



Development of a Decision Support System Framework for Intelligent Transportation System Adoption Evaluation Based on SEM-PLS Analysis

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Abstract

Implementing Intelligent Transportation Systems (ITS) requires an evaluation mechanism that considers technological, infrastructural, socioeconomic, financial, readiness, affordability, and policy-related conditions. Although previous studies have identified determinants of ITS adoption, they have rarely translated these findings into operational decision-support mechanisms. This study develops a model-driven Decision Support System (DSS) framework for evaluating ITS adoption readiness based on empirically validated Partial Least Squares Structural Equation Modeling (PLS-SEM) relationships. A sequential mixed-methods design was employed. The qualitative stage included a Focus Group Discussion with six participants: two subject-matter experts, two government representatives, and two academics. During the quantitative stage, 100 questionnaires were distributed to transportation users and stakeholders, and 75 usable responses were obtained, representing a 75% response rate. PLS-SEM was used to evaluate the measurement and structural models. The results indicated that Government Policy had the strongest significant direct relationship with ITS Adoption ($\beta = 0.454$; $p < 0.001$), followed by Smart Readiness ($\beta = 0.244$; $p = 0.001$). Social Affordability did not have a significant direct relationship with ITS Adoption ($\beta = 0.047$; $p = 0.515$). The validated relationships were transformed into a DSS comprising Data, Model, and Decision Layers. To ensure dimensional consistency, raw assessment values were standardized before applying the standardized path coefficients, while readiness categories were interpreted using percentile-based thresholds. The proposed framework extends PLS-SEM findings beyond hypothesis testing by providing a transparent basis for ITS readiness assessment and factor-specific policy prioritization. Further validation using larger samples and operational implementation remains necessary.

Keywords *Intelligent Transportation System, Decision Support System, PLS-SEM, Technology Adoption, Smart Mobility*

INTRODUCTION

The development of digital technology has changed the way urban transportation systems are planned, managed, and operated. Population growth, increasing vehicle ownership, and rising mobility demand have created substantial challenges for local governments in providing transportation services that are efficient, safe, accessible, and environmentally sustainable (Almatar, 2024). Intelligent Transportation Systems (ITS) offer a strategic response by integrating information and communication technologies, sensing devices, and data analytics into transportation infrastructure and services (Alanazi & Alenezi, 2024; Duarte et al., 2021). ITS applications, including intelligent traffic management, real-time travel information, electronic ticketing, vehicle monitoring, and digitally enabled mobility services, can improve travel efficiency, support congestion management, enhance road safety, and contribute to more sustainable urban

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transportation ([Jagatheesaperumal et al., 2024](#); [Lu et al., 2022](#)). Consequently, ITS has become an important component of smart-city development, creating a growing need for systematic and data-driven mechanisms to evaluate cities' readiness to adopt and implement these systems.

Despite their recognized benefits, implementing ITS remains challenging, particularly in developing countries and rapidly growing urban areas. Inadequate technological and transportation infrastructure, limited institutional readiness, financial constraints, and fragmented policy coordination can restrict the effective implementation and continued operation of ITS initiatives ([Alanazi & Alenezi, 2024](#); [Almatar, 2024](#); [Himawan et al., 2025](#)). Socioeconomic disparities, differences in digital readiness, and the affordability of technology-enabled transportation services may also affect individuals' and communities' ability to access, accept, and use ITS applications. These conditions show that successful ITS implementation depends not only on technological capability but also on the interaction of infrastructure, funding support, socioeconomic conditions, system readiness, social affordability, and government policy ([Himawan et al., 2025](#); [Vrščaj et al., 2021](#); [Wey & Peng, 2021](#)). Therefore, a comprehensive evaluation mechanism is required to assess ITS adoption readiness, identify critical implementation barriers, and support evidence-based policy and investment decisions.

In response to these challenges, this study proposes a model-driven Decision Support System (DSS) framework for evaluating ITS adoption readiness. The proposed framework is based on the empirical relationships generated through PLS-SEM analysis of primary survey data collected in this study rather than on coefficients adopted directly from previously published research. It transforms the statistically validated relationships among Technology, Infrastructure, Social Economy, Funding Support, Smart Readiness, Social Affordability, Government Policy, and ITS Adoption into a structured evaluation mechanism. To maintain methodological consistency, the framework processes standardized construct scores before applying standardized PLS-SEM path coefficients. The resulting DSS is designed to generate an overall readiness assessment, identify factors requiring policy attention, and support local governments and transportation stakeholders in establishing evidence-based ITS implementation priorities.

