0.1 SLIDE 1: Title Slide

Excellencies, ladies, and gentlemen. My name is Monireach, a Master's research student in AI. Today I'll present our design study on privacy governance-driven AI architecture for elderly safety monitoring in Cambodia. This research demonstrates how privacy governance principles can inform architectural decisions from the beginning, rather than being retrofitted or added after deployment. The work aligns with this conference's theme of governing emerging intelligent technologies, because it examines the combination of privacy governance, edge computing, and accessibility in resource-constrained healthcare contexts.

Let me start by framing the challenge we're addressing.

0.2 SLIDE 2: The Challenge - Elderly Safety Dilemma

Southeast Asia is facing a rapidly aging population, according to World Health Organization in 2025, elderly population is estimated to increase from 12.2% in 2024 to nearly 23% by 2050. Falls are the leading cause of injury-related deaths among elderly, with 684,000 annual fatalities globally, and 60% concentrated in the Western Pacific and Southeast Asia regions. In Cambodia specifically, we're projecting 2.1 million elderly by 2030.

Current monitoring solutions force families to choose between privacy and effectiveness. Cloud-based cameras transmit video to third-party servers, creating facial recognition and re-identification risks. A similar commercial product–the Kami Fall Detect Camera, for example, requires continuous cloud connectivity and costs 1719 US Dollars over three years due to mandatory subscriptions. Wearables offer better privacy but come with particular challenges—elderly users must remember to wear devices consistently and maintain charging, which is particularly difficult at nighttime.

We're targeting middle-income Cambodian households—families earning 870 to 1622 US Dollars per month according to Cambodia National Institute of Statistics in 2021. For them, a 45 US Dollars monthly cloud subscription means paying 5.2% or more of their income every month, indefinitely. That's not sustainable. But these families still need reliable safety monitoring for

their aging parents at home.

This brings us to our research question.

0.3 SLIDE 3: What We're Investigating

Let me explain what we're investigating in plain terms.

With the previously specified issues of privacy and compliance, we're asking: can we design a system that protects privacy by keeping all data at home, works 24/7 without requiring wearables, and costs less than cloud alternatives?

In academic framing, our research question is: how can privacy governance principles—the rules about handling personal data—inform the architectural design of AI-based elderly monitoring systems in resource-constrained contexts like Cambodia or other developing countries?

This is a design study. We're demonstrating how governance principles can drive architecture choices. We validate three things: whether affordable infrared cameras work with AI pose detection, whether edge-based systems cost less than cloud alternatives, and whether our architecture eliminates facial data collection by design.

We're not validating fall detection accuracy—that's future work. We're not deploying in real homes yet. We're only showing that privacy-first edge architecture is technically and economically viable.

So what specifically are we exploring?

0.4 SLIDE 4: Three Design Propositions

We explore three design propositions.

First: can privacy governance translate directly into technical architecture? If privacy rules say "must protect privacy," can we translate that into specific choices—edge computing, pose-only data

storage, and deleting video frames immediately after processing?

Second: does privacy-first design yield cost reduction? Our hypothesis is that eliminating cloud infrastructure for privacy reasons also eliminates expensive subscription fees, creating an economic benefit beyond privacy protection.

Third: can body pose data alone enable safety monitoring? Can we detect falls using just skeletal keypoints—17 body joint coordinates—without storing actual video footage?

Our testing approach validates feasibility through NIR camera compatibility testing and cost-effectiveness analysis. We're showing this architecture is viable before investing in full system deployment.

Let me show you the architecture we designed based on these propositions.

0.5   SLIDE 5: Privacy Governance Architecture

Our architecture translates privacy requirements into two concrete design choices.

First, edge-first processing. This means that all the computing happens on a small box in your home—specifically, an NVIDIA GPU called Jetson Orin Nano. Nothing gets sent to the internet. Your elderly parent's health data physically cannot leave the house. That's what we mean by data sovereignty.

