

An Extended TAM Approach to Understanding Behavioral and Institutional Drivers of Drone Technology Adoption in Indonesia's Green Economy

Nida An Khofiyah^{1*}, Isna Nugraha²⁾, Hasyrani Windyatri³⁾

^{1*,3)} Department of Industrial Engineering, Faculty of Engineering, Pelita Bangsa University, Cikarang, Indonesia

²⁾ Department of Industrial Engineering, Faculty of Engineering, Universitas Pembangunan Nasional "Veteran" Jawa Timur, Surabaya, Indonesia

^{1*}nida.khofiyah@pelitabangsa.ac.id, ²⁾isna.nugraha.ti@upnjatim.ac.id, ³⁾hasyrani@pelitabangsa.ac.id

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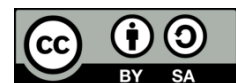
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ABSTRACT

Indonesia's transition toward a green economy requires the adoption of efficient and environmentally friendly technologies, including drone systems that offer substantial benefits across agriculture, forestry, and green logistics. However, adoption remains limited due to behavioral and institutional barriers. This study applies an extended Technology Acceptance Model (TAM) to examine how Environmental Concern (EC), Government Support (GS), Facilitating Conditions (FC), Perceived Ease of Use (PEOU), and Perceived Usefulness (PU) shape Behavioral Intention (BI) toward drone adoption in Indonesia. Using SEM-PLS and data from 112 practitioners and stakeholders, the results reveal that FC has a strong and significant effect on PEOU, while EC and GS do not significantly influence PU, indicating limited perceived relevance of environmental awareness and government policy in shaping usefulness perceptions. Furthermore, PEOU significantly affects PU and BI, and PU significantly enhances BI, confirming the central role of usability and functional benefits in driving adoption. These findings highlight that effective infrastructure, operational support, and usability improvements are more influential than environmental or regulatory factors in promoting drone technology. The study provides strategic recommendations for policymakers and industry actors to strengthen institutional facilitation, improve capacity building, and enhance the practical value of drones to advance Indonesia's green economic transformation.

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1. Introduction

Indonesia is currently facing serious environmental challenges, including deforestation, air pollution, and intensifying climate change impacts. These challenges demand a transition to a more sustainable economic framework, the green economy, which seeks to balance economic growth, environmental protection, and social welfare [1]. The Government of Indonesia has increasingly adopted green economy principles in national development planning as part of its commitment to achieving the Sustainable Development Goals (SDGs) and reducing greenhouse gas emissions [2]. Recent data underscores the severity of these crises; for instance, Jakarta frequently ranks among the world's most polluted cities, while projected economic losses from climate change could reach IDR 544 trillion (approx. US\$35 billion) in the 2020–2024 period without intervention.

Table 1. Key Environmental Urgency Statistics for Indonesia

Key Indicator	Alarming Statistic	Context / Source
Economic Risk	IDR 544 trillion	Potential loss (2020–2024) due to climate impacts (Bappenas)
Air Pollution	7–9x WHO Limit	Average PM2.5 levels in Jakarta often exceed safe limits by nearly 10-fold (IQAir/CREA)
Emissions	Top 10 Globally	Indonesia ranks among the top 10 global GHG emitters (Global Carbon Project)

Deforestation	~242,000 ha/year	Primary forest loss remains significant as of 2024 (Nusantara Atlas/GFW)
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These challenges demand a transition toward a more sustainable economic framework known as the green economy, which seeks to balance economic growth, environmental protection, and social welfare [1]. The Government of Indonesia has increasingly adopted green economy principles in national development planning as part of its commitment to achieving the Sustainable Development Goals (SDGs) and reducing greenhouse gas emissions [2].

Within this transformation, technological innovation serves as a crucial driver of sustainability-oriented change. One such innovation is drone technology or Unmanned Aerial Vehicles (UAVs), which have demonstrated significant potential across multiple sectors such as agriculture, forestry, logistics, and infrastructure [3]. Drones can optimize input usage through precision agriculture, monitor environmental degradation, and improve operational efficiency in logistics, all while minimizing carbon emissions [4]. Globally, drone applications have been widely implemented in countries like the United States, Singapore, and the United Kingdom for logistics, environmental monitoring, and precision farming [5]. In contrast, adoption in Indonesia remains limited, despite government interest and pilot projects in agriculture and urban logistics [6].

