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Factors Influencing Generative AI Adoption in Government: A Case Study in BPS-Statistics of Indonesia

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Abstract

Rapid technological developments hold great potential, one of which is generative AI. Technology that is easily accessible and user-friendly tends to spread quickly, and BPS-Statistics of Indonesia is no exception. The challenges currently faced by BPS-Statistics of Indonesia, such as rapid data growth, high data demand, and data analysis and representation, encourage the institution to be adaptive to new technologies that can accelerate work processes. This research aims to determine the factors influencing the acceptance and use of generative AI (*GenAI*), such as ChatGPT, Gemini, and others, among BPS-Statistics of Indonesia employees, using Behavioral Intention as the central mediating variable that bridges the influence of these predictor factors on Use Behavior. The model also examines the relationships between external factors, such as Social Influence and Trust, and Perceived Usefulness and Perceived Ease of Use, as well as their effects on Attitude. Additionally, it evaluates the influence of Hedonic Motivation, Facilitating Conditions, Perceived Severity, and Perceived Vulnerability on Behavioral Intention. Based on a survey of 166 respondents at BPS-Statistics of Indonesia, the results reveal that Attitude has a significant influence on Behavioral Intention, while Perceived Severity has a significant negative influence on Behavioral Intention. Furthermore, Behavioral Intention is also shown to have a significant positive influence on Use Behavior. These findings contribute theoretically to the development of technology adoption models in the public sector and have practical implications for BPS-Statistics of Indonesia in formulating AI usage policies.

Keywords:
Generative Artificial Intelligence, Technology Acceptance, Public Sector, Use Behavior

INTRODUCTION

Artificial Intelligence (AI) is a disruptive technology that profoundly influences individuals and organizations in how they think, work, and make decisions (Storey et al., 2025; Bright et al., 2024). A recent form of AI, enabled by deep learning neural networks and natural language processing, is known as Generative AI (GenAI) (Storey et al., 2025). This technology is designed to be easily accessible to users and includes tools that are available either for free or via subscription, such as ChatGPT, Gemini, and others. Therefore, this accessibility makes the technology potentially usable by nearly every worker in the public sector (Bright et al., 2024).

Worldwide, the application of GenAI has expanded across various domains, including education, healthcare, and business analytics, among others (Philippe Lorenz et al., 2023). This widespread adoption is due to GenAI's ability to generate text, images, or code based on user-provided prompts (Lu & Zeng, 2025). Alongside this growth, various international bodies have established regulations concerning the use of GenAI, emphasizing the importance of transparency, accountability, and risk management to mitigate issues such as data misuse, bias, and the spread of disinformation (Philippe Lorenz et al., 2023).

However, at present, there are no comprehensive laws in Indonesia specifically regulating the use of AI technologies, including GenAI (Prawiratama et al., 2024). The implementation process may be challenging due to potential risks such as copyright violations, data breaches, the spread of misinformation, and unclear accountability (Philippe Lorenz et al., 2023; Šarčević et al., 2024; Al-kfairy et al., 2024; López-Borrull & Lopezosa, 2025). The absence of clear guidelines may also delay the adoption of GenAI technologies within the governmental sector (Andrews et al., n.d.; Lahusen et al., 2024).

Despite these challenges, they represent only one side of the equation, as GenAI also offers significant opportunities within the public sector. The European Commission reported that approximately 30% of managers in seven member states are already using GenAI, while 44% are likely to adopt the technology in the future to assist with document preparation, report compilation, and big data analysis (European Commission, 2024). Additionally, according to The Alan Turing Institute, GenAI could reduce the time spent on bureaucratic tasks from 50% to 30% among public sector employees in the United Kingdom, provided it is used effectively (Bright et al., 2024).

BPS-Statistics of Indonesia, a non-ministerial government agency responsible for national statistics, faces several critical challenges. These include rapid organizational growth, pressure on conventional approaches (Hassani & MacFeely, 2023), delays in data availability despite high demand (Velasco-López et al., 2024), and a lack of sufficiently representative digital data (Hsiao et al., 2024). These challenges are among the reasons BPS-Statistics of Indonesia is adopting technologies that can support its work processes, including the implementation of Generative AI. In line with this, BPS-Statistics of Indonesia actively promotes human resource development through knowledge sharing and training related to AI, with a focus on improving efficiency in document preparation and report writing, as well as reducing errors through the automation of repetitive tasks (BPS, 2025). These efforts indicate that BPS is beginning to embrace the use of GenAI to support digital transformation and innovation in statistical services.

