*Journal of Infrastructure, Policy and Development* 2024, 8(10), 7944.
https://doi.org/10.24294/jipd.v8i10.7944

Article

# Transforming midwifery healthcare services in rural Indonesia: A comprehensive analysis of artificial intelligence integration

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**CITATION**

Ardan M, Rahman FF, Noorbaya S, et al. (2024). Article title. Journal of Infrastructure, Policy and Development. 8(10): 7944. https://doi.org/10.24294/jipd.v8i10.7944

**ARTICLE INFO**

Received: 11 July 2024
Accepted: 5 September 2024
Available online: 27 September 2024



**Abstract:** The rapid advancement of information and communication technology has greatly facilitated access to information across various sectors, including healthcare services. This digital transformation demands enhanced knowledge and skills among healthcare providers, particularly in comprehensive midwifery care. However, midwives in rural areas face numerous challenges such as limited resources, cultural factors, knowledge disparities, geographic conditions, and technological adoption. This research aims to evaluate the impact of AI utilization on midwives' knowledge and behavior to optimize the implementation of healthcare services in accordance with Delima Midwife Service standards in rural settings. The analysis encompasses competencies, characteristics, information systems, learning processes, and health examinations conducted by midwives in adopting AI. The research methodology employs a cross-sectional approach involving 413 rural midwives selected proportionally. Results from Partial Least Squares Structural Equation Modeling indicate that all reflective evaluation variables meet the required criteria. Fornell-Larcker criterion demonstrates that the square root of AVE is greater than other variables. The primary findings reveal that information systems (0.029) and midwives' competencies (0.033) significantly influence AI utilization. Furthermore, midwives' competencies (0.002), characteristics (0.031), and AI utilization (0.011) also significantly impact midwives' knowledge and behavior. Midwives' characteristics also significantly affect their competencies (0.000), while midwives' learning influences health examinations (0.000). Midwives' knowledge and behavior affect the transformation of healthcare services in rural midwifery (0.022). The model fit results in a value of 0.097, empirically supporting the explanation of relationships among variables in the model and meeting the established linearity test.

**Keywords:** information systems; artificial intelligence; transformation; rural; midwifery services

## 1. Introduction

The rapid development of information and communication technology continues to progress. As of January 2022, the number of internet users in Indonesia reached approximately 204.7 million people, marking a 1.03% increase from the previous year (Prasetiyo et al., 2022). Consequently, internet penetration in Indonesia has reached 73.7% of the total population (Puspitasari et al., 2023). The evolution of internet technology has facilitated public access to information across various sectors such as business, education, entertainment, and healthcare services (Aceto et al., 2018).

Over the past five years, the number of healthcare facilities such as Maternity Hospitals (RSIA), Community Health Centers (Puskesmas), Clinics, and Independent

Midwife Practices (PMB) in Indonesia has steadily increased each year (Ardan et al., 2023). According to BPS 2022 data, the average growth rate of healthcare facilities reached 1.5% per year (Schaefers et al., 2022). The development of digital technology and the Covid-19 pandemic have influenced global access to healthcare services (Filip et al., 2022; Pujolar et al., 2022). Meanwhile, according to DMN3 2020 data, 47% of consumers seek information about healthcare professionals such as doctors, midwives, and nurses, 38% seek information about hospitals and other healthcare facilities, and 77% schedule health examinations online (Hills and Shah, 2020; Mackintosh et al., 2020).

This data underscores the importance of integrated digital systems within healthcare facilities, both at the user institution level and among service providers such as midwives (O'Connor et al., 2023; Rahman et al., 2020). To accelerate digital transformation in healthcare services, healthcare professionals need to enhance their knowledge and skills in healthcare service digitalization, particularly in the context of comprehensive midwifery care (Laksono, 2022).

Midwives play a crucial role in public health. According to the Indonesian Midwives Association (IBI), approximately 60% of babies in Indonesia are delivered by midwives, 5% by obstetricians, and the remainder by non-medical services (Rusdi et al., 2018). Based on SISDMK 2023 data, there are approximately 375,467 midwives in Indonesia, with 70%–75% of them serving in communities, including rural areas, thereby facilitating healthcare access (Rohana et al., 2020). BPS 2023 data indicates that there are 4861 midwives in East Kalimantan and 1214 in North Kalimantan. However, in 2023, East Kalimantan reported 46 maternal deaths and 302 infant deaths, while North Kalimantan reported 194 maternal deaths during pregnancy.

The distribution of midwives in rural areas facilitates community reliance on midwifery services for accessing maternal, infant, and child healthcare, as well as family planning programs, particularly concerning reproductive health (Carbonell et al., 2024). Therefore, ongoing technological development is essential for sustainable development, which positively impacts healthcare services, especially in comprehensive midwifery care (Shakibazadeh et al., 2018). With the increasing adoption of Artificial Intelligence (AI) in healthcare, service systems are expected to improve in quality in the future, including midwifery care (O'Connor et al., 2023; Shinners et al., 2020). AI can aid in early disease detection or health issues before they escalate, prevent fatalities, and reduce treatment costs (O'Connor et al., 2023). AI offers innovative solutions for primary healthcare services for midwives, such as early detection of anxiety or depression in pregnant women and early detection of premature births through machine learning-based approaches (Kivuti-Bitok, 2024; Rahman et al., 2023). Furthermore, AI can enhance midwives' performance through mHealth applications (Darwitri et al., 2023; Rikawarastuti and Kemal, 2020).

