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Original Research Article

Modelling Public Acceptance of Biofuels in Indonesia: A Structural Equation and Mediation Analysis of Knowledge, Attitude, and Perception

Nugroho Agung Pambudi[*1], Rinna Untari*[1], Hening Asti Rahayu*[2]

[1]Department of Mechanical Engineering Education, Universitas Sebelas Maret, Surakarta 57126, Indonesia

[2]Energy and Society Laboratory, Department of Mechanical Engineering Education, Universitas Sebelas Maret, Surakarta 57126, Indonesia

e-mail: heningasti@gmail.com, agung.pambudi@staff.uns.ac.id, rinnauntari12@gmail.com

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ABSTRACT

The transition to renewable energy is essential for addressing climate change, with biofuel positioned as a key transport alternative. Despite Indonesia's B20 and B30 mandates, public acceptance remains limited, highlighting the need to understand behavioural factors. This study examines the relationships between knowledge, attitude, and perception of biofuel and tests the mediating role of attitude. Data were collected through a 20-item survey completed by 256 public transport users. Structural Equation Modelling was performed using the semopy library in Python. The results indicate that knowledge has a positive but statistically non-significant effect on attitude ($\beta = 0.10$; $p > 0.05$; 95% CI [−0.07, 0.26]), whereas attitude strongly and significantly predicts perception ($\beta = 0.62$; $p < 0.001$; 95% CI [0.38, 0.85]). The direct effect of knowledge on perception was non-significant, suggesting that higher knowledge alone does not necessarily translate into favourable public perception. Mediation analysis also shows that attitude does not significantly mediate the knowledge–perception pathway, as the bootstrap confidence interval includes zero. Model fit indices demonstrate acceptable fit (Root Mean Square Error of Approximation = 0.07; Comparative Fit Index = 0.92; Standardized Root Mean Square Residual = 0.06). Overall, attitude plays a much stronger role than direct knowledge in shaping public perception of biofuel. These findings imply that policy strategies emphasizing attitude formation—such as value framing, community engagement, and trust-building— may be more effective than purely informational campaigns in enhancing biofuel acceptance.

KEYWORDS

Biofuel, Renewable energy, Public acceptance, Structural equation modelling, Confirmatory factor analysis, Mediation, Indonesia, Energy transition.

INTRODUCTION

Different challenges are experienced in reducing greenhouse gas emissions, which are the main cause of global climate change [1]. The Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation (SREX) emphasises that adaptation and mitigation must be pursued concurrently to reduce climate-related disaster risks [2]. On the other hand, global trends in greenhouse gas emissions from 1990–2018 indicate that mitigation efforts remain limited, with significant emission increases observed in the energy, industry, building, transport, and Agriculture, Forestry, and Other Land Use (AFOLU) sectors across many developing regions. Only a few areas, such as Europe and North

[*] Corresponding author

America, showed moderate decarbonisation through the shift to renewable energy [3]. In this context, Lamb *et al*. [3] reviewed global greenhouse gas emission trends by sector from 1990 to 2018 and reported that the energy sector contributes approximately 25% of total global emissions. Bogdanov *et al*. [4] analysed energy transition pathways and showed that energy-related emissions, particularly in developing countries, continue to increase despite ongoing electrification efforts. Therefore, the transition to a cleaner and more sustainable energy system is prioritised in many countries. Renewable energy is promoted as a primary alternative to fossil fuels, supporting low-carbon development [5] and reducing dependence on environmental pollutants [6].

Biofuel is a renewable energy form sourced from biomass and organic materials, with the potential to reduce carbon emissions and enhance national security [7]. In Indonesia, the mandatory B20 and B30 policies, as well as Government Regulation No. 79 of 2014 on the National Energy Policy, represent a commitment to supporting the use of biofuel [8]. However, the success of implementing this policy is primarily determined by the acceptance of the public as end users.

Several studies have shown that public resistance to new energy technologies is affected by psychosocial factors, including a lack of knowledge, an ambiguous attitude, inaccurate risk perceptions, and distrust of the technology's effectiveness. Studies by Kardooni *et al*. (2016) in Malaysia found that cost, perceived ease of use, and an underdeveloped business environment contributed to negative attitudes toward renewable energy adoption [9]. In Indonesia, Avicenna and Febriani (2021) highlighted the roles of income, education, infrastructure, and government policy as key determinants of acceptance [10], while Yulianjani *et al*. (2024) demonstrated that perceptions of environmental benefits, regulatory barriers, government support, and economic considerations influence adoption intentions within the framework of the Expanded Technology Acceptance Model [11]. Collectively, these studies underscore that the success of energy transition depends heavily on the synergy between psychosocial, structural, and public policy factors. In the context of geothermal energy, public perception and acceptance of renewable energy projects are influenced by the level of knowledge and understanding. However, although prior research has described public views on biofuel in Indonesia, studies examining the causal relationships that influence attitudes and behavioural intentions remain very limited. Limited information and communication from developers or the government can strengthen negative perception and public doubts about renewable energy projects [12]. Therefore, technocratic and behavioural methods are needed to understand the factors affecting public acceptance.

This analysis depends on the initial descriptive investigation of the pattern of public knowledge, attitudes, and perceptions regarding biofuel in the context of public transportation in Surakarta. The research shows that knowledge levels remain limited, even though public attitude and perception are positive. An initial analysis with a descriptive method cannot explain the causal relationship between constructs. Therefore, a structural model is needed to test the relationships among variables.

Based on the description, this research aims to evaluate the effects of knowledge on public perception directly and through attitude mediation using the Python library (semopy). The selection of Semopy was based on its flexibility in handling complex structural equation modelling and its compatibility with the open-source Python ecosystem, which enables a more transparent, easily replicable, and computationally efficient analysis process [13]. These advantages provide added value compared with conventional SEM software such as AMOS or LISREL, which exhibit limitations in automation, scripting, and reproducibility [14]. Simultaneous testing of direct and indirect effects is enabled to strengthen the construct's validity within a measurable theoretical framework. This analysis contributes to the behavioural energy literature by integrating mediation analysis into the context of biofuel in developing countries. The results are essential for energy policy designers in formulating communication and education strategies, focused on improving public perception.

LITERATURE REVIEW AND FRAMEWORK

The Literature Review and Framework section positions biofuels within the broader discourse on renewable energy, highlighting both their potential contribution to the transition toward a sustainable energy system and the challenges inherent in their implementation. This section includes the following sub-sections.

Biofuel in the Renewable Energy Context

Biofuel, a renewable energy source from biomass (e.g., agricultural byproducts), is a viable strategy for reducing carbon emissions and enhancing national energy security, particularly in developing countries like Indonesia [7]. Given rising energy demands and global pressure to reduce greenhouse gas emissions [1], biofuel development is essential for a sustainable transition [15].

The Indonesian government has implemented policies, such as the mandatory B20 and B30 programs and Government Regulation No. 79 of 2014, to increase the use of clean energy [8]. However, the efficacy of these policies is influenced by socio-economic and institutional factors, including incentive allocation, market readiness, and public acceptance of biofuel technology [16].

