maulana et al. (2022) and the literature on AI-enabled government, which shows that trust depends on ability, integrity, fairness, and uncertainty rather than on technological novelty (Gesk & Leyer, 2022; Wang et al., 2024; Schmager et al., 2024). Digital nativeness should therefore be understood as both a critical capacity and a capacity for use.

To distinguish psychometric results from substantive theoretical interpretation, Table 5 compares the structural and mixed-methods findings with prior empirical and theoretical work. The comparison shows where the present study converges with established evidence and where it adds a specific mediation mechanism linking governance to trust through perceived targeting fairness.

Table 5. Comparison with Prior Studies on Data Governance, Fairness, and Public Trust

Study	Context / focus	Relevant finding	Relation to this study
Sutanto et al. (2020)	Indonesia; RASKIN targeting	Targeting accuracy depends on registry and program design.	Supports the governance→fairness mechanism in an Indonesian social-assistance context.
Aiken et al. (2022)	Humanitarian aid targeting	Data and machine learning can improve beneficiary identification.	Supports the value of data quality while this study adds perceived fairness and trust.
Dietrich et al. (2024)	Data bias in social assistance	Aggregate predictive accuracy can conceal unequal welfare losses.	Reinforces the need to evaluate fairness, not accuracy alone.
Matheus et al. (2021)	Digital transparency	Transparency must be intentionally designed around usable information.	Explains why understandable decision information strengthens fairness and trust.
de Bruijn et al. (2022)	Explainable algorithmic decisions	Explanations can fail when they do not match user needs.	Qualifies the transparency finding; explanation must be actionable, not merely technical.
Aoki et al. (2024)	Government algorithm explanations	Explanation type affects perceived accuracy, fairness, and trustworthiness.	Closely aligns with the observed fairness→trust pathway.
Mutimukwe et al. (2020)	Privacy assurances in e-services	Organizational privacy assurances shape risk, trust, and disclosure.	Supports the direct governance→trust pathway through privacy and security.
Bodó & Janssen (2022)	Technologized public sector	Trust requires institutional safeguards beyond technical performance.	Supports the dual role of stewardship quality and experienced fairness.
Hooda et al. (2022)	E-government use	Trust is central to behavioral intention and use.	Supports public trust as an outcome of service and institutional evaluations.
Li & Shang (2023)	E-government and trust	Service experience can shape trust in government.	Supports the role of citizen-facing service experience in the model.
Halling & Bækgaard (2024)	Administrative burden	Citizen-state interactions create learning, compliance, and psychological costs.	Explains why correction and appeal burdens can reduce perceived fairness.
Shen et al. (2026)	Welfare participation and fairness	Fairness perceptions and administrative burden are associated with welfare participation.	Provides contemporary support for fairness as an evaluative mechanism in social welfare.
Ariansyah et al. (2026)	Indonesia; e-government maturity and trust	Digital-government maturity is related to trust in public officials.	Provides national context; this study specifies targeting fairness as a mediating pathway.

Source: Synthesis of literature cited in this study, 2026.

The quantitative and qualitative findings were subsequently translated into a governance improvement agenda. Table 6 is not intended to introduce new variables; rather, it presents an operational synthesis of the model and interview evidence so that policy implications can be traced directly back to the mechanisms identified in the study.

Table 6. Priority Agenda for Strengthening Social Protection Data Governance

Priority	Evidence base	Implementation direction
Event-based updating	Strong $X \rightarrow M$ path; theme of changing household circumstances	Rapid updating mechanisms when address, employment, household composition, or economic conditions change
Explainable targeting	Significant $M \rightarrow Y$ path; transparency theme	Status information and general decision rationales in plain language, not merely codes or categories

Priority	Evidence base	Implementation direction
Integrated correction	High DG5 loading; contestability theme	A single correction channel, ticket number, change history, service-level agreement, and case escalation
Privacy by design	$X \rightarrow Y$ remains significant; security theme	Data minimization, verified channels, access restrictions, logging, and anti-fraud education
Inclusive hybrid services	Digital-broker and digital-divide themes	Digital portals supported by staff assistance, offline options, and accessible design
Evidence-based accountability	Trust is linked to institutional responsibility	Publication of correction/complaint statistics, resolution times, and data-quality improvements

Source: Synthesis of PLS-SEM and interview findings, 2026.

