Journal of Trends and Challenges in Artificial Intelligence

Vol. 03, No. 01 (2026) 1-12, DOI: 10.61552/JAI.2026.01.001 - http://jai.aspur.rs

RURALITE ACCEPTANCE ON ARTIFICIAL INTELLIGENCE TECHNOLOGY ON STUNTING PREVALENCE REDUCTION

Ella Lesmanawaty Wargadinata [1]

Received 12.10.2024.
Revised 08.11.2024.
Accepted 28.01.2025.

Keywords:

Technology acceptance, organizational capability, self-efficacy.

Original research

A B S T R A C T

Artificial intelligence (AI) technology in healthcare has the potential to reach mass targets by providing rapid and free-cost services. The paper tries to reveal determinant factors on AI acceptance using the extended Technology Acceptance Model and testing correlations among organizational capability and self-efficacy as external variables to user's acceptance on the classic TAM variables. The study utilized a structural equation model for quantitative tests. It is revealed that using advanced technology in rural areas goes beyond simply developing a system that meets technological standards per se. Building local organization capability is a must when it gives a multiplier positive impact on other variables. The better the organizational capability, the higher the self-efficacy of the village users, leading to higher acceptance and increased use of the AI application at the village level. These results reaffirm the strength of TAM as a foundational framework for understanding user acceptance of technology in diverse settings and validate its continued relevance in contemporary research.

1. INTRODUCTION

In line with the global agenda, stunting prevalence reduction in Indonesia has become a priority program; since 21.6% of Indonesian children suffer from stunting in 2022. Though, it was decrease compare to the 2013 survey with 37.2%. However, the data is still alarming that about 4.7 million Indonesian children are at risk of stunting. Stunting is failure growth due to chronic malnutrition during the critical physical and cognitive development of the first two years of a child's life (Budiastutik & Nugraheni, 2018; Ejaz & Latif, 2010). The obvious stunted children are shorter and height below average for their age (Titaley et al., 2019). Stunting has severe long-term impacts on children's health and development. Stunting syndrome reflected linear and multiplied children retardation growth, which is associated with morbidity, physical and mental retardation and leads to metabolic disease in adulthood (Leroy & Frongillo, 2019; Soliman et al., 2021; UNICEF et al., 2023). It is also important to note that stunting is more prevalent in rural areas (Akram et al., 2018; Khuwaja et al., 2005; Nugroho & Putri, 2019; Sserwanja et al., 2021).

Stunted children become a global issue when the long-term consequences will impede their physical and mental development (Galasso & Wagstaff, 2018; McGovern et al., 2017; Perkins et al., 2017). Irreversible physical and cognitive failure leads to substantial economic losses for low—and middle-income countries. The annual economic loss is at least US$135.4 billion, and sufferers experience significant income reductions (Akseer, 2022). The issue of stunting is complex and needs a comprehensive public policy framework to solve the problems. How does national policy interpret and provide

[1] Corresponding author: Ella Lesmanawaty Wargadinata
Email: ellawarga@ipdn.ac.id

sufficient budget, human resources, and building network at the local level are key determinant factors (Arieffiani & Ekowanti, 2024). Injecting technology innovation proves accelerate stunting prevalence reduction in Indonesia (Yuliansyah et al., 2022).

Globally,there is now great interest in using Artificial intelligence (AI), and several studies have focused on its utilization. AI provides significant benefits due to its ability to perform complex tasks. Artificial intelligence benefited human life with its ability to increase efficiency and faster, accurate, and real-time services. AI powerful technology has a significant potential for modern human life (Davenport & Ronanki, 2018; Dwivedi et al., 2021; Mikalef & Gupta, 2021; Yigitcanlar et al., 2020). Despite the pros and cons of ethical violations, the unimaginable development of sciences and technology over the last five decades has shifted the world from the conventional human capacity to superhuman capabilities. Artificial intelligence consistently performs specific tasks with mathematical precision and speed far exceeding human capabilities (Davenport, 2019; X. Zhang & Wen, 2021).

Artificial intelligence technology have utilized into broad spectrum human life (Jiang et al., 2017; Russell & Norvig, 2016). AI used in public administration since it contributes on decision making policy process (Dziundziuk et al., 2024) for better policy implementation (Mikhaylov et al., 2018). The use of AI in the health sector has been widely known and revealed it has the potential to improve quality of life (Alowais et al., 2023; Bajwa et al., 2021; Davenport, 2019; Jiang et al., 2017). Artificial intelligence is vital in improving diagnosis accuracy, personalized care, and health data management to provide more effective and affordable healthcare services (Lee et al., 2024; Ramezani et al., 2023; Wu, 2024). Though it less effective for complex case.

AI is an effective instrument for stunting. However, implementing this advanced technology in areas with low socio-economic and technological levels is questionable. Sumedang Regency area is 1.559 km2, divided into 26 sub districts and 270 villages at rural and 7 in town, the human index development is 72,69. In 2018, the number of stunting sufferers almost spread across villages. While the Sumedang Government believes in the potential of AI inline with the policy of smart-government and take advantages of gadget ownership among villagers, however several factors have to be considered.

Whereas, AI closely relate with urban context, well educated and well informed (Yigitcanlar et al., 2020), therefore how it utilized in rural areas is intersting to be exposed. Some paper reveal that community participation and its involvement as users are the main keys to the successful implementation of AI (Boyce et al., 2024; Dahawy & Kamel, 2005), especially for the advance-latest technology such as AI. Though the perception of AI still polarized among people, the controversy is around benefits and ethics, still debatable (Gerlich, 2023). Recent papers provide rich sources on how AI technology utilized and accepted. Some paper pointes direct dimension of AI' acceptance. Determinant factors of AI' acceptance is depend on country and individual digital capacity (Demaidi, 2023; Vu & Lim, 2022) trust comes as hinder factor for medical doctor (Tamori et al., 2022) to some extent, cultural is important factor when AI can't replicate human (Kelly et al., 2023). The most important factor for developing countries is that increasing capacity building, public-private partnerships, and tailored policy frameworks to address infrastructure limitations and skill gaps (Kelly et al., 2023) .

The Sumedang government acknowledges its shortcomings and has taken significant steps to implement the AI' stunting prevalence application. Collaborated with the private sector to strengthen technological infrastructure and utilize CSR funds to distribute smartphones for health and development volunteers, and government officials at the village level. Creating a comprehensive business processes involving different municipal agencies such as health, social, education, public works, regional planning, sub-district, and village organizations. The municipal government facilitates digital knowledge transfer through dissemination and training for village users. However, the impact of these efforts on the acceptance of artificial intelligence technology in rural communities still requires scientific validation. Accepting artificial intelligence technology in rural communities still needs to be scientifically proven.

The injection of AI as a mass-healthcare tool at the municipal administration level in developing countries is an interesting phenomenon that poses an intriguing question about how rural communities with a low level of economic-societal-digital literacy can accept this technology to their benefits and what the municipal' do to get optimum result.

