

DOI: https://doi.org/10.48009/4_iis_2026_144

Development and conditional validation of the Community Data Center Impact Survey (CDIS): Measuring community perceptions of data center infrastructure

Kembley Lingelbach, *Middle Georgia State University*, kembley.lingelbach@mga.edu

Kevin S. Floyd, *Middle Georgia State University*, kevin.floyd@mga.edu

Abstract

This study empirically validates the Community Data Center Impact Survey (CDIS), an instrument designed to measure resident perceptions of data center development and related infrastructure impacts within local communities. The instrument was initially developed around six theoretically derived constructs: perceived environmental risks, perceived infrastructure burden, quality-of-life impacts, perceived economic benefits, institutional trust, and community acceptance. Each construct included survey items designed to assess specific dimensions of resident perceptions regarding data center development. Using a quantitative instrument development and validation design, data were collected from 240 residents across the United States who lived in communities with operational, proposed, or planned data center development. Exploratory factor analysis was conducted to examine the underlying structure of the instrument. Although the CDIS was originally organized around six theoretical constructs, the pilot data produced a more parsimonious three-factor empirical structure. The resulting factors were identified as environmental and infrastructure impacts, economic impacts, and general awareness & perceptions. These findings provide preliminary evidence that the CDIS is a reliable and interpretable instrument for measuring multidimensional public perceptions of data center development and its perceived community impacts.

Keywords: Data centers, community acceptance, environmental risk perception, infrastructure burden, institutional trust, survey validation

Introduction

Data centers have become essential infrastructure supporting cloud computing, artificial intelligence (AI), cybersecurity operations, financial systems, and digital communication. The rapid growth of AI and cloud-based services has accelerated the expansion of large-scale data center development worldwide. Recent estimates indicate that global data centers consumed approximately 415 terawatt-hours (TWh) of electricity in 2024, representing about 1.5% of global electricity consumption, with energy demand increasing by nearly 12% annually over the last five years (IEA, 2026). In the United States, data centers accounted for more than 4% of total electricity consumption in 2023 and are projected to reach between 6.7% and 12% by 2028 due largely to AI-driven computing demands (Belfer Center, 2026). Furthermore, more than 10,000 data centers now operate globally, with over 5,000 located in the United States, and some hyperscale facilities consuming electricity comparable to that of small cities (MIT Energy Initiative, 2026). Recent

research suggests that hyperscale data centers supporting artificial intelligence and cloud computing are placing substantial demands on regional electrical infrastructure due to their extremely high electricity consumption and concentrated energy requirements (Chen et al., 2026; Guidi et al., 2024). Recent IEEE research suggests that AI-focused data centers are increasingly placing substantial demands on regional electrical infrastructure due to their high computational workloads and energy-intensive cooling requirements (Zhang et al., 2025). Additional IEEE reports estimate that data centers could consume between 9% and 17% of U.S. electricity generation by 2030, with some AI training facilities operating at power levels comparable to midsize cities (Walz & Genkina, 2026). As data center development accelerates, concerns regarding energy consumption, environmental sustainability, water usage, infrastructure strain, and community impacts have become increasingly prominent in both academic literature and public discourse. Although data centers are often promoted for economic development, technological innovation, and employment opportunities, communities may also perceive environmental, social, and infrastructural risks associated with these facilities. Public concerns frequently include energy consumption, water usage, land-use changes, noise, traffic, and long-term sustainability impacts. Research on environmental risk perceptions suggests that public responses to technological infrastructure are influenced by perceived fairness, uncertainty, and procedural justice (Slovic, 1987; Slovic et al., 1980). Infrastructure-siting literature also demonstrates that community acceptance is shaped by procedural fairness, place attachment, and institutional trust (Devine-Wright, 2009; Gross, 2007). More recent research by Devine-Wright and Peacock (2024) emphasizes that community responses to infrastructure projects are strongly connected to how residents experience, value, and identify with place, particularly when large-scale infrastructure is perceived as altering landscapes, local identity, or quality of life. Therefore, the purpose of this study is to develop and empirically validate the Community Data Center Impact Survey (CDIS), an instrument designed to assess resident perceptions of data center impacts across six proposed constructs/components consisting of perceived environmental risks, perceived infrastructure burdens, quality of life impacts, perceived economic benefits, institutional trust and community acceptance. The following research question will be addressed.

RQ: Are the six constructs/components (perceived environmental risks, perceived infrastructure burdens, quality of life impacts, perceived economic benefits, institutional trust and community acceptance) reliable and interpretable among their associated variables?