Theoretically, this study makes three bounded contributions. First, it operationalizes data governance as an institutional antecedent whose strongest modeled association is with perceived targeting fairness. Second, partial mediation indicates two empirically distinguishable trust pathways: a fairness pathway tied to how targeting decisions are experienced and a direct stewardship pathway tied to privacy, security, transparency, and accountability. Third, the mixed-methods joint display connects these latent relationships to concrete service mechanisms especially correction, nondiscrimination, explanation, and responsible data handling. These contributions extend, rather than replace, established procedural-justice and digital-government explanations of institutional trust.

From a policy perspective, the findings position quality assurance as a process that should be oriented toward the full data lifecycle. Periodic updating is insufficient when household circumstances change between update cycles. The model shows that governance is strongly associated with fairness; therefore, performance indicators for data-managing institutions should measure not only completeness and interoperability but also update latency, the proportion of corrections completed, sources of error, and the effects of errors on beneficiary status. This principle is consistent with the targeting literature's attention to the distribution of errors and their welfare consequences (Aiken et al., 2022; Dietrich et al., 2024).

The second implication is the need for service-oriented explainability. Citizens do not require every technical detail of a scoring model, but they do require sufficient explanation to understand their status, correct inputs, or submit an appeal. This form of transparency differs from simply making data public; what is needed is actionable transparency. Digital transparency designed around citizens' next actions is more likely to build legitimacy than large volumes of information that are not operationally useful (Matheus et al., 2021; Grimmelikhuijsen, 2023).

The third implication is that correction mechanisms should be treated as a core system component rather than as a residual channel activated only when problems occur. The high loading of DG5, the strong $X \rightarrow M$ path, and the consistent interview themes show that correction capacity is simultaneously an element of governance and of procedural fairness. A system that provides ticketing, tracking, service-level expectations, and a history of changes can reduce administrative burden and strengthen predictability. Such an approach also reduces citizens' dependence on knowing which agency they must visit to resolve a problem.

The fourth implication concerns privacy by design and anti-fraud communication. In social protection services, identity and economic data are highly sensitive. Trust may be damaged not only by data breaches but also when citizens do not understand who is authorized to request documents or why the same data are repeatedly requested. Legitimate-channel verification, data minimization, clear notice of purpose, role-based access, audit logs, and anti-fraud education should therefore be positioned as elements of the service experience. This perspective is consistent with findings on privacy assurances and trust in e-services (Mutumukwe et al., 2020; Saura et al., 2022).

The fifth implication is the importance of hybrid service delivery. Digital government can improve efficiency, but a design that assumes all citizens can navigate digital processes risks shifting administrative costs onto families. Generation Z may provide temporary assistance, but the existence of informal digital brokers should not become a prerequisite for accessing social rights. The transformation of DTSEN and related services should therefore retain human assistance, integrated offline channels, and interfaces that are easy to understand. Research on the digital divide and inclusive engagement indicates that a combination of channels is often more inclusive than a digital-only approach (Pérez-Morote et al., 2020; Coles-Kemp et al., 2020; Townley & Koop, 2024).

This study has several limitations that bound interpretation and generalizability. First, the quantitative design is cross-sectional; therefore, PLS-SEM coefficients indicate associations consistent with the proposed

theory rather than causal effects. Second, recruitment metadata and respondent demographics are absent from the analytical file, so sampling representativeness and heterogeneity by age, gender, region, income, or beneficiary status cannot be evaluated. Third, all quantitative constructs were measured in one questionnaire, leaving common-method variance as a plausible alternative source of covariance. Fourth, the qualitative phase is restricted to 20 Generation Z informants with personal or family service experiences and does not establish prevalence across the Indonesian population. Fifth, the model explains 45.2% of the variance in public trust, leaving 54.8% unexplained. Future studies should test alternative mechanisms such as prior institutional reputation, broader service quality, digital capability, socioeconomic vulnerability, and prior benefit experiences, ideally with longitudinal or multi-source data, probability-based sampling, multi-group analysis, and objective indicators of data quality and correction-processing time.

