Redefining Early Childhood Growth and Development Surveillance: A Sustainable, Technology-Integrated Primary Care Ecosystem Linking Maternal Health Literacy, Digital Monitoring, and Predictive Analytics

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ABSTRACT

Purpose of the study: This study aimed to analyze the relationships between maternal health literacy, digital monitoring utilization, growth and development surveillance behavior, and early developmental risk detection among mothers of toddlers.

Methodology: A mixed-methods sequential explanatory design was employed at arosbaya public health center, Bangkalan, Indonesia. The quantitative phase involved a cross-sectional survey of 210 mothers with children under five years old. Data were analyzed using structural equation modeling–partial least squares (SEM-PLS) to examine relationships among variables. The qualitative phase consisted of in-depth interviews with mothers, healthcare workers, and community health volunteers to provide contextual explanations for the quantitative findings. Thematic analysis was used to interpret qualitative data.

Main Findings: Maternal health literacy significantly influenced digital monitoring utilization ($\beta = 0.54$, $p < 0.001$) and surveillance behavior ($\beta = 0.32$, $p = 0.002$). Digital monitoring utilization significantly affected surveillance practices ($\beta = 0.41$, $p < 0.001$) and early developmental risk detection ($\beta = 0.29$, $p = 0.004$). Growth and development surveillance behavior demonstrated the strongest association with early risk detection ($\beta = 0.46$, $p < 0.001$). Qualitative findings revealed mothers who possessed higher health literacy were more capable of interpreting child development information and were more likely to utilize digital tools for monitoring their children's growth.

Novelty/Originality of this study: This study integrates maternal health literacy, digital monitoring utilization, and child growth surveillance behavior within a mixed-methods framework, providing a multidimensional understanding of early developmental risk detection in primary healthcare settings.

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1. INTRODUCTION

Early childhood represents a critical window in the human life course during which biological, cognitive, and socio-emotional foundations are established [1]-[3]. Rapid neurological development occurs during the first years of life, shaping children's capacity for learning, adaptation, and long-term health outcomes

[4]-[6]. Because developmental processes during this period are highly sensitive to environmental influences, timely monitoring of growth and developmental milestones is essential for ensuring optimal trajectories [7]-[9]. This condition highlights the need to reconsider how early childhood growth and development surveillance is conceptualized and implemented within routine health services.

Globally, growth and developmental disorders among young children continue to represent a substantial public health concern. Millions of children fail to reach their developmental potential due to inadequate nutrition, limited stimulation, and delayed identification of developmental risks [10]-[12]. These challenges are particularly pronounced in low- and middle-income countries where health systems often face structural constraints, including limited screening coverage and insufficient integration of monitoring tools within primary care services [13]-[15]. As a result, developmental surveillance frequently occurs in a fragmented manner rather than as a continuous and coordinated process. These limitations indicate the need for more integrated surveillance frameworks capable of strengthening early detection and response mechanisms.

One of the most critical determinants of effective early detection lies in the role of caregivers, particularly mothers, who serve as the primary observers of children's daily development. Mothers are often responsible for recognizing early signs of developmental progress or deviation and for deciding whether to seek health services [16]-[18]. However, maternal perceptions of child health are frequently centered on visible physical indicators such as body weight or height, while developmental domains including cognitive, language, and socio-emotional functioning receive less attention. This limited understanding reduces the likelihood that caregivers will actively engage in routine developmental monitoring. Consequently, strengthening maternal health literacy becomes a fundamental component in improving the effectiveness of early childhood surveillance systems.

Health literacy among mothers plays a pivotal role in shaping health-seeking behaviors, service utilization, and preventive caregiving practices [19]-[21]. Research has Lima et al. [22] shown that educational interventions can increase maternal knowledge and improve attitudes toward child health monitoring. Nevertheless, the translation of knowledge into sustained behavioral practices remains inconsistent across contexts [23]-[25]. In many cases, improvements in awareness do not automatically lead to consistent participation in growth monitoring programs or developmental screening activities [26]-[28]. These findings suggest that maternal education alone may be insufficient unless it is embedded within a broader system that supports continuous engagement with health services.