Pambudi *et al.* (2022) reported that the success of renewable energy deployment was heavily reliant on acceptance, a factor shaped by perception, knowledge, and social interactions between the public and project developers [17]. In the specific case of Indonesia, public acceptance is critical due to social and geographical complexities, including resistance to risk perception and limited access to transparent information [18].

Public Acceptance of New Energy

Public acceptance is an essential determinant in the successful deployment of novel and renewable energy technologies. Lappe-Osthege & Andreas (2017) showed that the efficacy of the energy program depended on infrastructural readiness and societal response [19]. Various social barriers, including a lack of trust, constrained access to information, and an inherent resistance to change, can affect the adoption process [9]. Furthermore, public perception of biofuels is influenced by the comprehension of the associated environmental risks and climate benefits [20].

The acceptance of new energy technologies is significantly impacted by perceived risks and benefits rather than technical attributes [21]. Therefore, psychosocial variables, such as knowledge, attitudes, and perceptions, should be critically analysed to understand the complexities of public acceptance concerning biofuel. This opinion was supported by Pambudi *et al*. (2022), who found that the public residing near renewable energy projects showed hesitant attitudes and required meaningful engagement in decision-making processes despite the potential for accuracy. Major factors affecting social acceptance include limited access to information and insufficient public participation in the progression of technology development [17].

Knowledge–Attitude–Perception Model

The Knowledge–Attitude–Perception (KAP) model is a conceptual framework used in analyses of behavioural change, specifically in environmental issues, health, and adoption of new technologies, including in the renewable energy field [22].

The model in biofuel research is primarily focused on three core dimensions. First, knowledge refers to the extent of understanding the characteristics, benefits, and impacts of biofuel, covering technical and socio-environmental aspects. Second, attitude reflects an individual's evaluative orientation toward biofuel, including a positive perception of it as a clean energy solution. Third, perception concerns the subjective interpretation of biofuels, such as the assessment of potential risks, economic advantages, and practical utility in everyday contexts. These three elements are interdependent and can influence decisions on whether to adopt or reject biofuel in the energy transition. The model proposes that sound knowledge cultivates a positive attitude, leading to supportive perception concerning the considered technology [23]. Furthermore, empirical data from research on public behaviour regarding renewable energy shows that affective components, such as attitude, possess greater predictive power for behavioural intentions than technical knowledge [24].

The Mediating Role of Attitude in the Knowledge–Attitude–Perception Model

In several recent studies, attitude acts as a mediating variable between knowledge and perception or behavioural intention [25], [26]. Good knowledge can only form a positive perception in the presence of attitude. In addition, attitude mediation has been demonstrated across contexts, such as the use of environmentally friendly products [27] and green financial investments [25].

In biofuel acceptance, the mediating role of attitude must be evaluated, as this variable serves as a psychological filter [28]. Therefore, this research examined the relationship in a structural model to determine the bridging function of attitude between knowledge and perception [26].

Relevant Previous Research

Several previous studies have discussed acceptance of energy technologies using descriptive and linear regression methods. For example, Hidrue *et al*. (2011) examined the factors influencing the purchase intention of electric vehicles [29]. Sovacool *et al*. (2019) emphasised the importance of social values and fairness perception in energy acceptance [30]. However, there is little research examining the causal relationship between KAP constructs simultaneously using the SEM method. A previous preliminary investigation identified descriptive patterns of KAP and did not test structural relationships among variables.

Logical Framework and Hypothesis

Based on the results of the literature review in the previous sub-chapter, the relationship among knowledge, attitude, and perception of biofuel technology is explained using a behavioural approach derived from the KAP Model. This model declares that an individual's understanding of an issue or technology affects the evaluative attitude. Subsequently, attitude forms a final perception that reflects acceptance or rejection of technology [28], [29].

In the context of renewable energy adoption, such as biofuel, previous literature has noted that individuals with high levels of knowledge tend to form a more positive attitude towards its use. Mukonza [31] showed that greater biofuel-related knowledge is associated with more positive attitudes toward biofuel use, a finding consistent with the results reported by Balogh *et al*. [32] among car drivers. This observation can shape an individual's perception of the benefits, risks, and reliability of biofuel in everyday life [33]. However, knowledge does not directly affect perception; it is mediated by attitude, which serves as a psychological link. This research formulated the following thinking framework by considering the theory and empirical results of previous analysis.

a) Better knowledge of biofuels increases a positive attitude towards their use.
b) A positive attitude towards biofuels increases public perception of the technology.
c) Knowledge has a direct effect on perception, with varying levels of strength.
d) Attitude acts as a mediating variable in the relationship between knowledge and perception.
e) The following hypotheses are formulated based on the logical framework.
    a) H1: Knowledge has a positive effect on Attitude
    b) H2: Attitude has a positive effect on Perception
    c) H3: Knowledge has a direct effect on Perception
    d) H4: Attitude mediates the relationship between Knowledge and Perception

This framework is presented in the conceptual diagram in **Figure 1**, which shows the direct and indirect paths between variables, along with attitude as a mediator.

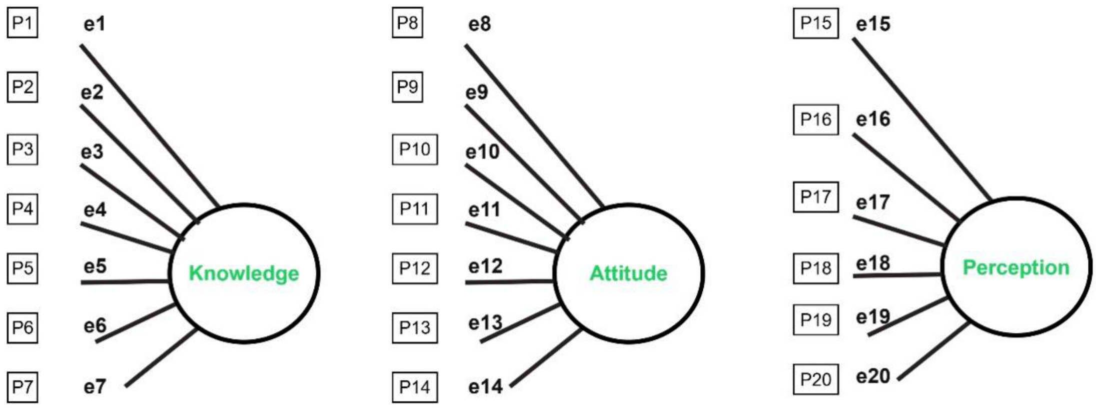

Figure 1. The proposed Structural Equation Model (SEM) to describe the relationship between Knowledge, Attitude, and Perception towards Biofuel, with Attitude as a mediating variable.

