**Using simulation processes to research human behavior in sensitive contexts**

Nate Bachmeier

CMP-9701: Precandiacy Prospectus for Computer Science

December 26, 2021

Northcentral University

# Table of Contents

[Table of Contents 2](#_Toc89613846)

[Background 4](#_Toc89613847)

[Problem Statement 6](#_Toc89613848)

[Purpose Statement 7](#_Toc89613849)

[Research Questions 8](#_Toc89613850)

[Hypotheses 10](#_Toc89613851)

[Research Methodology 10](#_Toc89613852)

[Artifact Driven Approach 12](#_Toc89613853)

[Runtime System Design 12](#_Toc89613854)

[Test Case Definition 13](#_Toc89613855)

[Data Generation Process 13](#_Toc89613856)

[Simulation Process 14](#_Toc89613857)

[Intent Extraction Process 15](#_Toc89613858)

[Rule Engine Process 16](#_Toc89613859)

[Feedback System Design 16](#_Toc89613860)

[Decision History Store 17](#_Toc89613861)

[Aggregation Process 17](#_Toc89613862)

[Evaluation Process 17](#_Toc89613863)

[Report Generation Process 18](#_Toc89613864)

[Contributions 18](#_Toc89613865)

[Measurements and Evaluation 19](#_Toc89613866)

[Key Performance Indicators (KPIs) 19](#_Toc89613867)

[Existing Benchmarks 20](#_Toc89613868)

[Summary 20](#_Toc89613869)

[References 22](#_Toc89613870)

[Annotated Bibliography 26](#_Toc89613871)

[Human Activity Recognition 26](#_Toc89613872)

[Integrating IoT Systems 27](#_Toc89613873)

[Enhancing Security 27](#_Toc89613874)

[Healthcare and Cloud 28](#_Toc89613875)

**Using simulation processes to research human behavior in sensitive contexts**

Numerous challenges prohibit researchers from studying human behaviors. These issues originate from security and privacy, safety concerns, and economic practicality matters. Without collecting data on these topics, those same researchers cannot improve people’s quality of life. For instance, in the health care industry, elderly patients falling is a critical concern. Using AI/ML CV advancements, technology solutions detect these incidents and prevent the injury preemptively. Nevertheless, patients refuse to deploy these systems due to privacy concerns. This situation prevents researchers from iterating on algorithms and improving patient safety.

This constructive research project examines a data collection mechanism for situations where personal privacy and safety prevent traditional observations. It aims to demonstrate this capability using a physics simulation process and Motion Capture (MoCap) animations. Given the potential breadth, it is critical to find a concrete business case that exemplifies this approach. That specific example comes from raising the elderly care quality bar while minimizing costs. Using Human Activity Recognition (HAR) through computer vision and machine learning, the solution tracks the patient’s skeletal structure. After observing behaviors and determining intents, the system orchestrates Cyber-Physical Systems (CPS) to provide further assistance.

# Background

A demographic timebomb will create significant pressure on the global health care system because people live longer, have fewer children, and medical costs continue to increase (Piggott, 2016; Stone, 2017). When patients cannot afford the required care, the quality decreases, or social programs must fund the difference. Demographic specialists predict that by 2050 nearly “80% of the global elderly population will be from low- to middle-income countries (Muhsin, Munyogwa, Kibusi, & Seif, 2020, p. 1).” Economic constraints within those countries will limit the effectiveness of their welfare programs and the availability of adequate services. Additionally, over one billion globally have a limiting disability that requires additional support (Morris, 2008). Medical facilities need mechanisms to defuse the situation by reducing costs and deferring the transition to assisted living centers.

Inversely, the explosive growth across IoT, Cloud, Big Data, and Mobile (ICBM) continuously decreases costs and enables new opportunities. These technologies have the potential to revolutionize the health care and wellbeing industries. Academic and commercial vendors are continuously delivering innovations across these domains. However, mainstream offerings primarily focus on measuring simple body metrics (Koreshoff, Robertson, Leong, 2013). While these products provide incremental value, they do not move the needle. Nearly eight years later, the industry myopically drives toward wearable IoT devices (Tun et al., 2021). Researchers concentrating on these areas make sense due to the low barrier to entry. Though, that same ease is commoditizing the products selection and stifling creativity.