Definition of Terms

Perceived Environmental Risks – Residents’ perceptions that data center development may negatively affect environmental conditions, including water use, energy demand, air quality, noise, land use, and sustainability (Slovic, 1987).

Perceived Infrastructure Burden – Residents’ perceptions that data center development may place pressure on roads, utilities, electrical grids, water systems, and public infrastructure (Gross, 2007; Wolsink, 2007).

Quality-of-Life Impacts – Residents’ perceptions that data center development may affect community character, traffic, noise, visual landscape, and overall quality of life (Devine-Wright, 2009; Devine-Wright & Peacock, 2024).

Perceived Economic Benefits – Residents’ perceptions that data center development may generate economic benefits such as tax revenue, jobs, infrastructure investment, and business growth (Gross, 2007; Wolsink, 2007).

Institutional Trust – Residents’ trust in local government officials, developers, and institutions involved in planning and regulating data center development (Gross, 2007).

Community Acceptance – Residents’ overall support for or opposition to data center development based on perceived risks, benefits, fairness, and trust (Devine-Wright, 2009; Devine-Wright & Peacock, 2024; Gross, 2007; Wolsink, 2007).

Review of Literature

Environmental risk perception research has shown that public judgments regarding technological infrastructure are influenced by perceived severity, uncertainty, trust, and control (Slovic, 1987). Communities may therefore respond differently to data center development depending on perceived environmental impacts and institutional transparency. Infrastructure-siting research also emphasizes the importance of procedural fairness and place attachment. Gross (2007) found that residents are more likely to support infrastructure projects when decision-making processes are transparent and inclusive. Similarly, Devine-Wright (2009) explained that community opposition often occurs when residents perceive threats to local identity and quality of life. Recent scholarship has expanded the role of place attachment and spatial identity in understanding infrastructure acceptance. Devine-Wright and Peacock (2024) conducted a systematic review of place-based energy infrastructure research and found that public responses to infrastructure development are strongly influenced by emotional attachment to place, perceptions of landscape compatibility, and community identity. Their findings suggest that infrastructure acceptance cannot be explained solely through economic or technical considerations but must also account for how residents perceive changes to meaningful places and community environments. These findings are highly relevant to data center development, particularly in rural and semi-rural communities where residents may perceive data centers as altering local landscapes, environmental conditions, and community identity.

Existing data center research has primarily focused on energy consumption, operational sustainability, and technological efficiency rather than community perceptions. Consequently, limited validated instruments currently exist to measure resident perceptions of data center infrastructure and development (Masanet et al., 2020; Jin et al., 2016).

Perceived Environmental Risks

Perceived environmental risk refers to the extent to which residents believe data center development may create or intensify environmental harms, including water demand, electricity consumption, air quality concerns, land-use change, and ecological disruption. Risk perception theory explains that public judgments of environmental and technological risks are shaped not only by technical evidence, but also by uncertainty, perceived severity, trust, and perceived control (Slovic, 1987). This is especially relevant to data centers because residents may not fully understand the technical operations of these facilities, yet may still perceive potential risks from cooling systems, backup generators, land disturbance, and increased utility demand. Recent data center research supports the inclusion of environmental risk as a core construct. Data centers are energy-intensive facilities, and their environmental impacts are often discussed in relation to electricity use, cooling needs, water consumption, and carbon emissions. Masanet et al. (2020) noted that data center energy use must be understood in relation to both growing demand and efficiency improvements. More recent work continues to emphasize the need for greater transparency regarding the carbon and water footprints of data centers, particularly as artificial intelligence workloads increase demand for computational infrastructure (Masanet et al., 2020).

Perceived Infrastructure Burden

Perceived infrastructure burden refers to residents' beliefs that data centers may place additional strain on local roads, utilities, electrical grids, water systems, and public services. Infrastructure-siting literature suggests that public acceptance of development projects is strongly influenced by how communities perceive the distribution of local burdens and benefits. Wolsink (2007) argued that public opposition to infrastructure projects is often better explained by concerns about fairness, equity, and local impacts than by simple "not in my backyard" resistance. Similarly, Gross (2007) emphasized that procedural justice and community fairness are central to how residents evaluate infrastructure development outcome. For data centers, infrastructure burden is particularly important because these facilities may require substantial electricity capacity, water resources, fiber connectivity, road improvements, and utility upgrades. Residents may question whether the local community, taxpayers, or utility customers will bear the cost of infrastructure improvements needed to support private development. Therefore, perceived infrastructure burden is a necessary construct for measuring whether residents view data center development as placing pressure on community systems.