METHOD

The methodology section outlines the systematic approach used to achieve the research objectives and test the hypotheses. This study applies the KAP model to analyse the relationships among Knowledge, Attitude, and Perception regarding public acceptance of biofuel use. The analysis was conducted using Structural Equation Modelling (SEM) with the semopy library in Python, following the stages of model specification, parameter estimation, model fit evaluation using Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), and Standardised Root Mean Square Residual (SRMR) and a bootstrapping procedure to assess the mediation effect. This explanation provides a comprehensive overview of the analytical steps used to test both direct and indirect relationships among the constructs. To provide a clear structure, this section includes the following subsections.

Research Design

This research used a quantitative explanatory approach to test the causal relationship between variables within a previously established framework. The design was in line with the primary objective of developing and testing a structural model to explain the effect of knowledge on public perception of biofuel, both directly and through attitude as a mediating variable.

The theoretical model developed was based on the KAP framework, a widely used framework in the research of energy behaviour. Furthermore, SEM was used to test the model simultaneously and comprehensively. This approach enabled the analysis of complex relationships between latent constructs and observed indicators, allowing for direct and indirect testing within a single integrated model.

The inclusion criteria for this research required respondents to be at least 17 years old, to use public transportation (bus or train) in the Surakarta area, and to be willing to complete the survey voluntarily. Incomplete responses and individuals who did not meet these criteria were excluded from the final analysis.

Population and Sampling Methods

The population consisted of bus and train users in the Surakarta area. This selected area experienced high public transportation activity and has the potential to be a target for implementing renewable energy policies, specifically the use of biofuels (B20 and B30) in the transportation sector. The population was estimated to reach around 4,000 individuals per day.

The selection of respondents was carried out systematically at major bus terminals and main public transport stops during morning to late-afternoon hours. Potential participants were approached randomly, informed about the study's purpose, and given the questionnaire only if they met the inclusion criteria: being ≥18 years old and an active public transportation user. Participation refusals were recorded, and no incentives were provided. This approach ensured equal opportunity for each member of the target population to be selected and enabled the collection of a representative sample of public transport users present at the data-gathering locations.

The number of samples was determined by referring to the Isaac and Michael table, with an error rate of 10%. leading to a minimum of 256 respondents needed for the analysis [34]. A partial dataset comprising responses from the 256 respondents is available in **APPENDIX 1**. The sociodemographic characteristics included age, gender, and educational level. This sampling approach aligns with the exploratory nature of the study, which focuses on mapping preliminary causal relationships in the context of energy behaviour. The selected sample size is considered adequate for SEM analysis, given the exploratory nature of the study and the moderate complexity of the proposed model. Previous methodological studies indicate that SEM can be reliably estimated with a moderate sample size when the model structure remains relatively simple and the number of estimated parameters is limited [35]. Therefore, the use of the Isaac and Michael sample size table is considered appropriate for an early-stage behavioural study with limited resources, while still meeting the minimum requirements for estimating both the measurement and structural models.

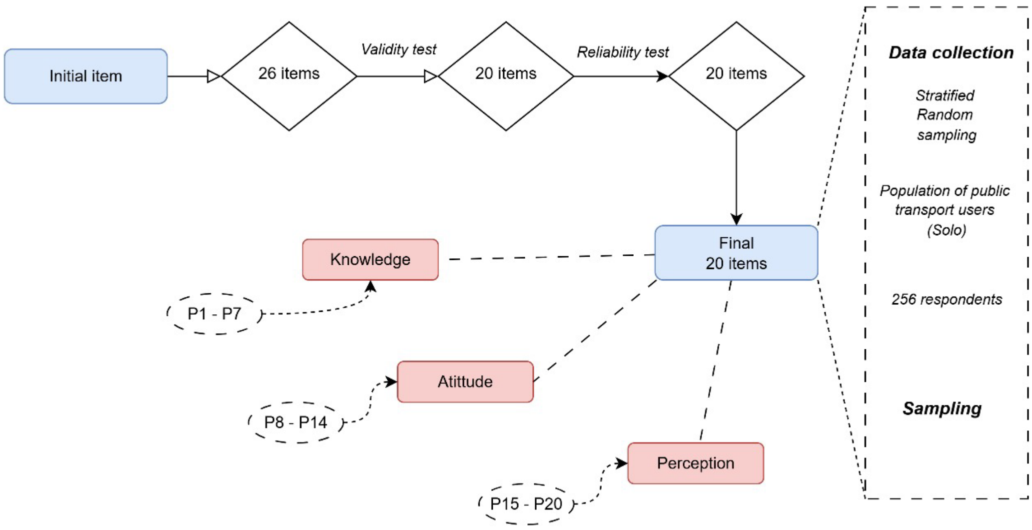

Figure 2. Instrument-development flow based on the Knowledge–Attitude–Perception (KAP) model

A probability sampling method was used to ensure each individual had an equal chance of being selected. This method was chosen because sampling was conducted without considering certain strata or categories. Therefore, the research results could be generalised more objectively to the target population, as shown in **Figure 2**. The scheme illustrates the progression from initial item generation to validity testing, reliability testing, and final selection of 20 measurement items mapped to knowledge, attitude, and perception constructs, followed by data collection using stratified random sampling of 256 public transport users in Solo.

Instruments and Variable Measurement

Data were collected using a closed-ended questionnaire instrument on a 5-point Likert scale, ranging from 1 = "Strongly Disagree" to 5 = "Strongly Agree." The questionnaire was designed to measure three main constructs, namely Knowledge, Attitude, and Perception regarding the use of biofuel in Indonesia.

The total number of items used in the final analysis consisted of 20 questions, derived from an initial pool of 26 items after content validity and reliability screening. The complete research instrument grid for these 20 items is presented in **Table 1** and detailed in **APPENDIX 2**. These items were subsequently evaluated through Confirmatory Factor Analysis (CFA) to determine their validity within the measurement model.

Table 1. Research instrument grid for measuring Knowledge, Attitude, and Perception towards Biofuel

Variable	Indicator	Item code	Number of items
Knowledge (X1)	Biofuel policy and technical information	P1–P7	7
Attitude (X2)	Emotional support and evaluation	P8–P14	7
Perception (X3)	Risks, benefits, and acceptance	P15–P20	6
Total		P1–P20	20

Content validity was confirmed through an expert judgment process, including energy and public policy experts. Furthermore, construct validity was tested through Confirmatory Factor Analysis (CFA), using benchmarks of loading factor values ≥ 0.5, Average Variance Extracted (AVE) ≥ 0.5, and Composite Reliability (CR) ≥ 0.7.

AVE was calculated using the following formula:

$$\mathrm{AVE} = \frac{\sum \lambda^2}{\sum \lambda^2 + \sum \theta} \tag{1}$$

Where λ is the loading factor (the coefficient between the indicator and the latent construct), λ^2 is variance explained by the construct for a specific indicator, and θ is Error variance (residual or measurement error of the indicator). Meanwhile, CR was calculated by using the following formula:

$$\mathrm{CR} = \frac{(\sum \lambda)^2}{(\sum \lambda)^2 + \sum \theta} \tag{2}$$

Internal reliability was assessed using Cronbach's Alpha, and all constructs showed a value of α ≥ 0.7.