The research uses a case study approach. The case study method is an in-depth research approach to a particular phenomenon or subject in a real situation (Priya, 2021). The main goal is to gain a deep understanding of how a phenomenon or specific issue operates in a specific context (Coombs, 2022) . The method selected based on some considerations: 1) The Sumedang government is the first local government organization to use AI formally on a wide scale to reduce stunting, 2) Sumedang is considered to be among the first AI' user and the leading reduce-stunting prevalence municipal in Indonesia.3) The use of AI has succeeded in reducing the prevalence of stunting significantly. 4) The central government then adopted the e-simpati application used in Sumedang for apply in 50 other municipalities that have high stunting prevalence rates. The question raises on this paper is How do ruralites accept artificial intelligence applications, and what is the determinant factor? The novelty of the paper is reveal the local organizational capability is determinant factor on how the technology accepted in rural areas.

2. LITERATURE REVIEW

The Technology Acceptance Model is a well-establishes framework for measuring individual-user reactions to the new technology (Martin, 2022). It covers two main variables: perceived usefulness (PU) and perceived ease of use (PEOU), which influence users' attitudes toward technology, affecting their intention to use it and, ultimately, their actual usage on its technology (Vogelsang et al., 2013) . PU refers to the increase in user job performance using a particular system. PEOU refers to the user's belief that the system is effortless. By understanding these factors, TAM helps predict and explain user adoption of new technologies. The user's belief that the system is effortless. By understanding these factors, TAM helps predict and explain user adoption of new technologies (Davis, 1989; Venkatesh & Davis, 1996). Suppose the 'common' technology acceptance tools are available in various models. Given its deep intervention in daily human activities, how is AI technology accepted when it replaces human work with machines and when utilized in public services? Public acceptance of AI services is related to the government's capacity as a provider (Gesk & Leyer, 2022), where trust and the practical applications of AI are significant factors shaping public opinion and engagement with the technology. Despite of uniformity acceptance tool for AI technology, however the recent studies revealed that the modified-extended Davis' TAM' model is the most preference models for explaining the factors that influence the acceptance of various artificial intelligence technologies across different user groups, settings, and (Agustini et al., 2023; Alhashmi et al., 2019; Aziz et al., 2020; Darayseh, 2023; Hercheui & Mech, 2021; Jimenez et al., 2021; Kim, 2024; Na et al., 2022; Sohn & Kwon, 2020; Wang et al., 2023; C. Zhang et al., 2023) . Along with technology development, TAM has evolved into an open model for adapting to different technological contexts, revealing new determinant factors on TAM generic (Alshammari & Rosli, 2020; Aziz et al., 2020; Marangunić & Granić, 2015).

In addition to the core variables of PEOU, PU, Attitude, Behavioral Intention, and Actual Use, the Technology Acceptance Model (TAM) also identifies external variables that influence AI technology acceptance. These external variables are frequently modified and extended in research on AI acceptance.These external variables addition include user characteristic: self efficacy, anxiety & stress (Darayseh, 2023; Liao et al., 2018; Marangunić & Granić, 2015; Navarro et al., 2023; C. Zhang et al., 2023), enjoymeny, effort, performance (Kim, 2024) experiences & skills (Agustini et al., 2023) ; innovation characteristic: compatibility, complexity (Hercheui & Mech, 2021), image: reliability, security , well being benefits (Kim, 2024) ; environmental characteristic: trust & subjective norm (AlQudah et al., 2021; Wang et al., 2023), innovativeness (Cornelissen et al., 2022).

Self-efficacy is a crucial external factor that affects the adoption of new technology, it is pertains to an individual's belief in their ability (Liao et al., 2018), know-how (Pan, 2020), desire (Darayseh, 2023) , confidence (Navarro et al., 2023), competence (Zhang et al., 2023) to use technology effectively. Research on technology acceptance in different areas, including rural and remote regions, shows that self-efficacy is the strong predictor, meaning that technology will only be used by users if they have adequate capacity to navigate it and help their tasks . Self-efficacy is rooted in the psychological concept of how people perceive and engage with new technologies.. Varying levels of individual self-efficacy lead to different outcomes in technology acceptance. This paper measures self-efficacy across three dimensions: knowledge, ability, and experience.is measured by three dimensions: knowledge, ability, and experiences.

The primary results of the TAM research are focused on individual decisions on whether the user will take or leave the new technology. Here, we can say that acceptance of AI depends on the user's preferences; however, who has responsibility for it? Do they increase digital capability on their own? The answer is yes if the user has adequate knowledge and socio-economic level and link with the new innovation, but how does it happen in for rural community in developing countries?

Some papers mention that formal institutions take part in TAM (Na et al., 2022). added TOE (technology-organization-environment) framework as important external variables for AI acceptance. The importance of organizational support with individual capacity on technology acceptance is also mentioned by Nasongkhla & Shieh (Nasongkhla & Shieh, 2023). Applied technology in the public sector in developing countries exposed organizational culture as a determinant factor of its acceptance (Corvalán, 2018) . The success of AI implementation is digital and intelligence government capacity'(Indra & Khoirunurrofik, 2022; Weber et al., 2023).

However, the ultimate goal of artificial intelligence in the public sector, particularly when engaging vulnerable groups, is to encourage collective action for their benefit. Achieving this requires robust governmental organizational capabilities that can provide technological and non-technological support to foster trust and understanding among these groups. The role of organizational capability in stunting reduction at the village level is revealed by previous research; when the budget is available, the local organization and administration capacity are capable enough, and the program will succeed (Debbarma & Chinnadurai, 2023). Utilization technology at the grassroots level needs comprehensive strategies and strengthening local organization capability (Konopik et al., 2022).

Herein, the framework on organizational capabilities enlightens what the municipal government has to do (Östlund et al., 2011) . He mentioned six dimensions: strategy and ecosystem, innovation thinking, data technology, operations, organizational design and leadership. Based on those literatures, the research reveal extended TAM model which emphasis on organizational capability and self efficacy as determinant factors.

3. METHOD

The study utilized a mixed method approach, structural equation model, SEM-PLS for quantitative test. Focusing on determinant factor as statistical test result to support and complement deep understanding of research objective conducted for qualitative approach. The research method used the survey questionnaires among AI application users at village level as research population Figure 1.