Technology within special needs and elderly care settings has unique challenges and requirements (Ferati, Kurti, Vogel, & Raufi, 2016). These persons need unobtrusive systems that continuously monitor and respond to their behaviors. Specific vendors utilize voice-enabled Personal Digital Assistants (PDA) (e.g., Amazon Alexa) to effectively set reminders and record activities (Tan et al., 2020). However, it becomes challenging to globalize these voice-specific technologies to assist non-native speakers and individuals with vocal disorders.

Assisted living facilities use trained nurses to mitigate these issues. Having a human inspect the patient visually is an effective but expensive tool. The median compensation rate for registered nurses is $75,330 annually ($36.22 per hour) (US Bureau of Labor Statistics, 2020). Due to the high cost, few patients have private nurses and receive fractional supervision. In contrast, video-centric monitoring and Human Activity Recognition (HAR) apply to a diverse population. When a person falls or drinks a glass of water, their skeleton moves in predictable ways, enabling AI/ML processes to respond through CPS systems. Businesses could deliver these capabilities economically and consistently across global markets, ultimately improving the quality of care at lower costs.

However, ethical concerns and privacy issues prevent researchers from collecting data at scale. Image the complexity that small-to-medium businesses face between vetting volunteers and ensuring diversity across participants. There are also budgetary considerations to deploying IP cameras and other CPS in numerous households. These challenges prevent quality research from occurring and improve patients’ quality of care. Instead, processes must exist to simulate these interactions and iterate toward more sophisticated systems.

# Problem Statement

Senior citizens live longer than ever before 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 (Westergren et al., 2021). However, this solution increases health care costs and collects limited patient health data. In addition, these infrequent visits might miss critical issues, especially with those most reluctant to relocate. Modern solutions must bridge the differentiation between remaining in the home and still receiving 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 economic impacts (e.g., deferring private health care costs). For instance, patients with memory impairment might forget to empty the dishwasher, take medication, or bathe regularly. Medical facilities can address these challenges through real-time video monitoring services that analyze patients’ actions and recommend care.

# Purpose Statement

This constructive research demonstrates a simulation procedure for collecting human data in private and sensitive contexts. It aims to show this capability by combining various artifacts under the real-world scenario of elderly and special needs care. These existing artifacts include resources spanning MoCap databases, physics simulators, and AI/ML CV algorithms. While this specific project examines elderly care, the implications are generalizable to other scenarios. Those scenarios encompass childcare (e.g., babysitting), school safety systems, and virtual office secretary situations, to name a few. Beyond privacy, the approach applies to high-risk health and safety research. For example, it would be challenging to set numerous apartments ablaze to assess an evacuation procedure. However, actors can perform animation sequences within virtual environments and enable researchers to observe those behaviors.

Building these capabilities and verifying them at scale is challenging. First, the research must find patients willing to share continuous in-home video streams. In addition to the privacy concerns, it would be difficult for others to reproduce the findings. Third, validating the solution against numerous home layouts requires significant effort. Lastly, purchasing and configuring hardware components is prohibitively expensive in terms of time and money (Elloumi et al., 2020; Das et al., 2019). This project mitigates these issues through a virtual world simulation process.

The Robot Operating System (ROS) is a framework for writing robot software (Stanford Artificial Intelligence Laboratory et al., 2018). It exposes features for rapidly designing complex cyber-physical interactions through a Message Passing Interface (MPI). The meta-operating system integrates with physics engines (e.g., Gazebo) and machine learning platforms (e.g., OpenAI Gym). Additionally, developers can package these tools into containerized workloads and leverage public cloud services (e.g., Amazon Web Services and Microsoft Azure). The cloud enables researchers to validate their designs in numerous world permutations efficiently and economically. Furthermore, the software can test situations that are not practical or feasible within the physical world (e.g., set the kitchen ablaze). Together, these different technologies culminate into an elegant solution that monitors, predicts, and responds in real-time to patient needs.