Quality-of-Life Impacts

Quality-of-life impacts refer to residents' perceptions that data center development may affect daily living conditions, community character, traffic, noise, visual landscape, property enjoyment, and overall residential well-being. Place-based infrastructure research shows that residents often respond to development based on how it affects their sense of place and community identity. Devine-Wright (2009) argued that opposition to infrastructure development may reflect place-protective action when residents perceive that a project threatens local identity, landscape, or community character. Devine-Wright and Peacock (2024) further argued that infrastructure projects frequently trigger "place-protective" responses when communities perceive that development threatens socially or emotionally meaningful places. This construct is relevant to data center development because residents may perceive impacts beyond environmental or economic concerns. Construction activity, traffic, lighting, noise from cooling systems or backup generators, and changes to the visual landscape may affect how residents experience their neighborhoods. Quality-of-life concerns are especially important in rural or semi-rural communities where residents may value natural landscapes, quiet surroundings, and lower-density development. Thus, quality-of-life impacts capture the lived experience of data center development and help explain why residents may support or oppose projects even when economic benefits are proposed.

Perceived Economic Benefits

Perceived economic benefits refer to residents' beliefs that data center development may produce positive local outcomes, including tax revenue, job creation, infrastructure investment, local business growth, and broader regional economic development. Public acceptance literature suggests that communities often evaluate infrastructure projects by weighing perceived benefits against perceived risks and burdens. Gross (2007) and Wolsink (2007) both emphasize that acceptance is shaped by whether residents believe the benefits and costs of development are distributed fairly across the community. In the data center context, economic benefits are often central to public and governmental support. Local officials may promote data centers as sources of tax revenue, economic modernization, and regional competitiveness. However, residents may question whether these benefits are meaningful, widely distributed, or primarily captured by outside corporations. Because data centers may create fewer permanent local jobs than other types of industrial development, perceived economic benefit must be measured as a distinct construct rather than assumed. This construct helps determine whether residents believe data center development provides tangible value to the community.

Institutional Trust

Institutional trust refers to the extent to which residents trust local government officials, developers, utility providers, and regulatory institutions to communicate honestly, protect community interests, and make fair decisions about data center development. Trust is a central factor in both risk perception and infrastructure acceptance. Slovic (1987) emphasized that trust influences how people interpret risk information, particularly when risks are complex or uncertain. Gross (2007) further showed that perceived fairness and transparency in decision-making can increase acceptance of infrastructure outcomes. Institutional trust is especially important for data center development because residents often rely on government officials, developers, and technical experts for information about environmental impacts, utility demands, zoning, and long-term community effects. If residents perceive that decisions are made without transparency or meaningful public input, they may be less likely to accept the development, even if economic benefits are promised. Therefore, institutional trust serves as both an independent perception and a possible mediator between perceived risks, perceived benefits, and community acceptance.

Community Acceptance

Community acceptance refers to residents' overall support for, tolerance of, or opposition to data center development based on perceived risks, benefits, fairness, quality-of-life effects, and trust. Infrastructure-siting literature shows that acceptance is multidimensional and shaped by more than economic rationality. Devine-Wright (2009) emphasized the role of place attachment and place identity, while Gross (2007) and Wolsink (2007) emphasized procedural fairness, justice, and equity in shaping public responses to infrastructure development. Devine-Wright and Peacock (2024) further emphasized that social acceptance of infrastructure projects is closely tied to how residents perceive the relationship between infrastructure and place, including whether development is viewed as compatible with local identity, landscape, and community values. For data centers, community acceptance may depend on whether residents believe development is environmentally responsible, fairly governed, economically beneficial, and compatible with local needs. Residents may accept data centers when they perceive transparent planning, meaningful public participation, clear mitigation of harms, and fair distribution of benefits. Conversely, residents may oppose data center development when they perceive environmental risks, infrastructure burdens, limited local benefits, or low institutional trust. As the outcome construct in the CDIS model, community acceptance captures the overall evaluative judgment residents make after considering the combined effects of the other five constructs.

Methodology

Instrument

Based on an extensive review of the research literature, the initial instrument for this study was designed to include six constructs/components with associated survey items. The constructs are perceived environmental risks, perceived infrastructure burden, quality-of-life impacts, perceived economic benefits, institutional trust, and community acceptance. 8 demographic questions were used in the instrument, which may be useful for describing and analyzing group differences but are not part of the CDIS factor structure. Two open-ended questions were used in the survey which can provide a qualitative context but should be analyzed separately from the validated Likert-scale instrument. The instrument development process followed established scale development and validation recommendations (Boateng et al., 2018; DeVellis & Thorpe, 2021; Hinkin, 1998; Worthington & Whittaker, 2006).