However, healthcare providers, especially midwives in underserved and rural areas, face increasingly complex challenges. These challenges include inadequate infrastructure and facilities, socio-cultural factors within communities, midwives' knowledge and behavior, geographic conditions, and the transformation of healthcare services through digitalization (Gamberini et al., 2022). In-depth research is needed to identify successful healthcare service transformations, particularly in rural areas (Bolan et al., 2021).

The improvement of healthcare services in rural Indonesia is an urgent necessity due to the substantial gap between urban and rural healthcare services. Integrating AI into midwifery services in rural areas has the potential to enhance accessibility, quality, and efficiency of healthcare services in these regions, thus necessitating fundamental research in this area.

## 2. Materials and methods

### 2.1. Study design and variables

This research employs a quantitative method with a cross-sectional design. Data collection involves questionnaires and interviews to analyze competencies, characteristics, information systems, learning processes, and health examinations conducted by midwives in utilizing AI. The analysis aims to examine how AI utilization influences the improvement of midwives' knowledge and behavior, thereby optimizing the transformation of healthcare services in rural areas in accordance with the Delima Midwife Service standards.

### 2.2. Population dan sample

The study population includes all midwives in East Kalimantan and North Kalimantan provinces, totaling 6075 individuals spread across 1522 villages in 15 districts/cities.

The research sample is selected through purposive sampling from midwives in rural areas of East Kalimantan and North Kalimantan provinces, who meet the following inclusion criteria: 1) Willingness to participate as respondents; 2) Minimum educational attainment of Diploma-III in Midwifery; 3) Minimum age of 22 years as of June 2024; 4) Serving as a midwife in rural areas; 5) Minimum 1 year of experience working as a midwife in rural settings; 6) Possession of a mobile phone or laptop for daily activities. Exclusion criteria include: 1) Midwives with psychological disorders; 2) Midwives who have not provided midwifery care since completing their education; 3) Midwives on leave for more than 6 months.

Based on the Slovin formula with a 5% margin of error (Anugraheni et al., 2023), the minimum sample size required is 375 individuals. To account for potential dropouts, an additional 10% is added (Márquez-Vera et al., 2016), bringing the total sample size to 413 participants. The sample will be obtained proportionally based on regional characteristics and the number of midwives to ensure representativeness of respondents.

### 2.3. Establishment of prediction model and statistics

The Partial Least Squares (PLS) technique, which is a statistical analysis method based on Structural Equation Modeling (SEM), is utilized in this study to measure and validate the proposed model and the relationships among hypothesized constructs (Ali et al., 2018).

The research employs a structured approach utilizing Partial Least Squares Structural Equation Modeling (PLS-SEM) to comprehensively evaluate various facets of midwifery services in rural East Kalimantan and North Kalimantan provinces.

Initially, a reflective measurement model is constructed to assess constructs such as Midwife Characteristics, Information Systems, Midwife Learning, Health Examinations, Midwife Competencies, Utilization of Artificial Intelligence, Midwife Knowledge and Behavior, and Transformation of Healthcare Services. Criteria including loadings > 0.70, composite reliability > 0.70, Cronbach's alpha > 0.60, and Average Variance Extracted (AVE) > 0.50 are applied to validate this model. Subsequently, discriminant validity is rigorously evaluated using Fornell and Lacker criteria to ensure each construct is empirically distinct. The structural model is then scrutinized for multicollinearity (VIF < 5), significant variable relationships ($p < 0.05$, 95% CI), and effect sizes ($f^2$) indicating direct effects at low (0.02), moderate (0.15), and high (0.35) levels. Finally, model goodness-of-fit is assessed through metrics including *R* Square thresholds for effect levels, *Q* Square for predictive relevance, SRMR for model fit, and a linearity test confirming no quadratic effects. These steps collectively validate the research model's theoretical underpinnings and predictive capabilities in enhancing midwifery services in rural settings.

## 3. Results

### 3.1. Baseline characteristics

The study involved 413 rural midwives selected proportionally based on regional characteristics and the number of midwives in those areas, ensuring the data's representativeness and accuracy. Respondents met predefined inclusion criteria, reflecting a range of ages from 25 to 50 years, with an average work experience exceeding 5 years in midwifery. Educational backgrounds varied from diploma to master's degrees in midwifery, indicating diversity in education and training backgrounds. Sampling locations spanned across 5 districts/cities, providing insights into the conditions and challenges faced by midwives in these regions. The majority of rural midwives reported regular use of technology such as smartphones, computers, and laptops in their daily activities. This diverse demographic profile offers a holistic perspective on the challenges and opportunities in adopting advanced technology in rural environments, facilitating the design of more effective and targeted interventions to enhance healthcare service quality in remote areas.