This dissertation leverages these tools to implement an intelligent home simulation environment. Next, it will populate the virtual home with ROS devices and sensors to observe and respond to ROS actors (patients). The actors will perform animation sequences based on motion-capture records. Lastly, the researcher will assess the observations and responses against the labeled data. While this specific test scenario focuses on elderly care, the solution is broadly applicable to any Cyber-Physical simulation.

# Research Questions

Researchers are innovating across health care using Internet of Things (IoT) devices (Tun et al., 2021). Significant investments into this space focus on incremental improvements and wearable technologies. This approach makes sense due to the low barrier to entry and access to mass production capabilities. In contrast, high-quality research must be challenging, elegant, and move the needle (Zeller, 2014). Meeting these requirements necessitates a different approach, such as utilizing cameras and real-time video processing to deliver a superior experience. Though, video-centric systems encounter more complexity in several aspects. For instance, patients can freely move around their residence and change its configuration (e.g., move furniture or turn off a light). Addressing the noise within these dynamic environments is challenging and creates multiple research questions.

**R1** – What mechanisms are best suited for extracting the subject’s *intent* when dealing with noisy video stream data? Noise enters the processing pipeline from numerous situations, such as out-of-focus images and the subject’s distance to the camera.

**R2** – What affordances do Cyber-Physical Systems (CPS) allow for acting on the extracted intents from R1? Nurses at assisted living centers provide a helping hand literally and figuratively. Smart devices must serve this same function across various tasks (e.g., medication management).

This constructive research does not evaluate mechanisms for protecting the subject’s data privacy. Subjects will only use a continuous in-home video recording solution if they trust its security and privacy controls. There must be explicit and deliberate decisions regarding storing and replicating information. Future researchers need to define procedures for efficiently scaling these mechanisms globally. Suppose healthcare workers could remotely deliver world-class services to homes using CPS systems. In that case, the businesses could leverage this capability to decrease costs, increase profit margins, and maintain quality standards. While both topics are critical toward productizing this work, they are beyond the dissertations’ scope.

# Hypotheses

This constructive research project aims to simulate people moving around virtual homes. Virtual IP-Cameras arbitrarily placed within the home can monitor the subjects and map their behaviors to intents. A data enrichment process can attach metadata that describes the intent in greater detail (e.g., holding an object versus holding a spoon). This enrichment process would need to be extensible to cover a reasonable action space. Next, the remediation process(es) can subscribe to intent-specific message buses after publishing instructions to CPS Systems. Then, CPS systems will convert the instructions into device-specific operations (e.g., turn on light versus activate power to the green wire). Lastly, the subject should express a positive benefit from the environmental change. A feedback collection process can aggregate these decisions and map them against the simulators’ configuration (e.g., performing the patient falling motion). It expects that these subsystems holistically would be an effective and intuitive method for acting on patients’ health and provide real-time guidance for persons with special needs.

While this specific set of experiments focuses on simulating elderly care and special needs, the data collection procedure is more broadly applicable. Future researchers can reuse this technique to study other problem domains that are too personally sensitive or high risk. This research does not attempt to prove that the approach is superior to measurements in the physical world. Though, it should demonstrate an acceptable mechanism for estimating reliable results.

# Research Methodology

Design-science is a standard methodology for researching Information Technology (IT) problems. Hevner et al. (2004) propose a collection of guidelines for implementing this methodology (see Table 1). There are three phases to implementing this process. First, the researcher(s) must identify a domain-specific challenge. Next, that researcher creates artifacts that study this phenomenon. Third, those artifacts assess the topic and communicate answers to the research questions.