During the CFA process, several indicators did not meet the recommended loading factor threshold of 0.50. Specifically, five items (P7, P8, P9, P10, and P11) showed insufficient factor loadings and were removed to improve construct validity and overall model fit. After this refinement, a total of 15 validated items were retained for further CFA and SEM analyses: P1–P6 for Knowledge, P12–P17 for Attitude, and P18–P20 for Perception. This refined indicator set aligns with the CFA loading factor tables and the Python SEM code presented in **APPENDIX 3**.

Data Analysis Method

Data analysis was conducted using the SEM method, which allowed simultaneous testing of the relationships between latent constructs and their indicators. The analysis was performed using Python software and the semopy library, compatible with the CFA and SEM based on the lavaan-style model. The data analysis procedure was carried out in several stages as follows. The full Python script used for SEM analysis, including CFA, path analysis, and bootstrapping procedures, is documented in **APPENDIX 3**.

Measurement Model Evaluation

Convergent validity was shown by a loading factor of each indicator ≥ 0.5 and AVE ≥ 0.5 [35]. Furthermore, a reliability test was conducted using CR and Cronbach's Alpha, with values above 0.70 considered ideal. Discriminant evaluation was also performed by comparing the roots of AVE and the correlations between constructs.

Structural Model Evaluation

Testing of direct relationships between constructs was conducted through the examination of hypotheses H1, H2, and H3, using estimated parameter values (β), t-statistics, and p-values to assess the statistical significance of each relationship. Additionally, an evaluation of the overall model fit indicated that the structural model was consistent with the empirical data. This evaluation used several goodness-of-fit indices as suggested in **Table 2**. Based on the criteria of Kline (2016) [37], Byrne (2016) [38], and Hu and Bentler (1999) [39], a model was reported to have a good fit when the following requirements are met: 1) Chi-square/df value was less than 3, 2) RMSEA and SRMR were less than 0.08, and 3) CFI and TLI values were more than 0.90. These criteria ensured that the developed model was valid and could be interpreted reliably.

Table 2. Model Suitability Criteria (Goodness-of-Fit) in SEM Analysis

Index	Ideal Criteria
Chi-square/df	< 3
RMSEA	< 0.08
CFI	> 0.90
TLI	> 0.90
SRMR	< 0.08

Mediation Analysis

This research analysed the direct and indirect effects, with Attitude construct acting as a mediator between Knowledge and Perception. Mediation hypothesis testing was conducted to determine the effect of Attitude as a mediating construct between Knowledge and Perception [36], [40], according to the following formula.

$$\text{Indirect Effect} = a \times b \tag{3}$$

A bootstrapping method (bias-corrected confidence interval) of 1000 samples was used to assess the indirect effect. The mediation effect was considered significant when the CI value did not include zero, or the p value was < 0.05 [26]. This method produced an estimate of the indirect effect with a 95% confidence interval (CI) according to the following formula.

$$\mathrm{CI}_{95\backslash\%} = \mathrm{Percentile}_{2.5\backslash\%,\,97.5\backslash\%}\left(\mathrm{IE}_{\mathrm{bootstrap}}\right) \tag{4}$$

Subsequently, the total effect was classified as full or partial mediation [41]. The entire analysis process, including SEM modelling and bootstrapping, was carried out in Python using the semopy library. The source code and technical documentation were openly available through the GitHub repository and Zenodo.

Research Ethics

This research was conducted observing the principles of academic ethics. Each respondent was provided with a clear explanation of the purpose of the study, the voluntary nature of their participation, and the confidentiality of the collected data. Participation was entirely anonymous, without incentives, and respondents had the right to withdraw from the questionnaire at any time without any consequences.

Informed consent was obtained from all respondents prior to their participation. Respondents gave their consent after being fully informed about the objectives of the study and the confidentiality of their responses.

This research involved no intervention or experimentation on humans and therefore did not require ethical approval from an official ethics committee. However, all procedures complied with the ethical standards for social research.

RESULTS AND DISCUSSION

The Results and Discussion section presents the main research findings obtained through data analysis and interprets their meaning in both theoretical and practical contexts. The Results subsection systematically presents the data in accordance with the research objectives and hypotheses, while the Discussion section connects the findings to theory, previous research, and relevant implications.

Description of Respondent Characteristics

The 256 respondents were public transportation users in the Surakarta area. The characteristics of the respondents included age, gender, and education level. Based on age, the majority were in the 18–24 years age range (46%), followed by the 25–34 (13%) and 35–44 (13%). Other age groups were represented at lower percentages: < 18 (12%), 45–54 (7%), 55–64 (6%), and > 65 years (3%). In terms of gender, the respondents were 54% male and 46% female, indicating a relatively balanced distribution. The education levels were also quite diverse, with the majority coming from undergraduate (40%) and senior/vocational high school (28%) backgrounds. The remaining respondents consisted of junior high school (15%), associate's degree (6%), elementary school (7%), master's degree (3%), and doctoral degree (1%). This background information provided a general overview of the diversity of social characteristics that affect knowledge, attitudes, and perceptions of biofuel use in public transportation.

Although sampling was conducted using a probability sampling approach without stratification, the findings only reflect the perceptions of users who were present at terminals and bus stops during the data collection period. Therefore, generalising the results to the entire population of public transport users in Surakarta or other regions should be done with caution, given the potential variation in user characteristics or behaviours outside the sampled locations and time window.

Results of Measurement Model Evaluation Confirmatory Factor Analysis

The measurement model evaluation aimed to test the extent to which the indicators validly and reliably represented the latent constructs. In this research, the model consisted of three main constructs, namely Knowledge (X1), Attitude (X2), and Perception (X3).

The analysis was carried out using the Confirmatory Factor Analysis (CFA) method with the semopy library in Python to confirm the consistency of the hypothesised indicator structure with the empirical data, as shown by the loading factor values, AVE, and CR.

Common Method Bias Diagnostic. A diagnostic assessment for potential common method bias (CMB) was conducted because all indicators originated from the same questionnaire. Conceptually, CMB risk was mitigated by ensuring that the three constructs – Knowledge, Attitude, and Perception – were theoretically distinct. Empirically, discriminant validity remained strong, as HTMT values were below 0.85 and the Fornell–Larcker criterion was satisfied. An auxiliary check using alternative model specifications (allowing free correlated residuals) did not indicate the presence of a latent method factor. Distributional diagnostics also confirmed that the data had no extreme outliers, acceptable skewness and kurtosis for ML estimation, and less than 5% missing values, which were handled via listwise deletion. These results collectively suggest that common method bias did not substantially affect the measurement model.

Loading factor. A loading factor indicates the strength of the relationship between each indicator and its latent construct. For interpretation purposes, the standardised loading threshold of ≥ 0.50 was used to assess indicator validity. Although CFA interpretations in this study follow standardised loading criteria, **Table 3** presents the unstandardised loading coefficients generated by the semopy estimation procedure. In unstandardised solutions, latent construct variances are not constrained to 1.0, and therefore loadings may exceed 1.0 without indicating multicollinearity or model instability.