Previous research has explored various factors influencing the acceptance and use of AI technologies across organizational contexts. One prominent model, the Unified Theory of Acceptance and Use of Technology (UTAUT), explains that individual behavior in adopting technology is influenced by performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). This model has been further developed by incorporating non-technical factors such as public trust, regulatory frameworks, and organizational readiness (Zuiderwijk et al., 2021), along with other models as required by specific research contexts.

Although several studies have highlighted both the potential and challenges of AI in the public sector, empirical research on the acceptance and usage behavior of Generative AI within

Indonesian government agencies remains limited. BPS-Statistics of Indonesia, as a national statistical agency focused on data and public services, provides a compelling case for examining GenAI adoption in the public sector, given the technology's significant potential to enhance work efficiency, report generation, and statistical analysis. However, the integration of GenAI within government agencies is influenced by various individual and organizational factors, including perceived benefits, complexity, trust, and associated risks. Addressing these gaps, this study focuses on analyzing the variables that influence the acceptance and adoption of Generative AI systems within BPS-Statistics of Indonesia by developing a combined Technology Acceptance Model (TAM) and UTAUT framework. The study aims to contribute theoretically to the development of technology adoption models in the public sector, while also supporting government agencies in formulating effective strategies and policies for AI implementation.

METHODOLOGY

This study employed a quantitative explanatory research design to examine the factors influencing the acceptance and use of Generative AI among employees of BPS-Statistics of Indonesia. The explanatory design was chosen because the study aimed to test the causal relationships among variables in the proposed model, particularly the influence of Social Influence, Trust, Perceived Usefulness, Perceived Ease of Use, Attitude, Hedonic Motivation, Facilitating Conditions, Perceived Severity, and Perceived Vulnerability on Behavioral Intention and Use Behavior.

A structured questionnaire consisting of statements representing the research variables served as the instrument for this study. Each variable was measured through several items using a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

The variables measured in this study included Behavioral Intention, Social Influence, Trust, Perceived Usefulness, Perceived Ease of Use, Attitude, Hedonic Motivation, Facilitating Conditions, Perceived Severity, Perceived Vulnerability, and Use Behavior.

A quantitative approach was employed, with data primarily collected through surveys. BPS staff from both headquarters and regional offices participated in the survey through questionnaire distribution, with a total population of 17,969 employees. This method was selected as an appropriate way to assess how individuals perceive, feel about, and intend to adopt new technologies such as Generative AI (GenAI).

Data processing was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS software. This approach was justified due to its robustness in handling complex models and its flexibility regarding data distribution assumptions (i.e., it does not require normality) (Hair et al., 2017).

The analysis was conducted in two main stages: measurement model evaluation and structural model evaluation (Hair et al., 2017). During the measurement model evaluation, tests were performed on convergent validity, discriminant validity, and construct reliability. The purpose of this phase was to ensure that each construct was accurately measured by its indicators. Once the measurement model met the required criteria, the next stage—structural model evaluation—was conducted. This stage involved testing the relationships between constructs through path coefficient analysis, R-square, and f^2 analysis (Hair et al., 2019; Hair et al., 2011; Hair et al., 2021). Significance testing was performed using the bootstrapping technique.

RESULT

A. Respondent Demographics

Based on the results of data collection using an online questionnaire, there were 166 respondents consisting of 84 men and 82 women. In addition, based on age group, most respondents were in the under-30 age group with 63.25 percent, and the fewest were in the over-45 age group with 9.04 percent. Regarding educational background, the predominant number of participants were DIV/S1 graduates, while the smallest number were DI/DII/DIII graduates. Details of the distribution of respondents can be seen in Table 1.

Table 1. Demographic Distribution

Demographic	Category	total	percentage
Gender	Male	84	50,60%
	Female	82	49,40%
Age	<30	105	63,25%
	31 – 45	46	27,71%
	> 45	15	9,04%
Education	Senior High School	10	6,02%
	DI/DII/DIII	7	4,22%
	DIV/bachelor	127	76,51%
	Master/Doctoral	22	13,25%

Source: Processed primary data (2026)

B. Measurement Model

In this study, measurements were conducted on the model in several stages, including internal validity using loading factors, followed by analysis of the discriminant validity results using the Fornell-Larcker Criterion and cross loadings, and finally a reliability test through construct reliability and validity (Gholian-Aval et al., 2025).