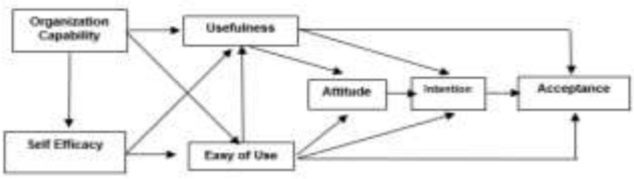

Figure 1. Research Model

The questionnaire was divided into three parts: the first contained an introduction and general information about the study's subject, the second contained user's demographic information gender, academic level and age. The third consisted 26 items that measured 7 variables: organization capability-six items; self-efficacy- 3 items; perceived of usefulness- 4 items; Easy of use-5 items; attitude towards AI applications- 2 items; behavioural intention-5 items and actual use- 1 item. The questions used a five-point Likert scale, a widely used method in social science research, to rate the level of user' response. The scale ranged from 1-5, with 1 indicating 'strongly disagree' and 5 indicating 'strongly agree'. Data analyzed by SEM-PLS. Data gathered from 27 villages in 27 sub-districts within Sumedang Regency, Indonesia. Data encompass 256 questionnaire anwers from village AI application's users: human development cadres, village officials, village integrated service volunteers who deal with todlers' health, family welfare empowerment' volunteers, the number of population is 378. The questionnaire was distributed with a return ratio of 67.7%, resulting in 256 AI users responding to the questionnaire. Study conducted in March-June 2024.
The questionnaire was designed according to the research objectives based on previous research (Cornelissen et al., 2022; Corvalán, 2018; Darayseh, 2023; Indra & Khoirunurrofik, 2022; Kelerey et al., 2020; Liao et al., 2018; Navarro et al., 2023; Östlund et al., 2011; Pan, 2020) . The objective of the question was to illustrate and examine the relationship between the research variables by measuring AI applications user' perception.
Scoping focus on determinant factor as statistical test result to support and complement deep understanding of research objective conducted for qualitative approach. Data gathered through interview with key informants who involve directly with this program: Sumedang's Regent, Regency's secretary, Regency officials, IT's enterprise, university's students, primary health center's officers, and supported by secondary data from scientific papers and related documents.
Combining the qualitative approach sequence with quantitative data will facilitate the researcher's finding of a comprehensive result. While the quantitative data offered statistical trends and measurable outcomes, the qualitative data allowed in-depth interpretation of the results. The method provides a better understanding of the links between theory and empirical findings (Shorten & Smith, 2017; Ursachi et al., 2015; Vebrianto et al., 2020) .

4. RESULT AND DISCUSSION

4.1 Respondents characteristic

The respondents reflect the general demographic of Indonesia in terms of education and age (Table 1).

Table 1. Respondent characteristic

Characteristics		Number	%
Gender	Male	55	21.5
	Female	201	78.5
Education	Elementary-Middle School	20	7.8
	High School	125	48.8
	College	76	29.7
	Graduate -Post Grad	35	13.7
Age	≥ 30	72	28.1
	30 40	150	58.6
	≥ 40	34	13.3

The majority attain a middle education level 48.8%) and belong to a productive age group (58.6%). In terms of gender, most of the respondent are women (78.5%), which reflects the typical high involvement of women in family-children health care program at the village level and women empowerment agenda in the same time (Sugiarto, 2020).

Reliability and Validity

This research employed a quantitative approach, utilizing the Structural Equation Modeling-Partial Least Squares (SEM-PLS) technique for statistical analysis. During the evaluation process, the results revealed that the constructs met the required standards for validity and reliability.
Validity: Research uses convergent and discriminant validity to measure construct validity. Average Variance Extracts (AVE) measure convergent validity. The threshold value for the AVE is ≥ 0.5.

Table 2. Convergent Validity

Variabel	Indikator	Loading Factor	Cut Value	AVE	Keterangan
Attitude Toward	A1	0,920	0,7	0,857	Valid
	A2	0,932	0,7		Valid
Actual Use	AU1	1,000	0,7	1,000	Valid
Behavior Intention Use	BI1	0,935	0,7	0,853	Valid
	BI2	0,908	0,7		Valid
	BI3	0,933	0,7		Valid
	BI4	0,876	0,7		Valid
	BI5	0,964	0,7		Valid
Perceived Easy to Use	E1	0,905	0,7	0,82	Valid
	E2	0,901	0,7		Valid
	E3	0,943	0,7		Valid
	E4	0,861	0,7		Valid
	E5	0,916	0,7		Valid
Oragnizational Capitacy	OC1	0,917	0,7	0,823	Valid
	OC2	0,866	0,7		Valid
	OC3	0,944	0,7		Valid
	OC4	0,947	0,7		Valid
	OC5	0,853	0,7		Valid
	OC6	0,913	0,7		Valid
Self Efficacy	SE1	0,919	0,7	0,858	Valid
	SE2	0,915	0,7		Valid
	SE3	0,945	0,7		Valid
Perceived Usefulness	U1	0,881	0,7	0,823	Valid
	U2	0,924	0,7		Valid
	U3	0,908	0,7		Valid
	U4	0,914	0,7		Valid

The result of reliability and validity shows that all the constructs have ≥ 0.5, which is convergently valid (Sarker et al., 2021). Convergent validity is presented in table 2.

Tabel 3. Fornell- Larcker Criteria

	A	AU	BI	E	OC	SE	U
Attitude	0,926						
Actual Use	0,798	1,000					
Behavioral Intention	0,680	0,872	0,924				
Perceived Easy to Use	0,708	0,644	0,562	0,906			
Organization Capability	0,688	0,779	0,604	0,663	0,907		
Self Efficacy	0,692	0,795	0,659	0,701	0,740	0,926	
Perceived Usefulness	0,765	0,810	0,685	0,658	0,758	0,805	0,907

The research construct validity is measured by Fornell-Larcker, HTMT ratio, and cross-loading (Table 3). The Fornell Larcker criteria show that all the diagonal values are more significant than the values of the table, which are horizontal and vertical diagonal values. While all the self-loading values of the individual items were also more significant than the cross-loading of the other items. (Sarker et al., 2021). Discriminant validity was verified using the Fornell-Larcker criterion and cross-loadings, ensuring that each construct was distinct (Afthanorhan et al., 2021).

The validity of the constructs and indicators in this study was evaluated using the Heterotrait-Monotrait (HTMT) ratio of correlations (Table 4).

Table 4. Heterotrait-Monotrait Ratios

	A	AU	BI	E	OC	SE	U
Attitude							
Actual Use	0,871						
Behavioral Intention	0,757	0,888					
Perceived Easy to Use	0,798	0,659	0,588				
Organization Capability	0,767	0,794	0,628	0,694			
Self Efficacy	0,788	0,826	0,696	0,751	0,782		
Perceived Usefulness	0,865	0,839	0,720	0,697	0,801	0,868	

The HTMT analysis demonstrated that all values were below the recommended threshold of 0.90, indicating satisfactory discriminant validity. This result confirms that the constructs in the model are distinct and that the indicators accurately measure their respective constructs (Yusoff et al., 2020). Both convergent and discriminant validity were confirmed. Convergent validity exceeded the recommended thresholds.

Table 5. Composite Reliability

Construct	Cronbach's Alpha	Composite Reliability	Reliability
A	0,834	0,923	reliabel
AU	1,000	1,000	reliabel
BI	0,957	0,967	reliabel
E	0,945	0,958	reliabel
OC	0,957	0,965	reliabel
SE	0,917	0,948	reliabel

Reliability: The instrument reliability classified if the outer loading value of each item close to or above 0.7 (Table 5). The test shows that items have loading values more significant than the threshold, the cronbach's alpha and the composite reliability above 0.7. Internal consistency through Cronbach's alpha and composite reliability scores above the acceptable benchmark of 0.7, indicating consistent measurements across items (Ursachi et al., 2015).These results validate the robustness of the measurement model, confirming that the constructs and indicators used in the study are reliable and valid for capturing the underlying phenomena.