Accordingly, this study's main objective is to develop an empirically grounded and methodologically consistent DSS framework for evaluating ITS adoption readiness. Specifically, the study aims to: (1) validate the measurement and structural models of ITS adoption using PLS-SEM; (2) transform the validated structural relationships into a dimensionally consistent DSS calculation model; (3) design a DSS architecture comprising data, model, and decision layers; and (4) translate the evaluation results into interpretable policy priorities for ITS planning and implementation.

Previous studies have employed technology-adoption models and PLS-SEM to identify the factors influencing the acceptance and implementation of intelligent transportation technologies ([Gündoğan & Keçeci, 2024](#); [Himawan et al., 2025](#); [Sutarto et al., 2023](#); [Wang et al., 2021](#)). However, these studies primarily explain relationships among constructs and test research hypotheses, with limited attention to translating validated relationships into operational decision-support mechanisms. Conversely, existing transportation DSS applications generally address operational problems such as route planning, traffic management, infrastructure prioritization, and transportation safety rather than multidimensional ITS adoption readiness ([Lu et al., 2022](#); [Wey & Peng, 2021](#); [Zhou et al., 2025](#)). Consequently, a gap remains in integrating empirically validated PLS-SEM relationships into a methodologically consistent DSS that evaluates ITS adoption readiness and generates interpretable policy priorities.

This study's novelty and contribution are reflected in three aspects. First, it provides a methodologically consistent procedure for transforming empirically validated PLS-SEM relationships into a DSS calculation model by aligning standardized path coefficients with standardized construct inputs. Second, it integrates technological, infrastructural, socioeconomic,

financial, readiness, affordability, and policy dimensions within a unified DSS architecture, thereby enabling a more comprehensive evaluation of ITS adoption readiness. Third, it translates statistical relationships into interpretable readiness assessments and factor-specific policy priorities to help local governments and transportation stakeholders identify areas requiring intervention. Accordingly, the proposed framework bridges the gap between explanatory adoption research and practical decision support, providing a foundation for more transparent, systematic, and evidence-based ITS planning.

LITERATURE REVIEW

Previous Studies on ITS Adoption and Readiness

Previous studies have applied technology-adoption models to explain the acceptance and implementation of intelligent transportation technologies from different perspectives. [Wang et al. \(2021\)](#) integrated the Technology Acceptance Model (TAM) with trust and perceived risk to explain users' adoption of smart transportation services, while [Sutarto et al. \(2023\)](#) combined TAM and the Unified Theory of Acceptance and Use of Technology (UTAUT) to examine public acceptance of fully autonomous vehicles. In the transportation-logistics context, [Gündoğan and Keçeci \(2024\)](#) employed a TAM-based approach to evaluate the adoption of digital transformation. Extending the analysis beyond individual acceptance, [Himawan et al. \(2025\)](#) proposed a multidimensional ITS adoption framework that incorporated technological, infrastructural, socioeconomic, financial, readiness, affordability, and government-policy factors. Although these studies provide empirical evidence about the determinants of transportation-technology adoption, their primary contributions remain explanatory, focusing on construct relationships and hypothesis testing rather than translating the validated relationships into operational decision-support mechanisms.

Meanwhile, transportation-related decision models have been developed for prioritizing smart-transportation projects through the Kano model ([Lu et al., 2022](#)), assessing smart and sustainable cities using big data and the Analytic Network Process ([Wey & Peng, 2021](#)), and supporting the safe and efficient transportation of hazardous materials ([Zhou et al., 2025](#)). These approaches demonstrate the value of analytical decision support, but they do not evaluate multidimensional ITS adoption readiness using an empirically validated PLS-SEM model. Therefore, a research gap remains in transforming validated PLS-SEM relationships into a methodologically consistent DSS that can assess ITS adoption readiness, identify factor-specific weaknesses, and generate interpretable policy priorities.

