Week 8: Elderly Care 2.0 User Acceptance Test Plan

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# Elderly Care 2.0

Senior citizens live longer than ever and want to defer moving into nursing homes until later in life. This constructive research project defines the business case for meeting these conflicting needs. Next, a literature review examines Smarthome use cases that improve the quality of care for elderly persons. Then a proof-of-concept is proposed to address those conflicts using state-of-the-art video processing. Lastly, a detailed User Acceptance Test (UAT) plan outlines the requirements necessary to ensure the system’s security, reliability, privacy, and validity.

## Problem Statement

Senior citizens live longer than ever and want to defer moving into nursing homes until later in life. Transitioning into elderly care comes as a double edge sword. On the one hand, nurses can provide 24-hour supervision. This assistance could mean the difference between life and death (e.g., during a fall). However, on the other hand, the medical services are prohibitively expensive, nearing $90,000 annually (Tan et al., 2020). Additionally, these medical facilities lack the personalization available within one’s home. Further, specific individuals with diseases like dementia and Alzheimer’s require even greater levels of attention.

Traditionally, addressing the situation requires increasing human capital, such as more traveling nurses or family member oversight. However, this solution increases health care costs and collects limited patient health samples. In addition, these infrequent visits might miss critical issues, especially with those most reluctant to relocate. Alternatively, researchers are exploring wearable IoT devices. These sensors provide mechanisms for requesting assistance and receiving continuous monitoring. However, there are many limitations to wearable solutions. Most notably, the person must remember to wear them, which raises challenges for early-onset memory loss patients.

## Building the Business Case

Many senior citizens want to remain in their homes and still receive the attentiveness typically found in assisted living facilities (Tan et al., 2020). When this gap narrows, the patient can remain in familiar settings for more prolonged periods. That situation has numerous psychological benefits (e.g., higher morale) and economically (e.g., deferring private health care costs). For instance, patients with memory impairment might forget to empty the dishwasher, take medication, or bathe regularly. These scenarios are challenging to address through wearable devices. Medical facilities can address these challenges through real-time video monitoring services that analyze the patients’ actions and recommend care. However, an in-home camera system transforms into a watchful eye to spot those missing actions through computer vision. After detecting an issue, the system alerts the person using Text-to-Speech (TTS) services (e.g., Amazon Alexa or Google Home).

Medical facilities also benefit from massive deployments of in-home monitoring systems. First, the in-home camera system tracks patient movements enabling early behavioral regression detection (e.g., reduced mobility). Next, centralized teams can provide higher-quality care to more remote patients. This configuration increases profit margins by reducing operational overhead (e.g., excess staff and fewer physical beds). Finally, when patient care issues arise, the system can prioritize and audit its resolution. The business can leverage this competitive position to avoid cutting corners and provide world-class care.

Additionally, having the option to remain in-home expands the caregiver’s addressable market. These populations include healthy widows, lower-income families, and even younger children with disabilities. While adult children might stress putting their mother in a facility, they are more willing to pay for a low-expense monthly service. Lower-income households cannot afford private health care and are at the mercy of public options. Likewise, special education children need additional oversight, not removal from the household. The family in each situation gains peace of mind and improves their quality of life.

# Literature Review

Examining the Northcentral University (NCU) Library with search terms such as elderly care, IoT, and video health monitoring uncovers several industry-wide trends.

## Just Walk-Out (2018)

Amazon Go enables customers to purchase goods from physical stores without cashiers (Amazon, 2021). Their solution uses Deep Neural Network (DNN) algorithms that process real-time video streams. Wankdhede et al. (2018) assessed the system’s sophistication through a series of shoplifting test cases. Their malicious attempts to steal items failed, proving that real-time video monitoring is an effective real-world tool. However, several critical changes are necessary before engineers can transpose the solution directly into a person’s home.

## Consumer RGB-D Cameras and Applications (2012)

Action tracking systems require sophisticated machine learning algorithms that classify spatiotemporal movements. They typically follow a process that collects RGB+D (Color and Depth) camera frames and decodes them into 3-D space (Litomisky, 2012). Next, a series of filters must crop, resize, and align the principal subject. These steps are necessary because people can freely move around the room. Third, a feature extract process outputs matrices representing the body’s location, pose, and orientation. Finally, those tensors flow into Long-Term Short-Term (LTSM) algorithms that classify the movement into gestures.