### 3.2. Reflective measurement model evaluation

Results of the reflective measurement model evaluation analysis that describe the results of Outer Loading, Composite Reliability, Cronbach's Alpha and Average Variance Entranced (AVE), are as follows:

**Table 1** shows that midwife characteristics are measured using three valid items with outer loading values ranging from 0.708 to 0.922, reliably reflecting midwife characteristics with a reliability level (0.855) Cronbach's alpha (0.810), and AVE value (0.728). Overall, the measurement items achieve 72.8%, with the professional midwife item representing the context of midwife characteristics.

**Table 1.** Measurement model evaluation based on outer loading, composite reliability, Cronbach's alpha, and average variance extracted (AVE).

| Variable | Measurement Item | Indicator | Outer Loading* | Composite Reliability** | Cronbach's Alpha*** | AVE**** |
|---|---|---|---|---|---|---|
| a) Characteristics (KaB) | KaB1 | Midwife's Knowledge | 0.708 | 0.855 | 0.810 | 0.728 |
| | KaB2 | Midwife's Experience | 0.913 | | | |
| | KaB3 | Midwife's Professionalism | 0.922 | | | |
| b) Information System (SI) | SI1 | Information Knowledge | 0.947 | 0.894 | 0.894 | 0.827 |
| | SI2 | Utilization of Information | 0.834 | | | |
| | SI3 | Use of Telemedicine | 0.944 | | | |
| c) Learning Processes (PeB) | PeB1 | Training | 0.918 | 0.808 | 0.808 | 0.839 |
| | PeB2 | Education | 0.914 | | | |
| d) Competencies (KoB) | KoB1 | Competencies of Midwives Related to Reproductive Health | 0.930 | 0.959 | 0.958 | 0.827 |
| | KoB2 | Competencies of Midwives Related to Pregnancy | 0.935 | | | |
| | KoB3 | Competencies of Midwives Related to Childbirth | 0.894 | | | |
| | KoB4 | Competencies of Midwives Related to Newborn Baby | 0.874 | | | |
| | KoB5 | Competencies of Midwives Related to Postpartum | 0.928 | | | |
| | KoB6 | Competencies of Midwives Related to Family Planning | 0.894 | | | |
| e) Health Examinations (PK) | PK1 | Reproductive Health Examination | 0.776 | 0.901 | 0.893 | 0.653 |
| | PK2 | Pregnancy Health Examination | 0.869 | | | |
| | PK3 | Childbirth Health Examination | 0.800 | | | |
| | PK4 | Newborn Baby Health Examination | 0.840 | | | |
| | PK5 | Postpartum Health Examination | 0.805 | | | |
| | PK6 | Family Planning Health Examination | 0.751 | | | |
| f) Utilization of Artificial Intelligence (PAI) | PAI1 | Reliability and Accuracy of AI Systems | 0.861 | 0.783 | 0.763 | 0.682 |
| | PAI2 | Integration with Healthcare Systems | 0.886 | | | |
| | PAI3 | Training and Technical Support | 0.721 | | | |

**Table 1.** (*Continued*).

| Variable | Measurement Item | Indicator | Outer Loading* | Composite Reliability** | Cronbach's Alpha*** | AVE**** |
|---|---|---|---|---|---|---|
| g) Knowledge And Behavior (PPB) | PPB1 | Understanding AI Technology and Training for Midwives | 0.865 | 0.862 | 0.857 | 0.778 |
| | PPB2 | Attitudes and Openness Towards New Technology | 0.878 | | | |
| | PPB3 | Collaborative Skills and Professional Ethics | 0.902 | | | |
| h) Transformation of Healthcare Services in Rural Areas (TPKBD) | TPKBD1 | Training and Development of Rural Midwives' Competencies | 0.890 | 0.909 | 0.907 | 0.784 |
| | TPKBD2 | Access to Technology and Implementation Midwifery | 0.824 | | | |
| | TPKBD3 | Healthcare Infrastructure and Facilities for Rural Midwives | 0.918 | | | |
| | TPKBD4 | Community-Based Approach and Health Education | 0.907 | | | |

Note: * Outer Loading > 0.70; ** Composite Reliability > 0.70; *** Cronbach's Alpha > 0.60; **** Average Variance Extracted > 0.50.

Information systems are measured using three valid items with outer loading values ranging from 0.834 to 0.947, reliably reflecting information systems with a reliability level (0.894) Cronbach's alpha (0.894), and AVE value (0.827). Overall, the measurement items achieve 82.7%, with the information knowledge item representing the context of information systems.

Midwife learning is measured using two valid items with outer loading values ranging from 0.914 to 0.918, reliably reflecting midwife learning with a reliability level (0.808) Cronbach's alpha (0.808), and AVE value (0.839). Overall, the measurement items achieve 83.9%, with the training item representing the context of midwife learning.

Competency of midwives is measured using six valid items with outer loading values ranging from 0.874 to 0.935, reliably reflecting midwives' competencies with a reliability level (0.959) Cronbach's alpha (0.958), and AVE value (0.827). Overall, the measurement items achieve 82.7%, with the pregnancy item representing the context of midwives' competencies.