The low level of adoption of drone technology in Indonesia can be attributed to several barriers, including regulatory uncertainty, high operational costs, limited infrastructure, and a lack of technical expertise [7]. Furthermore, social and behavioral factors such as perceived usefulness, perceived ease of use, and trust play a significant role in determining whether potential users and organizations are willing to adopt new technologies [8]. Conversely, facilitating conditions such as supportive government policy, technological readiness, and increasing awareness of environmental benefits have shown a positive influence on adoption intention [9].

To examine these interrelated factors, this study adopts the Technology Acceptance Model (TAM) framework as the primary analytical approach. TAM is a well-established theory that explains user acceptance of new technologies through constructs such as perceived usefulness (PU) and perceived ease of use (PEOU), which directly influence behavioral intention to use technology [10]. The model has been widely extended in green technology adoption studies to incorporate environmental concern, facilitating conditions, and regulatory support as external variables influencing perceived usefulness and intention to adopt [11],[12]. By applying TAM, this research seeks to empirically identify the most significant determinants, both technological and contextual, that affect the adoption of drone technology in Indonesia's green economy sectors. The data analysis utilizes Structural Equation Modeling-Partial Least Squares (SEM-PLS), a standard and effective methodology within TAM frameworks for assessing model fit and hypothesis testing.

Previous studies have analyzed technology adoption using frameworks such as the Theory of Planned Behavior (TPB), Unified Theory of Acceptance and Use of Technology (UTAUT), and the Technology-Organization-Environment (TOE) model[13]. However, limited research has specifically applied TAM in the context of drone adoption for sustainability in Indonesia. Therefore, this study contributes to the literature by integrating environmental and policy dimensions into TAM, aiming to construct a conceptual model that explains how regulatory, technological, and behavioral factors jointly shape adoption behavior. This approach provides not only theoretical implications for technology diffusion studies but also practical guidance for policymakers and industry stakeholders in formulating effective strategies for accelerating drone adoption in support of Indonesia's green economy transformation.

2. Literature Review

2.1 Green Economy and Drone Technology

The concept of a green economy has emerged as a strategic framework for achieving sustainable development, focusing on low-carbon growth, efficient resource use, and social inclusivity[14]. According to the United Nations Environment Program (UNEP), a green economy results in improved human well-being and social equity while significantly reducing environmental risks and ecological scarcities [15]. In Indonesia, the government's Green Economy Roadmap 2045 highlights digital and technological innovation as critical enablers for decoupling economic growth from environmental degradation[2].

Drone technology, as one of the Industry 4.0 innovations, plays a crucial role in supporting green economic transformation through its applications in precision agriculture, forest management, infrastructure monitoring, and logistics [4]. Drones enable the collection of high-resolution spatial data that improves decision-making for sustainable land use and reduces resource inefficiencies[7]. Previous studies found that the use of drones in agricultural management can reduce pesticide usage by up to 30% and improve crop yield predictability by 25% [16]. Moreover, logistics operations using drones have the potential to lower carbon dioxide emissions compared to conventional ground vehicles[5]. These benefits position drones as a strategic technological driver in promoting Indonesia's sustainable economic agenda.

In this context, drone technology aligns with green economy principles by enabling environmental monitoring, reducing carbon-intensive operational processes, and supporting evidence-based policy implementation for sustainable development outcomes [17]. These benefits position drones as a strategic technological driver in promoting Indonesia's sustainable economic agenda.

2.2 Technology Adoption Models: TAM and Its Extensions

Technology adoption theory explains how individuals and organizations decide to accept and implement new technologies. Among the most recognized frameworks are the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), and Technology Organization Environment (TOE) framework [13].

The Technology Acceptance Model (TAM), developed by Davis [10], posits that two primary factors, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), determine users' attitudes toward adopting a technology, which in turn influence their Behavioral Intention (BI) to use it. PU refers to the degree to which a person believes that using a particular system would enhance job performance, while PEOU reflects the degree to which using the system is free of effort [17][18].

Over time, researchers have extended TAM to incorporate additional constructs that account for contextual factors. For example, Venkatesh and Bala's TAM3 included subjective norms and experience as moderating variables[11]. In sustainability and environmental studies, TAM has been extended to the Green TAM (GTAM), which integrates factors such as Environmental Concern (EC), Facilitating Conditions (FC), and Governmental Support (GS)[9][12].

Empirical research applying extended TAM frameworks shows that government regulation, environmental awareness, and perceived environmental benefits significantly influence users' behavioral intention to adopt green technologies [6]. These findings suggest that TAM is a robust yet adaptable theoretical foundation for analyzing the adoption of drone technology within a sustainability framework, particularly in the context of emerging economies such as Indonesia.