Decision Support System (DSS) for ITS Adoption Evaluation

A Decision Support System (DSS) is an interactive, computer-based system that helps decision-makers address structured and semi-structured problems by integrating relevant data, analytical procedures, models, and information-presentation facilities. Rather than replacing managerial judgment, a DSS organizes evidence, processes decision variables, and presents interpretable results that allow decision-makers to compare conditions, identify priorities, and evaluate possible courses of action ([Sharda et al., 2020](#)). In the context of ITS adoption, a DSS can connect empirical evidence on technological and contextual readiness with the information policymakers need to plan appropriate interventions.

A conventional DSS architecture includes data-management, model-management, and user-interface components. The data-management component stores, organizes, and retrieves the information required for analysis, whereas the model-management component applies statistical, mathematical, or rule-based procedures to process the input data. The user interface enables decision-makers to enter assessment data, review analytical results, and interpret the resulting recommendations ([Sharda et al., 2020](#)). In this study, these conventional components are

operationalized as three interconnected layers: the Data Layer, which manages standardized construct inputs; the Model Layer, which processes the validated PLS-SEM relationships; and the Decision Layer, which converts the calculated results into readiness assessments and factor-specific policy priorities.

In transportation research, decision-support approaches have been applied to urban-mobility information integration, smart-city assessment, transportation-project prioritization, and transportation safety. Duarte et al. (2021) proposed an integrated information-system framework to support urban mobility, while Wey and Peng (2021) combined big data and the Analytic Network Process to assess smart and sustainable city development. Lu et al. (2022) used the Kano model to prioritize smart-transportation development projects, and Zhou et al. (2025) developed a decision-support scheme for the safe and efficient transportation of hazardous materials. Although these studies demonstrate the value of data and analytical models in transportation decision-making, they primarily focus on operational management, project prioritization, or infrastructure assessment. Limited attention has been given to developing a DSS that transforms empirically validated PLS-SEM relationships into a comprehensive mechanism for evaluating ITS adoption readiness. This limitation provides the basis for the DSS framework proposed in this study.

PLS-SEM-Based ITS Adoption Evaluation

Partial Least Squares Structural Equation Modeling (PLS-SEM) is a variance-based multivariate method used to estimate complex relationships among observed indicators and latent constructs. It enables researchers to evaluate both the measurement model, which examines the reliability and validity of the constructs, and the structural model, which assesses the direction, strength, significance, and predictive relevance of relationships among constructs. PLS-SEM is particularly appropriate for prediction-oriented and exploratory research involving complex models, multiple latent variables, and data that do not satisfy multivariate normality assumptions (Hair et al., 2022). However, interpreting structural relationships must be preceded by evidence that the measurement model meets acceptable criteria for indicator reliability, internal consistency reliability, convergent validity, and discriminant validity.

In the ITS context, technology-adoption and structural-equation models have been used to examine factors associated with the acceptance and implementation of intelligent transportation technologies. Previous studies have investigated user perceptions, technology readiness, infrastructure conditions, socioeconomic factors, financial support, institutional readiness, and government policy as determinants of transportation-technology adoption (Gündoğan & Keçeci, 2024). These studies provide valuable empirical explanations of the relationships among adoption determinants. Nevertheless, they generally report findings as path coefficients, significance levels, and hypothesis-testing results, with limited translation into operational mechanisms that can support regional readiness evaluation and policy prioritization. This study addresses that limitation by using validated PLS-SEM relationships as the structural basis of a DSS while ensuring that standardized coefficients are applied to standardized construct inputs.

RESEARCH METHOD

Research Design

This study employed a sequential mixed-methods design followed by model-driven DSS development. The design combined a qualitative Focus Group Discussion (FGD), a quantitative questionnaire survey, PLS-SEM analysis, and the transformation of the validated empirical model into a DSS framework. The sequential design was selected because the qualitative stage provided contextual input to refine the research constructs and indicators, while the quantitative stage empirically evaluated the measurement and structural models. The validated relationships then

served as the analytical foundation for the proposed DSS. This sequence ensured that the framework was both empirically grounded and relevant to ITS implementation requirements in an urban context (Creswell & Creswell, 2023). Figure 1 presents the overall research process.