Hypothesis Testing

Hypothesis testing by path analysis through R square and Q square, SRMR, and multi-co-linearity measurements are the final step in drawing conclusions and testing research model assumptions (Figure 2).

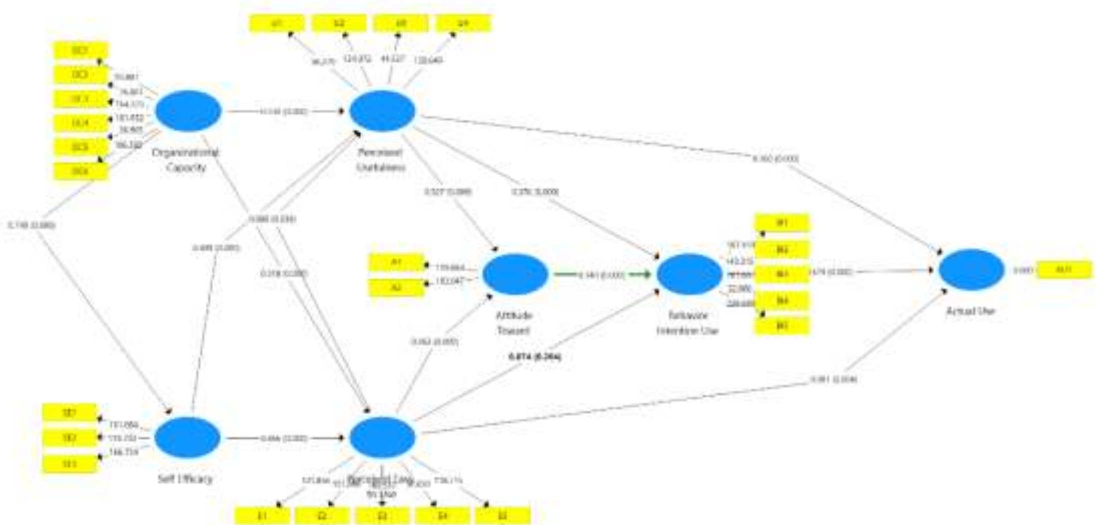

Figure 2. Path analysis model estimation results

The significance and direction of direct influence can be seen from the p-value, t-statistics, and path coefficients on each path connecting endogenous and exogenous variables. If the p-value <0.05, and the T statistic is > 1.96 (t value two tail, α 5%), and the T statistic is > 1.65 in the one-tail test, then it can be concluded that the exogenous variable has an influence significant towards endogenous with the direction of influence according to the sign attached to the path coefficient. Furthermore, if the p-value is > 0.05 and the T statistic < 1.96 (t value two tail, α 5%) in the two-tail test and the T statistic < 1.65 in the one-tail test, it is concluded that the exogenous variable has no significant effect on endogenous (Hair et al., 2017).

After establishing the model fit in the Partial Least Squares (PLS) analysis, the next step involved testing the relationships between variables. The influence testing was conducted through path analysis, including assessments of direct, indirect, and total effects. These tests provide a comprehensive understanding of the relationships among the constructs in the model. The bootstrapping method was employed to estimate the path coefficients and evaluate their significance. This non-parametric resampling technique enhances the reliability of the results by generating confidence intervals and t-statistics for hypothesis testing. The path analysis model estimation results are presented, demonstrating the significance of the direct, indirect, and total effects among the variables.

Table 6 shows the strength of all the direct relationships of the constructs, indicating fourteen direct relationships research's structural model. The first direct relationship is between the attitude of use and behavioral intention, p-value 0,000 < 0,05 T statistic 4,777 > 1,96 and positive path value in 0,340. The result significantly reflects a positive effect; the higher the attitude, the higher the behavior intention to use, and vice versa; a low attitude toward tends to have a low intention to use. The second direct relationship is between behavioral intention and actual use. p-value 0,000 < 0,05 T statistic 25,830 > 1,96 and positive path coefficient is 0,579. The result reflects a positive effect and significance; the higher the behavior intention to use, the higher the actual use, and vice versa; a low behavioral intention to use AI applications leads to low actual use.

The third direct relationship is between perceived ease of use and attitude toward use. .p value 0,000 < 0,05 T statistic 8,009 > 1,96 and positive path coefficient is 0,362. The result reflects a significant positive effect; the higher the perceived ease of use, the higher the attitude toward use, and vice versa; low perceived ease of use tends to a low attitude toward the use of the AI application.

The fourth direct relationship is between perceived ease of use and actual use. p-value is 0,004 < 0,05 T statistic 2,906 > 1,96 and positive path coefficient in 0,081. The result reflects a significant positive effect; the higher the perceived ease of use, the higher the actual use of AI application among ruralites, and vice versa; a low perceived easy to use tend to a low acceptance of ruralites in the *e-simpati* application.

The fifth direct relationship is between perceived usefulness and *behavior intention use*. p value is 0,264 > 0,05, T statistic 1,119 < 1,96. The relation is insignificant. The sixth, Perceived easy to use, has a positive and significant effect on perceived usefulness as shown by a p-value of 0.039 < 0.05 T statistic 2.074 > 1.96 and a coefficient on the positive path of 0.089; this means that the higher the perceived ease of use, the higher the perceived usefulness, and conversely low perceived ease of use tends to have low perceived usefulness.

The seventh: Organizational capability has a positive and significant effect on perceived ease of use, shown by a p-value of 0.000 < 0.05 T statistic 4.150 > 1.96 and a coefficient on the positive path of 0.318; the higher the organizational capacity, the higher the perceived ease. to use, and vice versa. Low organizational capacity tends to have low perceived ease of use.

The eighth direct relationship is that organizational capability has a positive and significant effect on self-efficacy, shown by a p-value of 0.000 < 0.05 T statistic 23.659 > 1.96 and a coefficient on the positive path of 0.740; the higher the organizational capability, the higher the self-efficacy. conversely, low organizational capacity tends to have low self-efficacy.

The tenth, Self-efficacy, has a positive and significant effect on perceived ease of use, shown by a p-value of 0.000 < 0.05 T statistic 6.476 > 1.96 and a coefficient on the positive path of 0.466; this means that the higher the self-efficacy, the higher the perceived ease to use, and vice versa, low self-efficacy tends to have low perceived ease of use.

The eleventh direct relationship: Self-efficacy has a positive and significant effect on perceived usefulness, shown by a p-value of 0.000 < 0.05 T statistic 8.620 > 1.96 and a coefficient on the positive path of 0.499; this means that the higher the self-efficacy, the higher perceived usefulness, and conversely low self-efficacy tends to have low perceived usefulness.

The twelfth, Perceived usefulness, has a positive and significant effect on attitude toward as indicated by a p-value of 0.000 < 0.05 T statistic 11.020 > 1.96 and a coefficient on the positive path of 0.527; this means that the higher the perceived usefulness, the higher the attitude toward to use. Conversely, those with low perceived usefulness tend to have a low attitude toward using the AI application.