Health examinations are measured using six valid items with outer loading values ranging from 0.751 to 0.869, reliably reflecting health examinations with a reliability level (0.901) Cronbach's alpha (0.893), and AVE value (0.653). Overall, the measurement items achieve 65.3%, with the pregnancy item representing the context of health examinations.

Utilization of artificial intelligence is measured using three valid items with outer loading values ranging from 0.721 to 0.886, reliably reflecting utilization of artificial intelligence with a reliability level (0.783) Cronbach's alpha (0.763), and AVE value (0.682). Overall, the measurement items achieve 68.2%, with the health system item representing the context of utilizing artificial intelligence.

Midwife knowledge and behavior are measured using three valid items with outer loading values ranging from 0.865 to 0.902, reliably reflecting midwives' knowledge and behavior with a reliability level (0.862) Cronbach's alpha (0.857), and AVE value (0.778). Overall, the measurement items achieve 77.8%, with collaborative skills and professional ethics item representing the context of midwives' knowledge and behavior.

Transformation of healthcare services for rural midwives is measured using four valid items with outer loading values ranging from 0.824 to 0.918, reliably reflecting transformation of healthcare services for rural midwives with a reliability level (0.909) Cronbach's alpha (0.907), and AVE value (0.784). Overall, the measurement items achieve 78.4%, with infrastructure and healthcare facilities item representing the context of transformation of healthcare services for rural midwives.

### 3.3. Fornell and Larcker measurement model evaluation

The results of the measurement model evaluation analysis of Fornell and Lacker which describe the results of the diagonal value of the AVE root against the correlation value, as follows:

**Table 2** shows that the variables have AVE roots for each midwife characteristic (0.877), midwife competency variable (0.942), artificial intelligence utilization variable (0.826), midwife learning variable (0.916), health check variable (0.956), midwife knowledge and behavior variable (0.886), information system variable (0.910), and health service transformation variable in village midwives (0.885), which have a greater correlation than other variables. These results indicate that the discriminant validity of all variables is met.

**Table 2.** Measurement model evaluation based on Fornell and Larcker criteria.

| Factor | Code | KaB | KoB | PAI | PeB | PK | PPB | SI | TPKBD |
|---|---|---|---|---|---|---|---|---|---|
| Characteristics | KaB | 0.877* | | | | | | | |
| Competencies | KoB | 0.812 | 0.942* | | | | | | |
| Utilization of Artificial Intelligence | PAI | 0.796 | 0.797 | 0.826* | | | | | |
| Learning Processes | PeB | 0.829 | 0.873 | 0.783 | 0.916* | | | | |
| Health Examinations | PK | 0.861 | 0.935 | 0.802 | 0.892 | 0.956* | | | |
| Knowledge And Behavior | PPB | 0.749 | 0.804 | 0.772 | 0.827 | 0.883 | 0.886* | | |
| Information System | SI | 0.853 | 0.795 | 0.801 | 0.812 | 0.900 | 0.695 | 0.910* | |
| Transformation of Healthcare Services in Rural Areas | TPKBD | 0.786 | 0.809 | 0.773 | 0.860 | 0.808 | 0.882 | 0.815 | 0.885* |

Note: *Diagonal values are the square root of AVE, and the other values are correlations (Square root of AVE > Correlation values).

### 3.4. Structural model evaluation

Structural model evaluation is related to hypothesis testing regarding the influence between research variables. Structural model evaluation examination is carried out by testing the Inner Variance Inflated Factor (VIF) value, path analysis, standard deviation, *p*-value, path confidence interval (95% path confidence interval), and f square, as follows:

**Table 3** evaluating the policy on transforming health services for village midwives shows that: 1) If there is a change in the characteristics of midwives, it will increase the competence of midwives (CI: 0.690–0.890), knowledge and behavior (CI: 0.318–0.498), and use of artificial intelligence (CI: −0.094–0.524); 2) Therefore, every change in the information system will increase the use of artificial intelligence (CI: 0.043–0.798); 3) Even though, in midwifery education will improve health examination (CI: 0.814–0.946): , knowledge and behavior (CI: 0.319–0.446), and the use of artificial intelligence (CI: −0.139–0.488); 4) Furthermore, in health examination will increase the use of artificial intelligence (CI: −1.050–0.210), knowledge and behavior (CI: −0.242–0.619), and the transformation of health services for village midwives (CI: 0.332–0.852); 5) More than, midwives competence will boost the use of artificial intelligence (CI: 0.065–0.920), knowledge and behavior (CI: 0.143–0.929), and the transformation of health services for village midwives (CI: 0.006–0.611); 6) Moreover, the use of artificial intelligence will enhance midwives knowledge and behavior (CI: 0.019–0.411); and 7) And then midwives knowledge and behavior will increase the transformation of health services for village midwives (CI: 0.060–0.472).