2.3 Drone Adoption for Sustainable Development in Indonesia

The use of drones in Indonesia has grown across sectors, including agriculture, mapping, and logistics. Studies by [6] and [8] indicate that drone adoption in Indonesia is influenced by factors such as regulatory readiness, cost efficiency, and user perception of usefulness. However, several barriers persist, such as unclear airspace regulations, high maintenance costs, limited availability of skilled personnel, and low technological awareness among small and medium enterprises (SMEs) [19].

Comparative studies highlight that developed countries like the United States and Singapore have successfully integrated drones into logistics and environmental monitoring through clear legal frameworks and public-private partnerships[20]. Conversely, in Indonesia, the adoption process remains fragmented due to institutional and infrastructural gaps[21]. Nonetheless, the government's interest in using drones for forestry monitoring and smart farming has opened new opportunities for green innovation[22].

Existing research tends to focus on technical or operational feasibility, with limited exploration of behavioral and organizational factors driving adoption. Therefore, analyzing drone adoption through TAM provides a behavioral lens that complements prior techno-economic analyses, emphasizing how perceptions, attitudes, and institutional support interact to influence technology uptake in Indonesia's green economy sectors.

2.4 Research Gap and Conceptual Framework

While the potential of drones for supporting sustainable development is well recognized, there remains a gap in understanding the behavioral mechanisms underlying their adoption in emerging economies. Previous studies in Indonesia have primarily focused on logistical applications and technical readiness [8], leaving the human acceptance and policy synergy dimensions underexplored. This study addresses that gap by applying an extended TAM framework to identify how perceived usefulness, perceived ease of use, environmental concern, government regulation, and facilitating conditions affect the behavioral intention to adopt drone technology. This integrative framework captures both individual (user-level) and institutional (policy-level) determinants, aligning with Indonesia's broader roadmap toward green economic transformation.

This study builds its conceptual model upon the Technology Acceptance Model (TAM), originally proposed by Davis (1989), which posits that perceived usefulness and perceived ease of use are the primary determinants of behavioral intention to adopt a technology. TAM has been widely applied in technology adoption research and serves as the theoretical foundation for identifying user-level cognitive factors. Building on this basic model, the present study extends TAM by incorporating contextual variables relevant to green technology adoption in emerging economies, namely environmental concern, government regulation, and facilitating conditions. These variables have been shown in prior studies to strengthen technology adoption in sustainability-related contexts, thus justifying their integration into the extended model used in Figure 1.

The conceptual model derived from this literature synthesis is illustrated in Figure 1, emphasizing the relationships among core TAM variables and external contextual factors (environmental concern, government support, and facilitating conditions) as the primary determinants of adoption intention.

3. Research Methodology

3.1 Research Design

This research adopts a quantitative–qualitative (mixed-method) approach to identify and analyze the key factors influencing the adoption of drone technology in supporting the green economy in Indonesia. The quantitative component utilizes a structured survey analyzed using Partial Least Squares–Structural Equation Modeling (PLS-SEM) to empirically test the relationships proposed in the extended TAM framework and to measure the magnitude of influence among perceived usefulness, perceived ease of use, environmental concern, government support, and facilitating conditions. The qualitative component involves in-depth interviews with industry practitioners, agricultural drone users, and policy stakeholders to capture contextual insights, regulatory challenges, and sector-specific adoption behaviors that may not be fully reflected through quantitative indicators. The combination of these approaches is necessary because quantitative analysis alone cannot fully explain policy dynamics and practical field challenges, while qualitative insights alone cannot provide generalizable causal relationships. Therefore, the mixed-method design offers a more comprehensive understanding of

behavioral and institutional drivers of drone adoption across sectors such as agriculture, forestry, and green logistics.