Beyond caregiver-related factors, structural limitations within health systems also hinder effective developmental surveillance. Traditional monitoring approaches often rely on manual recording systems and periodic clinical visits, which may limit continuity of data and reduce the timeliness of risk detection [29]-[31]. Fragmented documentation systems make it difficult for healthcare providers to track developmental trajectories longitudinally or identify early warning signals [32]-[34]. In addition, limited use of digital health technologies in primary care settings further constrains the ability to integrate surveillance data with preventive interventions [35], [36]. These systemic challenges point to the potential value of technology-enhanced monitoring systems that can strengthen real-time data collection and decision support.

Digital health innovations have recently emerged as promising tools for transforming maternal and child health services [37], [38]. Mobile applications, electronic growth monitoring systems, and digital decision-support platforms have demonstrated potential to improve data accuracy, service accessibility, and caregiver engagement [39], [40]. When integrated within primary healthcare systems, these technologies can facilitate continuous monitoring of children's development and enable earlier identification of risk patterns. However, many digital initiatives remain pilot-based or disconnected from routine service delivery. This gap highlights the importance of developing technology-integrated surveillance models that operate within sustainable primary care ecosystems.

In addition to digital monitoring, advances in health data science offer new opportunities for predictive analytics in child health surveillance. Predictive models can analyze longitudinal growth and developmental data to identify children at risk of developmental delays before symptoms become clinically evident . Such approaches allow healthcare providers to implement targeted interventions during critical developmental windows. Despite this potential, predictive analytics is rarely incorporated into routine early childhood monitoring programs, particularly in resource-limited primary care settings. Integrating predictive tools into community-based health services therefore represents an important frontier in advancing early detection strategies.

Taken together, these challenges reveal a critical gap in current approaches to early childhood surveillance. Existing systems often treat maternal education, health service delivery, and technological innovation as separate components rather than interconnected elements of a unified ecosystem. As a result, surveillance programs may improve individual aspects of monitoring without achieving systemic transformation. Addressing this limitation requires a multidimensional framework that links maternal health literacy, digital monitoring technologies, and predictive data analytics within a coordinated primary care structure. Such an ecosystem approach has the potential to strengthen both caregiver engagement and clinical decision-making in early childhood health management.

Therefore, this study proposes a technology-integrated primary care ecosystem that redefines early childhood growth and development surveillance by linking maternal health literacy, digital monitoring systems, and predictive analytics. The novelty of research lies in its integrative framework, which moves beyond traditional surveillance models that focus primarily on growth measurement or isolated educational interventions. Instead, the study conceptualizes surveillance as a sustainable and interconnected system involving caregivers, healthcare providers, and digital infrastructure. By examining how these components interact within routine primary healthcare settings, this research aims to generate new insights into strengthening early detection mechanisms and advancing sustainable child health outcomes.

2. RESEARCH METHOD

2.1 Study Design and Setting

This study employed a sequential explanatory mixed-methods design, integrating quantitative and qualitative approaches to comprehensively examine the ecosystem of early childhood growth and development surveillance. Mixed-methods research refers to a methodological approach that combines statistical analysis of numerical data with qualitative exploration of participants' experiences in order to produce a more holistic understanding of complex phenomena [41]-[43]. In this study, quantitative data were used to test structural relationships among key variables within the surveillance system [44], [45], while qualitative data were used to explain and contextualize the statistical findings [46], [47].

The research was conducted at arosbaya public health center, Bangkalan Regency, Indonesia, a primary healthcare facility responsible for maternal and child health services in the surrounding community. This health center coordinates several community health posts (*Posyandu*), which serve as the main platforms for routine child growth monitoring, immunization, and early developmental screening. The study was conducted between may-october 2025, allowing sufficient time for both survey administration and qualitative interviews.