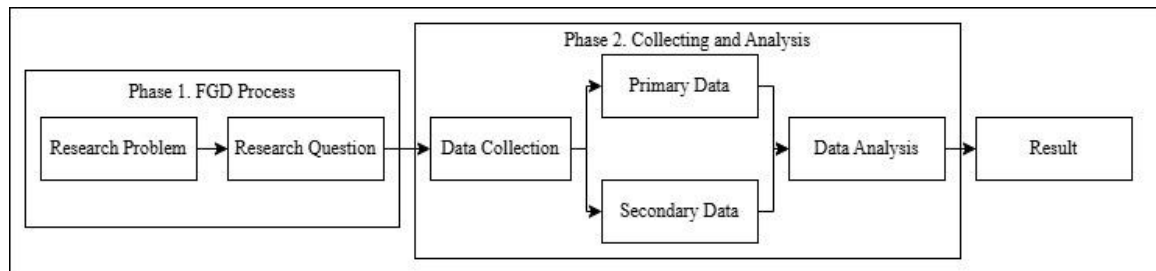


Figure 1. Design Research Methodology

The first stage involved an FGD with six purposively selected participants, comprising two subject-matter experts, two government representatives, and two academics. The FGD examined the contextual relevance of the proposed constructs, the clarity and suitability of the measurement indicators, the relationships represented in the conceptual model, and the information requirements of prospective DSS users. A semi-structured discussion guide was used to maintain consistency across the topics discussed. The discussion results were documented, organized into relevant themes, and used to refine the questionnaire and conceptual model before the quantitative data-collection stage.

The second stage involved a questionnaire-based survey of transportation users and stakeholders who had relevant knowledge or experience of technology-enabled transportation services. A total of 100 questionnaires were distributed, of which 75 complete and usable responses were returned, resulting in a response rate of 75%. The primary survey data were analyzed using PLS-SEM. The analysis evaluated the measurement model to establish construct reliability and validity, then evaluated the structural model to estimate the direction, strength, significance, and predictive relevance of the relationships affecting ITS adoption readiness (Hair et al., 2022).

The third stage transformed the validated PLS-SEM relationships into a model-driven DSS framework. The main calculation and policy-prioritization mechanisms were developed using only relationships supported by the structural-model results. Because the structural model reported standardized path coefficients, the DSS design required standardizing the construct inputs before applying the coefficients. The resulting framework was organized into Data, Model, and Decision Layers, which collectively support data input, readiness calculation, result interpretation, and the generation of factor-specific policy priorities. Accordingly, the research was conducted through three sequential stages:

1. Qualitative evaluation and refinement of the constructs, measurement indicators, conceptual relationships, and DSS requirements through the FGD
2. Quantitative assessment of the measurement and structural models using primary survey data and PLS-SEM
3. Transformation of the validated PLS-SEM relationships into a standardized, model-driven DSS framework for evaluating ITS adoption readiness

Sample and Population

The target population comprised transportation users and stakeholders involved in adopting and implementing technology-enabled transportation services in Yogyakarta, Indonesia.

The population included active users of digital transportation services, potential ITS users with relevant knowledge of smart-transportation applications, and stakeholders involved in transportation management, policy, or planning. Because a complete sampling frame for these groups was unavailable and the study required respondents with relevant experience or knowledge, the study used purposive sampling. The study recruited respondents from transportation-user and stakeholder groups within the study area.

The inclusion criteria required respondents to: (1) be at least 18 years old; (2) reside in Yogyakarta; and (3) have experience with or sufficient knowledge of technology-enabled transportation services. We excluded from the analysis respondents who did not meet these criteria, submitted incomplete questionnaires, or provided duplicate responses. A total of 100 questionnaires were distributed, and 75 complete, usable questionnaires were returned, yielding a response rate of 75%.

Sample adequacy was assessed based on the complexity of the structural model. The largest number of predictors directed toward a single endogenous construct was three. A statistical sensitivity analysis with three predictors, a significance level of 0.05, a power of 0.80, and a sample size of 75 indicated that the study was capable of detecting an effect size of approximately ($f^2 = 0.154$), which is close to the conventional medium-effect threshold of ($f^2 = 0.15$). The sample also exceeded the minimum of 30 observations indicated by the 10-times rule. Nevertheless, because the achieved sample size provided limited power for detecting small effects, the findings should be interpreted as exploratory and validated using a larger sample in future research.