Second, our privacy layer combines pose-only storage with immediate frame disposal. The system extracts just 17 body joint coordinates—those skeleton points you see on the left. After extraction, the video frame gets deleted immediately. We keep only the pose data, never the actual video. This means you cannot reverse-engineer a person's face because facial information literally doesn't exist in our data, and there's no video to go back and review later.

This approach is called privacy by design. The difference from typical systems: we're building privacy into the architecture from day one, not adding privacy controls after the system is already deployed. The system enforces privacy through what it physically can and cannot do, not through

policies that someone might violate later.

Let me briefly outline the technical implementation.

0.6 SLIDE 6: Technical Approach Overview

Let me give you a quick overview of the technical setup. I'll keep this simple.

Hardware: Four cameras positioned around the room, 90 degrees apart, so they cover the entire space—360-degree coverage. These are ordinary security cameras, but they have infrared night vision. That means they work in complete darkness, 24/7. No need to keep lights on at night. Total cost for the whole system: $672 one-time payment. No monthly fees.

Software: Three steps. First, the system detects where the person is in the video frame—just finds the person. Second, it extracts the body pose—those 17 skeleton points we talked about earlier. Third, our privacy layer kicks in—deletes the video frame immediately, keeps only the pose coordinates for further deep leaning model processing.

Now, let's have a look at the results of our validation using this architecture.

0.7 SLIDE 7: Results - NIR Camera Compatibility

Let's look at our first validation result: does AI pose detection actually work on infrared night vision cameras?

Testing approach: We collected 20 commercial security camera videos from different manufacturers—Hikvision, EZviz, dome cameras, bullet cameras—filmed in different environments, both indoor and outdoor. These are real infrared videos at 1080p and 4K resolution. We tested to see if our software works across different camera types, not just one specific model.

The results: The system detected body poses in 91.3% of video frames. That's detecting about 30 out of 33 body points per frame. The confidence score averaged 0.868—in simple terms, the

system is quite certain about what it's detecting. False negatives—situations where a person is there but the system fails to detect their pose—happened 12.3% of the time. Processing speed was about 20 frames per second.

Why this matters: The AI model we're using—MediaPipe—was originally trained on regular color images in daylight. Very little research has actually tested whether pose detection works on the specific infrared wavelength used in affordable security cameras. We're testing it on infrared footage in complete darkness. And it works. This confirms you can monitor elderly people 24/7 using economical security cameras without needing facial recognition technology.

Now let me show you the cost-effectiveness analysis.

0.8   SLIDE 8: Results - Cost-Effectiveness Analysis

Now, we are analyzing if privacy-first design actually saves money.

Our system costs $672 upfront. That's $252 for four cameras, $250 for the edge processor, and $170 for accessories like storage and cables. One-time payment. No monthly fees. Ever.

Compare that to cloud alternatives. We looked at the Kami Fall Detect Camera—it's a camera-based elderly fall detection system, similar to what we're building. The hardware costs $99, which sounds cheap. But there's a mandatory subscription: $45 every month. Do the math over three years: $99 hardware plus $1,620 in subscription fees equals $1,719 total.

The savings: 61% cost reduction. Our system saves families $1,047 over three years. The breakeven point? Month 13 of year two. After that, every month the cloud alternative keeps charging $45 while our system costs nothing.

Who can afford this? We're targeting middle-income Cambodian households—families earning 870 to 1622 US Dollars per month. That's the fourth and fifth income quintiles. For these families, a $45 monthly subscription means paying 5.2% of their income every single month, indefinitely. Our $672 one-time cost is equivalent to about half a month's income. Families can save up for it,

or pool money together.

Market reach: We estimate this could reach 8 to 12% of Cambodia's elderly population—those living in urban middle-income households (4th-5th income quintiles), totalling 168,000 to 252,000 people by 2030.

Here's the key point: we eliminated cloud infrastructure for privacy reasons. The cost savings is a side benefit. Privacy governance actually enables affordability.

Let me explain a key design trade-off we encountered.