Table 2. Outer Loadings

Indicators	LF	Indicators	LF	Indicators	LF
AT1	0.891	HM3	0.889	PV2	0.973
AT2	0.873	HM4	0.899	PV3	0.914
AT3	0.879	PEOU1	0.809	SI1	0.868
AT4	0.876	PEOU2	0.854	SI2	0.770
BI1	0.946	PEOU3	0.762	SI3	0.792
BI2	0.962	PS1	0.968	SI4	0.802
BI3	0.871	PS2	0.982	TR1	0.779
FC1	0.703	PS3	0.968	TR2	0.700
FC2	0.729	PU1	0.903	TR3	0.732
FC3	0.853	PU2	0.891	TR4	0.797
FC4	0.624	PU3	0.868	UB1	0.954
HM1	0.920	PU4	0.893	UB2	0.951
HM2	0.923	PV1	0.941	UB3	0.946
	Values less than 0.70				

AT = Attitude, BI = Behavioral Intention, FC = Facilitating Condition, HM = Hedonic Motivation, PEOU = Perceived Ease of Use, PS = Perceived Severity, PU = Perceived Usefulness, PV = Perceived Vulnerability, SI = Social Influence, TR = Trust, UB = Use Behavior

Source: Processed primary data using SmartPLS (2026)

In the internal validity analysis using loading factors, the standard for a valid indicator is a loading factor greater than 0.70. Based on the data in Table 2, it is known that there is one indicator that has a loading factor below the standard, namely FC4 in the Facilitating Condition variable with a value of 0.624. Therefore, this indicator was excluded from the measurement to ensure the quality and validity of the measurement. After the indicator was excluded, the measurement was repeated and it was found that all indicators had a loading factor greater than 0.70.

To ensure that each variable is conceptually and empirically different from other variables, a discriminant validity test was conducted. The first test was conducted using the Fornell-Larcker criterion, which compares the square root of the AVE value of each variable with other variables; the AVE value of a variable must be greater than the correlation value with other variables. Based on the results in Table 3, it is known that the square root of the AVE value of each variable is greater than its correlation value with other variables.

Table 3. Fornell-Larcker Criterion

Variable	AT	BI	FC	HM	PEOU	PS	PU	PV	SI	TR	UB
AT	0.880										
BI	0.862	0.927									
FC	0.574	0.548	0.790								
HM	0.854	0.761	0.566	0.908							
PEOU	0.560	0.442	0.510	0.554	0.809						
PS	-0.146	-0.221	-0.050	-0.200	-0.002	0.973					
PU	0.834	0.757	0.537	0.762	0.626	-0.068	0.889				
PV	-0.216	-0.167	-0.027	-0.190	0.038	0.491	-0.089	0.943			
SI	0.350	0.360	0.197	0.327	0.370	0.042	0.336	0.030	0.809		
TR	0.619	0.540	0.523	0.622	0.574	-0.073	0.680	-0.116	0.375	0.753	
UB	0.803	0.767	0.532	0.807	0.530	-0.175	0.686	-0.115	0.239	0.530	0.950

Source: Processed primary data using SmartPLS (2026)

Furthermore, in the cross-loadings test in Table 4, it is also known that the value of each indicator has a higher value in the variable it measures. Therefore, based on this, it can be concluded that the model meets the discriminant validity requirements.

Table 4. Cross Loadings

Indicator	AT	BI	FC	HM	PEOU	PS	PU	PV	SI	TR	UB
AT1	0.887	0.738	0.458	0.744	0.492	-0.100	0.765	-0.181	0.313	0.536	0.646