Perceived Environmental Risks Construct (Defines water use, energy demand, air quality, environmental stress, land use, and sustainability concerns)

Q7. I am concerned about the environmental impacts of data centers.

Q8. Data centers place pressure on local water resources.

Q9. Data centers increase strain on the regional electricity supply.

Q10. Backup generators or equipment associated with data centers affect air quality.

Q11. Data centers negatively affect local ecosystems or land use.

Perceived Infrastructure Burden Construct (Defines infrastructure strain, traffic, utility demand, and public service burden)

Q12. Data centers place additional pressure on local infrastructure.

Q13. Data center construction or operations increase traffic in the area.

Q14. Data centers increase demand on utilities such as electricity or water.

Q15. The community bears infrastructure improvement costs associated with data centers.

Quality-of-Life Impacts Construct (Defines visual landscape, noise, community character, and quality-of-life concerns)

Q16. Data centers affect the visual landscape of the community.

Q17. Data centers reduce the natural character of my community.

Q18. Noise from data center facilities affects nearby residents.

Q19. Living near a data center reduces the quality of life.

Q20. I would not be comfortable living very close to a data center.

Perceived Economic Benefits Construct (Defines jobs, tax revenue, local economy, and business growth)

Q21. Data centers do not create meaningful local jobs.

Q22. Data centers do not contribute positively to the local economy.

Q23. Data centers do not increase local tax revenue.

Q24. Data centers benefit outside companies more than residents.

Q25. Data centers do not stimulate growth for local businesses.

Institutional Trust Construct (Defines transparency, communication, procedural fairness, and trust in regulation)

Q26. Local government officials are transparent about data center developments.

Q27. Residents are given opportunities to voice concerns in local government.

Q28. Data center companies communicate honestly with the community.

Q29. I do not trust local government to regulate data center impacts effectively.

Q30. Community concerns about data centers are taken seriously by local government decision makers.

Community Acceptance Construct (Defines support, opposition, and acceptance of future data center development)

Q31. Additional data centers should not be built in my community.

Q32. The potential harms of data centers outweigh the benefits of data centers.

Q33. Data centers are a good fit for communities like mine.

Q34. I would oppose future data center development in my community.

The instrument used a five-point Likert-type scale with the following scoring strategy: 5 = Strongly Agree, 4 = Agree, 3 = Neutral, 2 = Disagree, and 1 = Strongly Disagree.

Procedure and Sample

After Institutional Review Board approval, the survey instrument was administered electronically using SurveyMonkey™ to a purposive sample of adult residents living near existing, proposed, or approved data center developments within the United States via social media sites. According to Field (2018), purposive sampling is a non-probability sampling technique in which researchers deliberately select participants because they possess characteristics, experiences, or knowledge relevant to the research question. A total of 282 responses were collected. Of the 282, 42 were eliminated because of incomplete data. This yielded 240 complete survey responses for data analysis. All subjects were 18 years and older and were assured confidentiality and anonymity

Demographics

A total of 240 participants completed the survey. Complete demographic information is presented in Table 1.

Table 1. Demographics

Demographic Variable	Category	n	%
Age Group	18-24	14	5.76%
	25-34	37	15.23%
	35-44	60	24.69%
	45-54	47	19.34%
	55-64	36	14.81%
	65+	49	20.16%
Gender	Male	106	43.62%
	Female	129	53.09%
	Other	0	0%
	Prefer Not to Answer	8	3.29%
Highest Level of Education	High School or less	10	4.10%
	Some college	24	9.84%
	Associate degree	18	7.38%
	Bachelor's degree	98	40.16%
	Graduate degree	94	38.52%

Table 1. Demographics Continued.

Demographic Variable	Category	n	%
Income Status	Under \$15,000	12	5.08%

	\$15000 - \$29999	10	4.24%
	\$30,000 - \$49,999	15	6.36%
	\$50,000 - \$74,999	40	16.95%
	\$75,000 - \$99,999	38	16.10%
	\$100,000 - \$150,000	61	25.85%
	Over \$150,000	60	25.42%
Employment Status	Full-time	137	57.32%
	Part-time	16	6.69%
	Self-employed	13	5.44%
	Retired	56	23.43%
	Student	8	3.35%
	Unemployed	9	3.77%
Race/Ethnicity	American Indian or Native American	5	2.14%
	Asian or Asian American	9	3.85%
	Black or African American	21	8.97%
	Hispanic or Latino	13	5.56%
	Middle Eastern or North African	2	.85%
	Native Hawaiian or other Pacific Islander	1	.43%
	White	180	76.92%
	Another race	3	1.28%
Housing Status	Homeowner	192	80.33%
	Renter	38	15.90%
	Other	9	3.77%

Data Analysis

Exploratory Factor Analysis (EFA) was conducted to identify the underlying factor structure of the survey instrument and evaluate the extent to which items measured common latent constructs. EFA is a multivariate statistical technique used to reduce a large set of observed variables into a smaller number of interpretable factors based on patterns of correlations among items (Field, 2018).