The thirteenth direct relationship: Perceived usefulness has a positive and significant effect on actual use as shown by a p-value of 0.000 < 0.05 T statistic 11.646 > 1.96 and a coefficient on the positive path of 0.360; this means that the higher the perceived usefulness, the higher the actual use, and vice versa, low perceived usefulness tends to have low actual use.

The Fourteenth direct relationship: Perceived usefulness has a positive and significant effect on behavior intention to use as indicated by a p-value of 0.000 < 0.05 T statistic 5.685 > 1.96 and a coefficient on the positive path of

0.376, this means that the higher the perceived usefulness, the higher behavior intention to use, conversely, perceived usefulness, which tends to be low, has low behavior intention to use.

Table 6. Path Coefficient

Relationship	ß	T Stat	P Values
A -> BI	0,340	4,777	0,000
BI -> AU	0,579	25,830	0,000
E -> A	0,362	8,009	0,000
E -> AU	0,081	2,906	0,004
E -> BI	0,074	1,119	0,264
E -> U	0,089	2,074	0,039
OC -> E	0,318	4,150	0,000
OC -> SE	0,740	23,659	0,000
OC -> U	0,330	5,970	0,000
SE -> E	0,466	6,476	0,000
SE -> U	0,499	8,620	0,000
U -> A	0,527	11,020	0,000
U -> AU	0,360	11,646	0,000
U -> BI	0,376	5,685	0,000

The role of organizational capability in technology acceptance has already been mentioned. However, more is needed to cover how it is run. Here are the details of what the organization does to trigger advanced technology among rural people. The Sumedang regency fully realizes its standpoint, which is a lack of capacity in terms of budget, human resources, technology, and low digital literacy among the user’s target. The first step, which The Sumedang Regency does, is to optimize corporate social Responsibility in collaboration with *Telkomsel,* a state-owned IT enterprise, to create and develop applications. Simultaneously, the Sumedang formed an IT workforce to absorb the advanced digital technology knowledge and prepare IT facilities through Provincial aid. When the application was available, the task force trained to take over the IT technology. The second step is to disseminate the mobile AI application and distribute the smartphone – as CSR from the private sector to the *Posyandu*- integrated health service post cadres at the forefront of maternal and child health at the village level. They have to collect, update, and input vital stunting indicators, which will be able to give real-time data. Meanwhile, the regency and the University collaborate when the number of stunted targets is scattered. The Sumedang Regency Government is collaborating with higher education service institutions in Region IV by holding thematic internships in 2023 and 2024, involving 1,500 students from 111 universities. The new collaboration model between academicians and government creates mutual benefits for both sides, helping the government reach its mission. On the other hand, students benefit from how public policy is implemented in real life.

The study utilized the Technology Acceptance Model (TAM) to examine factors influencing the acceptance of new technology. The model included perceived usefulness, perceived ease of use, attitude toward use, and behavioral intention to use as endogenous variables. Hypothesis testing, conducted using Structural Equation Modeling-Partial Least Squares (SEM-PLS), revealed that all endogenous variables significantly influenced the acceptance of new technology.

In addition to the core constructs of the Technology Acceptance Model (TAM), this study extended the model by incorporating self-efficacy and organizational capability as endogenous variables to provide a more comprehensive understanding of user acceptance of new technology especially for AI. The hypothesis testing revealed that self-efficacy and organizational capability significantly affected user acceptance.

The findings of this study are consistent with and provide empirical support for the Technology Acceptance Model (Davis, 1989; Venkatesh & Davis, 1996). The significant relationships identified among perceived usefulness, perceived ease of use, attitude, and behavioral intention align closely with the theoretical foundations of TAM. Add self-efficacy and organizational capability as extended variables further corroborates the model’s adaptability in addressing broader contextual factors influencing technology acceptance. These results reaffirm the strength of TAM as a foundational framework for understanding user acceptance of technology in diverse settings and validate its continued relevance in contemporary research.

5. CONCLUSION

Building organizational capability is fundamental to how advanced technology is used in peripheral areas with multifaceted conditions. Research findings fill the gap on how local organizations build and strengthen themselves to support digital innovation for local people, which needs to be revealed from previous research. The local capability translates into different efforts; collaboration with different external actors and how rural people are empowered through training-education on AI applications and supported by distributing smartphones resulted in ruralites' self-efficacy level. Self-efficacy is an essential factor in the Technology Acceptance Model because it influences users' perceptions of the ease of use and usefulness of technology and their intention to adopt and use the technology. By increasing user self-efficacy through training, support, and intuitive design, organizations can increase the acceptance and use of new technologies.

Acknowledgements.
We sincerely thank The Sumedang regency officials who facilitated this research, thanks to the IPDN, which provides a research stimulant grant. Our appreciation for the enumerators who assist in data collection.

References:

Abdullah, F., Ward, R., & Ahmed, E. (2016). Investigating the influence of the most commonly used external variables of TAM on students' Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) of e-portfolios. *Computers in Human Behavior, 63*, 75–90. https://doi.org/https://doi.org/10.1016/j.chb.2016.05.014

Afthanorhan, A., Ghazali, P. L., & Rashid, N. (2021). Discriminant Validity: A Comparison of CBSEM and Consistent PLS using Fornell & Larcker and HTMT Approaches. *Journal of Physics: Conference Series*, *1874*(012085), 1–6. https://doi.org/doi:10.1088/1742-6596/1874/1/012085

Agustini, K., Gaffar, V., Dirgantari, P. D., & Furqon, C. (2023). Behavioral Technology Acceptance Model In Health Care Industry: Systematic Literature Review. *Indonesian Journal of Pharmaceutical Science and Technology*, *5*(2), 131–139. https://doi.org/https://doi.org/10.24198/ijpst.v0i0.50591

Akram, R., Sultana, M., Ali, N., Sheikh, N., & Sarker, A. R. (2018). Prevalence and Determinants of Stunting Among Preschool Children and Its Urban–Rural Disparities in Bangladesh. *Food and Nutrition Bulletin*, *39*(4), 521–535. https://doi.org/10.1177/0379572118794770

Akseer, N. (2022). Economic costs of childhood stunting to the private sector in low- and middle-income countries. *EClinicalMedicine*, *45*(101320).

Alam, A., & Saputro, I. A. (2022). A Qualitative analysis of user interface design on a sharia finethech application based on Technology Acceptance Model (TAM). *Jurnal TAM (Technology Acceptance Model)*, *13*(1), 9–16.

Alhashmi, S. F., Salloum, S. A., & Mhamdi, C. (2019). Implementing Artificial Intelligence in the United Arab Emirates Healthcare Sector: An Extended Technology Acceptance Model. *International Journal of Information Technology and Language Studies (IJITLS)*, *3*(3), 27–42.