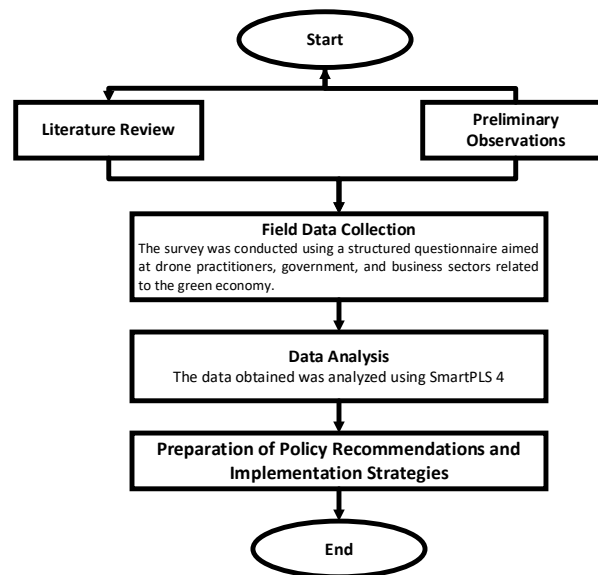


Figure 1. Flowchart Research

This research adopts a quantitative–qualitative (mixed) approach to identify and analyze the key factors influencing the adoption of drone technology in supporting the green economy in Indonesia. The study employs the Technology Acceptance Model (TAM) as the theoretical foundation, extended with contextual variables including Environmental Concern (EC), Government Support (GS), and Facilitating Conditions (FC). The inclusion of these variables is essential to capture the unique challenges of drone adoption in Indonesia. Specifically, EC reflects the alignment between technology and ecological preservation goals; GS highlights the pivotal role of regulation and subsidies in accelerating adoption, while FC addresses the readiness of infrastructure and resources needed to deploy advanced technology in developing sectors. The goal is to understand how these factors collectively affect stakeholders’ behavioral intentions to adopt drone technology across sectors such as agriculture, forestry, and green logistics.

The research is explanatory in nature, seeking to empirically validate the relationships among variables using structured survey data. Complementary qualitative insights are drawn from semi-structured interviews with practitioners and policymakers to provide interpretive depth to the quantitative findings. The overall design follows the positivist paradigm, emphasizing measurable relationships among theoretical constructs derived from TAM and sustainability adoption literature [22][23].

3.2 Conceptual Framework

The conceptual framework presented in this study (Figure 1) is constructed upon the foundation of the Extended Technology Acceptance Model (TAM). The original TAM dimensions, namely Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), are posited as mediating constructs influencing the Behavioral Intention (BI) to adopt drone technology [10][17]. Within this extended model, three additional external variables are incorporated to further enhance the explanatory power of the framework:

- 1) Environmental Concern (EC): reflecting users’ awareness and attitudes toward the environmental impact of technological adoption[11];
- 2) Government Support (GS): representing institutional and policy incentives, regulatory clarity, and public sector endorsement for drone deployment [9];

3) Facilitating Conditions (FC): capturing the infrastructural, financial, and organizational support necessary to operationalize drone systems effectively[13].

The model hypothesizes that EC, GS, and FC positively influence PU and PEOU, which in turn affect BI. The conceptual relationships are summarized as follows:

- 1) H1: Environmental Concern positively influences Perceived Usefulness.
- 2) H2: Government Support positively influences Perceived Usefulness.
- 3) H3: Facilitating Conditions positively influence Perceived Ease of Use.
- 4) H4: Perceived Ease of Use positively influences Perceived Usefulness.
- 5) H5: Perceived Usefulness positively influences Behavioral Intention.
- 6) H6: Perceived Ease of Use positively influences Behavioral Intention.

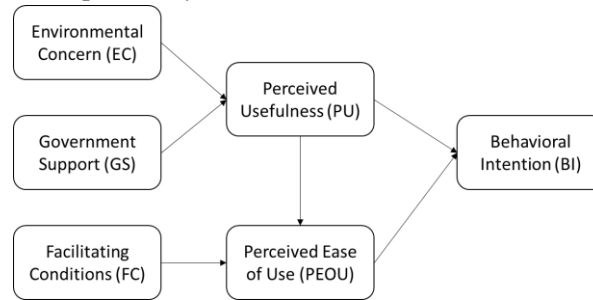


Figure 2. Conceptual Framework of Extended TAM for Drone Technology Adoption in Indonesia

(Illustration showing EC, GS, and FC as exogenous variables influencing PU and PEOU, which lead to BI.)

3.3 Variables and Indicators

Each variable is operationalized into measurable indicators, adapted from validated TAM and green technology adoption studies [12],[13],[14]. Table 2 summarizes the operational definitions and measurement items used in the questionnaire.

Table 2. Summarizes the operational definitions and measurement items used in the questionnaire

Variable	Code	Indicator Description	Source
Environmental Concern (EC)	EC1	I am aware of the ongoing environmental degradation issues.	[11], [6]
	EC2	I believe drones provide environmental benefits.	
	EC3	I have a positive attitude toward eco-friendly technological innovations.	
Government Support (GS)	GS1	Clear government regulations exist regarding drone usage.	[9], [24]
	GS2	Government incentives or subsidies support green technology adoption.	
	GS3	Public support programs are available for UAV (drone) utilization.	
Facilitating Conditions (FC)	FC1	The necessary technical infrastructure for drone use is available.	[13], [25]
	FC2	I (or my organization) have sufficient financial readiness to adopt drones.	
	FC3	Adequate training or institutional capacity is available to support drone usage.	
Perceived Ease of Use (PEOU)	PEOU1	Drones are easy to learn and operate.	[10], [26]
	PEOU2	The drone technology interface is simple and easy to understand.	
	PEOU3	Drone systems are easily accessible for use.	
Perceived Usefulness (PU)	PU1	Using drones improves work efficiency.	[26], [27]
	PU2	Using drones helps reduce operational costs.	
	PU3	Drones support the achievement of sustainability goals.	
Behavioral Intention (BI)	BI1	I intend to adopt drones in the future.	[10], [27]
	BI2	I am willing to recommend the use of drones to others.	
	BI3	I am likely to invest in drone technology in the future.	