**Table 3.** Structural model evaluation results based on variance inflated factor (VIF) values, paths, standard deviation, *p*-values, 95% confidence interval of path coefficients, and *f* squared.

| Hypothesis | VIF* | Path | STDEV | *p*-value** | 95% Confidence Interval | | *f* Square *** |
|---|---|---|---|---|---|---|---|
| | | | | | Min | Max | |
| Characteristics → Competencies (H1) | 1.000 | 0.812 | 0.051 | 0.000 | 0.690 | 0.892 | 1.934 |
| Characteristics → Knowledge and Behavior (H2) | 4.612 | 0.419 | 0.105 | 0.031 | 0.318 | 0.498 | 0.024 |
| Characteristics → Utilization of Artificial Intelligence (H3) | 4.424 | 0.192 | 0.158 | 0.226 | −0.094 | 0.524 | 0.015 |
| Information System → Utilization of Artificial Intelligence (H4) | 4.644 | 0.419 | 0.192 | 0.029 | 0.043 | 0.798 | 0.085 |
| Learning Processes → Health Examinations (H5) | 1.000 | 0.892 | 0.034 | 0.000 | 0.814 | 0.946 | 3.915 |
| Learning Processes → Knowledge and Behavior (H6) | 4.697 | 0.379 | 0.146 | 0.047 | 0.319 | 0.446 | 0.021 |
| Learning Processes → Utilization of Artificial Intelligence (H7) | 4.601 | 0.170 | 0.157 | 0.279 | −0.139 | 0.488 | 0.019 |
| Health Examinations → Utilization of Artificial Intelligence (H8) | 4.950 | −0.323 | 0.323 | 0.317 | −1.050 | 0.210 | 0.022 |
| Health Examinations → Knowledge and Behavior (H9) | 4.697 | 0.180 | 0.218 | 0.408 | −0.242 | 0.619 | 0.017 |
| Health Examinations → Transformation of Healthcare Services in Rural Areas (H10) | 4.221 | 0.574 | 0.133 | 0.000 | 0.332 | 0.852 | 0.603 |
| Competencies → Utilization of Artificial Intelligence (H11) | 4.592 | 0.462 | 0.217 | 0.033 | 0.065 | 0.920 | 0.138 |
| Competencies → Knowledge and Behavior (H12) | 4.750 | 0.626 | 0.199 | 0.002 | 0.143 | 0.929 | 0.267 |
| Competencies → Transformation of Healthcare Services in Rural Areas (H13) | 4.742 | 0.314 | 0.152 | 0.039 | 0.006 | 0.611 | 0.138 |
| Utilization of Artificial Intelligence → Knowledge and Behavior (H14) | 3.413 | 0.331 | 0.084 | 0.011 | 0.019 | 0.411 | 0.030 |
| Knowledge and Behavior → Transformation of Healthcare Services in Rural Areas (H15) | 4.682 | 0.427 | 0.083 | 0.022 | 0.060 | 0.472 | 0.027 |

Note: * VIF < 5; ** *p*-value < 0.05; *** *f* Square (0.02 Low; 0.15 Middle and 0.35 High).