Data Collection

Data were collected sequentially through two complementary methods: a qualitative Focus Group Discussion and a quantitative questionnaire survey. The FGD was conducted first to assess the contextual relevance of the proposed constructs, measurement indicators, conceptual relationships, and DSS information requirements. The refined research instrument was subsequently administered through the questionnaire survey to obtain the primary data required for PLS-SEM analysis.

The FGD involved six purposively selected participants comprising two subject-matter experts, two government representatives, and two academics. Participants were selected based on their knowledge or experience related to intelligent transportation, information systems, digital transformation, transportation policy, or urban planning. A semi-structured discussion guide was used to ensure that the participants addressed four principal areas: (1) the relevance of the proposed ITS adoption constructs; (2) the clarity and contextual suitability of the measurement indicators; (3) the relationships represented in the conceptual model; and (4) the information and outputs required by prospective DSS users. The discussion documented and analyzed the participants' responses by grouping them into themes related to Technology, Infrastructure, Social Economy, Funding Support, Smart Readiness, Social Affordability, Government Policy, ITS Adoption, and DSS requirements. The results were used to refine the questionnaire wording, confirm the contextual relevance of the constructs, and specify the expected DSS outputs, including readiness assessment and factor-specific policy priorities.

After the FGD, we collected quantitative data using a structured questionnaire. The measurement items were adapted from established technology-adoption and ITS studies and refined according to the FGD findings. The questionnaire measured eight constructs: Technology (TECH), Infrastructure (INF), Social Economy (SE), Funding Support (FS), Smart Readiness (SR), Social Affordability (SA), Government Policy (GP), and ITS Adoption (ITS). The sources and operational definitions of the measurement items should be reported in a separate measurement-instrument table. All items were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). We distributed 100 questionnaires to eligible transportation users

and stakeholders in Yogyakarta. After applying the inclusion criteria and screening the returned questionnaires for completeness and duplicate responses, 75 usable responses were retained for PLS-SEM analysis, producing a response rate of 75%.

Data Analysis

The quantitative data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS. The analysis comprised measurement-model and structural-model assessments. The measurement model was evaluated using outer loadings (≥ 0.708), Cronbach's alpha and composite reliability (0.70–0.95), average variance extracted (AVE ≥ 0.50), and the heterotrait-monotrait ratio (HTMT < 0.90) to establish indicator reliability, internal consistency, convergent validity, and discriminant validity ([Hair et al., 2022](#)).

After the measurement criteria had been satisfied, the structural model was assessed using variance inflation factors (VIF < 5.00), standardized path coefficients (β), bootstrapped t-statistics and p-values, coefficients of determination (R^2), effect sizes (f^2), predictive relevance ($(Q^2 > 0)$), and the standardized root mean square residual (SRMR < 0.08). Relationships with ($p < 0.05$) were considered statistically significant. The validated structural relationships were subsequently used as the empirical basis for developing the DSS framework.

DSS Architecture

The proposed DSS framework was developed to transform the SEM-PLS results into an evaluation mechanism that policymakers can use directly to assess the readiness level of ITS implementation. This framework is based on the empirical relationships between variables validated through structural models and implemented as a model-based decision support system. Conceptually, the DSS consists of three main components: the Data Layer, the Model Layer, and the Decision Layer.

Data Layer

The Data Layer serves as the main data source used in the evaluation process. In this layer, the user enters the assessment results for indicators that represent the actual conditions of ITS implementation. The data used include Technology (TECH), Infrastructure (INF), Social Economy (SE), and Funding Support (FS). Each variable is measured using indicators validated through the SEM-PLS process to ensure adequate reliability and validity.

Model Layer

The Layer Model is the core of DSS, which functions to process data using a mathematical model built based on the results of SEM-PLS analysis. In this layer, the relationships between variables are represented by significant path coefficients, allowing the system to automatically calculate the readiness value and adoption rate of ITS. The variables included Smart Readiness (SR), Social Affordability (SA), and Government Policy (GP). These three variables are then used to produce the final ITS adoption value.