Alowais, S. A., Alghamdi, S. S., Alsuhebany, N., Alqahtani, T., Alshaya, A. I., Almohareb, S. N., Aldairem, A., Alrashed, M., Saleh, K. Bin, Badreldin, H. A., Yami, M. S. Al, Harbi, S. Al, & Albekairy, A. M. (2023). Revolutionizing healthcare: the role of artificial intelligence in clinical practice. *BMC Medical Education*, *23*(689), 1–15. https://doi.org/https://doi.org/10.1186/s12909-023-04698-z

AlQudah, A. A., Al-Emran, M., & Shaalan, K. (2021). Technology Acceptance in Healthcare: A Systematic Review. *Applied Science*, *11*(22), 10537. https://doi.org/https://doi.org/10.3390/app112210537

Alshammari, S. H., & Rosli, M. S. (2020). A Review of Technology Acceptance Models and Theories. *Innovative Teaching and Learning Journal*, *4*(2), 12–22.

Arieffiani, D., & Ekowanti, M. R. L. (2024). Evaluating Local Government Policy Innovations. *Jurnal Bina Praja*, *16*(1), 1–20. https://doi.org/https://doi.org/10.21787/jbp.16.2024.1-20

Aziz, M. N. A., Norlizaiha, S., Baharom, M. K., & Kamaruddin, N. (2020). The evolution of the technology acceptance mosel (TAM). In N. F. Habidin, S. Y. Y. Ong, C. T. Waheda, M. U. Aiman, & N. M. Fuzi (Eds.), *The Interdisciplinary of Management, Economic and Social Research* (p. 272). Kaizentrenovation Sdn Bhd Tanjung Malim.

Bajwa, J., Munir, U., Nori, A., & Williams, B. (2021). Artificial intelligence in healthcare: transforming the practice of medicine. *Future Healthcare*, *8*(2), 188–194. https://doi.org/doi: 10.7861/fhj.2021-0095

Boyce, L., Harun, A., Prybutok, G., & Prybutok, V. R. (2024). The Role of Technology in Online Health Communities: A Study of Information-Seeking Behavior. *Healthcare*, *12*(3), 336. https://doi.org/10.3390/healthcare12030336

Budiastutik, I., & Nugraheni, S. A. (2018). Determinants of Stunting in Indonesia: A Review Article. *International Journal Of Healtcare Research*, *1*(2), 43–49.

Coombs, H. (2022). *Case Study Research Defined - Single or Multiple? (White Paper)*. https://doi.org/DOI: 10.5281/zenodo.7604301

Cornelissen, L., Egher, C., Beek, V. van, Williamson, L., & Hommes, D. (2022). The Drivers of Acceptance of Artificial Intelligence–Powered Care Pathways Among Medical Professionals: Web-Based Survey Study. *JMIR Form Res*, *6*(6), e33368.

Corvalán, J. G. (2018). Digital and Intelligent Public Administration: transformations in the era of artificial intelligence. *A&C – Revista De Direito Administrativo & Constitutucional*, *18*(71), 55–87. https://doi.org/https://doi.org/10.21056/aec.v18i71.857

Dahawy, K., & Kamel, S. (2005). How Do We Accept Technology? The Effect of Individual Differences. *Managing Modern Organizations Through Information Technology*, 271–276.

Darayseh, A. Al. (2023). Acceptance of artificial intelligence in teaching science: Science teachers' perspective. *Computers and Education: Artificial Intelligence*, *4*(100132). https://doi.org/https://doi.org/10.1016/j.caeai.2023.100132

Dash, G., & Paul, J. (2021). CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting. *Technological Forecasting & Social Change*, *173*(121092). https://doi.org/https://doi.org/10.1016/j.techfore.2021.121092

Davenport, T. (2019). The potential for artificial intelligence in healthcare. *Future Healthcare*, *6*(2), 94–98. https://doi.org/https://doi.org/10.7861%2Ffuturehosp.6-2-94

Davenport, T., & Ronanki, R. (2018). Artificial intelligence for the real world. Harvard. *Harvard Business Review*, *96*(1), 108–116. https://blockqai.com/wp-content/uploads/2021/01/analytics-hbr-ai-for-the-real-world.pdf

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, *13*(3), 319–339. https://doi.org/DOI: 10.2307/249008

Debbarma, A., & Chinnadurai, A. S. (2023). Digital transformation in local governance: opportunities challenges and strategies. *International Journal of Social Science Educational Economics Agriculture Research and Technology (IJSET)*, *3*(1), 152–156.

Demaidi, M. N. (2023). Artificial intelligence national strategy in a developing country. *AI & SOCIETY*. https://link.springer.com/article/10.1007/s00146-023-01779-x

Dwivedi, Y. K., Hughes, L., Ismagilova, E., G., Coombs, C., CricAartsk, T., . . ., & Eirug, A. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, *57*, 1–47. https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Dziundziuk, V., Dziundziuk, B., Karamyshev, D., Krutii, O., & Sobol, R. (2024). Artificial intelligence-Based Decision-Making in Public Administration. *Public Policy And Adminsitration*, *23*(24), 422–440. https://doi.org/DOI: 10.13165/VPA-24-23-4-01

Ejaz, M. S., & Latif, N. (2010). Stunting and micronutrient deficiencies in malnourished children. *Journal of Pakistan Medical Association*, *60*(7), 543–547.

Galasso, E., & Wagstaff, A. (2018). *The Aggregate Income Losses from Childhood Stunting and the Returns to a Nutrition Intervention Aimed at Reducing Stunting* (Policy Research Working Paper 8536).

Gerlich, M. (2023). Perceptions and Acceptance of Artificial Intelligence: A Multi-Dimensional Study. . . *Social Sciences*, *12*(502), 1–24. 10.3390/socsci12090502

Gesk, T. S., & Leyer, M. (2022). Citizens' acceptance of artificial intelligence in public services. *Government Information Quarterly*, *39*(3), 101704. https://doi.org/https://doi.org/10.1016/j.giq.2022.101704

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)* (2nd editio). Sage. https://eli.johogo.com/Class/CCU/SEM/_A Primer on Partial Least Squares Structural Equation Modeling_Hair.pdf

Hercheui, M., & Mech, G. (2021). Factors affecting the adoption of artificial intelligence in healthcare. *Global Journal of Business Research*, *15*(1), 77–88.

Indra, J., & Khoirunurrofik, K. (2022). Understanding the role of village fund and administrative capacity in stunting reduction: Empirical evidence from Indonesia. *PLOS ONE*, *17*(1), e0262743. https://doi.org/https://doi.org/10.1371/journal.pone.0262743

Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., Wang, Y., Dong, Q., Shen, H., & Wang, Y. (2017). Artificial intelligence in healthcare: past, present and future. *Stroke and Vascular Neurology*, *2*(e000101), 230–243. https://doi.org/https://doi.org/10.1136/svn-2017-000101

Jimenez, I. A. C., García, L. C. C., Violante, M. G., Marcolin, F., & Vezzetti, E. (2021). Commonly Used External TAM Variables in e-Learning, Agriculture and Virtual Reality Applications. *Future Internet*, *13*(1), 1–21. https://doi.org/https://doi.org/10.3390/fi13010007

Kelerey, B., Djatmika, . Eri Tri, & Siswanto, E. (2020). The effect of technology acceptance model and organizational culture to the employee performance and attitude as mediator variable (A study at academic and library employee in Universitas Negeri Malang,Indonesia). *South East Asia Journal of Contemporary Business, Economics and Law*, *21*(5), 10–20.