AT2	0.870	0.713	0.463	0.701	0.433	-0.106	0.714	-0.141	0.280	0.509	0.646
AT3	0.883	0.798	0.539	0.749	0.553	-0.188	0.715	-0.188	0.355	0.566	0.792
AT4	0.879	0.784	0.561	0.811	0.492	-0.123	0.740	-0.250	0.285	0.566	0.744
BI1	0.811	0.946	0.504	0.699	0.360	-0.195	0.712	-0.162	0.343	0.485	0.687
BI2	0.815	0.962	0.522	0.719	0.399	-0.235	0.728	-0.172	0.348	0.512	0.708
BI3	0.772	0.871	0.496	0.697	0.471	-0.185	0.663	-0.131	0.309	0.503	0.737
FC1	0.296	0.339	0.763	0.323	0.309	0.012	0.325	0.009	0.104	0.437	0.247
FC2	0.398	0.338	0.733	0.345	0.448	-0.006	0.305	0.037	0.157	0.269	0.423
FC3	0.601	0.562	0.869	0.599	0.447	-0.092	0.571	-0.076	0.192	0.500	0.539
HM1	0.787	0.680	0.539	0.920	0.537	-0.166	0.694	-0.162	0.268	0.533	0.742
HM2	0.774	0.664	0.527	0.923	0.438	-0.213	0.689	-0.175	0.230	0.521	0.719
HM3	0.781	0.730	0.498	0.889	0.453	-0.152	0.661	-0.145	0.306	0.573	0.736
HM4	0.760	0.684	0.492	0.899	0.583	-0.198	0.725	-0.210	0.380	0.627	0.730
PEOU1	0.332	0.272	0.467	0.333	0.809	0.066	0.394	0.096	0.277	0.405	0.340
PEOU2	0.609	0.501	0.414	0.572	0.854	-0.086	0.668	-0.052	0.396	0.585	0.534
PEOU3	0.314	0.193	0.365	0.362	0.762	0.084	0.345	0.120	0.148	0.318	0.349
PS1	-0.138	-0.216	-0.059	-0.189	-0.010	0.968	-0.062	0.484	0.038	-0.075	-0.177
PS2	-0.137	-0.210	-0.058	-0.203	-0.011	0.982	-0.062	0.471	0.019	-0.071	-0.163
PS3	-0.155	-0.220	-0.028	-0.191	0.013	0.968	-0.074	0.476	0.064	-0.066	-0.171
PU1	0.765	0.670	0.451	0.703	0.547	-0.074	0.903	-0.096	0.281	0.564	0.642
PU2	0.683	0.596	0.446	0.638	0.529	-0.015	0.891	-0.100	0.301	0.578	0.580
PU3	0.700	0.691	0.538	0.660	0.589	-0.118	0.868	-0.043	0.247	0.644	0.601
PU4	0.807	0.724	0.474	0.703	0.559	-0.033	0.893	-0.080	0.362	0.627	0.613
PV1	-0.203	-0.152	-0.044	-0.185	0.006	0.469	-0.093	0.941	0.061	-0.129	-0.107
PV2	-0.219	-0.180	-0.054	-0.199	0.039	0.507	-0.087	0.973	0.019	-0.107	-0.128
PV3	-0.189	-0.136	0.032	-0.148	0.066	0.401	-0.072	0.914	0.003	-0.092	-0.085
SI1	0.426	0.436	0.269	0.413	0.383	-0.078	0.417	-0.034	0.868	0.421	0.324
SI2	0.147	0.125	0.047	0.129	0.239	0.172	0.140	0.036	0.770	0.187	0.097
SI3	0.135	0.166	0.040	0.114	0.202	0.161	0.116	0.115	0.792	0.181	0.042
SI4	0.147	0.154	0.056	0.103	0.225	0.141	0.123	0.123	0.802	0.202	0.039
TR1	0.474	0.381	0.340	0.439	0.375	-0.073	0.444	-0.222	0.305	0.779	0.387

TR2	0.377	0.303	0.348	0.400	0.298	-0.027	0.430	-0.081	0.213	0.700	0.305
TR3	0.432	0.395	0.367	0.466	0.327	0.078	0.439	-0.026	0.285	0.732	0.425
TR4	0.538	0.491	0.476	0.535	0.604	-0.130	0.649	-0.043	0.309	0.797	0.451
UB1	0.787	0.745	0.521	0.787	0.485	-0.165	0.663	-0.130	0.220	0.489	0.954
UB2	0.760	0.719	0.441	0.748	0.526	-0.156	0.643	-0.104	0.283	0.500	0.951
UB3	0.746	0.722	0.555	0.765	0.502	-0.178	0.650	-0.093	0.180	0.522	0.946

Source: Processed primary data using SmartPLS (2026)

The cross-loadings test showed that each indicator loaded most strongly on its respective construct, confirming that the model satisfies discriminant validity criteria. To assess construct validity further, composite reliability was computed, with a required threshold above 0.70. Separately, Cronbach's alpha was also evaluated using the same cutoff. Table 5 displays the composite reliability values, alongside Cronbach's alpha results, all of which exceed the minimum acceptable level, demonstrating that the measurement model is reliabl.