Table 1: Design-science Guidenlines (Hevner et al. 2004)

|  |  |
| --- | --- |
| Guideline | Description |
| Design as an Artifact | Design-science research must produce a viable artifact in the form of a construct, a model, a method, or an instantiation. |
| Problem Relevance | Design-science research aims to develop technology-based solutions to important and relevant business problems. |
| Design Evaluation | A design artifact's utility, quality, and efficacy must rigorously demonstrate well-executed evaluation methods. |
| Research Contributions | Effective design-science research must provide transparent and verifiable contributions to design artifacts, foundations, and/or design methodologies. |
| Research Rigor | Design-science research relies on rigorous methods to construct and evaluate the design artifact. |
| Design as a Search Process | The search for a compelling artifact requires utilizing available means to reach desired ends while satisfying laws in the problem environment. |
| Communication of Research | Design-science research must be presented effectively both to technology-oriented and management-oriented audiences. |

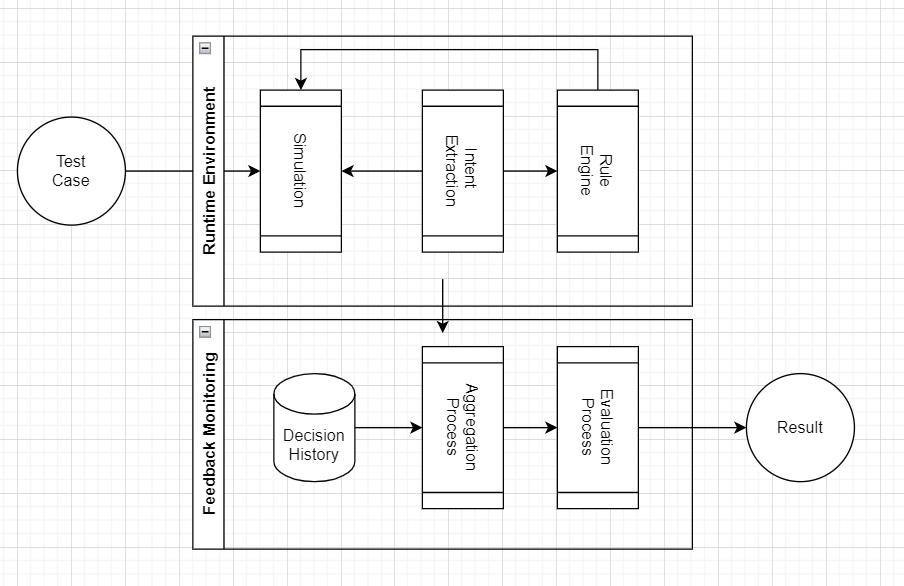
This dissertation employs this methodology to improve special needs and elderly care with AI/ML and CV applications. Scalability, security, and privacy challenges prohibit studying this topic through traditional means. People are generally unwilling to undergo 24/7 video monitoring and disclose their most intimate conversations in the name of science. Future research needs to address those concerns. Meanwhile, this effort provisions industry-standard physics simulation environments to examine those interactions. Next, this project creates virtual devices (e.g., IP cameras) to extract a subject’s behavior and respond accordingly. Third, a data telemetry collection pipeline will assess the performance of virtual devices within a simulated world.

## Artifact Driven Approach

Artifacts are a principal component of the constructive design methodology. This constructive research project will simulate human activity and then predict the subject’s intents using video streams. The solution uses open source tooling, enabling other researchers to extend these efforts for their projects. Derived works could include social studies, game theory, film production, and other fields of study. These diverse researchers need activity recognition capabilities across industry-standard video formats (e.g., RGB+D). Also, future researchers will need to extend the action-space taxonomy to support domain-specific intents. For instance, this research project does not support observing a soccer match. Though, this project should expose primitives for adding those future requirements.