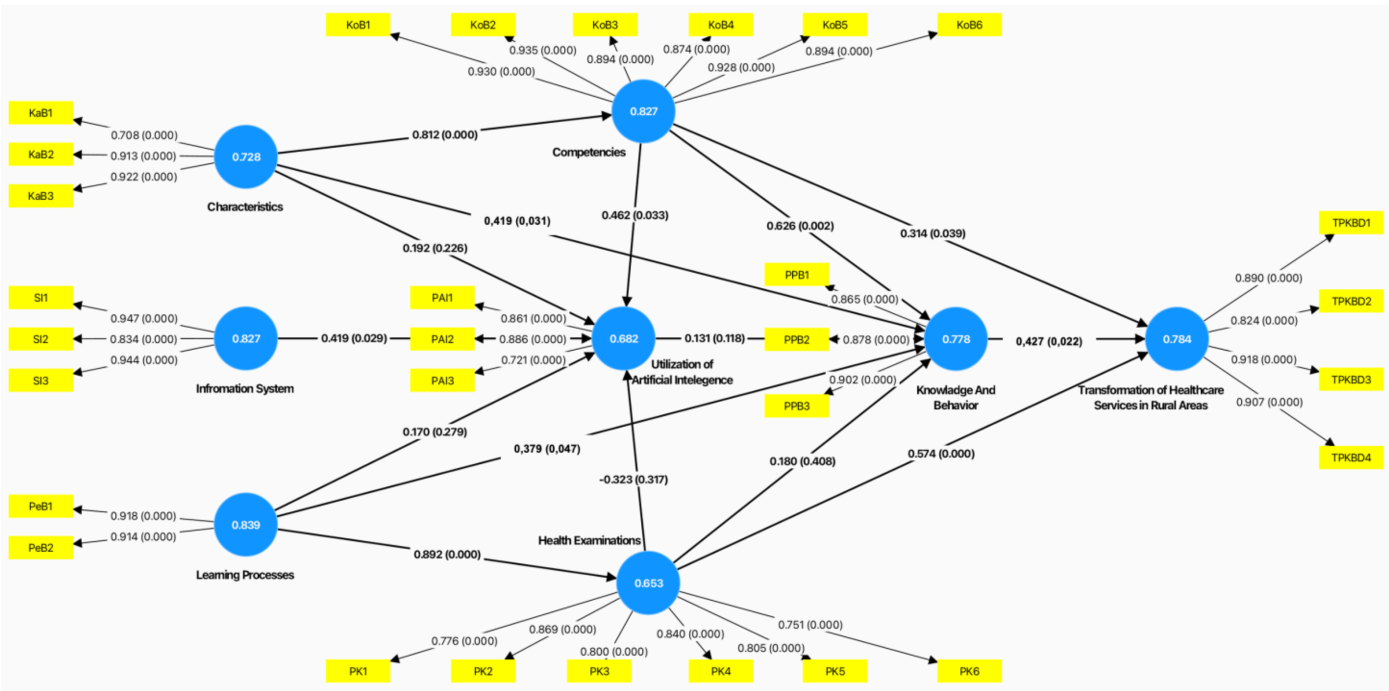


**Figure 1.** Evaluation results of structural model path coefficients.

**Figure 1** and **Table 3** estimated inner VIF values for all variables are <5, indicating low multicollinearity among variables and allowing us to conclude that the parameters in PLS-SEM are robust (unbiased). The primary findings reveal that information systems (0.029) and midwives' competencies (0.033) significantly influence AI utilization. Furthermore, midwives' competencies (0.002), characteristics (0.031), and AI utilization (0.011) also significantly impact midwives' knowledge and behavior. Midwives' characteristics also significantly affect their competencies (0.000), while midwives' learning influences health examinations (0.000). Midwives' knowledge and behavior affect the transformation of healthcare services in rural midwifery (0.022).

### 3.5. Goodness of fit model evaluation

PLS results constitute a variance-based SEM analysis focusing on testing the theoretical model with an emphasis on predictive study. The analysis results are substantiated by *R* Square values, *Q* Square values, Standardized Root Mean Residual (SRMR) values, and linearity test values, as follows:

**Table 4** indicates the significant influence of each variable as follows: midwives' competence (68.2%), utilization of artificial intelligence (74.9%), health examinations (79.9%), midwives' knowledge and behavior (7.97%), and transformation of health services in rural midwifery (93.7%). These percentages signify high impact. Furthermore, the predictive accuracy measures show the following values for each variable: midwives' competence 0.539 (high), utilization of artificial intelligence 0.465 (moderate), health examinations 0.504 (high), midwives' knowledge and behavior 0.622 (high), and transformation of health services in rural midwifery 0.721 (high). Regarding model fit measures, the correlation matrix between observed data and the estimated model yields a value of 0.097, which is empirically acceptable. This value indicates the model adequately explains the relationships between variables.

**Table 4.** Model goodness-of-fit evaluation based on *R* square, *Q* square, and standardized root mean residual.

| **Indicator** | ***R* Square*** | ***Q* Square**** | **SRMR***** |
|---|---|---|---|
| Competencies | 0.682 | 0.539 | |
| Utilization of Artificial Intelligence | 0.749 | 0.465 | |
| Health Examinations | 0.797 | 0.504 | 0.097 |
| Knowledge and Behavior | 0.840 | 0.622 | |
| Transformation of Healthcare Services in Rural Areas | 0.937 | 0.721 | |

Note: * *R* Square (0.19 Low, 0.33 Middle dan 0.66 High); ** *Q* Square (0 Low, 0.25 Middle dan 0.50 High); *** SRMR between 0.08–0.10.

**Table 5** linearity test has an influence between variables. The results of the analysis explain that the influence of each variable pair has a *p*-value greater than the alpha of 0.05, which means they are not statistically significant. Therefore, each variable pair is assumed to be linear, and the linearity assumption of the model is met (robust).

**Table 5.** Goodness-of-fit evaluation and model suitability based on quadratic effect linearity test values.

| Quadratic Effect (QE) | Path Coefficient | *p*-value* | Description |
|---|---|---|---|
| Characteristics → Competencies | −0.104 | 0.070 | Linearity Fulfilled |
| Characteristics → Knowledge and Behavior | 0.076 | 0.513 | Linearity Fulfilled |
| Characteristics → Utilization of Artificial Intelligence | 0.184 | 0.211 | Linearity Fulfilled |
| Learning Processes → Health Examinations | 0.001 | 0.980 | Linearity Fulfilled |
| Learning Processes → Knowledge and Behavior | −0.123 | 0.339 | Linearity Fulfilled |
| Learning Processes → Utilization of Artificial Intelligence | −0.017 | 0.919 | Linearity Fulfilled |
| Health Examinations → Utilization of Artificial Intelligence | −0.278 | 0.182 | Linearity Fulfilled |
| Health Examinations → Knowledge and Behavior | 0.081 | 0.743 | Linearity Fulfilled |
| Health Examinations → Transformation of Healthcare Services in Rural Areas | −0.104 | 0.357 | Linearity Fulfilled |
| Competencies → Utilization of Artificial Intelligence | 0.089 | 0.631 | Linearity Fulfilled |
| Competencies → Knowledge and Behavior | −0.074 | 0.742 | Linearity Fulfilled |
| Competencies → Transformation of Healthcare Services in Rural Areas | −0.009 | 0.939 | Linearity Fulfilled |
| Knowledge and Behavior → Transformation of Healthcare Services in Rural Areas | −0.014 | 0.093 | Linearity Fulfilled |

Note: * $p$-value > 0.05.