Table 5. Validity And Reliability Analysis

Variable	**rho_a**	**rho_c**	**Cronbach's alpha**	**AVE**
AT	0.903	0.932	0.903	0.774
BI	0.918	0.948	0.917	0.860
FC	0.780	0.832	0.710	0.625
HM	0.929	0.949	0.929	0.824
PEOU	0.845	0.850	0.759	0.655
PS	0.972	0.981	0.972	0.946
PU	0.914	0.938	0.911	0.790
PV	0.960	0.960	0.938	0.890
SI	1.320	0.883	0.879	0.654
TR	0.816	0.839	0.761	0.567
UB	0.947	0.966	0.946	0.903

Source: Processed primary data using SmartPLS (2026)

C. Structural Model

In the structural model assessment, testing was conducted by looking at the coefficient of determination or R-square (Low et al., 2025). This value shows how much the endogenous variable can be explained by the exogenous variables that influence it. Based on the PLS-SEM results in Table V and the standard (R^2 0.75=substantial, 0.50=moderate, 0.25=weak) (Gholian-Aval et al., 2025), it can be seen that the Behavioral Intention (BI) variable has an R-square value of 0.776. This means that 77.6% of the variance in BI can be explained in this study, where this value can be categorized as substantial (strong). For the Attitude (AT) variable (R-square 0.698) and Use Behavior (UB) variable (R-square 0.588), it is known that both values can be categorized at a moderate level. Meanwhile, for Perceived Usefulness (PU) (R-square 0.405) and Perceived Ease of Use (PEOU) (R-square 0.329), these R-square values are categorized as weak, which means that 40.5% and 32.9% of the variance, respectively, can be explained by this research model

Table 6. R-Square Analysis

Variable	Value	Adjusted Value
AT	0.698	0.694
BI	0.776	0.766
PEOU	0.329	0.325
PU	0.405	0.398
UB	0.588	0.586

Source: Processed primary data using SmartPLS (2026)

To test the hypothesis, an analysis was conducted based on the path coefficient value derived from the path coefficient measurement and specific indirect effect measurement using PLS-SEM. Measurements were made by looking at the original sample values to determine the direction of the path. If the original sample value is positive, it indicates that there is a unidirectional relationship, which means that if there is an increase in one construct, there will be an increase in the related construct. Meanwhile, if the value is negative, an increase in one construct will cause a decrease in the other construct.

In addition, to determine the significance of the path, an analysis was conducted based on the p-value with a significance level of 5% and 10%. Based on this, six hypotheses tested in this study were accepted at a significance level of 5%, and one other hypothesis was accepted at a significance level of 10%. Table 7 and Figure 2 show the findings from the hypothesis testing.

Table 7. Path Coefficients

	Hypothesis	Original sample	P values	Result	f2	Levels
H01	SI -> PU	0.121	0.083	S*	0.021	Weak
H02	TR -> PEOU	0.574	0.000	S	0.491	Strong
H03	PEOU -> PU	0.582	0.000	S	0.491	Strong
H04	PEOU -> AT	0.063	0.369	NS	0.008	
H05	PU -> AT	0.795	0.000	S	1.270	Strong
H06	AT -> BI	0.714	0.000	S	0.407	Strong
H07	PU -> BI	0.168	0.123	NS	0.033	
H08	PEOU -> BI	-0.131	0.059	NS	0.042	
H09	HM -> BI	0.032	0.747	NS	0.001	
H10	FC -> BI	0.091	0.110	NS	0.022	
H11	PS -> BI	-0.134	0.002	S	0.059	Weak
H12	PV -> BI	0.082	0.051	NS	0.021	
H13	BI -> UB	0.767	0.000	S	1.427	Strong

* Accepted at a significance level of 10%

S = Supported, Ns = Not Supported.

Source: Processed primary data using SmartPLS (2026)