Table 3. Unstandardised loading factors for the measurement items

Indicator	Construct	Unstandardised loading factor	Indicator	Construct	Unstandardised loading factor
P1	X1	1.000	P14	X2	0.554
P2	X1	1.254	P15	X	0.398
P3	X1	1.605	P16	X2	0.444
P4	X1	1.412	P17	X2	0.468
P5	X1	1.471	P18	X3	1.000
P6	X1	0.496	P19	X3	0.664
P12	X2	1.000	P20	X3	0.454
P13	X2	0.948			

The loadings shown in **Table 3** are unstandardised coefficients generated by semopy. Because latent variable variances are not constrained to 1.0 in the unstandardised solution, loadings can exceed 1.0 without implying model misspecification or multicollinearity. All substantive CFA interpretations in the paper are based on standardised factor loadings (≤1.0). Loading factor values reported that most indicators had values above 0.5, suggesting adequate convergent validity. However, P15 and P20 had values approaching the lower limit, which required further attention in discussing construct reliability.

Average variance extracted and composite reliability. The convergent validity and construct reliability were evaluated through average variance extracted (AVE) and composite reliability (CR) after conducting loading factor tests. The obtained values are shown in **Table 4**. AVE and CR values are computed from the unstandardised CFA output. As a mathematical consequence of unstandardised loadings > 1.0, the resulting AVE or CR may exceed 1.0. The interpretation of construct validity relies solely on the standardised solution, where AVE and CR fall within the acceptable theoretical range (0–1).

Table 4. AVE and CR values for each construct

Construct	AVE	CR
X1	1.59	1.07
X2	0.46	0.82
X3	0.55	0.77

AVE reported the average indicator variance successfully explained by the latent construct. A good value of ≥ 0.5 showed that the construct explained more than 50% of the variance. Meanwhile, CR measured the internal consistency of indicators within a single construct, with an ideal value of above 0.70. This variable was considered more accurate than Cronbach's Alpha in the context of SEM.

Knowledge (X1) showed very high AVE and CR values, indicating good validity and reliability. The AVE value exceeded 1.0 because it was computed from the unstandardised CFA output, where large unstandardised loadings and small error variances may mathematically result in AVE > 1.0. This does not imply model instability, as all validity interpretations in this study were based on the standardised solution.

Attitude (X2) had an AVE slightly below the ideal threshold of 0.50, indicating moderate convergent validity, although its CR value met the reliability requirement. Perception (X3) met both AVE and CR criteria, confirming that the construct was valid and reliable. After establishing validity and reliability through CFA, the structural model was evaluated to test the hypothesised relationships using empirical data.

Structural Equation Modelling Results

The evaluated structural model represented the relationship between Knowledge (X1), Attitude (X2), and Perception (X3). This model was analysed using SEM to determine the strength and direction of the effect between constructs, as well as to test the previously formulated hypotheses (H1, H2, and H3).

Path coefficient and significance. Structural path analysis aimed to determine the extent of effect between latent constructs (X1, X2, X3) defined in the model. The estimated value of the path parameter (β) represented the strength and direction of the effect between constructs. In addition, p-value was used to test the significance of the effect, and $p < 0.05$ was considered significant. These results supported hypothesis H3 (X2 → X3), where attitude had a significant effect on perception. Meanwhile, H1 (X1 → X2) and H2 (X1 → X3) were not significant since knowledge did not directly affect attitude or perception, as shown in **Table 5**.

Table 5. Path coefficients and significance of relationships between the constructs

Path	*β* (estimate)	p-value	Description
X1 → X2	0.10	0.26	Not significant
X1 → X3	–0.16	0.10	Not significant
X2 → X3	0.62	<0.001	Significant

Path X1 → X2: The estimated value of 0.10 showed that knowledge had an insignificant positive effect on attitude (p = 0.26). Therefore, increasing knowledge did not directly change attitude. Path X1 → X3: The relationship between knowledge and perception was also not significant (p = 0.10), and the direction of the effect was negative. In this context, knowledge did not play a direct role in shaping perception. Path X2 → X3: was statistically significant with $\beta = 0.62$ and $p < 0.001$. This showed that attitude had a strong and significant effect on shaping perception of renewable energy.

Model fit criteria. Model fit evaluation aimed to assess the structural model fit of the data obtained. Several goodness-of-fit indices were used as references, with a specific meaning and threshold. **Table 6** summarises the indices and presents the model fit evaluation based on several main goodness-of-fit. The RMSEA value of 0.07 was below the maximum limit of 0.08, showing that the model had an acceptable level of approximation error. Furthermore, the CFI value of 0.92 exceeded the threshold of 0.90, suggesting that the model had a good fit relative to the baseline.

Table 6. Model fit evaluation

Index	Model value	Ideal criteria	Description
RMSEA	0.07	< 0.08	Fit
CFI	0.92	> 0.90	Good fit
SRMR	0.06	< 0.08	Fit

The SRMR value of 0.06 was also below the limit of 0.08, showing a low average residual between the model covariance matrix and empirical data. The model built had an adequate level of fit based on these indicators.

Mediation Analysis

Mediation analysis aimed to determine the mediating effect of Attitude (X2) in the relationship between Knowledge (X1) and Perception (X3) towards biofuel. A bootstrapping method of 1000 iterations was carried out based on resampling to estimate the statistical significance of mediation effects. This approach was preferred over the classical method (Baron & Kenny) since a normal distribution of indirect effects was not assumed. The indirect mediation effect was calculated by multiplying the path coefficients a (from X1 to X2) and b (from X2 to X3).

Bootstrapping results of the mediation effect. A bootstrapping analysis of 1000 iterations was conducted on the indirect path from X1 (Knowledge) to X3 (Perception) via X2 (Attitude) to assess the statistical significance of the mediation effect. The results of the bootstrapping analysis were used to assess the mediating effect within the model, including estimating the direct and indirect effects and using 95% confidence intervals to determine statistical significance, as shown in **Table 7**.

Table 7. Bootstrapping results of mediation effects

Mediation path	Indirect effect	CI 95% lower	CI 95% upper	Description
X1 → X2 → X3 (Mediation)	0.05	–0.14	0.22	Not Significant

In interpreting bootstrap estimates, the indirect effect is considered statistically significant when the 95% confidence interval (CI) does not include zero, indicating that the effect is consistently positive or negative across the resamples. Conversely, when the CI includes zero, the mediation effect is deemed non-significant because the true effect may be zero.

Mediation analysis was conducted using standardised coefficients with 1,000 bootstrap resamples. Here, semopy provides percentile-based 95% confidence intervals, which are appropriate for large-sample SEM despite not supporting BCa intervals. The mediation effect was considered non-significant because the CI included zero. A simple robustness check comparing results before and after removing weaker CFA indicators showed no meaningful change in the indirect effect, supporting the stability of the null mediation result.