## 4. Discussion

### 4.1. The influence of midwife characteristics on each midwife competency variable, midwife knowledge and behavior and utilization of artificial intelligence

The research highlights that midwives' characteristics, including education, work experience, and professionalism, are essential in improving their competence. Education and training investments help develop vital skills in midwifery, where formal education serves as a foundation for knowledge, while practical experience enhances technical abilities and the management of complex medical situations. Midwives' competence is shaped by both theoretical understanding and hands-on experience, with those possessing more extensive work experience demonstrating greater capacity in providing care and making informed intervention decisions. Additionally, professionalism—encompassing ethical behavior, adherence to clinical standards, and ongoing education—also significantly influences midwives' abilities. These findings are consistent with research by Xue et al. (2023) in China, Abdul et al. (2020) in Malaysia, Smith et al. (2022) across Europe, and Nguyen et al. (2023) in Vietnam, all of which underscore the role of education and work experience in enhancing midwives' competence globally.

However, further analyses show that midwives' characteristics may not substantially impact the use of artificial intelligence (AI). Contributing factors include the lack of AI-specific training for midwives in maternal care, insufficient resources in remote areas, and limited psychological readiness for technology adoption. Organizational support and effective policies are also necessary for integrating AI in healthcare, as noted by Lestari et al. (2023), Lee et al. (2021), and Zeng et al. (2021), who emphasize the importance of infrastructure, awareness, and policy in enabling AI adoption in midwifery practices.

### 4.2. The influence of information systems on the utilization of artificial intelligence

The research findings indicate that there is an influence of information systems, such as knowledge, utilization, and use of telemedicine, on the utilization of artificial intelligence (AI) in midwifery practice. This is supported by several factors. Firstly, effective information systems can enhance midwives' knowledge about the potential and benefits of AI in midwifery practice, such as more accurate diagnosis or more efficient care planning. Secondly, the use of technologies like telemedicine allows midwives to access remote consultations or continuous education on AI, thereby expanding their skills and understanding in adopting this new technology.

Moreover, integrated information systems can facilitate the use of AI in health data analysis and data-driven decision-making, which in turn enhances the effectiveness and efficiency of midwifery services. Therefore, the integration of strong information systems in midwifery practice can substantially support the utilization of AI to improve the quality of maternal and child healthcare services in various settings, including rural or remote areas.

### 4.3. The influence of midwife learning on each health examination variable, midwife knowledge and behavior and utilization of artificial intelligence

Research shows that education and training play a critical role in improving health examinations performed by midwives. Formal education provides a solid foundation of knowledge, enabling midwives to conduct accurate and thorough health assessments. Midwives with higher education tend to understand effective examination procedures better. Meanwhile, practical training enhances technical skills, allowing midwives to gain experience in clinical settings and effectively manage various health conditions. Through hands-on practice, midwives learn to assess important clinical signs, ensuring comprehensive health examinations. This dual focus on education and practical training not only strengthens technical expertise but also fosters a commitment to delivering high-quality healthcare services. Studies like Adatara et al. (2021) emphasize the impact of additional training on prenatal and neonatal examinations in Uganda, highlighting improvements in examination accuracy and early detection of health problems. Similarly, James and Rimes (2018) demonstrated that continuous training in rural areas leads to better maternal and neonatal health outcomes.

Research by Elmi et al. in Australia further illustrates how midwifery education that blends theory and practical skills positively influences the quality of maternal and infant healthcare. Chaudhury's (2023) study in India also points to the benefits of information and communication technology (ICT) training in improving the accuracy and efficiency of health examinations. However, midwifery education does not always translate into increased use of artificial intelligence (AI). Rural or remote areas often face technological barriers, limiting AI integration. Although midwives may receive basic tech training, advanced AI applications are often not fully incorporated into midwifery curricula. Studies such as Xue et al. (2023) and Gamil et al. (2020) underscore the importance of developing AI-focused curricula, while Smith et al. (2022) highlights the need for continuous education and tailored training to overcome the challenges in AI adoption, ensuring midwives are well-prepared to utilize AI in practice.

### 4.4. The influence of health examination on each variable of artificial intelligence utilization, midwives' knowledge and behavior and transformation of health services in village midwives

The study reveals that health examinations related to reproductive health, pregnancy, childbirth, and family planning do not significantly impact the use of artificial intelligence (AI) in midwifery services. Several factors may explain this, including limited access to technology, lack of AI integration in routine check-ups, and a focus on clinical procedures. Additionally, challenges like insufficient infrastructure, lack of organizational support, and limited managerial backing for midwives in rural areas further hinder AI adoption. Many midwives may not have the technical skills required to use AI effectively. Routine health examinations often follow standard procedures that do not involve advanced technologies or offer AI training. As a result, these examinations do not significantly influence midwives' knowledge or behavior since they may not feel the need to update their skills or practices.