Kelly, S., Kaye, S.-A., & Oviedo-Trespalacios, O. (2023). What factors contribute to the acceptance of artificial intelligence? A systematic review. *Telematics and Informatics*, *77*(10.1016/j.tele.2022.101925).

Khuwaja, S., Selwyn, B. J., & Shah, S. M. (2005). Prevalence and Correlates of Stunting among Primary School Children in Rural Areas of Southern Pakistan. *Journal of Tropical Pediatrics*, *51*(2), 72–77. https://doi.org/10.1093/tropej/fmh067

Kim, S. D. (2024). *Application and Challenges of the Technology Acceptance Model in Elderly Healthcare: Insights from ChatGPT*. *12*(5), 68. https://doi.org/https://doi.org/10.3390/technologies12050068

Konopik, J., Jahn, C., Schuster, T., Hoßbach, N., & Pflaum, A. (2022). Mastering the digital transformation through organizational capabilities: A conceptual framework. *Digital Business*, *2*. https://doi.org/https://doi.org/10.1016/j.digbus.2021.100019

Lee, J., Park, J. S., Feng, B., & Wang, K. N. (2024). Cross-Sectional Analysis of Australian Dental Practitioners' Perceptions of Teledentistry. *EAI EndorsedTransactions on Scalable Information Systems*, *11*, 1–11. https://doi.org/doi: 10.4108/eetsis.5366

Leroy, J. L., & Frongillo, E. A. (2019). Perspective: What Does Stunting Really Mean? A Critical Review of the Evidence. *Advances in Nutrition*, *10*(2), 196–204. https://doi.org/https://doi.org/10.1093/advances/nmy101

Liao, S., Hong, J.-C., Wen, M.-H., Pan, Y.-C., & Wu, Y.-W. (2018). Applying Technology Acceptance Model (TAM) to explore Users' Behavioral Intention to Adopt a Performance Assessment System for E-book Production. *EURASIA Journal of Mathematics, Science and Technology Education*, *14*(10), em1601. https://doi.org/https://doi.org/10.29333/ejmste/93575

Luo, T., Moore, D. R., Franklin, T., & Crompton, H. (2019). Applying a Modified Technology Acceptance Model to Applying a Modified Technology Acceptance Model to Qualitatively Analyse the Factors Affecting Microblogging Qualitatively Analyse the Factors Affecting Microblogging Integration. *Int. J. Social Media and Interactive Learning Environments*, *6*(2).

Marangunić, N., & Granić, A. (2015). Technology acceptance model: a literature review from 1986 to 2013. *Universal Access in the Information Society*, *14*(1), 81–95. https://doi.org/https://doi.org/10.1007/s10209-014-0348-1

Martin, T. (2022). A Literature Review on The Technology Acceptance Model. *International Journal of Academic Research in Business and Social Sciences*, *12*(11), 2859 – 2884. https://doi.org/http://dx.doi.org/10.6007/IJARBSS/v12-i11/14115

McGovern, M. E., Krishna, A., Aguayo, V. M., & Subramanian, S. (2017). A review of the evidence linking child stunting to economic outcomes. *International Journal of Epidemiology*, *0*(0), 1–21. https://doi.org/doi: 10.1093/ije/dyx017

Mikalef, P., & Gupta, M. (2021). Artificial Intelligence Capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information and Management*, 1–48. https://doi.org/https://doi.org/10.1016/j.im.2021.103434

Mikhaylov, S. J., Esteve, M., & Campion, A. (2018). Artificial intelligence for the public sector: opportunities and challenges of cross-sector collaboration. *Phil. Trans. R. Soc. A*, *376*(: 20170357.). https://doi.org/https://doi.org/10.1098/rsta.2017.0357

Na, S., Heo, S., Han, S., Shin, Y., & Youngsook, R. (2022). Acceptance Model of Artificial Intelligence (AI)-Based Technologies in Construction Firms: Applying the Technology Acceptance Model (TAM) in Combination with the Technology–Organisation–Environment (TOE) Framework. *Buildings*, *12*(90). https://doi.org/. https:// doi.org/10.3390/buildings12020090

Nasongkhla, J., & Shieh, C.-J. (2023). Using technology acceptance model to discuss factors in university employees' behavior intention to apply social media. *Online Journal of Communication and Media Technologies, 13*(2), e202317. https://doi.org/https://doi.org/10.30935/ojcmt/13019

Navarro, R., Vega, V., Bayona, H., Bernal, V., & Garcia, A. (2023). Relationship between technology acceptance model, self-regulation strategies, and academic self-efficacy with academic performance and perceived learning among college students during remote education. *Frontiers in Psychology*, *14*. https://doi.org/https://doi.org/10.3389/fpsyg.2023.1227956

Nugroho, A., & Putri, S. (2019). Perbedaan Determinan Balita Stunting di Pedesaan dan Perkotaan di Provinsi Lampung. *Jurnal Ilmiah Keperawatan Sai Betik*, *15*(2), 84–94. https://ejurnal.poltekkes-tjk.ac.id/index.php/JKEP/article/view/1499/1058

Östlund, U., Kidd, L., Wengström, Y., & Rowa-Dewar, N. (2011). Combining qualitative and quantitative research within mixed method research designs: A methodological review. *International Journal of Nursing Studies*, *48*(3), 369–383. https://doi.org/doi: 10.1016/j.ijnurstu.2010.10.005

Pan, X. (2020). Technology Acceptance, Technological Self-Efficacy, and Attitude Toward Technology-Based Self-Directed Learning: Learning Motivation as a Mediator. *Front. Psychol.*, *11*(564294.). https://doi.org/doi: 10.3389/fpsyg.2020.564294

Perkins, J. M., Rockli, K., Krishna, A., McGovern, M., Aguayo, V. M., & Subramanian, S. V. (2017). Understanding the Association between Stunting and Child Development in Low- and Middle-Income Countries: Next Steps for Research and Intervention. *Social Science & Medicine*, *193*, 101–109. https://doi.org/https://doi.org/10.1016/j.socscimed.2017.09.039

Priya, A. (2021). Case Study Methodology of Qualitative Research: Key Attributes and Navigating the Conundrums in Its Application. *Sociological Bulletin*, *70*(1), 94–110. https://doi.org/https://doi.org/10.1177/0038022920970318

Ramezani, M., Takian, A., Bakhtiar, A., Rabiee, H. R., Ghazanfari, S., & Mostafavi, H. (2023). The application of artificial intelligence in health policy: a scoping review. *BMC Health Services Research*, *23*(1416), 1–11. https://doi.org/https://doi.org/10.1186/s12913-023-10462-2

Russell, S., & Norvig, P. (2016). *Artificial Intelligence: A Modern Approach* (4th ed.). Pearson education.