Conclusions

This study answers its central research question by showing that social-protection data governance is positively associated with perceived targeting fairness ($\beta = 0.603$) and public trust ($\beta = 0.339$), while perceived targeting fairness is positively associated with public trust ($\beta = 0.411$). The indirect association through fairness is significant ($\beta = 0.248$), consistent with partial mediation. In practical terms, the large governance→fairness effect ($f^2 = 0.572$) is stronger than the medium fairness→trust effect ($f^2 = 0.196$) and the smaller direct governance→trust effect ($f^2 = 0.133$). These estimates describe relationships within the analyzed sample; they should not be read as causal effects or national population parameters. The qualitative phase explains the mediation pattern rather than merely repeating it. Data updating and correction mechanisms clarify why governance is strongly associated with fairness; explainable targeting and appeal pathways clarify how fairness becomes relevant to trust; and privacy, security, and consistent official channels explain why a direct governance-trust association remains after fairness is included. Hybrid assistance and visible follow-up further show that technically integrated systems can still impose burdens when service design is difficult to navigate. Accordingly, the policy implications are bounded to mechanisms supported by the sample: timely updating, actionable explanations, traceable correction, privacy safeguards, and accessible digital-human service channels. The model explains 45.2% of public-trust variance, which also means that 54.8% remains outside the specified mechanism. This unexplained share is substantively important: prior institutional reputation, service quality in other government interactions, digital capability, socioeconomic position, and past beneficiary experiences may independently shape trust. Future research should therefore test these competing explanations before making stronger causal or population-wide claims. Within the present evidence, the most defensible conclusion is that citizens' evaluations of fairness provide a substantial though not exclusive link between how social-protection data are governed and how institutions are trusted.

Acknowledgments

The author gratefully acknowledges all parties who supported the conduct of this study and the data analysis process. Appreciation is also extended to the informants whose experiences helped clarify the relationships among data governance, targeting fairness, and public trust.

References

- Abdulkareem, A. K., & Ramli, R. M. (2021). Does trust in e-government influence the performance of e-government? An integration of information system success model and public value theory. *Transforming Government: People, Process and Policy*, 16(1), 1-17. <https://doi.org/10.1108/TG-01-2021-0001>
- Aiken, E., Bellue, S., Karlan, D., Udry, C., & Blumenstock, J. E. (2022). Machine learning and phone data can improve targeting of humanitarian aid. *Nature*, 603, 864-870. <https://doi.org/10.1038/s41586-022-04484-9>
- Almuqrin, A., Mutambik, I., Alomran, A., Gauthier, J., & Abusharhah, M. (2022). Factors influencing public trust in open government data. *Sustainability*, 14(15), 9765. <https://doi.org/10.3390/su14159765>