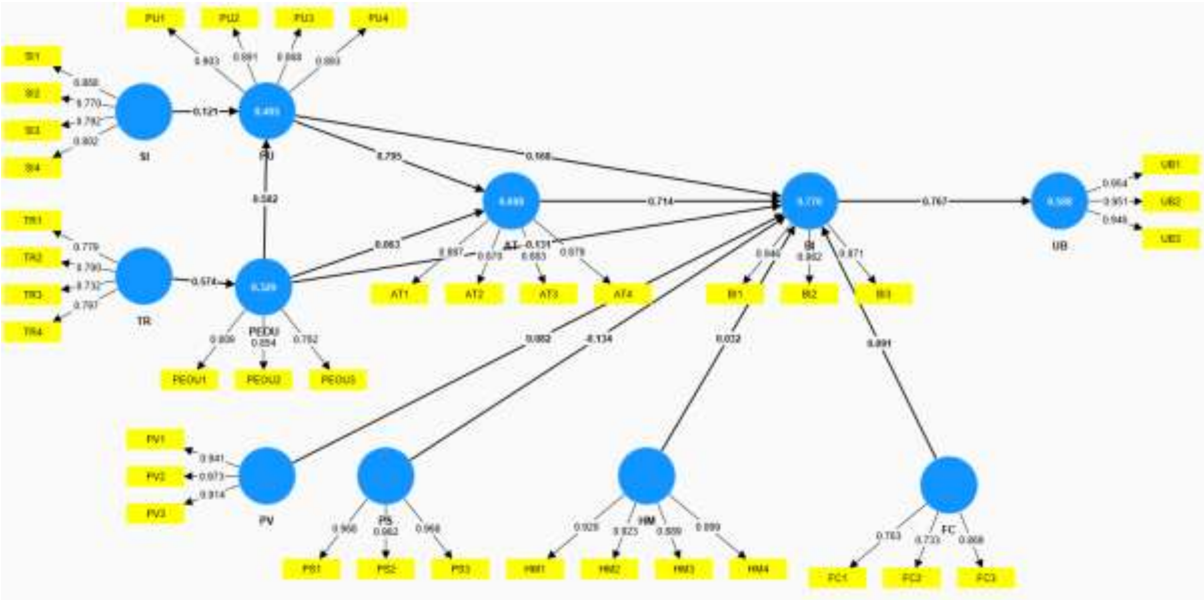

Figure 1. Smart-PLS Results

Source: Processed primary data using SmartPLS (2026)

Findings from a study of 166 respondents at BPS indicate that GenAI Use Behavior is significantly predicted by Behavioral Intention. Furthermore, Behavioral Intention was found to be directly and significantly shaped by two factors: positively by Attitude and negatively by Perceived Severity. The analysis also revealed that Perceived Usefulness only exerts an indirect influence on Behavioral Intention, which is mediated by Attitude. In a similar indirect pattern, Perceived Ease of Use was found to affect Attitude only through the mediating role of Perceived Usefulness. Regarding the antecedent variables, Trust demonstrated a significant positive effect on Perceived Ease of Use, while Social Influence positively predicted Perceived Usefulness. In contrast, variables such as Hedonic Motivation, Facilitating Condition, and Perceived Vulnerability did not show a statistically significant impact on their respective dependent variables.

To increase the acceptance and use of GenAI at BPS, the main focus that must be prepared by BPS is on shaping "Attitude" through "Usefulness". Therefore, BPS must focus on convincing employees that using GenAI is a good and wise idea. To achieve this, the organization cannot just provide access, but must actively demonstrate how GenAI can tangibly improve work quality, increase productivity, and save time in specific tasks at BPS.

BPS must also build Trust as a Foundation, because based on the results, it is known that employees will not feel that GenAI is easy to use if they do not trust it. Rather than just focusing on technical training, BPS must prioritize building trust. The organization needs to convince employees that GenAI applications are trustworthy, have the best interests of employees at heart, and are capable of helping to solve work problems.

In addition, to overcome one of the obstacles preventing employees from using GenAI, namely their significant concern that a data leak would have a severe and serious impact on the data processed by BPS, BPS must proactively mitigate risks to address this resistance. This can be done by providing a secure internal GenAI platform or issuing very clear and strict guidelines on what data classifications can and cannot be entered into external GenAI.

This research provides implications both theoretically and practically for government organizations, especially the case study organization, BPS-Statistics of Indonesia, in understanding the adoption and usage behavior of Generative AI.

Theoretical Implications

This study expands the understanding of factors that influence Use Behavior (UB) towards GenAI in government agencies by integrating the Technology Acceptance Model (TAM), UTAUT, and risk variables from the Protection Motivation Theory (PMT). Regarding the antecedent variable of Trust, this study supports and expands on previous findings that trust is an important foundation in technology adoption models. Specifically, these findings confirm that Trust has a significant effect on Perceived Ease of Use (PEOU) (H2). This is in line with studies that postulate trust as a prerequisite for users to feel comfortable and perceive technology as easy to use (Rathnayake et al., 2025; Rathnayake et al., 2025).