Sarker, T., Apurbo, S., Rabbany, M. G., Barmon, M., Roy, R., Rahman, M. A., Hossain, Z., Hoque, F., & Asaduzzaman, M. (2021). Evaluation of preventive, supportive and awareness building measures among international students in China in response to COVID-19: a structural equation modeling approach. *Global Health Research and Policy*, *6*(10), 1–10. https://doi.org/https://doi.org/10.1186/s41256-021-00192-5

Shorten, A., & Smith, J. (2017). Mixed methods research: expanding the evidence base. *Evid Based Nurs*, *20*(3), 74–75. https://doi.org/https://doi.org/10.1136/eb-2017-102699

Sohn, K., & Kwon, O. (2020). Technology Acceptance Theories and Factors Influencing Artificial Intelligence-based Intelligent Products. *Telematics and Informatics*, *47*(101324). https://doi.org/https://doi.org/10.1016/j.tele.2019.101324

Soliman, A., Sanctis, V. De, Alaaraj, N., Ahmed, S., Alyafei, F., Hamed, N., & Soliman, N. (2021). Early and Long-term Consequences of Nutritional Stunting: From Childhood to Adulthood. *Acta Biomedica*, *92*(1), e2021168. https://doi.org/https://doi.org/10.23750%2Fabm.v92i1.11346

Sserwanja, Q., Kamara, K., Mutisya, L. M., Musaba, M. W., & Ziaei, S. (2021). Rural and Urban Correlates of Stunting Among Under-Five Children in Sierra Leone: A 2019 Nationwide Cross-Sectional Survey. *Nutrition and Metabolic Insight*, *14*(11786388211047056.). https://doi.org/10.1177/11786388211047056

Sugiarto, S. (2020). Isu Pemberdayaan Perempuan dalam Pembangunan Desa. *Jurnal Sosial Soedirman*, *1*(1), 26–42. https://doi.org/https://doi.org/10.20884/juss.v4i1.3161

Tamori, H., Yamashina, H., Mukai, M., Morii, Y., Suzuki, T., & Ogasawara, K. (2022). Acceptance of the Use of Artificial Intelligence in Medicine Among Japan's Doctors and the Public: A Questionnaire Survey. *JMIR Hum Factors*, *9*(1), e24680. https://doi.org/10.2196/24680

Titaley, C. R., Ariawan, I., Hapsari, D., Muasyaroh, A., & Dibley, M. J. (2019). Determinants of the Stunting of Children Under Two Years Old in Indonesia: A Multilevel Analysis of the 2013 Indonesia Basic Health Survey. *Nutrients*, *11*(5), 1106. https://doi.org/https://doi.org/10.3390%2Fnu11051106

UNICEF, Hayashi, C., Krasevec, J., Kawakatsu, Y., Johnston, R., Mehra, V., Borghi, E., Dominguez, E., Flores-Urrutia, M., Gatica-Domínguez, G., Kumapley, R., Serajuddin, U., & Suzuki, E. (2023). *Levels and trends in child malnutrition*. https://data.unicef.org/resources/jme-report-2023/

Ursachi, G., Horodnic, I. A., & Zait, A. (2015). How reliable are measurement scales? External factors with indirect influence on reliability estimators. *Procedia Economics and Finance*, *20*, 679–686. https://doi.org/doi: 10.1016/S2212-5671(15)00123-9

Vebrianto, R., Thahir, M., Putriani, Z., & Diniya, D. (2020). Mixed Methods Research: Trends and Issues in Research Methodology. *Bedelau: Journal of Education and Learning*, *1*(1), 63–73.

Venkatesh, V., & Davis, F. . (1996). A Critical Assessment of Potential Measurement Biases in the Technology Acceptance Model: Three Experiments. *Three Experiments. International Journal of HumanComputer Study*, *45*(1), 19–45. https://doi.org/https://doi.org/10.1006/ijhc.1996.0040

Vogelsang, K., Steinhüser, M., & Hoppe, U. (2013). A Qualitative Approach to Examine Technology Acceptance. *Thirty Fourth International Conference on Information Systems*, 1–16.

Vu, H. ., & Lim, J. (2022). Effects of country and individual factors on public acceptance of artificial intelligence and robotics technologies: A multilevel SEM analysis of 28-country survey data. *Behaviour & Information Technology*, *41*(7), 1515–1528. https://doi.org/10.1080/0144929X.2021.1884288

Wang, C., Ahmad, S. F., Ayassrah, A. Y. A. B. A., Awwad, E. M., Irshad, M., Ali, Y. A., Al-Razgan, M., Khan, Y., & Han, H. (2023). An empirical evaluation of technology acceptance model for Artificial Intelligence in E-commerce. *Heliyon*, *9*(e18349). https://doi.org/https://doi.org/10.1016/j.heliyon.2023.e18349

Weber, M., Engert, M., Schafer, N., Weking, J., & Krcmar, H. (2023). Organizational Capabilities for AI Implementation—Coping with Inscrutability and Data Dependency in AI. *Information Systems Frontiers*, *25*, 1549–1569. https://doi.org/https://doi.org/10.1007/s10796-022-10297-y

Wu, B. (2024). Real Time Monitoring Research on Rehabilitation Effect of Artificial Intelligence Wearable Equipment on Track and Field Athletes. *EAI Endorsed Transactions on Pervasive Health and Technology*, *10*, 1–10. https://doi.org/doi: 10.4108/eetpht.10.5150

Yigitcanlar, T., Kankanamge, N., Regona, M., Maldonado, A., Rowan, B., Ryu, A., Desouza, K. C., Corchado, J. M., Mehmood, R., & Man, R. Y. (2020). Artificial Intelligence Technologies and Related Urban Planning and Development Concepts: How Are They Perceived and Utilized in Australia? . . *Open Innov. Technol. Mark. Complex. 2*, *6*(187), 1–21. https://doi.org/10.3390/joitmc6040187

Yuliansyah, H., Sulistyawati, S., & Mulasari, S. A. (2022). Technological Innovation is Needed to Accelerate Stunting Reduction in Indonesia. *Epidemiology and Society Health Review (ESHR)*, *4*(2), 89–90. https://doi.org/DOI: https://doi.org/10.26555/eshr.v4i2.6369

Yusoff, A. S. M., Peng, F. S., Razak, F. Z. A., & Wan Mustafa, A. (2020). Discriminant Validity Assessment of Religious Teacher Acceptance: The Use of HTMT Criterion. *Journal of Physics: Conference Series*, *1529*(042045), 1–7. https://doi.org/doi:10.1088/1742-6596/1529/4/042045

Zhang, C., Schieß, J., Plößl, L., Hofmann, F., & Gläser-Zikuda, M. (2023). Acceptance of artificial intelligence among pre-service teachers: a multigroup analysis. *International Journal of Educational Technology in Higher Education*, *20*(49), 1–22. https://doi.org/https://doi.org/10.1186/s41239-023-00420-7

Zhang, X., & Wen, Z. (2021). Thoughts on the development of artificial intelligence combined with RPA. *Journal of Physics: Conference Series*. https://doi.org/doi:10.1088/1742-6596/1883/1/012151

Ella Lesmanawaty Wargadinata
IPDN, Jatinangor, West Java,
Indonesia e
ellawarga@ipdn.ac.id
ORCID: 0000-0003-3089-1898