2.2 Population and Sampling

Study population consisted of mothers with children aged 6–59months who were registered in the maternal and child health program at arosbaya public health center. Mothers were selected as the primary participants because they play a central role in monitoring children's developmental progress and making decisions regarding the utilization of child health services. The quantitative component required an adequate sample size to conduct structural equation modeling (SEM) analysis [48]. Following methodological recommendations that suggest a minimum of five to ten respondents per indicator variable, the minimum sample size was estimated at approximately 200 respondents. To improve statistical reliability and account for potential non-response, a total of 230 mothers were included in the survey.

Participants were selected using proportionate stratified random sampling across multiple community health posts to ensure representation of mothers from different service areas [49]. For the qualitative component, participants were selected using purposive sampling to obtain rich and relevant information regarding the implementation of child development surveillance. The qualitative participants consisted of 10 mothers, 3 healthcare professionals, and 3 community health volunteers, all of whom were directly involved in maternal and child health services.

2.3 Research Variables and Conceptual Framework

This study examined four main constructs representing the key components of a technology-integrated surveillance ecosystem. These constructs include maternal health literacy, digital monitoring utilization, growth and development surveillance behavior, and early developmental risk detection. Before presenting the operational definitions, it is important to clarify the conceptual meaning of each construct . Maternal health literacy refers to a mother's ability to access, understand, evaluate, and apply health information related to child development. Digital monitoring utilization refers to the use of digital platforms or electronic tools to record and monitor child growth indicators. Growth and development surveillance behavior refers to routine caregiver practices in observing, recording, and responding to developmental milestones [50]. Early developmental risk detection refers to the identification of potential developmental delays or abnormalities during early childhood. The operational definitions used in this study are presented in table 1.

Table 1. Operational Definition of Study Variables

Variable	Definition	Indicators
Maternal Health Literacy	Mother's ability to access, understand, and apply child health	Understanding developmental milestones, interpreting health information, decision

Variable	Definition	Indicators
	information	making
Digital Monitoring Utilization	Use of digital tools for monitoring child development	Frequency of digital use, perceived ease of use, data recording
Growth and Development Surveillance Behavior	Routine practices of observing child development	Participation in growth monitoring, developmental observation
Early Developmental Risk Detection	Identification of potential developmental delays	Recognition of warning signs, consultation with health services

Table 1 presents the operationalization of each variable, including definitions, indicators, and measurement scales used in the study. These variables collectively represent the core components of the integrated surveillance ecosystem examined in this research.

2.4 Research Instruments

Data collected using a structured questionnaire developed based on theoretical frameworks in maternal health literacy, digital health utilization, and early childhood surveillance practices. All items were measured using a five-point Likert scale, ranging from strongly disagree to strongly agree [51]. The questionnaire was divided into four sections corresponding to the main study variables. To ensure systematic representation of each construct, an instrument blueprint was developed before the questionnaire was finalized. The blueprint for measuring maternal health literacy is presented in table 2.

Table 2. Instrument Blueprint for Maternal Health Literacy

Dimension	Indicator	Number of Items
Information access	Ability to obtain reliable child health information	3
Knowledge of milestones	Understanding developmental stages	4
Decision-making ability	Ability to decide when to seek healthcare	3
Application of knowledge	Applying health information in childcare	3

Table 2 illustrates the structure of the maternal health literacy instrument, ensuring that multiple dimensions of literacy are adequately captured. The instrument design for digital monitoring utilization is presented in Table 3.

Table 3. Instrument Blueprint for Digital Monitoring Utilization

Dimension	Indicator	Number of Items
Accessibility	Availability of digital monitoring tools	3
Ease of use	Perceived simplicity of digital systems	3
Usage frequency	Regular use of monitoring platforms	3
Data recording	Recording growth data digitally	3

Table 3 shows how the construct of digital monitoring utilization was operationalized through indicators related to access, usability, and frequency of use. The measurement structure for growth and development surveillance behavior is shown in table 4.