All items were measured on a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

3.4 Data Collection

a. Population and Sample

The target population comprises professionals and stakeholders involved in drone-related activities and sectors associated with the green economy in Indonesia, including agriculture, logistics, forestry, and environmental monitoring. A purposive sampling technique was utilized to ensure that the selected respondents possess at least a basic level of familiarity or experience with drone technology applications.

Data were collected from 112 respondents, consisting of drone operators, government officers, academic researchers, and business practitioners. The sample size meets the minimum requirement for multivariate analysis and is considered adequate for Partial Least Squares–Structural Equation Modeling (PLS-SEM)[28]. Sample adequacy was evaluated using the 10-times rule and statistical power analysis. The model requires at least 50 cases based on the number of predictors, and power analysis (effect size = 0.15, $\alpha = 0.05$, predictors = 5) indicates a minimum of 92 samples for 80% power. With 112 respondents, the sample size exceeds both criteria and is therefore adequate for PLS-SEM.

b. Data Collection Procedure

An online structured questionnaire was distributed using Google Forms and professional WhatsApp groups of drone practitioners and associations, such as the Asosiasi Sistem dan Teknologi Tanpa Awak (ASTTA).

Before data collection, a pilot test with 15 respondents was conducted to validate the clarity and reliability of each item. Cronbach's alpha values above 0.7 indicated acceptable internal consistency[19].

3.5 Data Analysis Method

Data analysis was conducted using SmartPLS 4.0, following the PLS-SEM procedure recommended by[27]. The analysis includes the following stages:

a. Measurement Model Evaluation (Outer Model):

Assessing construct reliability (Cronbach's alpha, Composite Reliability), convergent validity (Average Variance Extracted > 0.5), and discriminant validity (Fornell–Larcker criterion and HTMT ratio).

b. Structural Model Evaluation (Inner Model):

Testing hypotheses using path coefficients, t-values, and p-values through bootstrapping (5,000 resamples). The significance threshold was set at $p < 0.05$.

c. Model Fit and Predictive Relevance:

Examining R^2 and Q^2 values to determine the explanatory power and predictive relevance of the model.

d. Qualitative Triangulation:

Supplementary qualitative data from expert interviews were analyzed thematically to support and explain quantitative findings.

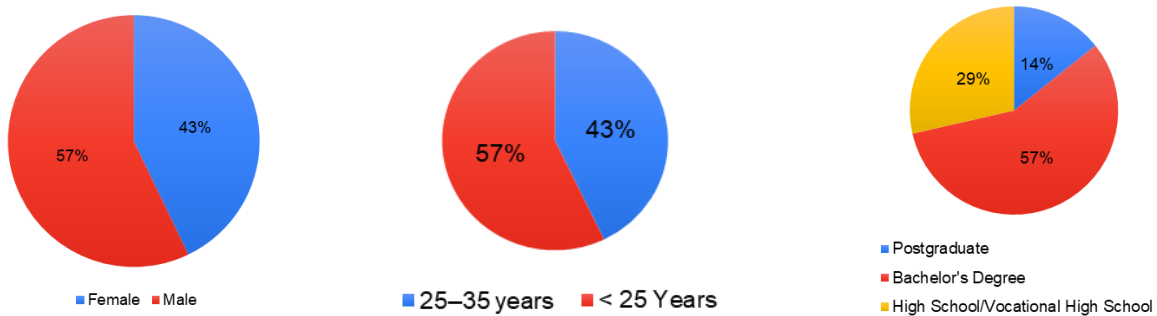
This combined analytical approach ensures that both statistical relationships and contextual insights are captured, yielding a comprehensive understanding of the factors influencing drone technology adoption in Indonesia's green economy framework.