- Alon-Barkat, S. (2020). Can government public communications elicit undue trust? Exploring the interaction between symbols and substantive information in communications. *Journal of Public Administration Research and Theory*, 30(1), 77-95. <https://doi.org/10.1093/jopart/muz013>
- Aoki, N. (2020). An experimental study of public trust in AI chatbots in the public sector. *Government Information Quarterly*, 37(4), 101490. <https://doi.org/10.1016/j.giq.2020.101490>
- Aoki, N., Tatsumi, T., Naruse, G., & Maeda, K. (2024). Explainable AI for government: Does the type of explanation matter to the accuracy, fairness, and trustworthiness of an algorithmic decision as perceived by those who are affected? *Government Information Quarterly*, 41(4), 101965. <https://doi.org/10.1016/j.giq.2024.101965>
- Ariansyah, K., Muttaqin, M., Pusvita, V., Takariani, C. S. D., Darmanto, D., Budhirianto, S., & Nuryana, M. (2026). Revisiting e-government and public trust relationship: Does higher maturity of e-government promote greater trust in public officials? *Transforming Government: People, Process and Policy*, 20(2), 374-394. <https://doi.org/10.1108/TG-07-2025-0219>
- Arshad, S., & Khurram, S. (2020). Can government's presence on social media stimulate citizens' online political participation? Investigating the influence of transparency, trust, and responsiveness. *Government Information Quarterly*, 37(3), 101486. <https://doi.org/10.1016/j.giq.2020.101486>
- Badan Pusat Statistik. (2025). Peraturan Badan Pusat Statistik Nomor 6 Tahun 2025 tentang Penyusunan dan Pengelolaan Data Tunggal Sosial dan Ekonomi Nasional.
- Indonesia. (2019). Peraturan Presiden Republik Indonesia Nomor 39 Tahun 2019 tentang Satu Data Indonesia.
- Indonesia. (2022). Undang-Undang Republik Indonesia Nomor 27 Tahun 2022 tentang Pelindungan Data Pribadi.
- Indonesia. (2025). Instruksi Presiden Republik Indonesia Nomor 4 Tahun 2025 tentang Data Tunggal Sosial dan Ekonomi Nasional.
- Berg, M., & Johansson, T. (2020). Building institutional trust through service experiences: Private versus public provision matter. *Journal of Public Administration Research and Theory*, 30(2), 290-306. <https://doi.org/10.1093/jopart/muz029>
- Bodó, B., & Janssen, H. (2022). Maintaining trust in a technologized public sector. *Policy and Society*, 41(3), 414-429. <https://doi.org/10.1093/polsoc/puac019>
- Busuioc, M. (2021). Accountable artificial intelligence: Holding algorithms to account. *Public Administration Review*, 81(5), 825-836. <https://doi.org/10.1111/puar.13293>
- Chatterjee, S., Khorana, S., & Kizgin, H. (2022). Harnessing the potential of artificial intelligence to foster citizens' satisfaction: An empirical study on India. *Government Information Quarterly*, 39(4), 101621. <https://doi.org/10.1016/j.giq.2021.101621>
- Clarke, A. (2020). Digital government units: What are they, and what do they mean for digital era public management renewal? *International Public Management Journal*, 23(3), 358-379. <https://doi.org/10.1080/10967494.2019.1686447>
- Coles-Kemp, L., Ashenden, D., Morris, A., & Yuille, J. (2020). Digital welfare: Designing for more nuanced forms of access. *Policy Design and Practice*, 3(2), 177-188. <https://doi.org/10.1080/25741292.2020.1760414>
- Dadap-Cantal, E. L., Fischer, A. M., & Ramos, C. G. (2021). Targeting versus social protection in cash transfers in the Philippines: Reassessing a celebrated case of social protection. *Critical Social Policy*, 41(3), 364-384. <https://doi.org/10.1177/02610183211009891>
- de Bruijn, H., Warnier, M., & Janssen, M. (2022). The perils and pitfalls of explainable AI: Strategies for explaining algorithmic decision-making. *Government Information Quarterly*, 39(2), 101666. <https://doi.org/10.1016/j.giq.2021.101666>
- Dietrich, S., Malerba, D., & Gassmann, F. (2024). Predicting social assistance beneficiaries: On the social welfare damage of data biases. *Data & Policy*, 6, e3. <https://doi.org/10.1017/dap.2023.38>
- Distel, B., Koelmann, H., Plattfaut, R., & Becker, J. (2022). Watch who you trust! A structured literature review to build a typology of e-government risks. *Information Systems and e-Business Management*, 20, 789-818. <https://doi.org/10.1007/s10257-022-00573-4>
- Gesk, T. S., & Leyer, M. (2022). Artificial intelligence in public services: When and why citizens accept its usage. *Government Information Quarterly*, 39(3), 101704. <https://doi.org/10.1016/j.giq.2022.101704>
- Gil-Garcia, J. R., & Flores-Zúñiga, M. Á. (2020). Towards a comprehensive understanding of digital government success: Integrating implementation and adoption factors. *Government Information Quarterly*, 37(4), 101518. <https://doi.org/10.1016/j.giq.2020.101518>