Indirect mediation effect. The indirect effect of Knowledge (X1) on Perception (X3) through Attitude (X2) was relatively small, as shown in **Table 7**. However, the mediation effect was declared statistically insignificant since the 95% CI was [−0.14; 0.22]. Attitude was not statistically proven as a significant mediator of the relationship between Knowledge and Perception in the context of biofuel. Thus, the mediation hypothesis (H4) was not supported by the data, and the effect of X1 on X3 occurred directly or through other pathways.

Discussion

Before discussing the structural and mediation results, it is important to clarify several numerical characteristics of the measurement model. A number of factor loadings and the corresponding AVE and CR values exceeded 1.0. These values originate from the unstandardised estimation output produced by semopy, in which latent construct variances are not constrained to 1.0. Such values are mathematically possible in unstandardised solutions and do not indicate multicollinearity or model misspecification. All assessments of construct validity in this study, including the evaluations of factor loadings, AVE, and CR, rely exclusively on the standardised solution, where all values fall within theoretical and empirical limits. With the measurement model confirmed, the structural results can be discussed as follows.

The results of mediation analysis using bootstrapping show that the indirect effect of knowledge (X1) on perception (X3) via attitude (X2) is 0.05 with a 95% CI between −0.14 and 0.22. Since the interval range includes a value of zero, the mediation effect is considered statistically insignificant. Theoretically, the KAP model assumes that attitude is a cognitive-emotional mechanism bridging knowledge and perception of an issue or technology. The mediation effect is unproven because the knowledge possessed by respondents tends to directly shape the perception of biofuel, without a change in attitude. This phenomenon can be explained through two possibilities. First, public transport users in the Surakarta area receive information about biofuel from direct channels such as government campaigns, personal experiences, or media coverage. In this context, perceptions are formed spontaneously based on factual information. Second, attitude as an affective variable has not been developed evenly among respondents.

Moreover, the structural regression analysis shows that the strongest and most significant pathway in the model is the influence of attitude on perception. This finding indicates that once attitudes are formed, affective factors have greater explanatory power than factual knowledge. In other words, public perception of biofuel is shaped not only by the information they receive but also by emotional values and judgments related to broader narratives such as environmental sustainability, energy security, and national interest. This suggests that public support often develops through emotional resonance, even when their technical understanding remains limited.

The practical implication is that biofuel socialisation or education programs should focus on enhancing the quality and quantity of information available to the community. This method is more efficient than attempting to form attitude in a community lacking a strong construct towards renewable energy issues. Therefore, strengthening the positive perception of biofuel can be achieved directly through knowledge-based strategies.

Main Results

The KAP model was successfully tested structurally using the SEM method. However, only the relationship between attitude (X2) and perception (X3) showed statistical significance. The constructs in the model were proven to have adequate reliability and validity convergently and discriminantly. In addition, no significant mediation effect of attitude was shown in bridging the effect of knowledge on perception. These results provided an important basis for formulating policies and intervention strategies for energy education targeted at public transportation users. Attitude-based method was reported as a more effective entry point than simply increasing knowledge.

CONCLUSION

In conclusion, this research provided a deeper understanding of the relationships among knowledge (X1), attitude (X2), and perception (X3) of the community regarding the use of biofuels among bus and train users in the Surakarta area. An explanatory quantitative method was adopted using SEM and CFA analysis as the primary tools. Several important conclusions were reported based on the results of data processing.

a) The theoretical model based on the KAP framework was applied in the context of biofuel. This suggested that the KAP model remained a relevant conceptual method for explaining public acceptance of energy innovations, but the effect of the components is not linear or direct.
b) The validity and reliability of the constructs were statistically confirmed. The CFA results showed that most indicators had loading factor values above the threshold of 0.5. The AVE values for the three constructs reached the minimum limit of 0.5, while CR was above 0.7. Therefore, the research instrument was quite reliable in representing the latent constructs.
c) The relationship between constructs showed a selective pattern. The path from Knowledge (X1) to Attitude (X2) suggested a positive and an insignificant coefficient. Meanwhile, the relationship between Attitude (X2) and Perception (X3) was significant ($p < 0.001$). This was because attitude plays a crucial role in shaping public perception of biofuel.
d) The direct effect of Knowledge (X1) on Perception (X3) was not significant. This showed that knowledge was insignificant in altering perception and necessitated additional mechanisms, such as direct experience or social reinforcement.
e) Mediation analysis through bootstrapping with 1000 iterations obtained an indirect effect of 0.05, with a 95% CI of [-0.14, 0.22]. There was no significant mediation effect of attitude (X2) on the relationship between knowledge and perception since the range of the interval includes zero.
f) The model had an adequate fit, as shown by the fit index evaluation results (RMSEA = 0.07, CFI = 0.92, and SRMR = 0.06). Since the reported values were consistent with the criteria suggested in the literature, the model was declared fit and used for further interpretation.

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AUTHOR STATEMENT

Nugroho Agung Pambudi: Conceptualization, Original Draft Preparation, Reviewing, Editing, and Data Investigation. Rinna Untari: Data Investigation and Editing. Hening Asti Rahayu: Drafting, Editing and Formatting.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY STATEMENT

The data supporting the findings of this study are openly available via the GitHub repository (https://github.com/agungpambudi11/kap-biofuel) and the DOI of Zenodo (https://doi.org/10.5281/zenodo.18013294) to support open science and research replication.

NOMENCLATURE

Symbols

a	path coefficient in mediation model (X1 → X2)
b	path coefficient in mediation model (X2 → X3)
a × b	indirect effect in the mediation model
N	number of respondents
P1–P20	questionnaire item codes
X1	knowledge construct
X2	attitude construct
X3	perception construct

Greek Letters

α	Cronbach's alpha, a measure of internal consistency
β	path coefficient in the SEM model
λ	loading factor (effect of indicator on construct)

Abbreviations

AVE	Average Variance Extracted
Bootstrapping	Resampling method for estimating the significance of the indirect effect
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CR	Composite Reliability
RMSEA	Root Mean Square Error of Approximation
SEM	Structural Equation Modelling
SRMR	Standardised Root Mean Square Residual

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APPENDIX 1.

This appendix presents partial survey data from a total of 256 respondents used in the research. To maintain brevity and readability, only the first 25 rows are shown as a representation of the data structure, including the question item scores from Knowledge, Attitude, and Perception constructs.

Note: Items P7–P11 appear in this partial dataset because they were part of the original 26-item questionnaire. These items were excluded from the final CFA/SEM model due to insufficient factor loadings and are not part of the final 15-item measurement model used in the analysis.