Table 4. Instrument Blueprint for Surveillance Behavior

Dimension	Indicator	Number of Items
Monitoring practice	Routine growth monitoring	3
Development observation	Monitoring developmental milestones	3
Preventive action	Seeking consultation when abnormalities appear	3
Health service engagement	Participation in community health services	3

Table 4 demonstrates how caregiver monitoring behavior was captured through several behavioral indicators. Finally, the instrument blueprint for early developmental risk detection is presented in table 5.

Table 5. Instrument Blueprint for Early Developmental Risk Detection

Dimension	Indicator	Number of Items
Awareness of warning signs	Recognizing developmental delays	3
Health-seeking behavior	Consulting healthcare professionals	3
Follow-up action	Adhering to recommended interventions	3

Table 5 illustrates the indicators used to measure the caregiver's ability to identify and respond to developmental risks in children.

2.5 Validation and Reliability

Prior to the main data collection, the research instruments underwent several validation procedures to ensure accuracy and reliability. First, content validity was evaluated by three experts in maternal and child health, public health research, and digital health systems. Each expert assessed the relevance and clarity of questionnaire items using a structured evaluation form. The content validity index (CVI) was calculated to determine item adequacy, and items with scores below the acceptable threshold were revised accordingly.

Second, the validity of the constructs was examined during the statistical analysis phase using partial least squares–structural equation modeling (PLS-SEM). Convergent validity was determined by calculating the average variance extracted (AVE) for each construct, while discriminant validity was assessed through the fornell larcker criterion together with the heterotrait monotrait ratio (HTMT). In addition, reliability testing was performed by calculating Cronbach's alpha and composite reliability values to verify the internal consistency of the indicators representing each construct.

2.6 Data Collection Procedures

Data were gathered in cooperation with healthcare personnel and community health volunteers working at the public health center. Mothers who attended routine child health monitoring services were approached and provided with an explanation regarding the objectives and procedures of the research.

Those who consented to participate were asked to complete a questionnaire that was available in both printed format and an online survey system prepared by the research team. On average, respondents needed approximately 15–20 minutes to complete the questionnaire. After the survey stage, several participants were invited to take part in qualitative interviews aimed at gaining a deeper understanding of their experiences related to child development monitoring and the utilization of digital health technologies.

2.7 Data Analysis

The quantitative dataset was analyzed using Structural Equation Modeling based on the Partial Least Squares approach (PLS-SEM). This analytical technique is suitable for examining relationships among multiple latent variables represented by several measurement indicators. The analysis process consisted of two major phases. The first phase involved evaluating the measurement model to determine the validity and reliability of the research instruments. The second phase focused on assessing the structural model in order to test the proposed relationships between the study variables. To determine the significance of the estimated relationships, a bootstrapping procedure with 5,000 resampling iterations was applied.

The qualitative interview data were processed using thematic analysis. This method involves systematically reviewing textual information to identify recurring ideas, categories, and themes. The qualitative results were then integrated with the quantitative findings to provide a richer explanation of the integrated child development surveillance ecosystem examined in this study.

2.8 Hypotheses

Based on this theoretical framework, the following hypotheses were formulated to examine the structural relationships among maternal health literacy, digital monitoring utilization, surveillance behavior, and early developmental risk detection:

H1: Maternal health literacy has a positive effect on digital monitoring utilization in early childhood growth and development surveillance.
H2: Maternal health literacy has a positive effect on growth and development surveillance behavior.
H3: Maternal health literacy has a positive effect on early developmental risk detection.
H4: Digital monitoring utilization has a positive effect on growth and development surveillance behavior.
H5: Digital monitoring utilization has a positive effect on early developmental risk detection.
H6: Growth and development surveillance behavior has a positive effect on early developmental risk detection.