- Gong, Y., Yang, J., & Shi, X. (2020). Towards a comprehensive understanding of digital transformation in government: Analysis of flexibility and enterprise architecture. *Government Information Quarterly*, 37(3), 101487. <https://doi.org/10.1016/j.giq.2020.101487>
- González-Gallego, N., & Nieto-Torrejón, L. (2021). Can open data increase younger generations' trust in democratic institutions? A study in the European Union. *PLOS ONE*, 16(1), e0244994. <https://doi.org/10.1371/journal.pone.0244994>
- Grimmelikhuijsen, S. (2023). Explaining why the computer says no: Algorithmic transparency affects the perceived trustworthiness of automated decision-making. *Public Administration Review*, 83(2), 241-262. <https://doi.org/10.1111/puar.13483>
- Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Sage.
- Halling, A., & Bækgaard, M. (2024). Administrative burden in citizen-state interactions: A systematic literature review. *Journal of Public Administration Research and Theory*, 34(2), 180-195. <https://doi.org/10.1093/jopart/muad023>
- Harrison, T. M., & Luna-Reyes, L. F. (2022). Cultivating trustworthy artificial intelligence in digital government. *Social Science Computer Review*, 40(2), 494-511. <https://doi.org/10.1177/0894439320980122>
- Hooda, A., Gupta, P., Jeyaraj, A., Giannakis, M., & Dwivedi, Y. K. (2022). The effects of trust on behavioral intention and use behavior within e-government contexts. *International Journal of Information Management*, 67, 102553. <https://doi.org/10.1016/j.ijinfomgt.2022.102553>
- Hyytinen, A., Tuimala, J., & Hammar, M. (2022). Enhancing the adoption of digital public services: Evidence from a large-scale field experiment. *Government Information Quarterly*, 39(3), 101687. <https://doi.org/10.1016/j.giq.2022.101687>
- Kleizen, B., Van Dooren, W., Verhoest, K., & Tan, E. (2023). Do citizens trust trustworthy artificial intelligence? Experimental evidence on the limits of ethical AI measures in government. *Government Information Quarterly*, 40(4), 101834. <https://doi.org/10.1016/j.giq.2023.101834>
- Kaiser, Z. R. M. Abdullah, & Boadu, Derrick Boakye. (2026). Local Government Transparency and Citizen Satisfaction: Examining the Role of Public Trust and Transformational Leadership Local Government Transparency and Citizen Satisfaction: Examining the Role of Public Trust and Transformational Leadership ABSTRACT. *International Journal of Public Administration*, 00(00), 1-21. <https://doi.org/10.1080/01900692.2026.2667210>
- Lee, T. D., Lee, B.-K., & Lee-Geiller, S. (2020). The effects of information literacy on trust in government websites: Evidence from an online experiment. *International Journal of Information Management*, 52, 102098. <https://doi.org/10.1016/j.ijinfomgt.2020.102098>
- Li, Y., & Shang, H. (2023). How does e-government use affect citizens' trust in government? Empirical evidence from China. *Information & Management*, 60(7), 103844. <https://doi.org/10.1016/j.im.2023.103844>
- Lind, E. A., & Tyler, T. R. (1988). *The social psychology of procedural justice*. Springer. <https://doi.org/10.1007/978-1-4899-2115-4>
- MacLean, D., & Titah, R. (2022). A systematic literature review of empirical research on the impacts of e-government: A public value perspective. *Public Administration Review*, 82(1), 23-38. <https://doi.org/10.1111/puar.13413>
- Masood, A., & Nisar, M. A. (2021). Administrative capital and citizens' responses to administrative burden. *Journal of Public Administration Research and Theory*, 31(1), 56-72. <https://doi.org/10.1093/jopart/muaa031>
- Matheus, R., Janssen, M., & Janowski, T. (2021). Design principles for creating digital transparency in government. *Government Information Quarterly*, 38(1), 101550. <https://doi.org/10.1016/j.giq.2020.101550>
- Maulana, A. O., Herfanda, G. C., & Hasan, F. (2022). Perceived trustworthiness of artificial intelligence implementation in Indonesia public sector services: Gen Z and Millennial perspectives. *Jurnal Akuntansi dan Auditing Indonesia*, 26(1), 65-75. <https://doi.org/10.20885/jaai.vol26.iss1.art7>
- Mesa, D. (2023). Digital divide, e-government and trust in public service: The key role of education. *Frontiers in Sociology*, 8, 1140416. <https://doi.org/10.3389/fsoc.2023.1140416>
- Mikkelsen, K. S., Madsen, J. K., & Bækgaard, M. (2025). Does administrative burden affect welfare recipients' institutional trust and political participation? Evidence from a recall experiment. *The American Review of Public Administration*, 55(6). <https://doi.org/10.1177/02750740251340068>