0.9   SLIDE 9: Design Trade-offs - Safety-Critical Priority

There are two possible approaches for human pose estimation. One is Baseline, using standalone MediaPipe, which means to just run pose detection on the whole video frame. The other one is Integrated, combining YOLOv8n with MediaPipe, which means to first detect where the person is, crop that area, then run pose detection on just that cropped region.

The trade-off: The integrated approach is 2.3 times slower. It only processes 20 frames per second, while baseline achieves 47. However, the integrated approach is far more accurate, detecting 5.7% more keypoints and having 22.2% better pose coverage than baseline. Pose Coverage refers to the percentage of frames with human where a pose is detected.

We've chosen the integrated pipeline, because accuracy matters more than speed in this context. If the system misses a fall—if grandma falls and the camera doesn't detect it—that could be fatal. Speed is nice to have. Accuracy is life-or-death.

And here's the important part: even the slower integrated pipeline runs at 20 frames per second. Standard real-time monitoring is 15 frames per second. We're still well above that threshold.

This shows a governance principle at work: technical metrics don't exist in a vacuum. We have to evaluate performance against consequences. In safety-critical healthcare applications, we optimize for accuracy first, speed second.

These technical results lead to broader governance implications.

0.10   SLIDE 10: What This Means for Governance

Let me connect the dots on what these results mean for governance.

First key finding: Privacy by design actually works. Our work proved we can build a privacy-first system that performs well—91.3% detection rate on infrared cameras. we don't have to choose between privacy and performance.

Second: Privacy governance creates unexpected economic benefits. We eliminated cloud infrastructure for privacy reasons, which also eliminated subscription costs. This makes healthcare AI affordable for middle-income markets in developing countries. Privacy governance enables accessibility governance.

Third: Context-specific design matters. We designed for Cambodia's economic constraints. This approach scales to other developing countries with similar resource constraints.

The bottom line: governance principles can drive technical architecture from inception, not as afterthoughts. We're showing how to do privacy-first AI design in practice.

Let me address limitations and future directions.

0.11   SLIDE 11: Limitations & Future Directions

Let me be honest about the limitations.

First limitation: Testing environment. We tested on commercial security camera footage, not actual elderly people. Elderly individuals may move differently—different gait patterns, body proportions. Our validation shows the technology works, but we need to test with the actual target population.

Second: Hardware deployment. We measured performance on standard laptop hardware, not the actual Jetson Orin Nano edge device we're proposing. We got 20 frames per second on the laptop. The Jetson might perform differently—could be faster, could be slower. We need to validate on the actual hardware.

Third: Market accessibility. Our $672 system targets middle-income urban households. What about low-income families? What about rural areas? Those populations need different deployment models—maybe government subsidies, maybe community-based financing. We haven't solved accessibility for everyone, just for the middle-income segment.

What's next? Three immediate priorities. First, test fall detection accuracy on benchmark datasets—actually measure how well the system detects falls. Second, deploy on the Jetson hardware and validate real-world performance. Third, collect our own dataset with Cambodian elderly participants—real people in real homes.

Longer-term, we need user acceptance studies. Will elderly people and their caregivers actually use this system? That's the ultimate test—not just technical performance, but real-world adoption.

Let me conclude with key takeaways.

0.12 SLIDE 12: Conclusion - Key Takeaways

To conclude: There are four key takeaways.

Privacy governance can drive architecture from inception—we demonstrated this is both technically and economically feasible. Edge-first design achieved strong performance while reducing costs and expanding accessibility. Cambodia serves as proof-of-concept for resource-constrained contexts globally.

Three groups should care about this work:

- Researchers should validate infrared camera compatibility before deployment, as we found performance varies significantly by camera type

- Policymakers should recognize that privacy-first architecture can actually expand accessibility in middle-income markets through cost reduction
- Practitioners building elderly care systems should consider zero-subscription models to reduce ongoing cost barriers in developing countries.

Thank you for your attention. I'm happy to take questions if any.