## Runtime System Design

This research project includes subsystems for simulating human movements, observing those behaviors, extracting intents, reacting through CPS systems, and evaluating prediction accuracies (Figure 1). An experiment begins with a test-case specification that describes the scene, actors, animations, and virtual devices. First, the Runtime Environment Pipeline simulates the scene requirements while virtual IP-Cameras monitors and reacts appropriately. Next, the Feedback Monitoring Pipeline Telemetry persists prediction history into a time-series database. Lastly, an evaluation process can compare the test-case definition against the Decision History Store to assess the system’s performance.

Figure : Experiment Design

### Test Case Definition

A test case encapsulates a specific experiment. An arbitrary number of subjects will perform pre-configured animation sequences during the experiment, such as walking or failing. These behaviors occur within a dynamic world that supports typical real-world transforms. For example, the subject can turn off a light, move furniture, not modify the floor plan.

### Data Generation Process

ROS actors represent the patients within the simulation environment, which performs an animation sequence while moving around the house. These animations originate from open-source motion-capture videos and map to a hierarchial action-space taxonomy. The action-space describes specific behaviors (e.g., walking versus sitting) and any derived actions (e.g., sitting on a chair versus couch). There are virtually infinite sequences, making it challenging to record the entire universe of movement. Instead, a randomization process initializes from a recording and mutates model-joint characteristics such as flexibility, strength, and weight. This approach both increases taxonomy coverage and prevents overfitting the limited data.

### Simulation Process

Figure : Simulation Instance

Diagram

Description automatically generated

ROS worlds represent the patient’s home or apartment and define models’ placement (e.g., actors and furniture), actor configuration, and devices (Bipin, 2018). Researchers use physics simulators (e.g., Gazebo) to examine interactions between these various components. For instance, the actor might perform walking to the kitchen table. Each camera will capture frames from its vantage point and transmit them to a message bus during this sequence (see Figure 2). Next, AI services subscribe to the event stream and process the visual data. Suppose the service detects a valuable signal (e.g., the refrigerator door is left open). In that case, it can post a notification to another message bus to mitigate the situation (e.g., use voice assistant).

Validating these interactions requires an ability to reconfigure these worlds without significant effort. World templating tools (e.g., AWS RoboMaker) can dynamically generate environments that meet a specification (AWS, 2021). This capability allows the researchers to create custom sensors and algorithms, not positioning furniture. That also means this dissertation aims to emphasize ROS components and world templates, not reinventing standard tooling. These components must implement an asynchronous and loosely coupled architecture.

### Intent Extraction Process

A machine learning algorithm will process short video clips and predict the subject’s intent based on their behavior. For instance, the simulator will load a humanoid into a virtual apartment and perform a walking sequence. These animation sequences will originate from open-source databases, such as Mixamo (Adobe, 2021) and MoCap Database (CMU, 2021). IP-cameras will track the subject’s skeleton movement changes into specialized sequence-to-binary classification models. For example, one model predicts that the subject raises their hand while another assesses jumping or falling. Next, an ensemble classification algorithm combines these binary predictors into a sophisticated intent. This approach should support future researchers iteratively adding more behaviors over time.

The input sequence will contain the relative positional changes to the subject’s skeletal joints (see Figure 3). There are several potential implementations, and those solutions must perform within the hardware constraints of an edge appliance. For instance, the simulated home might produce data from dozens of cameras and sensors. Suppose the algorithm requires too many compute resources. In that case, the solution would require remote compute (e.g., public cloud), raising security and privacy concerns. Maintaining the subjects’ privacy drives specific requirements into this design, though this research defers extensive investigations to a future researcher.

Figure : Intent Extract Logical View



### Rule Engine Process

Assume that the system determines that the subject has fallen, then what? Perhaps the system should ask if the person needs an ambulance through a text-to-speech device. Then, deciding which specific voice assistant adds nuances. Further complicating the matter, the fractured residential IoT market follows inconsistent protocols and standards. The second research question examines these integration challenges and proposes a rule engine. Addressing these issues requires design tenants and frameworks. While this research project explores these topics, the scope narrowly focuses on virtual devices (versus real-world integrations). These devices will likely exist as ROS plugins and services

## Feedback System Design

The second code artifact is a telemetry collection system that continuously assesses the Runtime System. Its core function is to produce the dissertation’s Results section (chapter four).