## Toyota Smarthome (2019)

Many general-purpose gesture detection libraries exist for behaviors such as sporting events and other high-energy actions. However, daily indoor activity tends to be more subtle and nuanced (Das et al., 2019). This discrepancy limits reusability and creates the need for purpose-built training sets that sufficiently cover patient-specific actions. Furthermore, these custom datasets necessitate vast quantities of examples with accurate labels, or the machine learning model will produce unreliable results. As a general rule of thumb, each model parameter needs at least ten examples to avoid overfitting (Snee, 2015). Gesture models can quickly explode into hundreds or thousands of parameters representing the 3-D space plus time. Mechanisms exist for accelerating building custom datasets (e.g., transfer learning). However, this is still an open research topic.

## Integration of SmartHome (2020)

After the system decodes the subject’s actions, it must act upon that information. While some responses are relatively trivial (e.g., dispatch an ambulance), other reactions must utilize Cyber-Physical Systems (CPS) to cross the digital boundary. Building these integrations is challenging as it draws upon knowledge spanning networking, sensors, embedded systems, and related concepts. Furthermore, CPS devices lack standardization which impacts component reusability.

Elloumi et al. (2020) propose a Smarthouse Operating System (SOS) that provides core services such as identity management, system state, and message routing. Their blueprint also outlines several automation applications profiles (e.g., heat management and fire detection). These capabilities enable developers to focus on their integrations value differentiation versus writing tedious generic code. Finally, the authors demonstrate the effectiveness of this approach using a CNC (Computer Numerical Control) machine to print a replica house (2 cubic feet).

## Privacy Enhanced Cloud-Based Facial Recognition (2021)

It can be helpful to think of identity within IoT as a profile of historical choices, stated preferences, user roles, and known associations (Wachter, 2018). When the device understands the user’s profile, the experience can be customized and produce more accurate predictions. However, the payment for access to these inferences and decision processes comes from personal information, such as calendars, contacts, and routines (Mickens, 2018). This trade creates privacy concerns that can be subtle and unnoticed issues for some time.

The monitoring system will collect intimate knowledge of its assigned patients and even capture private communications. Therefore, mechanisms must exist for protecting this information as it flows between different compute domains (e.g., local versus cloud providers). Yang et al. (2021) propose a Secure MultiParty Computation (SMC) model that locally encrypts sensitive images (e.g., faces). Afterward, they use Cheon-Kim-Kim-Song Homomorphic Encryption (CKKS HE) to predict the encrypted payload remotely (e.g., Bob’s face). Ideally, the system minimizes the information that leaves the patient’s private network. However, when sensitive images must upload into the cloud, the system can leverage encryption strategies like CKKS HE.

## Healthcare Monitoring using IoT (2020)

Software that uses cloud resources gains agility, elasticity, instantaneous provisioning, and cost management constructs. However, some businesses are reluctant to trust these environments entirely due to security concerns (Ali et al., 2015). Alternatively, systems engineers can deploy hardware appliances that bring cloud aspects into the home or medical facility. For example, Abdulameer et al. (2020) propose implementing a small replica house similar to Elloumi. Their solution uses various wearable device sensors, Arduino micro-controllers, and a Raspberry-PI. In addition, users can check their vitals and other health KPIs (Key Performance Indicators) through a web portal. Therefore, provisioning small on-premise appliances makes sense and handles scenarios such as failures at the ISP (Internet Service Provider). In addition, other benefits come from standardizing the control-plane versus assuming the patient’s personal computer is compatible and Always-On Always Connected (AoAC).

## Two-Way Video Healthcare System Design (2021)

Yi & Feng (2021) recently proposed a complete video-based injury rehabilitation solution that includes support for CPS and wearables. The authors leverage Carnegie Mellon University’s Open Pose library to map skeletal structures within images. Then, they publish this information and various sensor readings (e.g., smoke detectors) into a secure private cloud. Unlike Toyota (2019), the authors use Dynamic Time Warping (DTW) to compare and categorize the patients’ movements. Researchers use DTW to normalize time series and avoid discrepancies from action speeds (e.g., raising one’s hand within two versus four seconds).