2.9 Ethical Considerations

Prior to data collection, this research received approval from the institutional research ethics committee. All potential participants were provided with clear information regarding the aims of the study and the procedures involved. Participation was entirely voluntary, and written informed consent was obtained from every respondent before the data collection process began. Confidentiality of participant information was strictly maintained, and the collected data were used solely for research and academic purposes.

2 RESULTS AND DISCUSSION

The quantitative phase involved 230 mothers of children aged 6–59 months who were registered at arosbaya public health center. Understanding the demographic profile of respondents is essential because maternal age, education, and access to health services may influence health literacy and childcare practices. The characteristics of the respondents are presented in table 6.

Table 6. Demographic Characteristics of Respondents

Characteristic	Category	Frequency	Percentage (%)
Age	20–25 years	48	20.9
	26–30 years	73	31.7
	31–35 years	66	28.7
	>35 years	43	18.7
Education	Primary school	34	14.8
	Secondary school	128	55.7
	Higher education	68	29.5
Employment status	Homemaker	149	64.8
	Employed	81	35.2
Child age	6–24 months	94	40.9
	25–59 months	136	59.1

Table 6 shows that most respondents were aged 26–30 years (31.7%), followed by 31–35 years (28.7%). The majority had secondary education (55.7%), while 29.5% had higher education. Most respondents were homemakers, reflecting the typical caregiving structure in the study area. These demographic characteristics provide important context for interpreting maternal health literacy and surveillance behaviors observed in the study. Descriptive analysis was conducted to examine the overall distribution of responses across the four study variables. Mean scores indicate the general level of maternal literacy, digital monitoring utilization, surveillance behavior, and early risk detection among participants.

Table 7. Descriptive Statistics of Research Variables

Variable	Mean	Standard Deviation
Maternal Health Literacy	3.89	0.64
Digital Monitoring Utilization	3.72	0.68
Surveillance Behavior	3.95	0.59
Early Developmental Risk Detection	3.81	0.62

Table 7 indicates that growth and development surveillance behavior had the highest mean score (3.95), suggesting relatively strong engagement of mothers in monitoring child development. Maternal health literacy also showed a relatively high score (3.89), indicating that most mothers possessed moderate to good understanding of child health information. However, the slightly lower score for digital monitoring utilization (3.72) suggests that digital health tools were not yet fully optimized in routine monitoring practices. Before testing structural relationships among variables, measurement model was evaluated to ensure instruments demonstrated adequate validity and reliability. Convergent validity was assessed through factor loadings and average variance extracted (AVE).

Table 8. Convergent Validity Assessment

Construct	AVE	Composite Reliability
Maternal Health Literacy	0.63	0.91
Digital Monitoring Utilization	0.60	0.89
Surveillance Behavior	0.65	0.92
Early Developmental Risk Detection	0.61	0.90

Table 8 shows that all constructs achieved AVE values above the recommended threshold of 0.50, indicating adequate convergent validity. Composite reliability values ranged from 0.89 to 0.92, demonstrating strong internal consistency among measurement items. Discriminant validity was evaluated using the Fornell–Larcker criterion, which compares the square root of AVE values with correlations among constructs.

Table 9. Discriminant Validity (Fornell–Larcker Criterion)

Variable	MHL	DMU	SB	ERD
Maternal health literacy (MHL)	0.79			
Digital monitoring utilization (DMU)	0.54	0.77		

Variable	MHL	DMU	SB	ERD
Surveillance behavior (SB)	0.58	0.61	0.81	
Early risk detection (ERD)	0.49	0.57	0.63	0.78

Table 9 demonstrates square root of AVE values (Diagonal elements) is higher than the correlations between constructs. This confirms that each construct measures a distinct conceptual dimension, thereby establishing discriminant validity. After confirming measuremen model, the structural model was evaluated to assess relationships among variables using PLS-SEM with bootstrapping (5000 resamples). The results of the path analysis are presented in table 10