Prior to conducting the analysis, the suitability of the data for factor analysis was assessed using the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's Test of Sphericity.

A KMO value greater than .60 and a statistically significant Bartlett's test indicate that the data are appropriate for factor analysis (Field, 2018). The number of factors retained was determined by examining eigenvalues, the scree plot, and theoretical interpretability.

Based on the favorable results from the KMO, Bartlett's Test, and scree plot, principal component analysis with Varimax rotation was conducted to answer the research question. The principal component analysis with the Varimax rotation procedure forces the number of components and their associated factors/items to be retained. The internal consistency among the factors/items for each component will be determined by Cronbach's alpha reliability test. An acceptable reliability coefficient should be .70 or higher (Field, 2018).

Results

An exploratory factor analysis (EFA) was conducted to examine the underlying structure of survey items measuring perceptions of data centers. Principal Component Analysis (PCA) with Varimax rotation was used to identify latent constructs within the instrument. Prior to extraction, the suitability of the data for factor analysis was evaluated using the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's Test of Sphericity (Field, 2018).

The KMO value of .952 indicated excellent sampling adequacy, exceeding the recommended minimum threshold of .60. Bartlett's Test of Sphericity was statistically significant, $\chi^2(378) = 6788.564$, $p < .001$, demonstrating that sufficient intercorrelations existed among the variables to justify factor analysis (Field, 2018).

Table 2. KMO and Bartlett's Test

Kaiser-Meyer-Olkin (KMO)		.952
Bartlett's Test of Sphericity	Approx of Chi-Square	6788.564
	Df	378
	Sig	< .001

Following iterative refinement and removal of problematic cross-loading items, the final analysis retained 20 items across three factors. The final three-factor solution was retained based on eigenvalues greater than one and inspection of the scree plot. Together, the three factors explained 76.04% of the total variance.

Table 3. Total Variance Explained

Factor	Eigenvalue	% Variance Explained	Cumulative %
1	10.642	53.211	53.211
2	2.975	14.874	68.085
3	1.590	7.951	76.036

The scree plot in Figure 1 supported retention of a three-factor solution. A substantial decline in eigenvalues occurred between the first and third components, followed by a clear leveling off after the third factor, indicating that additional factors contributed minimal explanatory value. This pattern provided visual confirmation of the appropriateness of the three-factor structure.

The rotated factor matrix demonstrated strong and interpretable factor loadings with minimal problematic cross-loading. Factor loadings greater than .40 were considered meaningful for interpretation purposes. The three retained factors represented (1) perceived environmental and infrastructure impacts, (2) perceived economic benefits, and (3) general awareness and perceptions regarding data centers