### Decision History Store

A NoSQL time-series database records extracted intents, rule engine reactions, and various critical messages. These data points contain a foreign key to the experiment identifier and an association to the test case definition. This data store hydrates using a similar pattern for a subset of critical messages. Standard tooling already exists for recording ROS topics and persisting into binary files. Complete topic dumps will also exist outside the time-series database for troubleshooting requirements specifically.

### Aggregation Process

Residential homes have infinite configurations and permutations with unique floor plans, furniture layouts, camera placement, noise sources, and other distinctions influencing the solution’s accuracy. Unlike a physical home, the simulator leverages ubiquitous cloud resources to scale testing across numerous virtual homes. Each simulation instance mutates its exact data through a randomization process by modifying the actors’ flexibility, weight, and other variables. The Aggregation Process is responsible for grouping these variations and calculating range statistics. Suppose the patient has fallen predictor’s accuracy could depend on the amount of furniture in the room. In that case, the results chapter will need to quantify this influence through some data pivot and summation. This research does not aim to implement a novel aggregation system and defers to industry-standard tooling (e.g., Apache Spark).

### Evaluation Process

Creating high-quality software requires quality assurance procedures. There are several classes of defects for applications using simulation environments with AI/ML and CV, such as mixing-up actions, model non-convergence, model overfitting, code defects, performance degradation, and other issues. Automation can discover a subset of these problems using the Aggregation Process and Test Case Definitions. For example, the test case specifies that the actor will perform the jumping animation sequence. Suppose the intent prediction assumes the subject was instead sitting. In that case, the evaluation process can easily detect and report the failure. Then, specific erroneous actions and configurations require triage and troubleshooting.

### Report Generation Process

A simple test-cases has a subject performing an animation within a world. Derived test cases could also cover entire open-source Motion Capture (MoCap) databases through scripting and templating. Next, the data generation and simulation processes will run those experiments multiple times under different world configurations. This combinatorial property creates the need for a report generation process that collects and visualizes the evaluation assessments. Building a custom Business Intelligence (BI) solution is outside this project’s scope, so this project defers to industry-standard tooling (e.g., PowerBI and Tableau). Also, budgetary limitations will prohibit exploring every combination. Instead, this research will strategically choose representative examples within the supported action space.

## Contributions

This constructive research project’s core contribution demonstrates a procedure to study human behavior in sensitive situations. It aims to accurately extract intents from real-time video streams and map them to an action space. A smart home can subscribe to intent message buses and react through CPS systems. Existing publications discuss the various component within the solution under 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 defines a framework and design for integrating the intent extraction process into heterogeneous CPS systems. Domestic residences contain multiple devices from a diverse vendor population. The research demonstrates the proposal using ROS plugins and services. Though, expanding these ideas to existing product lines is out of scope.

# Measurements and Evaluation

This research project uses AI/ML and CV to monitor humanoids within simulated residential properties. While actors perform specific animation sequences, the system aims to convert their behaviors into intents. Next, a Rule Engine subscribes to this intent prediction stream and then routes remediate actions to CPS. Those actions modify the simulation and impact the actor’s behavior. The simulation continues executing this pipeline until a stop signal occurs. Meanwhile, multiple concurrent simulation instances also predict actions and learn from those responses.

## Key Performance Indicators (KPIs)

Like the Feedback System, mechanisms must exist to confirm that adding more instances increases predictive capabilities. Modeling the system’s health with numerical metrics, called Key Performance Indicators (KPIs), can provide this information throughout the pipeline. For example, one metric might measure the percentage of accurately identified animation sequences. Metric data points can also contain high-dimensional metadata, such as a Noise Ratio property (). Suppose the Noise Ratio positively correlates with the prediction difficulty levels. In that case, an algorithm that performs better with more noise is more sophisticated. Existing literature proposes suitable detection metrics under different sensing techniques, such as light versus infrared (Ding, Chen, Zheng, & Luo, 2020). Defining a unique baseline is outside this research project’s scope. Instead, it aims to achieve comparable performance results as recent publications.