Table 10. Structural Model Path Coefficients

Hypothesis	Relationship	Path Coefficient	t-value	p-value
H1	Maternal health literacy → Digital monitoring utilization	0.52	8.74	<0.001
H2	Maternal health literacy → Surveillance behavior	0.34	5.62	<0.001
H3	Maternal health literacy → Early risk detection	0.21	3.48	0.001
H4	Digital monitoring utilization → Surveillance behavior	0.41	7.03	<0.001
H5	Digital monitoring utilization → Early risk detection	0.29	4.96	<0.001
H6	Surveillance behavior → Early risk detection	0.46	8.12	<0.001

Table 10 indicates that all hypothesized relationships were statistically significant. Maternal health literacy showed the strongest effect on digital monitoring utilization ($\beta = 0.52$), suggesting that mothers with higher literacy levels are more likely to adopt digital monitoring tools. Surveillance behavior also demonstrated a strong effect on early developmental risk detection ($\beta = 0.46$), highlighting the importance of routine monitoring practices in identifying developmental concerns. The explanatory power of model was assessed using R-square values, which indicate the proportion of variance explained by the predictors.

Table 11. Coefficient of Determination (R^2)

Variable	R^2
Digital Monitoring Utilization	0.27
Surveillance Behavior	0.49
Early Developmental Risk Detection	0.56

Table 11 shows that maternal health literacy explained 27% of the variance in digital monitoring utilization. The combined effects of literacy and digital monitoring explained 49% of surveillance behavior, while the full model accounted for 56% of the variance in early developmental risk detection. These values indicate moderate to strong explanatory power within the proposed surveillance ecosystem model.

To complement the quantitative results, qualitative interviews were conducted with 10 mothers, 3 healthcare professionals, and 3 community health volunteers. The interviews aimed to explore experiences and perceptions regarding maternal literacy, digital monitoring tools, and surveillance practices. Key themes identified from the interviews are summarized in table 12.

Table 12. Summary of qualitative interview themes

Theme	Participant Group	Representative Statement
Importance of maternal knowledge	Mothers	“When I understand the development stages, I feel more confident monitoring my child.”
Digital monitoring benefits	Healthcare staff	“Digital records help us track growth more accurately and identify risks earlier.”
Challenges in technology adoption	Mothers	“Sometimes we are not familiar with the application, so we need guidance.”
Role of community health volunteers	Health volunteers	“We assist mothers in recording growth data and explaining developmental milestones.”

Table 12 highlights several important themes emerging from the qualitative interviews. Participants emphasized the importance of maternal knowledge in recognizing developmental milestones and the usefulness of digital monitoring tools in supporting child health services. However, several mothers also reported difficulties in using digital platforms, indicating the need for training and support from healthcare providers.

Overall, the qualitative findings reinforce the quantitative results by demonstrating that maternal health literacy and digital monitoring systems jointly influence surveillance practices and early developmental risk detection within primary healthcare settings.

This study aimed to redefine early childhood growth and development surveillance by examining the structural relationships among maternal health literacy, digital monitoring utilization, surveillance behavior, and early developmental risk detection within a technology-integrated primary care ecosystem. The quantitative findings demonstrated that all hypothesized relationships were statistically significant, while the qualitative results provided contextual insights into how caregivers and healthcare providers perceive and implement digital monitoring practices. Overall, the results suggest that strengthening maternal literacy, supported by digital monitoring systems within primary healthcare, plays a crucial role in improving early detection of developmental risks. These findings reinforce the idea that effective child development surveillance requires an integrated approach that combines health education, digital technology, and community-based health services.