Table A1a. Partial dataset of respondents, N = 256

R[a]	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16	P17	P18	P19	P20	T[b]
1	4	2	2	2	2	4	4	4	2	2	2	4	4	4	4	4	4	4	2	4	64
2	3	1	1	2	1	5	2	3	2	2	4	4	3	4	5	13	5	4	2	4	60
3	3	3	1	2	2	5	5	5	3	5	5	5	4	5	5	5	5	5	3	4	80
4	4	3	1	1	1	2	5	5	2	5	5	5	5	5	5	3	5	5	5	5	77
5	4	2	2	2	2	5	2	3	4	4	4	4	4	1	5	5	4	5	3	5	70
6	5	3	2	2	2	4	3	3	3	4	4	4	3	4	4	3	3	4	3	3	66
7	4	1	3	1	2	3	3	3	3	3	4	5	4	5	5	3	5	5	4	3	69
8	4	3	3	1	1	4	4	5	5	4	5	5	5	5	5	5	4	5	4	4	81
9	5	2	1	1	1	5	5	5	3	4	4	4	4	4	4	2	2	5	3	5	69
10	4	3	3	3	3	4	3	4	4	3	4	4	4	4	4	4	4	4	4	4	74
11	1	1	1	1	1	1	1	1	1	3	4	3	1	4	4	4	1	1	4	4	42
12	1	1	1	1	1	1	3	3	3	3	2	3	3	4	5	3	3	3	2	2	48
13	4	3	3	2	2	1	3	4	4	4	4	4	4	4	4	4	4	4	4	4	70
14	5	4	2	2	2	2	5	5	4	5	5	5	4	4	4	5	3	4	4	5	79
15	5	3	2	2	1	4	3	4	4	4	3	4	4	5	5	3	3	4	3	5	71
16	4	1	1	1	1	4	4	4	4	5	5	4	4	4	5	5	4	4	4	4	72
17	5	5	4	4	5	5	1	5	5	5	5	5	5	5	5	5	1	1	4	1	81
18	4	3	1	1	1	4	3	4	5	2	4	4	3	5	5	3	3	4	3	4	66
19	1	1	1	1	1	4	3	4	4	3	3	3	3	3	5	3	4	5	5	5	62
20	4	3	1	1	1	4	3	4	5	4	3	4	3	4	4	3	3	3	3	3	63
21	5	2	2	2	2	4	3	4	2	5	5	5	4	4	4	2	4	5	4	4	72
22	4	2	2	2	2	2	2	3	3	3	2	3	4	4	4	4	4	4	4	3	61
23	5	4	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	63
24	5	3	2	2	3	5	3	5	5	2	4	5	5	5	5	5	5	5	4	5	83
25	4	4	1	2	2	5	3	4	4	2	5	5	4	3	5	2	4	5	4	5	73
26	4	4	3	3	3	5	2	4	4	2	3	4	5	4	5	4	4	4	3	2	72
27	4	4	3	4	3	4	4	4	2	2	3	4	4	5	5	3	4	4	3	3	72
28	5	2	3	2	2	5	5	5	5	3	5	5	5	5	5	3	4	4	3	3	79
29	5	3	3	3	1	5	2	5	4	4	5	5	5	5	5	5	5	5	3	3	81
30	5	4	4	4	5	5	5	5	4	2	5	5	5	5	5	5	5	5	5	5	93

[a]R denotes Respondent; [b]T denotes Total

Table A1b. Partial dataset of respondents, N = 256 (continued from Table A1a)

R[a]	P 1	P 2	P 3	P 4	P 5	P 6	P 7	P 8	P 9	P 10	P 11	P 12	P 13	P 14	P 15	P 16	P 17	P 18	P 19	P 20	T[b]
31	4	4	2	2	2	4	4	5	5	2	5	4	5	4	5	3	4	4	4	2	74
32	4	4	2	2	2	3	3	4	4	3	3	4	4	4	4	3	3	3	4	4	67
33	4	4	1	2	1	3	3	4	4	4	2	4	4	5	5	4	4	4	3	4	69
34	4	3	1	1	2	5	3	5	5	4	5	5	4	4	3	4	4	4	4	3	73
35	5	5	4	4	3	4	2	4	4	4	4	4	4	4	4	3	4	4	4	4	78
36	3	3	3	2	3	3	3	4	4	3	3	4	3	3	3	3	4	3	3	4	64
37	4	4	3	2	3	4	2	4	4	2	3	4	3	4	5	4	3	4	4	5	71
38	5	2	2	2	2	5	3	5	5	1	4	5	5	5	5	4	4	4	4	5	77
39	5	4	1	2	2	5	5	5	5	2	5	5	5	5	5	5	5	5	5	2	83
40	4	3	2	1	2	4	4	4	4	4	3	4	4	4	5	4	3	4	4	4	71
41	5	3	3	3	3	4	4	5	4	4	3	4	4	4	5	3	3	4	3	3	74
42	3	2	3	2	3	3	3	4	2	1	1	4	3	1	5	3	3	4	3	4	57
43	3	3	4	2	2	4	3	4	4	2	4	5	5	4	4	3	3	4	4	2	69
44	2	3	1	2	2	4	3	4	4	3	4	4	4	4	4	3	4	4	4	4	66
45	4	2	5	4	4	2	2	2	2	2	3	5	4	4	4	3	4	4	2	3	65
46	3	4	2	4	1	4	1	3	4	4	2	3	5	5	5	2	3	3	4	5	67
47	4	3	3	2	3	4	1	4	5	2	1	4	4	4	4	2	4	4	4	2	64
48	5	5	4	5	5	4	3	3	3	2	3	5	4	5	4	3	3	3	2	3	74
49	4	2	2	2	2	4	3	4	4	2	4	4	4	4	4	4	4	4	4	4	69
50	3	2	2	4	2	4	3	3	2	2	3	4	4	4	4	3	3	4	4	3	63

[a]R denotes Respondent; [b]T denotes Total

APPENDIX 2.

This appendix contains the Research Instrument Grid (Revised), complete with Question Item column for each item. A total of 20 questions are divided into three constructs: Knowledge (X1), Attitude (X2), and Perception (X3):

Variable	Indicator	Item Code	Question Item (Summary)
Knowledge (X1)	General information and policies	P1	I have heard information regarding biofuels (fuels derived from plant-based raw materials), such as biogas, biomass, biodiesel, bioethanol, and others.
		P2	I know that biofuel is used to mix diesel.
		P3	I have heard of the government's B20 (a mixture of 20% Biodiesel and 80% Diesel) and B30 policies.
		P4	I understand that biofuel can reduce greenhouse gas emissions.
		P5	I know that biofuel has been used in the transportation sector.
		P6	I know that biofuel is produced from renewable energy sources.
		P7	I understand the challenges of biofuel production in Indonesia.
		P8	I know the difference between biofuel and fossil fuel.
		P9	I understand the contribution of biofuel to the national energy mix.
		P10	I know that biofuel can be used in diesel vehicles.
		P11	I know that the efforts to increase biofuel production will lead to competition over the use of fertile land.
Attitude (X2)	Emotional support and values	P12	I support the use of biofuel in the bus and train transportation sectors.
		P13	I feel the use of biofuel is important for the future of Indonesia's energy.
		P14	I feel biofuel is better than fossil fuel.
		P15	I believe biofuel is safe to use in public transportation.
		P16	I prefer traveling by bus and train that run on biofuel rather than fossil fuels.
		P17	I will support government policies on biofuel energy.
Perception (X3)	User risks and benefits	P18	I believe biofuel is a good fuel for making transportation more environmentally friendly.
		P19	I think biofuel can reduce dependence on oil imports.
		P20	I think biofuel can improve farmers' welfare. Because it can be produced from plants such as oil palm, jatropha, and sugarcane.