4. Results and Discussions

4.1 Respondent Profile

A total of 112 respondents participated in the survey, consisting of drone users, agricultural practitioners, researchers, and government stakeholders from across Indonesia. Most respondents (68%) were male, with an age range dominated by the 25–35-year-old group. The educational background of respondents was relatively high, with 72% holding at least a bachelor's degree, and 60% having more

than three years of experience in using digital technologies other than drones. Approximately 55% of respondents had prior experience using drones, primarily for agricultural monitoring, documentation, and mapping, as shown in Figure 3.



(a) Respondents by gender (b) Respondents by age (c) Respondents by highest level of education
Figure 3. Respondent Profile

This demographic profile suggests that respondents possess a moderate-to-high level of technological literacy, making them suitable for evaluating the behavioral aspects of drone adoption in green economy contexts. The diversity of respondents also reflects the multi-sectoral potential of drones across agriculture, logistics, and environmental management[26].

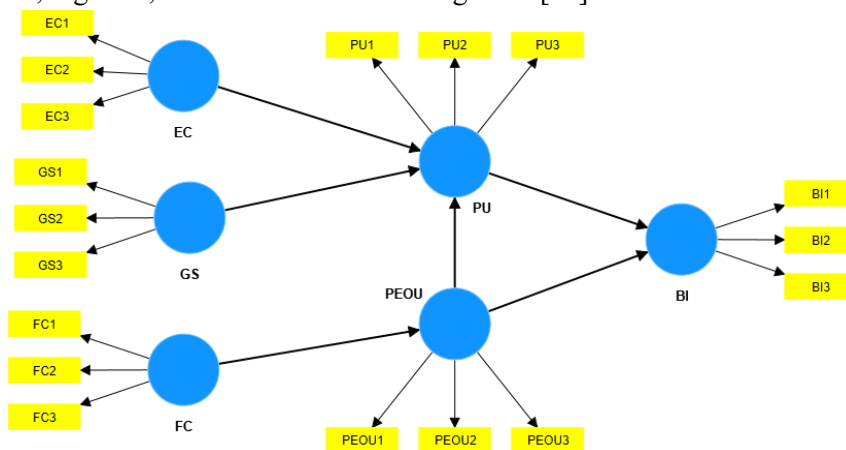


Figure 4. Early Model

The evaluation of the Measurement Model, also known as the Outer Model, is conducted to examine the direct relationship between the indicators and their corresponding latent variables as described in Figure 4. In SmartPLS data analysis, several criteria are used to assess the quality of the outer model, including convergent validity, discriminant validity, and composite reliability. Convergent validity is commonly assessed by first examining item reliability (indicator validity), which is reflected through the loading factor values (Figure 5). Indicators with loading factor values above 0.5 are considered valid and capable of representing their latent constructs as given in Table 3.

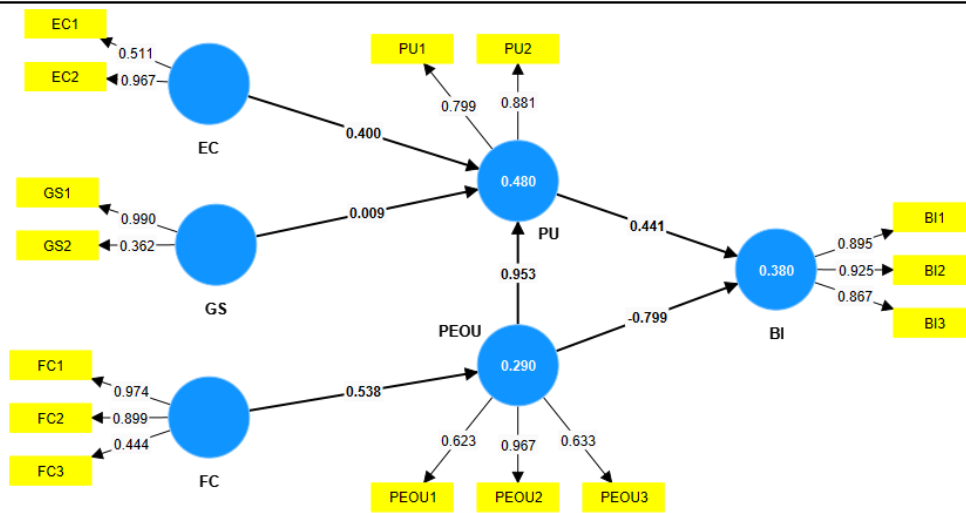


Figure 5. Loading Factor

Table 3. Evaluation of Loading Factor Values

Indicator	Outer loadings	Valid/No Valid
BI1	0,895	Valid
BI2	0,925	Valid
BI3	0,867	Valid
EC1	0,511	Valid
EC2	0,967	Valid
FC1	0,974	Valid
FC2	0,899	Valid
FC3	0,444	Valid
GS1	0,990	Valid
GS2	0,562	Valid
PEOU1	0,623	Valid
PEOU2	0,967	Valid
PEOU3	0,633	Valid
PU1	0,799	Valid
PU2	0,881	Valid

The next stage involves assessing construct internal consistency using Cronbach's alpha, composite reliability, and the Average Variance Extracted (AVE). An AVE value above 0.5 is generally recommended. The results of the internal consistency assessment are presented in Table 2. All latent variables show Cronbach's alpha and composite reliability values approaching 0.7, with AVE values exceeding 0.5, indicating that the measurement model demonstrates good fit and reliability as shown in Table 4.