Decision Layer

The Decision Layer translates the calculation results into information that can be used for decision-making. The outputs produced include the ITS Adoption Score, the level of readiness for ITS implementation, the ITS adoption category, and policy recommendations. Through this mechanism, DSS provides more objective evaluation results than conventional assessment approaches, which are generally still subjective.

DSS Calculation Model

The DSS calculation model is based on the relationships among significant variables from the SEM-PLS results. The obtained path coefficient is used as a weight in the value aggregation process.

Smart Readiness Calculation

The Smart Readiness variable is calculated using three exogenous variables that have a significant influence.

$$SR = (0.512 \times SE) + (0.331 \times TECH) + (0.287 \times INF) \dots\dots\dots(1)$$

where: SR = Smart Readiness; SE = Social Economy; TECH = Technology; INF = Infrastructure

This equation shows that socioeconomic factors contribute most to system readiness, followed by technology and infrastructure.

Social Affordability Calculation

The Social Affordability variable is calculated using funding factors and the community's socio-economic conditions.

$$SA = (0.421 \times FS) + (0.498 \times SE) \dots\dots\dots(2)$$

where: SA = Social Affordability; FS = Funding Support; SE = Social Economy

The results of this calculation illustrate the level of affordability of transportation technology for the community.

Government Policy Calculation

The Government Policy variable is calculated based on the direct influence of Funding Support.

$$GP = (0.693 \times FS) \dots\dots\dots(3)$$

where: GP = Government Policy; FS = Funding Support

The equation shows that funding support plays an important role in shaping policies and regulations that support the implementation of ITS.

ITS Adoption Score Calculation

The final ITS adoption score is calculated using variables that directly affect ITS Adoption.

$$ITS = (0.454 \times GP) + (0.284 \times SR) + (0.047 \times SA) \dots\dots\dots(4)$$

where: ITS = ITS Adoption Score; GP = Government Policy; SR = Smart Readiness; SA = Social Affordability

Based on this equation, Government Policy is the dominant factor determining the success of ITS implementation.

ITS Adoption Rate Calculation

To make the results easier to interpret, the final ITS Adoption Score is classified into four categories. Table 1 shows the detailed categories.

Table 1. ITS Adoption Rate Classification

Value Range	Category
0.00 – 0.25	Very Low
0.26 – 0.50	Low
0.51 – 0.75	Medium
0.76 – 1.00	High

Table 1 shows that this classification allows policymakers to quickly assess the readiness of a region for ITS implementation.

FINDINGS AND DISCUSSION

Summary of SEM-PLS Analysis Results

Following confirmation of measurement-model reliability and validity, the structural model was evaluated to determine the relationships associated with ITS adoption readiness. Bootstrapping results indicated that eight of the nine hypothesized relationships were statistically significant. Table 2 presents the standardized path coefficients, t-values, p-values, and hypothesis decisions.

Table 2. Summary of Results of Inter-Variable Relationships

Hypothesis	Structural Path	β	t-value	p-value	Decision
H1	Funding Support → Government Policy	0.693	21.143	<0.001	Supported
H2	Funding Support → Social Affordability	0.376	6.531	<0.001	Supported
H3	Social Economy → Smart Readiness	0.454	7.671	<0.001	Supported
H4	Social Economy → Social Affordability	0.218	3.209	<0.001	Supported
H5	Technology → Smart Readiness	0.244	3.402	<0.001	Supported
H6	Infrastructure → Smart Readiness	0.047	0.652	0.515	Not supported

Hyphotesis	Structural Path	β	t-value	p-value	Decision
H7	Smart Readiness $\rightarrow$ ITS Adoption	0.356	5.921	<0.001	Supported
H8	Government Policy $\rightarrow$ ITS Adoption	0.403	6.746	<0.001	Supported
H9	Social Affordability $\rightarrow$ ITS Adoption	0.275	4.238	<0.001	Supported

Government Policy had the strongest significant direct relationship with ITS Adoption ($\beta = 0.454$; $t = 7.671$; $p < 0.001$), followed by Smart Readiness ($\beta = 0.244$; $t = 3.402$; $p = 0.001$). In contrast, the relationship between Social Affordability and ITS Adoption was positive but not statistically significant ($\beta = 0.047$; $t = 0.652$; $p = 0.515$); therefore, H6 was not supported. These results indicate that policy support and system readiness were more strongly associated with ITS adoption readiness than social affordability within the analyzed model.