Moreover, without accompanying educational sessions, routine examinations fail to offer deep learning opportunities. Midwives may focus more on practical skills than theoretical knowledge, particularly in rural areas. Organizational culture, work environment, and health policies further limit learning and behavioral changes. These findings are consistent with Thompson and Schwartz (2019), who found that without additional education, routine examinations do not improve knowledge or behavior. Anderson and Putman (2020) similarly noted that health examinations do not lead to improvements without continuous training.

However, further analysis suggests that health examinations contribute significantly to transforming healthcare services provided by village midwives. Continuous training enhances clinical skills, public health knowledge, and emergency response abilities. Health education and counseling also raise community awareness and promote healthier behaviors. These findings align with Smith et al. (2022) and Johnson and Johnson (2020), who stressed the importance of training, infrastructure, and technology in improving rural healthcare outcomes.

### 4.5. The influence of midwife competence on each variable of artificial intelligence utilization, midwife knowledge and behavior and transformation of health services in village midwives

The research findings suggest that midwives' competence in areas such as reproductive health, pregnancy, childbirth, newborn care, postpartum care, and family planning significantly impacts the use of artificial intelligence (AI) in rural healthcare. This is attributed to village midwives' growing ability to adapt to advancing technology and internet access, enabling them to utilize AI for accessing updated references, predicting health risks, and improving diagnostic accuracy. Competent midwives leverage AI to enhance service quality, providing better patient care and making more informed decisions.

Competent midwives have a strong foundation in midwifery theory and practical skills, continuously updating their knowledge through ongoing education and training. Their expertise allows them to handle a range of medical situations effectively, from routine deliveries to emergencies, contributing directly to improved healthcare services in rural areas. These findings align with Xue et al. (2023) in China, Abdul et al. (2020) in Malaysia, and Smith et al. (2022) in Europe, all emphasizing the importance of education, experience, and professionalism in enhancing midwives' competence.

## 4.6. The influence of artificial intelligence utilization on midwives' knowledge and behavior

The research findings show that the use of artificial intelligence (AI) significantly enhances midwives' knowledge and skills. AI allows midwives to quickly access the latest information in midwifery, such as recent studies, clinical guidelines, and scientific articles, keeping them up-to-date with advancements in the field. AI also provides opportunities for midwives to improve their practical skills through realistic training simulations, enabling them to practice in various medical scenarios, including rare cases, without risking patient safety.

In clinical settings, AI supports midwives by offering fast and accurate data analysis, helping them make informed decisions. For example, AI can evaluate vital signs and health histories to provide care recommendations, improving midwives' diagnostic abilities and care planning. Additionally, AI automates administrative tasks like record-keeping, allowing midwives to focus more on patient care. This aligns with Xue et al. (2023), who found that AI improves diagnostic accuracy, and Gamil et al. (2020), who highlighted the role of AI in enhancing practical skills in emergencies.

## 4.7. The influence of midwives' knowledge and behavior on the transformation of health services in village midwives

The research indicates that midwives' knowledge and behavior significantly impact the transformation of healthcare services in rural areas. Midwives with deep knowledge and strong skills provide higher quality care, accurately diagnose, plan effective treatments, and manage complications, leading to improved health outcomes for mothers and children. Their expertise enables them to offer better care, which is vital for enhancing maternal and child health services in rural communities.

Moreover, knowledgeable midwives are more adaptable to new technologies like AI and health information systems, allowing them to improve the efficiency of health services. By continuously updating their skills through ongoing education, they are better equipped to implement modern practices and meet high service standards. This aligns with Smith et al. (2022), who found that midwives' clinical knowledge enhances service quality. Johnson and Johnson (2020) emphasized that continuous training helps midwives adopt new technologies, and Nguyen et al. (2023) highlighted the role of practical skills in transforming rural healthcare services.

## 5. Conclusion

The conclusion of this study highlights several important findings related to the factors influencing the integration of artificial intelligence (AI) in the transformation of midwifery health services in rural Indonesia. These findings align with theories emphasizing the importance of individual factors such as competence and learning in the adoption of technology in the healthcare sector. The study also underscores the role of information systems in supporting the effectiveness and efficiency of implementing technologies like AI. The results of this research contribute to a deeper understanding of the complex interactions between individual factors, information technology, and the transformation of health services, in line with the continuously evolving body of scientific knowledge.

**Author contributions:** Conceptualization, MA and FFR; methodology, MA and FFR; software, FA; validation, MA, FFR and SN; formal analysis, MA; investigation, HJ; data curation, FA; writing—original draft preparation, MA and FFR; writing—review and editing, MA, FFR and FA; visualization, HJ; supervision, MA, FFR and SN; project administration, MA and SN. All authors have read and agreed to the published version of the manuscript.

**Funding:** We extend our gratitude to the Ministry of Education, Culture, Research and Technology of the Republic of Indonesia, the National Research and Innovation Agency, and the Higher Education Service Institution of Region XI Kalimantan for their financial support of this research (decision number 0459/E5/PG.02.00/2024 and funding contract number 113/E5/PG.02.00/PL/2024).

**Acknowledgments:** We thank the Mutiara Mahakam College of Health Sciences Samarinda, Muhammadiyah University of East Kalimantan, Mulia University, and all respondents who participated in this study.

**Conflict of interest:** The authors declare no conflict of interest.

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