The first variable, Social Influence, is known to have a significant effect on Perceived Usefulness at a 10% significance level, but has no effect at a 5% significance level. This is similar to previous studies that state there is no significant effect between Social Influence and Perceived Usefulness (Abed, 2024; Rathnayake et al., 2025).

Regarding the Perceived Ease of Use variable, it is known that there are differences with previous studies. In this study, it is known that PEOU has no effect on Attitude and Behavioral Intention. This reinforces previous studies that also obtained the same results, namely that there is no effect between Perceived Ease of Use and Attitude. However, these results differ from previous studies that stated that there is a significant and positive influence between Perceived Ease of Use and Attitude in the use of GenAI (Alkadi & Abed, 2025). Meanwhile, regarding Behavioral Intention, these results differ from previous studies that stated that there is an influence from Perceived Ease of Use (Ma et al., 2025; Nawaz et al., 2024; Assaf et al., 2024).

In addition, the results of this study state the role of Attitude as a full mediator between Perceived Usefulness (PU) and Behavioral Intention (BI). It was found that PU does not directly influence BI. These results differ significantly from most of the literature, which states that there is a strong direct influence on BI (Ma et al., 2025; Assaf et al., 2024). This finding confirms that in the case study setting, affective attitude is a crucial bridge between cognitive perception and intention.

In terms of the UTAUT extension variables, there are differences from previous studies that state that variables such as Hedonic Motivation and Facilitating Condition have an influence (Nawaz et al., 2024). This study states that Hedonic Motivation and Facilitating Condition do not have a significant effect on Behavioral Intention. The insignificant finding of FC is in line with previous studies (Abed, 2024), indicating that at BPS, adoption is driven more by rational considerations (TAM) and risk (PMT) than by resource support or hedonistic motivation.

In the Protection Motivation Theory (PMT) variable, the finding of Perceived Severity having a significant negative effect supports the PMT framework. This result is in line with previous studies that found an effect on behavioral intention (Panggabean & Silalahi, 2025). This indicates that at BPS, the severity of the impact is a greater deterrent than the vulnerability to the occurrence of risk.

Practical Implications

This study provides actionable insights for government agencies, especially BPS-Statistics of Indonesia, aiming to formulate strategies for GenAI acceptance. Given that attitude was found to be a significant predictor of intention (BI), it is clear that a narrow or singular focus will be ineffective. Consequently, this study implies that BPS should adopt a holistic strategy that integrates cognitive, affective, system support, and intrinsic motivation components to successfully drive adoption.

BPS cannot only focus on technical training so that employees feel that GenAI is easy to use. This perception of ease will have no impact if employees do not see the real benefits of GenAI. Therefore, BPS must first prove the benefits to build attitudes, which are the main drivers of employees' intentions to use it. Employees may be reluctant to explore using GenAI if they do not trust the system. Thus, BPS must prioritize transparency, data security, and system reliability as a foundation before expecting widespread adoption. In addition, BPS can utilize influential leaders or employees to promote the benefits of GenAI. BPS should also not only focus on and believe that the use of GenAI is safe, but must focus on how best to mitigate the worst effects if a data breach occurs.

CONCLUSION

Based on data from 166 respondents at BPS-Statistics of Indonesia, the study found that Behavioral Intention was the only direct and significant predictor of Generative AI (GenAI) Use Behavior, with Behavioral Intention being positively influenced by Attitude and negatively affected by Perceived Severity. The results also revealed several indirect relationships: Perceived Usefulness influenced Behavioral Intention through Attitude, Perceived Ease of Use affected Attitude through Perceived Usefulness, Trust significantly influenced Perceived Ease of Use, and Social Influence impacted Perceived Usefulness, while Hedonic Motivation, Facilitating Conditions, and Perceived Vulnerability showed no significant effects. These findings highlight that strengthening positive employee attitudes—particularly by demonstrating the practical usefulness of GenAI in improving work quality, productivity, and efficiency—is critical for increasing adoption. Practically, organizations should encourage influential employees to act as early adopters, foster trust to enhance perceived ease of use, and reduce perceived risks by ensuring strong data security measures and clear governance policies. However, the study is limited by its focus on a single institution, a relatively small sample size, and modest explanatory power; therefore, future research should expand to multiple government institutions, include larger and more diverse samples, and incorporate additional variables to develop a more comprehensive understanding of GenAI adoption in the public sector.

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