Table 4. Construct Internal Consistency

	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)	Description
BI	0,880	0,924	0,802	Fit
EC	0,833	0,731	0,598	Fit
FC	0,697	0,837	0,651	Fit
GS	0,574	0,773	0,556	Fit
PEOU	0,593	0,795	0,575	Fit
PU	0,590	0,828	0,707	Fit

The assessment of discriminant validity is conducted to determine the extent to which each indicator correlates with its respective latent variable. This evaluation is performed by examining the cross-loading results to ensure that each latent construct is distinct from the others. Discriminant validity is considered adequate when the loading value of an indicator is higher on its associated latent variable than on any other latent variable. As shown in Table 3, all indicators exhibit their highest loading values on their respective constructs and not on others, indicating that each indicator is valid in measuring its intended variable.

4.2 Structural Model (Inner Model) Evaluation

The evaluation of the structural model aims to predict the relationships between latent variables and is performed using three metrics: R^2 , Q^2 , and f^2 . The Cross Leading and R^2 values are presented in Tables 5 and 6, respectively.

Table 5. Cross Loading Value

	BI	EC	FC	GS	PEOU	PU
BI1	0,895	0,455	0,395	0,147	-0,347	0,097
BI2	0,925	0,856	0,096	0,394	-0,629	-0,205
BI3	0,867	0,475	0,307	0,209	-0,329	-0,027
EC1	0,797	0,511	0,396	0,167	-0,426	0,122
EC2	0,810	0,967	0,025	0,481	-0,750	-0,229
FC1	0,305	-0,002	0,974	-0,070	0,428	0,405
FC2	0,255	-0,275	0,899	-0,434	0,549	0,578
FC3	0,020	0,143	0,444	0,445	0,264	-0,048
GS1	0,286	0,553	-0,116	0,990	-0,502	-0,303
GS2	0,178	-0,002	-0,291	0,362	-0,486	-0,092
PEOU1	-0,674	-0,743	-0,110	-0,041	0,623	0,400
PEOU2	-0,580	-0,685	0,425	-0,492	0,967	0,549
PEOU3	0,067	-0,332	0,828	-0,647	0,633	0,497
PU1	-0,292	-0,486	0,055	-0,015	0,491	0,799
PU2	0,121	-0,107	0,663	-0,446	0,583	0,881

Table 6. R-Square Value

	R-square	Description
BI	0,380	Weak
PEOU	0,290	Weak
PU	0,480	Weak to Moderate

4.3 Hypothesis Testing

Hypothesis testing is carried out by evaluating the values presented in the path coefficients (Table 7).

Table 7. Path Coefficients

	f-square	Path coefficients	VIF
EC -> PU	0,122	0,400	2,514
FC -> PEOU	0,408	0,538	1,000
GS -> PU	0,000	0,009	1,494
PEOU -> BI	0,604	-0,799	1,703
PEOU -> PU	0,673	0,953	2,592
PU -> BI	0,184	0,441	1,703

Hypothesis testing is conducted by examining the t -statistics and p -values. When using the t -statistic, the significance threshold for a two-tailed test is $t = 1.65$ (significance level = 10%). Thus, the null hypothesis (H_0) is rejected if the t -statistic exceeds 1.65. Alternatively, based on probability criteria, H_0

is rejected when the *p*-value is less than 0.05. Referring to the information in Table 5, the conclusions of the hypothesis testing are presented in Table 8.