# Examining the Competitive Landscape

Abdulameer et al.’s (2020) design fixate on collecting metadata from wearable IoT devices. Tun et al. (2021) surveyed fifty-five recent publications that discuss IoT use cases within elderly care. Their findings suggest that nearly all research focuses on wearable devices, mobility, and Personal Digital Assistants (PDA). Researchers focusing on these areas makes sense due to the low barrier to entry. Compare the effort necessary to clone a FITBIT mobile app versus transform 2-D images into spatiotemporal movements. Another set of challenges originates from insufficient training data. Aside from Das et al.’s (2019) open-sourced data set, few repositories (e.g., YouTube) contain appropriate training data. Lastly, numerous healthcare areas are improvable on a $25 RadioShack budget.

In contrast, video-centric systems are still novel inventions and full of green-field opportunities. Therefore, there need to be new approaches that simplify the technology requirements, promote extensibility, and maintain customer privacy. While each Lego block exists today, they are standalone components, not a holistic solution. Researchers need to mitigate this issue by building a purpose-built Elderly Care Smarthome Operating System (ECSOS).

# Artifacts and Contributions

Constructive design is one of the most common research methods for information systems and technology (Silvestrini & Sammito, 2012). These studies identify a problem, build solution artifacts, and communicate the implementation’s unique value (Hevner et al., 2004). In addition, many researchers follow this process to build proof-of-concept and execute case studies. Therefore, this methodology is appropriate for examining the effectiveness of the ECSOS solution and its abilities to improve elderly care.

## Artifacts

This research project has three core components which collectively form a proof-of-concept implementation and mechanism to measure results.

First, the team installs WiFi-enabled Eufycam 2C cameras to collect short recordings. These cameras use motion-sensing to trigger short Audio/Video (A/V) recordings (fifteen to sixty seconds). After the filming completes, its controller (Eufy Homebase) automatically uploads the file to Network Attached Storage (NAS). The file creation event triggers an analysis workflow that extracts and publishes metadata to message buses. Developers can author extensions using Function as a Service (FaaS) constructs that subscribe to the notifications.

Second, a machine learning algorithm will classify and annotate the video’s contents. There are several potential implementations (e.g., Open Pose versus Toyota’s approach). The performance and resource requirements between these strategies must exist. Ideally, the model can run in an edge appliance versus uploading into a Public Cloud Service (PCS). However, this raises concerns that the device has sufficient computing capabilities (e.g., parallel processing dozens of cameras). If analysis occurs within the cloud, it introduces security and privacy concerns. The artificial intelligence algorithm would require additional complexity to address these risks (e.g., supporting CKKS HE encryption protocols).

Third, the ECSOS solution routes the metadata into monitoring and response extensions. These extensions include central services (e.g., identity and state management) and auditing capabilities (e.g., inputs, predictions, and recommendations). One crucial extension is the central audit logs. These tables are queryable within a NoSQL time-series database (e.g., Influx). This technology provides two essential capabilities, native support for tracking system performance across time and Schema-at-Read versus Schema-at-Write (SAR versus SAW) semantics. Datastores that support SAR are more flexible and quickly adapt to future enhancements (e.g., extending data contracts).

## Contributions

The core contribution to the body of knowledge is the proof-of-concept design case study. Existing research reviews each component in a silo or distinctly different use cases (e.g., sports injuries). Das et al. (2019) explain that those resources are not directly reusable, and implementations must use domain-specific labeled content. This design requirement necessitates compositing a new solution from custom and open-source software.

Second, the research produces a purpose-built machine learning algorithm for elderly care action recognition. This deliverable also includes quantitative metrics that describe the algorithm’s resource utilization and F-measure accuracy. Data scientists use F-measurements as a “way of combining the precision and recall of the model, and [defines] the harmonic mean of the model’s precision and recall (Wood, n.d.).” Researchers can make trade-offs in their solution to optimize this value for their specific scenario. For instance, a critical health management system might enforce higher penalties on false negatives than over positives.

# User Acceptance Test Plan

The Elderly Care Smarthome Operating System must meet the business requirements, support the multiple user roles. Additionally, the solution must be secure, reliable, performant, economical, and enforce privacy controls.

## Core Design Tenants

The system’s primary purpose is to increase the patients’ quality of life by remaining within their residency longer. Therefore, this mission statement obliges the solution to detect human activity and respond reliably. Also, patients will only use a continuous video recording solution if they trust its security and privacy controls. There must be explicit and deliberate decisions regarding how information is stored or transferred.