## Existing Benchmarks

Numerous Human Activity Recognition (HAR) benchmarks exist with varying frame rates, actions, actors, backgrounds, resolutions, and problem domains (Singh & Vishwakarma, 2018). However, most benchmarks also focus on high-intensity outdoor sports footage (Das et al., 2019). Since those behaviors are very different from low-intensity indoor movements, they are not directly usable. Instead, several publications define movement taxonomies and curated lists of expected behaviors (Das et al., 2019). This research project uses a similar measurement that considers the supported actions within an action space. Though, it is outside this project’s scope to implement dozens of actions. This research takes a “quality-versus-quantity” approach and chooses a handful of distinctly individual and representative actions.

# Summary

Senior citizens and other debilitating populations live longer and need to defer transitioning into assisted living facilities. Delaying the move can save nearly ninety thousand dollars annually and provide additional value (e.g., personalized comfort). However, those savings typically require care degradation. The state-of-the-art solutions utilize real-time video processing to provide an equal or better experience without being obtrusive. Computer vision strategies typically employ a skeletal tracking process. This process must first convert the patient’s skeleton into 3D space then assess the changes. That operation requires a combination of CNN, RNN, and ensemble algorithms. Multiple challenges arise while implementing these pipelines. For instance, there are minimal open datasets for analyzing indoor low-activity behaviors. This limitation causes researchers to build everything from step one forward.

Luckily, existing tools and services simplify the development experience when designing complex behaviors. After determining the patient’s *intent*, the operating system must respond appropriately. This reaction frequently requires manipulating the physical world from the virtual domain. Cyber-Physical Systems create those communication bridges, enabling data analytics to manipulate the physical realm. There are several well-established patterns for approaching these challenges. Researchers must minimize adding complexity within this complicated problem space.

Lastly, unlocking these challenges could enable an extremely competitive service offering. Today, assisted living centers must employ numerous staff members and maintain the physical buildings. Instead, the ECSOS enables centralized nursing teams to scale across sales territories while reducing costs and increasing efficiencies. Additionally, since the patients remain within their residence, the business can leverage smaller facilities. Furthermore, the service is marketable to a broader audience. While traditional living centers only care for end-of-life patients. ECSOS applies to any widow or elderly parent. Children are often hesitant to “put their mom in a home” but will gladly subscribe to the piece of mind that “someone is watching mom.” The business can tap into those emotions to produce win-win scenarios.

# References

Adobe. (2021). *Mixamo*. Retrieved from Animate 3D characters for games, film, and more: https://www.mixamo.com/

Aguida, M., Ouchani, S., & Benmalek, M. (2020). A review on cyber-physical systems. *Enabling Technologies: Infrastructure for Collaborative Enterprise* (pp. 275-278). Virtual: IEEE. doi:10.1109/WETICE49692.2020.00060

Amazon. (2021, June 11). *Amazon Go*. Retrieved from Amazon: https://www.amazon.com/b?node=16008589011

Amazon. (2021). *Use Aamzon SageMaker Grouth Truth to Label Data*. Retrieved from Amazon: https://docs.aws.amazon.com/sagemaker/latest/dg/sms.html

Amin, S., Salahuddin, T., & Bouras, A. (2020). Cyber-Physical Systems and Smart Homes in Healthcare: Current State and Challenges. *International Conference on Informatics, IoT, and Enabling Technologies* (pp. 302-309). Virtual: IEEE. doi:10.1109/ICIoT48696.2020.9089638

AWS. (2021). *AWS RoboMaker*. Retrieved from Amazon Web Services: https://aws.amazon.com/robomaker/

Bell, Koren, & Volinsky. (2009). *The BellKor solution to the Netflix Prize.* Retrieved from Netflix Prize: https://netflixprize.com/assets/GrandPrize2009\_BPC\_BellKor.pdf

Bipin, K. (2018). *Robot Operating System Cookbook.* Packet Publishing.