Funding Support had a strong positive relationship with Government Policy ($\beta = 0.693$; $p < 0.001$) and a significant relationship with Social Affordability ($\beta = 0.376$; $p < 0.001$). Smart Readiness was significantly associated with Social Economy ($\beta = 0.356$; $p < 0.001$), Technology ($\beta = 0.275$; $p < 0.001$), and Infrastructure ($\beta = 0.218$; $p = 0.001$). Social Economy also had a significant positive relationship with Social Affordability ($\beta = 0.403$; $p < 0.001$). Collectively, these findings demonstrate that ITS adoption readiness is shaped by interconnected technological, infrastructural, socioeconomic, financial, and policy-related conditions.

DSS Results

To demonstrate the implementation of the proposed framework, a simulation was carried out using hypothetical assessment data obtained from the results of an area evaluation. The assessment inputs are shown in Table 3.

Table 3. DSS Input Value

Variable	Value (x)	Assumed mean (μ)	Assumed SD (σ)	Standardized value (z)
Technology (TECH)	4.00	3.4	0.6	1.000
Infrastructure (INF)	3.50	3.2	0.5	0.600
Social Economy (SE)	4.20	3.6	0.6	1.000
Funding Support (FS)	3.80	3.2	0.5	1.200

Next, the system performs calculations based on the developed model.

Stage 1: Smart Readiness Calculation

$$SR = 0.218zINF + 0.356zSE + 0.275zTECH$$

$$SR = (0.218 \times 0.600) + (0.356 \times 1.000) + (0.275 \times 1.000)$$

$$SR = 0.1308 + 0.356 + 0.275 = 0.762$$

Stage 2: Social Affordability Calculation

$$SA=0.376zFS+0.403zSE$$

$$SA=(0.376 \times 1.200)+(0.403 \times 1.000)$$

$$SA=0.4512+0.403=0.854$$

Stage 3: Government Policy Calculation

$$GP=0.693zFS$$

$$GP=0.693 \times 1.200=0.832$$

Stage 4: ITS Adoption Score Calculation

$$ITS=0.454GP+0.244SR$$

$$ITS=(0.454 \times 0.832)+(0.244 \times 0.762)$$

$$ITS=0.378+0.186=0.564$$

From the result, hypothetical means and standard deviations were assigned to demonstrate the standardized DSS calculation procedure. The raw values for Technology, Infrastructure, Social Economy, and Funding Support were converted into z-scores of 1.000, 0.600, 1.000, and 1.200, respectively. The standardized inputs produced a Smart Readiness Index of 0.762, a Social Affordability Index of 0.854, and a Government Policy Index of 0.832. Because the direct relationship between Social Affordability and ITS Adoption was not statistically significant, we retained Social Affordability as a diagnostic output but excluded it from the final readiness equation. The resulting ITS Adoption Readiness Index was 0.564. Under an illustrative standard-normal interpretation, this value corresponds approximately to the 71st percentile and is therefore classified as Moderate readiness.

Discussion

The DSS implementation results show that the SEM-PLS-based approach can be translated into a more practical, operational decision-making tool. In contrast to statistical models that are generally only used for academic analysis, DSS allows research results to be used directly by policymakers in the evaluation and planning process. Gamba1 shows the results of the DSS implementation that is carried out on the ITS model.

In addition, using weights derived from the SEM-PLS results provides a stronger empirical basis than conventional assessment methods that often rely on experts' subjective judgment. Thus, the proposed DSS can increase transparency, objectivity, and accuracy in evaluating ITS implementation readiness.