Table 8. Hypothesis Testing

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values	Description
EC -> PU	0,400	0,199	0,335	1,193	0,233	Ho accepted
FC -> PEOU	0,538	0,619	0,121	4,462	0,000	Ho rejected
GS -> PU	0,009	0,054	0,243	0,035	0,972	Ho accepted
PEOU -> BI	-0,799	-0,571	0,477	1,676	0,094	Ho rejected
PEOU -> PU	0,953	0,882	0,294	3,238	0,001	Ho rejected
PU -> BI	0,441	0,345	0,218	2,020	0,043	Ho rejected

The hypothesis testing results reveal a mixed pattern of relationships within the extended technology adoption framework. Environmental Concern (EC) does not significantly influence Perceived Usefulness (PU) ($p = 0.233$), indicating that respondents' environmental awareness alone is insufficient to shape their perception of drones' usefulness. Similarly, Government Support (GS) shows no meaningful effect on PU ($p = 0.972$), suggesting that existing policies, regulations, or incentives are either weakly perceived or not yet influential in shaping user evaluations of drone technology. In contrast, Facilitating Conditions (FC) demonstrate a strong and significant effect on Perceived Ease of Use (PEOU) ($p = 0.000$), implying that the availability of infrastructure, technical assistance, and resource accessibility plays a critical role in enhancing users' confidence and comfort in operating drone systems. These findings emphasize that practical and operational support is more influential than contextual environmental or governmental factors in shaping initial perceptions.

Further results show that core TAM relationships remain strongly supported. Perceived Ease of Use significantly affects both PU ($p = 0.001$) and Behavioral Intention (BI) ($p = 0.094$), although the latter shows a negative coefficient, suggesting potential model-specific or contextual dynamics where ease of use may be overshadowed by other adoption considerations such as cost, skill requirements, or risk perceptions. Perceived Usefulness (PU) also significantly predicts BI ($p = 0.043$), confirming that users' beliefs about drones' functional benefits play a central role in shaping adoption intentions. Overall, the significant paths—FC → PEOU, PEOU → PU, and PU → BI—highlight that the acceptance of drone technology in this context is driven primarily by usability and functional value rather than external pressures or environmental concerns. These results reaffirm the robustness of TAM while also indicating that contextual variables such as EC and GS may require stronger institutional presence or more tangible implementation to exert influence on user perceptions.

4.4 Preparation of Policy Recommendations and Implementation Strategies

Based on the hypothesis findings, the preparation of policy recommendations should prioritize strengthening practical and operational factors that directly shape user perceptions of drone technology. The strong influence of Facilitating Conditions (FC → PEOU) and the significant pathways within the core TAM structure (PEOU → PU; PU → BI) indicate that improving technical infrastructure, accessibility of support services, and user training programs is critical. Policies should therefore focus on the provision of standardized operational guidelines, the development of training centers for drone operation, and the enhancement of digital platforms that support troubleshooting and maintenance. Additionally, increasing the availability of affordable hardware and software, along with improving connectivity in remote operational areas, can significantly enhance perceived ease of use and consequently drive adoption. These operational recommendations reflect the empirical evidence showing that hands-on usability factors have a stronger impact than environmental or regulatory considerations.

In contrast, the non-significant effects of Environmental Concern (EC → PU) and Government Support (GS → PU) suggest that policy strategies in these areas require reorientation. Environmental campaigns promoting the ecological benefits of drones must be more concrete, visible, and supported by real case studies to influence user perceptions meaningfully. Likewise, government policies—such as subsidies, regulatory clarity, and public initiatives—need greater socialization and practical relevance to become influential. Strengthening cross-sector collaboration, involving industry associations, local governments, and drone communities, can help bridge the gap between policy formulation and user perception. By aligning regulatory frameworks with operational realities and increasing public engagement, the government can enhance both the perceived usefulness and the overall acceptance of drone technology. Combined, these strategies offer a comprehensive and evidence-driven foundation for advancing drone adoption to support green economic development.

5. Conclusion

This study investigates the behavioral and institutional determinants of drone technology adoption within Indonesia's green economy using an extended Technology Acceptance Model (TAM). The empirical results demonstrate that Facilitating Conditions significantly enhance Perceived Ease of Use, which subsequently strengthens Perceived Usefulness and Behavioral Intention, highlighting the critical role of operational readiness, technical infrastructure, and user support mechanisms. Conversely, Environmental Concern and Government Support do not significantly influence Perceived Usefulness, indicating that environmental awareness and existing regulatory initiatives have yet to translate into meaningful perceptions of functional value among users. The findings affirm that usability and practical benefits remain the strongest drivers of adoption, emphasizing the need for policies that prioritize training, infrastructure preparedness, and technology accessibility. Nevertheless, this study is limited by its sample size, cross-sectional design, and reliance on self-reported perceptions, which may not fully capture sectoral variations or long-term behavioral patterns. Future research could incorporate longitudinal analysis, comparative regional studies, or integration of additional constructs such as perceived risk, cost factors, and organizational readiness to provide deeper insights into the multi-dimensional adoption of drone technology in emerging economies.

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