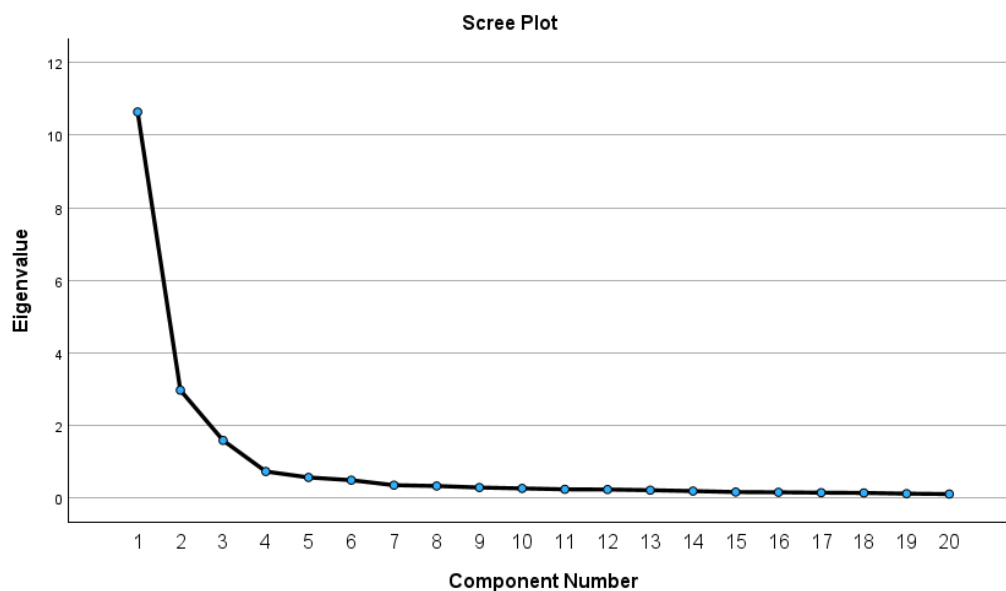


Figure 1: Scree Plot Test

Factor 1 included items related to environmental concerns, infrastructure strain, and operational impacts associated with data centers. Strong loadings on this factor included Q20 (.838), Q21 (.859), Q22 (.788), Q24 (.795), Q31 (.775), and Q30 (.743). This factor was interpreted as Perceived Environmental and Infrastructure Impacts.

Factor 2 included items reflecting positive perceptions and economic opportunities associated with data center development. Strong loadings included Q25 (.881), Q26 (.840), Q27 (.881), Q29 (.853), and Q32 (.790). This factor was interpreted as Perceived Economic Benefits.

Factor 3 included items measuring awareness, attitudes, and general perceptions regarding data centers. Strong loadings included Q7 (.809), Q8 (.878), Q11 (.843), and Q13 (.874). This factor was interpreted as General Awareness and Perceptions.

Communality estimates for the retained items ranged from .565 to .863, indicating that the extracted factors adequately explained the variance in the observed variables. Overall, the final

EFA supported a strong and interpretable three-factor structure with excellent psychometric properties.

The reliability tests for the components suggested the existence of internal consistency for the items of each component, Perceived Environmental and Infrastructure Impacts ($\alpha = .933$), Perceived Economic Benefits ($\alpha = .922$), and General Awareness and Perceptions ($\alpha = .944$).

Table 4. Rotated Component Matrix

Constructs	Items	Component		
		1	2	3
Factor 1 Environmental & Infrastructure Impacts	Q20	.838	-.175	.223
	Q21	.859	-.100	.192
	Q22	.788	.045	.003
	Q24	.795	-.159	.299
	Q30	.743	-.322	.420
	Q31	.775	-.254	.329
Factor 2 Economic Impacts	Q25	-.042	.881	-.111
	Q26	-.123	.840	.044
	Q27	-.185	.881	-.176
	Q29	-.189	.853	-.012
	Q32	-.289	.790	-.265
Factor 3 General Awareness & Perceptions	Q7	.421	-.110	.809
	Q8	.254	-.085	.878
	Q11	.367	-.132	.843
	Q13	.298	-.072	.874

Discussion

The primary purpose of this study was to empirically validate the Community Data Center Impact Survey (CDIS), an instrument developed to measure resident perceptions of the data center development and related community impacts. Although the instrument was initially conceptualized around six theoretically derived constructs perceived environmental risks, perceived infrastructure burden, quality of life impacts, perceived economic benefits, institutional trust, and community acceptance, the exploratory factor analysis produced a more parsimonious three-factor empirical structure. This finding suggests that residents may not conceptualize the impacts of the data center development as discrete theoretical domains but rather as broader, interconnected perceptions that combine environment, social, governance, and economic concerns. The findings partially answer the research question by demonstrating that the original six constructs were interpretable but not empirically distinct within the pilot sample. Instead, several theoretically separate domains clustered together into broader dimensions of perception. Such restructuring is not uncommon

during early instrument development, as exploratory factor analysis is designed to identify the latent organization of participant responses rather than confirm a priori conceptual model (Field, 2018; DeVellis & Thorpe, 2021). The emergence of fewer factors than originally proposed suggests that residents may evaluate data center development through more integrated evaluative judgements that combine perceived harms, governance concerns, and anticipated community outcomes. Unexpected factor consolidation during EFA does not necessarily invalidate theoretical constructs but may instead reflect how respondents cognitively organize perceptions during early instrument testing.

The first factor, interpreted as environmental and infrastructure impact appear to combine concerns associated with perceived environmental risks, infrastructure pressures, and broader lived experiences of data center development. This finding aligns with infrastructure siting research suggesting that residents often evaluate technological developments holistically rather than categorically, particularly when perceived threats involve local identity, environmental change, and daily quality of life (Devine-Wright, 2009; Devine-Wright & Peacock, 2024). Residents may therefore interpret environmental concerns, infrastructure strain, and perceived disruptions to everyday life as overlapping dimensions of a broader community impact experience.