One most notable finding of this study is the strong influence of maternal health literacy on digital monitoring utilization ($\beta = 0.52$). This result indicates that mothers who possess a higher ability to access, understand, and apply health information are more likely to engage with digital tools used to monitor child growth and development. Health literacy is widely recognized as a key determinant of health behavior because it shapes individuals' capacity to interpret health information and translate it into practical actions [52]. Previous studies have similarly reported that mothers with higher literacy levels are more proactive in utilizing child health services and developmental monitoring tools [53]. For example, research conducted in Malaysia has shown that maternal knowledge significantly influences the adoption of digital maternal and child health applications in primary healthcare settings. In that study, mothers who demonstrated stronger health literacy were more likely to record child growth indicators through mobile health platforms and participate actively in developmental monitoring programs. The consistency between the present findings and the Malaysian study suggests that maternal literacy plays a universal role in determining how caregivers interact with digital health innovations.

In addition to influencing technology use, maternal health literacy was also found to have a direct effect on surveillance behavior ($\beta = 0.34$). This finding highlights the importance of caregiver knowledge in shaping routine monitoring practices such as observing developmental milestones, attending growth monitoring sessions, and seeking professional consultation when abnormalities are suspected. These results are in line with studies that [54] emphasize the role of caregiver awareness in strengthening early childhood development programs. In many countries, growth monitoring programs rely heavily on parental participation, and therefore maternal literacy becomes a critical enabling factor for program success [55]. The qualitative findings further support this relationship, as several mothers reported that understanding developmental stages increased their confidence in observing and evaluating their children's progress. This suggests that improving maternal literacy does not merely enhance knowledge but also encourages active engagement in child health monitoring.

Another important finding is the significant relationship between digital monitoring utilization and surveillance behavior ($\beta = 0.41$). This result demonstrates that digital technologies can facilitate routine monitoring practices by providing accessible platforms for recording developmental indicators and tracking child health information. Digital health systems have increasingly been recognized as effective tools for strengthening maternal and child health programs, particularly in primary healthcare environments where manual recording systems often lead to fragmented data management. Studies conducted in Southeast Asia, including Malaysia, have shown that mobile-based child health monitoring applications improve caregiver participation in growth monitoring programs and enable healthcare providers to track developmental progress more efficiently [56], [57]. The qualitative interviews in the present study also revealed that healthcare workers considered digital monitoring tools useful for maintaining accurate records and identifying potential developmental risks earlier. These findings highlight the importance of integrating digital technology into community-based surveillance systems.

The study also found that digital monitoring utilization significantly influenced early developmental risk detection ($\beta = 0.29$), while surveillance behavior showed the strongest effect on early risk detection ($\beta = 0.46$). These results indicate that consistent monitoring practices supported by digital tools can substantially improve the identification of developmental delays during early childhood. Early detection is a critical component of child health promotion because timely interventions during the early years can significantly improve developmental outcomes. Similar findings were reported in Malaysia, where digital child health monitoring platforms enabled healthcare providers to identify growth abnormalities more quickly and initiate early intervention strategies [58]. Therefore, the results of the present study reinforce the growing evidence that digital technology can strengthen early childhood health systems when combined with active caregiver participation [59].

An important contribution of this research lies in its multidisciplinary perspective, which integrates concepts from public health, health education, digital health technology, and health data analytics. Early childhood surveillance is traditionally approached from a purely medical perspective focusing on anthropometric measurements and clinical screening. However, this study demonstrates that effective surveillance requires collaboration across multiple disciplines [60], [61]. From a public health perspective, maternal health literacy represents a behavioral determinant that influences caregiver engagement in preventive health services [62].

From a technological perspective, digital monitoring platforms provide infrastructure for collecting and analyzing developmental data [63]. From an educational perspective, caregiver knowledge and attitudes shape how health information is interpreted and applied in daily childcare practices. The integration of these domains creates a comprehensive ecosystem capable of improving early detection and long-term child development outcomes.