From a policy perspective, the results of the study show that increasing the adoption rate of ITS should be focused on strengthening government policies and increasing system readiness. These two factors have proven to contribute most to the success of ITS implementation. Therefore, local governments need to prioritize the preparation of regulations that support the transformation of digital transportation and strengthen infrastructure and technology readiness as the main foundation for ITS development

CONCLUSIONS

This study developed a model-driven Decision Support System framework to evaluate Intelligent Transportation Systems adoption readiness using Partial Least Squares Structural Equation Modeling. The framework integrates Technology, Infrastructure, Social Economy, Funding Support, Smart Readiness, Social Affordability, and Government Policy within a structured decision-support mechanism comprising Data, Model, and Decision Layers.

The structural-model results indicated that Government Policy had the strongest significant direct relationship with ITS Adoption, followed by Smart Readiness. Funding Support was strongly associated with Government Policy, while Technology, Infrastructure, and Social Economy contributed to Smart Readiness. In contrast, Social Affordability did not have a statistically significant direct relationship with ITS Adoption. Within the analyzed model, these findings suggest that policy support and system readiness were more strongly associated with ITS adoption readiness than social affordability.

This study's main contribution is transforming empirically validated PLS-SEM relationships into a methodologically consistent DSS framework. Standardized construct inputs were aligned with standardized path coefficients to avoid applying PLS-SEM coefficients directly to raw Likert-scale scores. The resulting framework demonstrates how explanatory adoption research can be extended into readiness assessment and factor-specific policy prioritization. However, the proposed DSS should be regarded as a decision-support framework rather than a fully validated operational system.

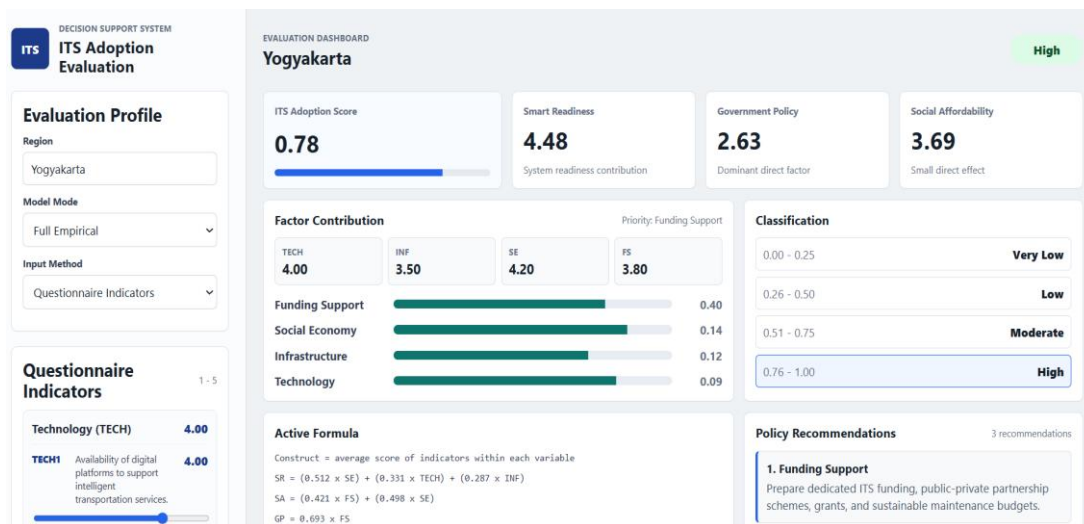


Figure 2. Implementation of DSS in ITS

LIMITATIONS & FURTHER RESEARCH

This study has several limitations. First, the survey used purposive sampling and included 75 usable responses from a single urban context, limiting statistical power to detect small effects and restricting the generalizability of the findings. Second, the DSS simulation employed hypothetical reference means and standard deviations to demonstrate the standardized calculation procedure; therefore, the resulting readiness score and category should not be interpreted as an empirical assessment of a specific region. Third, the proposed framework has not yet been implemented and evaluated as a fully operational software system. Its usability, recommendation accuracy, and practical effectiveness therefore remain unestablished.

Future research should validate the model with larger, more diverse samples, apply empirical construct distributions when establishing readiness categories, and conduct cross-regional comparisons. The framework should also be implemented as a web-based DSS and evaluated with policymakers, transportation authorities, and other prospective users. Further studies may integrate operational transportation data, such as traffic sensors, public-transport usage, vehicle movements, and infrastructure performance, to complement survey-based readiness

assessments.

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