The second factor, economic impacts reflected economic and governance related perceptions, suggesting that residents may evaluate economic beliefs in relation to institutional trust, transparency, and fairness. Prior infrastructure acceptance literature indicates that perceived procedural justice and trust in institutions frequently influence where residents view promised economic benefits as legitimate or equitable (Gross, 2007; Wolsink, 2007). For example, residents may perceive tax incentives, employment claims, or infrastructure investments differently depending on whether local officials and developers are viewed as transparent and accountable. These findings support previous research emphasizing the importance of institutional trust in shaping public responses to infrastructure development (Slovic, 1987; Gross, 2007; Wolsink, 2007).

The third factor, general awareness and perceptions suggest that perceptions regarding data centers may also reflect a more generalized awareness and attitudinal orientation toward development. Items loading onto this factor indicate that residents may possess an overarching impression regarding data center impacts that influence how specific risks and benefits are interpreted. The finding is consistent with environment risk perception literature which suggests that public attitudes toward complex technological systems are often shaped by trust, uncertainty, perceived control, and broader mental models of technological risks (Slovic, 1987; Slovic et al., 1980).

The high internal consistency estimates observed across retained factors ($\alpha = .922-.944$) provide preliminary evidence that the instrument demonstrates strong reliability. While coefficients above .90 suggest excellent internal consistency, future studies should evaluate whether item redundancy exists and determine whether a shorter version of the instrument may preserve psychometric strength while improving efficiency (DeVellis & Thorpe, 2021).

Several limitations should be acknowledged. First, this study relied on a purposive, non-probability sample recruited through social media, which may limit generalizability beyond residents who are more civically engaged, technologically aware, or motivated to express opinions regarding local development. Second, the demographic composition of the sample included disproportionately high levels of educational attainment and homeownership, which may shape perceptions of infrastructure development and community change. Third, because this study represents a pilot validation effort, the results should be considered preliminary

and interpreted within the context of exploratory analysis. Exploratory factor analysis is intended to identify latent structure, but confirmatory procedures are necessary to evaluate the stability and generalizability of the proposed factor model (Field, 2018).

Future research should replicate the CDIS using larger and more geographically diverse samples and conduct confirmatory factor analysis (CFA) to assess model fit and construct validity. Researchers may also examine measurement invariance across demographic groups, including age, education, homeownership status, and proximity to data center developments. Additionally, mixed-methods research incorporating interviews or open-ended responses may provide richer insight into how residents interpret environmental risks, procedural fairness, economic expectations, and quality-of-life concerns associated with data center development.

While the primary purpose of this research was to validate the instrument; it is worth noting respondent perceptions. The resulting descriptive statistics indicate that respondents generally perceived data center development as having more negative than positive impacts on their communities. Participants expressed particularly strong concerns regarding environmental effects, infrastructure strain, utility demand, and quality-of-life impacts, with most items in these constructs receiving high levels of agreement. In contrast, perceptions of economic benefits were more mixed, suggesting that while some respondents recognized potential economic advantages, many remained uncertain about whether these benefits outweighed the perceived environmental and community costs.

Conclusion

This study provides preliminary empirical support for the Community Data Center Impact Survey (CDIS) as an instrument for measuring resident perceptions of data center development and related community impacts. Although the instrument was originally developed around six theoretically derived constructs, exploratory factor analysis revealed a more parsimonious three-factor structure, suggesting that residents may perceive data center development through broader and more interconnected dimensions than originally hypothesized. These findings highlight the importance of empirically validating theoretically informed instruments to ensure that observed perceptions align with how respondents cognitively organize experiences and concerns. The results contribute to a limited but emerging body of research focused on the social and community dimensions of data center development. Existing scholarship has largely emphasized technological performance, sustainability, energy efficiency, and operational optimization (Masanet et al., 2020; Jin et al., 2016), while comparatively little research has examined how residents perceive data center development within local communities. The CDIS addresses this gap by offering a preliminary instrument capable of capturing multidimensional public perceptions related to environmental concerns, infrastructure impacts, economic expectations, governance trust, and community acceptance.

The findings also have practical implications for policymakers, planners, developers, and community leaders involved in siting and regulating data center infrastructure. Because resident perceptions appear to reflect interconnected concerns involving environmental conditions, quality of life, institutional trust, and perceived benefits, public engagement strategies should move beyond technical explanations of infrastructure and incorporate transparent communication, procedural fairness, and meaningful opportunities for community participation (Gross, 2007; Devine-Wright & Peacock, 2024). Early and sustained engagement may improve trust and reduce perceived conflict surrounding future development. Despite encouraging reliability and interpretability findings, additional validation is warranted. Future studies should confirm the factor structure through confirmatory factor analysis, assess convergent and discriminant validity, and evaluate the instrument across diverse geographic and demographic populations. Over time, refinement of the CDIS may provide researchers and practitioners with a robust tool for

understanding community perceptions of large-scale technological infrastructure and informing evidence-based planning and decision-making related to data center development.