## System Architecture

Elderly Care SOS requires cameras, network storage, and a custom-built appliance (see Figure 1). Optionally patients can extend the system with various CPS device integrations (e.g., remote smoke detector). The appliance must have enough computing and storage resources to perform model predictions, persist state, and execute several micro-services. Periodically, the on-premise system needs to synchronize with an external cloud component. These synchronization operations include sending status reports, downloading updates, and issuing assistance requests.

Figure 1: Abstract Design

Diagram

Description automatically generated

## User Roles

Aside from patients, there are three additional user roles: nurses and healthcare providers, family members, and administrators. These users can use a mobile app or web portal to access the relevant data. All operations from either UI (User Interface) require Authentication, Authorization, and Auditing (AAA). When systems mandate AAA enforcement, it prevents negligence or malicious actions while increasing transparency. It is also critical that the patient maintains control of their privacy. For example, they might want to share a weekly aggregate health report with family members, not verbose details.

## System Reliability

The architecture’s components communicate over WiFi, Zigbee, and Bluetooth protocols. Time-sensitive messages (e.g., the subject has fallen) require a primary and secondary communication channel, such as phone line or mobile phone pairing. These messages are likely to encounter transfer failures due to radio interference or devices being offline. There must be support within the message buses to cache and reattempt any message delivery failures using exponential backoff policies. Otherwise, the state management’s perspective can become distorted.

The appliance must locally run several services that handle core scenarios like identity and message routing. Developers can also load custom extensions that subscribe to event notifications. Those various subsystems require isolation and controls to limit the blast radius of a specific failure. An industry-standard approach would be to use micro-service designs and container orchestration technologies (e.g., Kubernetes)(Wen et al., 2020). These products can manage fail-over replicas and promptly restart crashed instances.

## Data Collection Process

Most information enters the system through the WiFi cameras. Ideally, those cameras are accessible only through a dedicated Virtual Local Area Network (VLAN). This recommendation protects the unencrypted Real-Time Streaming Protocol (RTSP) from eavesdropping and tampering attacks. After the video clip is available, ECSOS must process it through several machine learning models (e.g., facial recognition, object detection, and action recognition). These metadata annotations persist into a time-series database. Lastly, populating the database requires the patient(s) to behave normally and let the system collect the video recordings.

Initially, the system will not have any training data and cannot make recommendations. However, researchers can accelerate data labeling with online products like Amazon SageMaker Ground Truth (Amazon, 2021). This service offers clustering capabilities to group related artifacts and streamlines manual tasks. Alternatively, users can crowd-source labeling jobs through Amazon Mechanical Turk.

## System Validity

Feedback loops must confirm that the predictions and recommendations are accurate. Without this capability, it would be challenging to discover issues and prioritize machine learning model changes. One potential solution is to collect these responses through a patient mobile app. App users can enumerate previous recordings and see the associated metadata. Those filmings are subject to a retention policy that automatically deletes old content. If they disagree with the predictions, they can make corrections inline. After making the manual update, the user can help improve the experience by submitting the footage to the ECSOS Cloud.

The ECSOS Cloud maintains a history of all incorrect predictions. Data scientists can review those responses, look for patterns (e.g., mixing up two actions), and make the necessary modifications. There must be some mechanism to include user feedback and avoid introducing biases into the model (García-Pérez, 2012). For example, an individual user could post thousands of feedback comments containing inaccurate data change requests. This situation could regress other users’ experiences. Similar biases can enter the system due to insufficient test subjects’ racial diversity (e.g., only validating white men).

## Quotas and Limits

The appliance and other components have physical capacity constraints. For example, the computing resources might support real-time analysis across sixteen camera sources. If the household wants to provision thirty-two cameras, they need to install a second appliance. Systems that declare their quotas and limits can ensure that the user’s configuration works and provide a positive user experience. During the case study, the researchers will determine reasonable appliance support limits. These limits must minimize the hardware costs proportional to the monitored environment’s total cost.

After selecting limits, the engineering team must validate that the system achieves Service Level Objectives (SLO). Next, operations teams assess SLO attainment through a Quality of Service (QoS) model, which considers availability, reliability, response time, and throughput. Finally, the service administrators require a mechanism to centralize this telemetry into the ECSOS Cloud. This capability enables the service team to uncover issues at remote patient homes.

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