- Ministry of Finance of the Republic of Indonesia. (2024, October 2-3). Profil dan alokasi anggaran penyaluran bantuan sosial [Presentation]. Indonesia Social Protection Technical Seminar (ISPTS). World Bank.
- Mutumukwe, C., Kolkowska, E., & Grönlund, Å. (2020). Information privacy in e-service: Effect of organizational privacy assurances on individual privacy concerns, perceptions, trust and self-disclosure behavior. *Government Information Quarterly*, 37(1), 101413. <https://doi.org/10.1016/j.giq.2019.101413>
- Pérez-Morote, R., Pontones-Rosa, C., & Núñez-Chicharro, M. (2020). The effects of e-government evaluation, trust and the digital divide in the levels of e-government use in European countries. *Technological Forecasting and Social Change*, 154, 119973. <https://doi.org/10.1016/j.techfore.2020.119973>
- Pribadi, U. (2024). Nexus of public organization, transparency, and accountability in Indonesia's digital governance. *Journal of Public Affairs*, 24(3), e2940. <https://doi.org/10.1002/pa.2940>
- Ringle, C. M., Wende, S., & Becker, J.-M. (2024). SmartPLS 4. SmartPLS. <https://www.smartpls.com>
- Saura, J. R., Ribeiro-Soriano, D., & Palacios-Marqués, D. (2022). Assessing behavioral data science privacy issues in government artificial intelligence deployment. *Government Information Quarterly*, 39(4), 101679. <https://doi.org/10.1016/j.giq.2022.101679>
- Schmager, S., Grøder, C. H., Parmiggiani, E., Pappas, I., & Vassilakopoulou, P. (2024). Exploring citizens' stances on AI in public services: A social contract perspective. *Data & Policy*, 6, e19. <https://doi.org/10.1017/dap.2024.13>
- Selten, F., & Klievink, B. (2024). Organizing public sector AI adoption: Navigating between separation and integration. *Government Information Quarterly*, 41(1), 101885. <https://doi.org/10.1016/j.giq.2023.101885>
- Shen, Y., Wei, W., An, C., & Chen, Z. (2026). Fairness perception, administrative burden, and social welfare participation. *Public Administration. Advance online publication*. <https://doi.org/10.1111/padm.70067>
- Simonofski, A., Clarinval, A., Vanderose, B., Dumas, B., & Snoeck, M. (2021). What influences citizens' expectations towards digital government? An exploratory survey. *Digital Policy, Regulation and Governance*, 23(2), 154-172. <https://doi.org/10.1108/DPRG-12-2020-0173>
- Smythe, I. S., & Blumenstock, J. E. (2022). Geographic microtargeting of social assistance with high-resolution poverty maps. *Proceedings of the National Academy of Sciences*, 119(32), e2120025119. <https://doi.org/10.1073/pnas.2120025119>
- Sutanto, W., Sakaguchi, M., Amrullah, E. R., Rusyiana, A., & Ishida, A. (2020). Accurate targeting in the Indonesian RASKIN program. *International Journal of Social Economics*, 47(11), 1363-1379. <https://doi.org/10.1108/IJSE-03-2020-0124>
- Townley, C., & Koop, C. (2024). Exploring the potential and limits of digital tools for inclusive regulatory engagement with citizens. *Government Information Quarterly*, 41, 101901. <https://doi.org/10.1016/j.giq.2023.101901>
- Tyler, T. R. (2006). *Why people obey the law* (2nd ed.). Princeton University Press. <https://doi.org/10.2307/j.ctv1j66769>
- van Noordt, C., & Tangi, L. (2024). The dynamics of AI capability and its influence on public value creation of AI within public administration. *Government Information Quarterly*, 41, 101860. <https://doi.org/10.1016/j.giq.2023.101860>
- van Zoonen, L. (2020). Data governance and citizen participation in the digital welfare state. *Data & Policy*, 2, e10. <https://doi.org/10.1017/dap.2020.10>
- Vetrò, A., Torchiano, M., & Mecati, M. (2021). A data quality approach to the identification of discrimination risk in automated decision making systems. *Government Information Quarterly*, 38(4), 101619. <https://doi.org/10.1016/j.giq.2021.101619>
- Virnandes, S. R., Shen, J., & Vlahu-Gjorgievska, E. (2024). Building public trust through digital government transformation: A qualitative study of Indonesian civil service agency. *Procedia Computer Science*, 234, 1183-1191. <https://doi.org/10.1016/j.procs.2024.03.114>
- Wang, Y.-F., Chen, Y.-C., Chien, S.-Y., & Wang, P.-J. (2024). Citizens' trust in AI-enabled government systems. *Information Polity*, 29(3), 293-312. <https://doi.org/10.3233/IP-230065>