APPENDIX 3. PYTHON SEM CODE

This appendix contains the Python script used in the research data through semopy library. The analysis included three main stages, namely (1) CFA to test the validity and reliability of Knowledge, Attitude, and Perception constructs, (2) Structural Equation Modelling (SEM) to test the direct and indirect relationships between constructs, including evaluation of model fit, and (3) Bootstrapping of 1000 iterations to test the mediating effect of Attitude. Furthermore, the script was written in Visual Studio Code and replicated with the pandas, numpy, and semopy libraries.

(1) Confirmatory Factor Analysis (CFA)

```
import pandas as pd
import numpy as np
from semopy import Model
from semopy.inspector import inspect

# Load data
df = pd.read_excel('Data.xlsx')
columns = ['P1', 'P2', 'P3', 'P4', 'P5', 'P6',
          'P12', 'P13', 'P14', 'P15', 'P16', 'P17',
          'P18', 'P19', 'P20']
df = df[columns].apply(pd.to_numeric, errors='coerce').dropna()

# CFA Model
model_desc = """
X1 =~ P1 + P2 + P3 + P4 + P5 + P6
X2 =~ P12 + P13 + P14 + P15 + P16 + P17
X3 =~ P18 + P19 + P20
"""
model = Model(model_desc)
model.fit(df)

# Retrieve loading factor from inspect results
estimates = inspect(model)
lambda_rows = estimates[estimates['op'] == '~']

print("\nFactor Loadings:")
print(lambda_rows[['lval', 'rval', 'Estimate']])

# Calculate AVE and CR for each construct
def calculate_ave_cr(loadings):
    squared = np.square(loadings)
    ave = np.mean(squared)
    cr = np.sum(loadings)**2 / (np.sum(loadings)**2 + np.sum(1 - squared))
    return ave, cr

summary = []
for konstruk in ['X1', 'X2', 'X3']:
    loads = lambda_rows[lambda_rows['rval'] == konstruk]['Estimate'].astype(float).values
    ave, cr = calculate_ave_cr(loads)
    summary.append({'Konstruk': konstruk, 'AVE': round(ave, 3), 'CR': round(cr, 3)})
```

```
print("\nAVE and CR:")
print(pd.DataFrame(summary))
```

(2) Structural Equation Modelling (SEM)

```
import pandas as pd
from semopy import Model
import matplotlib.pyplot as plt
import networkx as nx

# Load data
df = pd.read_excel("Data.xlsx")
columns = ['P1', 'P2', 'P3', 'P4', 'P5', 'P6',
          'P12', 'P13', 'P14', 'P15', 'P16', 'P17',
          'P18', 'P19', 'P20']
df = df[columns].apply(pd.to_numeric, errors='coerce').dropna()

# Define SEM model with mediation
desc = """
X1 =~ P1 + P2 + P3 + P4 + P5 + P6
X2 =~ P12 + P13 + P14 + P15 + P16 + P17
X3 =~ P18 + P19 + P20

X2 ~ X1
X3 ~ X1 + X2
"""

model = Model(desc)
res = model.fit(df)

# Estimate parameters
est = model.inspect()
print("\nParameter Estimates:")
print(est[['lval', 'op', 'rval', 'Estimate', 'Std. Err', 'p-value']])

# Model fit summary (Chi-square/df, etc) - if supported
print("\nModel Fit (summary):")
print(res)  # Displays log likelihood, AIC, BIC, Chi2 if available

# Path Diagram Visualization
def plot_path_diagram():
    edges = est[est['op'].isin(['~', '=~'])]
    G = nx.DiGraph()
    for _, row in edges.iterrows():
        G.add_edge(row['rval'], row['lval'], weight=round(row['Estimate'], 2))
    pos = nx.spring_layout(G, seed=42)
    nx.draw(G, pos, with_labels=True, node_size=3000, node_color='lightgreen', font_size=9)
    edge_labels = nx.get_edge_attributes(G, 'weight')
    nx.draw_networkx_edge_labels(G, pos, edge_labels=edge_labels, font_size=8)
    plt.title("Final SEM Path Diagram")
    plt.show()

print(est[['lval', 'op', 'rval', 'Estimate', 'Std. Err', 'p-value']])
```

```
print("\nModel Fit Summary:")
print(res)

plot_path_diagram()
```

(3) Bootstrapping

```
# boot.py
import pandas as pd
import numpy as np
from semopy import Model

# Load data
file_path = "Data.xlsx"
df = pd.read_excel(file_path)

# Select relevant columns
columns = ['P1', 'P2', 'P3', 'P4', 'P5', 'P6',
           'P12', 'P13', 'P14', 'P15', 'P16', 'P17',
           'P18', 'P19', 'P20']
df = df[columns].apply(pd.to_numeric, errors='coerce').dropna()

# Define SEM model (mediation): X1 → X2 → X3
desc = """
X1 =~ P1 + P2 + P3 + P4 + P5 + P6
X2 =~ P12 + P13 + P14 + P15 + P16 + P17
X3 =~ P18 + P19 + P20

X2 ~ X1
X3 ~ X1 + X2
"""

# Setup bootstrapping
boot_n = 1000
indirect_effects = []
success = 0
fail = 0

for i in range(boot_n):
    sample = df.sample(n=len(df), replace=True)
    model = Model(desc)
    try:
        model.fit(sample)
        estimates = model.inspect()

        a_row = estimates.loc[(estimates.lval == 'X2') & (estimates.rval == 'X1')]
        b_row = estimates.loc[(estimates.lval == 'X3') & (estimates.rval == 'X2')]

        if not a_row.empty and not b_row.empty:
            a = a_row['Estimate'].values[0]
            b = b_row['Estimate'].values[0]
            indirect_effects.append(a * b)
            success += 1
```

```
        else:
            fail += 1
    except:
        fail += 1
        continue

print(f"Success: {success} iterations, Failures: {fail} iterations")

# Final result
if indirect_effects:
    indirect_effects = np.array(indirect_effects)
    mean_indirect = np.mean(indirect_effects)
    ci_low = np.percentile(indirect_effects, 2.5)
    ci_high = np.percentile(indirect_effects, 97.5)

    print("\nBootstrapping Results for Mediation Effect (X1 → X2 → X3):")
    print(f"Indirect Effect Mean: {mean_indirect:.3f}")
    print(f"95% Confidence Interval: [{ci_low:.3f}, {ci_high:.3f}]")

    if ci_low > 0 or ci_high < 0:
        print("Conclusion: Mediation effect is SIGNIFICANT.")
    else:
        print("Conclusion: Mediation effect is NOT significant.")
else:
    print("Bootstrapping failed: no valid iterations.")
```

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