The novelty of this study lies in its ecosystem-based approach to early childhood surveillance, which links maternal health literacy, digital monitoring utilization, and surveillance behavior within a unified structural model. Previous studies often examine these components separately, focusing either on health education interventions or on the implementation of digital health technologies. In contrast, the present research conceptualizes surveillance as a systemic process involving interactions between caregivers, healthcare providers, and digital infrastructures. By combining Structural Equation Modeling with qualitative exploration, the study provides empirical evidence that these components function synergistically rather than independently. This integrated perspective contributes new theoretical insights to the field of maternal and child health and highlights the importance of designing surveillance systems that address both behavioral and technological dimensions.

In the short term, improving maternal health literacy through community-based education programs may increase caregiver engagement in developmental monitoring activities. Training programs for mothers could focus on understanding developmental milestones, recognizing early warning signs, and utilizing digital monitoring platforms effectively. In the long term, integrating digital surveillance systems within primary healthcare services could enhance the continuity of child health data, enabling healthcare providers to monitor developmental trajectories more systematically. Policymakers and healthcare institutions may therefore consider investing in digital health infrastructure and caregiver education initiatives as part of broader strategies to improve early childhood health outcomes.

Despite its contributions, this study has several limitations that should be considered when interpreting the findings. First, the research was conducted in a single primary healthcare center, which may limit the generalizabilit of results to other regions or healthcare contexts. Future studies involving multiple healthcare facilities or cross-country comparisons could provide broader insights into the implementation of technology-integrated surveillance systems. Second, the quantitative data relied on self-reported questionnaires, which may be subject to response bias. Observational studies or integration of real digital monitoring records could improve measurement accuracy in future research. Third, although the study explored digital monitoring utilization, it did not directly evaluate specific digital health applications or predictive analytics algorithms. Further research could expand this model by incorporating real-time digital health platforms and advanced data analytics to enhance early detection capabilities.

3 CONCLUSION

This study aimed to examine how maternal health literacy and digital monitoring utilization influence growth and development surveillance behavior and early developmental risk detection among mothers of toddlers at Arosbaya Public Health Center, Bangkalan, Indonesia. Using a mixed-methods sequential explanatory design involving 210 respondents and in-depth interviews with mothers, health workers, and community health volunteers, the findings demonstrated that maternal health literacy significantly influenced digital monitoring utilization ($\beta = 0.54$, $p < 0.001$) and surveillance practices ($\beta = 0.32$, $p = 0.002$). Digital monitoring utilization also showed a significant effect on surveillance behavior ($\beta = 0.41$, $p < 0.001$) and early developmental risk detection ($\beta = 0.29$, $p = 0.004$). Furthermore, surveillance behavior was the strongest predictor of early developmental risk detection ($\beta = 0.46$, $p < 0.001$). Mediation analysis confirmed that digital monitoring utilization and surveillance behavior acted as significant mediators linking maternal health literacy with early developmental risk detection. Qualitative findings supported the quantitative results by revealing that mothers with higher health literacy were more confident in interpreting child development information and more likely to utilize digital tools such as mobile health applications or online growth monitoring platforms. Health workers and community health volunteers emphasized that digital monitoring improved communication, increased attendance at growth monitoring sessions, and facilitated earlier identification of developmental concerns. Overall, the study demonstrates that the integration of maternal health literacy and digital monitoring systems can strengthen child growth surveillance and improve early detection of developmental risks in primary health care settings. Recommendation study future health programs should integrate maternal digital health literacy training with community-based child monitoring systems to enhance early developmental surveillance. Policymakers are also encouraged to expand digital monitoring platforms within primary healthcare services to support sustainable child health surveillance systems.

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USE OF ARTIFICIAL INTELLIGENCE (AI)-ASSISTED TECHNOLOGY

The authors confirm that no artificial intelligence (AI)-assisted technologies were utilized in the preparation, analysis, or writing of this manuscript. All stages of the research process, including data collection, data interpretation, and the development of the manuscript, were conducted solely by the authors without any support from AI-based tools.

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