References

- Belfer Center for Science and International Affairs. (2026). AI, data centers, and the U.S. electric grid: A watershed moment for energy policy. <https://belfercenter.org>
- Boateng, G. O., Neilands, T. B., Frongillo, E. A., Melgar-Quinonez, H. R., & Young, S. L. (2018). Best practices for developing and validating scales for health, social, and behavioral research: A primer. *Frontiers in Public Health*, 6, 149. <https://doi.org/10.3389/fpubh.2018.00149>
- Chen, D., Zhou, Z., Cai, Y., Qin, J., Katchova, A., & Chen, L. (2026). Concentrated siting of AI data centers drives regional power-system stress under rising global compute demand. arXiv. <https://doi.org/10.48550/arXiv.2604.06198>
- DeVellis, R. F., & Thorpe, C. T. (2021). *Scale development: Theory and applications* (5th ed.). SAGE Publications.
- Devine-Wright, P. (2009). Rethinking NIMBYism: The role of place attachment and place identity in explaining place-protective action. *Journal of Community & Applied Social Psychology*, 19(6), 426–441.
- Devine-Wright, P., & Peacock, A. (2024). Putting energy infrastructure into place: A systematic review. *Renewable and Sustainable Energy Reviews*, Volume 197, 2024, 114272, ISSN 1364-0321, <https://doi.org/10.1016/j.rser.2023.114272>.
- Field, A. P. (2018). *Discovering statistics using IBM SPSS statistics* (5th ed.). Sage Publications.
- Gross, C. (2007). Community perspectives of wind energy in Australia: The application of a justice and community fairness framework to increase social acceptance. *Energy Policy*, 35(5), 2727–2736. <https://doi.org/10.1016/j.enpol.2006.12.013>
- Guidi, G., Dominici, F., Gilmour, J., Butler, K., Bell, E., Delaney, S., & Bargagli-Stoffi, F. J. (2024). Environmental burden of United States data centers in the artificial intelligence era. arXiv. <https://doi.org/10.48550/arXiv.2411.09786>
- Hinkin, T. R. (1998). A brief tutorial on the development of measures for use in survey questionnaires. *Organizational Research Methods*, 1(1), 104–121.
- International Energy Agency. (2026). Energy demand from AI. <https://www.iea.org>
- Jin, X., Zhang, F., Vasilakos, A. V., & Liu, Z. (2016). *Green data centers: A survey, perspectives, and future directions*. <https://arxiv.org/abs/1608.00687>

- Masanet, E., Shehabi, A., Lei, N., Smith, S., & Koomey, J. (2020). Recalibrating global data center energy-use estimates. *Science*, 367(6481), 984–986.
<https://doi.org/10.1126/science.aba3758>
- MIT Energy Initiative. (2026). Data center power demand. https://energy.mit.edu/strategic-priorities/data-center-power-demand/?utm_source=chatgpt.com
- Slovic, P. (1987). Perception of risk. *Science*, 236(4799), 280–285.
<https://doi.org/10.1126/science.3563507>
- Slovic, P., Fischhoff, B., & Lichtenstein, S. (1980). Facts and fears: Understanding perceived risk. In R. Schwing & W. A. Albers Jr. (Eds.), *Societal risk assessment How safe is enough?* (pp. 181-216). Springer.
- Walz, E., & Genkina, D.(2026). Your Next AI Query May Travel Where the Power Is. *IEEE Spectrum*. <https://spectrum.ieee.org/distributed-inference-data-centers>
- Wolsink, M. (2007). Wind power implementation: The nature of public attitudes: Equity and fairness instead of “backyard motives.” *Renewable and Sustainable Energy Reviews*, 11(6), 1188–1207. <https://doi.org/10.1016/j.rser.2005.10.005>
- Worthington, R. L., & Whittaker, T. A. (2006). Scale development research: A content analysis and recommendations for best practices. *The Counseling Psychologist*, 34(6), 806–838.
- Zhang, Y., Tang, H., Li, H., & Wang, S. (2025). Integration and interaction of next-generation AI-focused data centers with smart grids and district energy systems: The state-of-the-art, opportunities and challenges. *Renewable and Sustainable Energy Reviews*, 224, 116097.