CMU. (2021). *CMU Graphics Lab Motion Capture Database*. Retrieved from Carnegie Mellon University: http://mocap.cs.cmu.edu/

Das, S., Dai, R., Koperski, M., Minciullo, L., Garattoni, L., Bremond, F., & Francesca, G. (2019). Toyota Smarthome: Real-World Activities of Daily Living. *International Conference on Computer Vision* (pp. 833-842). Seoul, Korea: IEEE. doi:10.1109/ICCV.2019.00092

Delgado, R. (2021). A semi-hard voting combiner scheme to ensemble multi-class probabilistic classifiers. *Applied Intelligence, 1*, 1-25. doi:10.1007/s10489-021-02447-7

Ding, S., Chen, Z., Zheng, T., & Luo, J. (2020). RF-net: a unified meta-learning framework for rf-enabled one-shot human activity recognition. *Proceedings of the 18th Conference on Embedded Networked Sensor Systems* (pp. 517-530). Nanyang Technological University, Singapore: ACM. doi:11.1145/3384419.3430735

Ferati, M., Kurti, A., Vogel, B., & Raufi, B. (2016). Augmenting requirements gathering for people with special needs using IoT. *International Workshop on Cooperative and Human Aspects of Software Engineering* (pp. 48-52). ACM. doi:10.1145/2897586.2897617

García-Pérez, M. A. (2012). Statistical conclusion validity. *Frontiers in Psychology, 3*. doi:10.3389/fpsyg.2012.00325

Hevner, A., March, S., Park, J., & Ram, S. (2004). Design science in information systems research. *MIS Quarterly, 28*(1), 75-105. doi:10.2307/25148625

Koreshoff, T., Robertson, T., & Leong, T. (2013). Internet of Things: a review of literature and products. *CHI’13, November 25 - 29 2013, Adelaide, Australia*.

Litomisky, K. (2012). *Consumer RGB-D Cameras and their Applications*. Retrieved from University of California: https://alumni.cs.ucr.edu/~klitomis/files/RGBD-intro.pdf

Mickens. (2018, August 16). *Why Do Keynote Speakers Keep Suggesting That Improving Security Is Possible?* Retrieved from YouTube: https://www.youtube.com/watch?v=ajGX7odA87k

Morris, J. (2008). *Disability research and policy: current perspectives.* Lawrence Erlbaum Associates.

Muhsin, A., Munyogwa, M., Kibusi, S., & Seif, S. A. (2020). Poor knowledge on elderly care despite positive attitude among nursing students in Zanzibar Island: findings from a cross-sectional study. *BMC Nursing, 19*(1), 1-8. doi:10.1186/s12912-020-00488-w

Parker, R. (1993). Threats to the validity of research. *Rehabilitation Counseling Bulletin, 36*(3), 130-138. Retrieved from https://search-ebscohost-com.proxy1.ncu.edu/login.aspx?direct=true&db=eric&AN=EJ458938&site=eds-live

Piirainen, K., & Gonzalez, R. (2013). Constructive Synergy in Design Science Research: A Comparative Analysis of Design Science Research and the Constructive Research Approach. *Liiketaloudellinen Aikakauskirja, 3*(4), 206-234. Retrieved from https://search.ebscohost.com/login.aspx?direct=true&AuthType=ip,shib&db=bth&AN=95116694&site=eds-live

Silvestrini, R. P., & Sammito, G. (2012). Design of Experiments for Information Technology Systems. *Defense AT&L, 41*(5), 30-35. Retrieved from https://search-ebscohost-com.proxy1.ncu.edu/login.aspx?direct=true&db=bth&AN=80409129&site=eds-live

Singh, T., & Vishwakarma, D. (2018). *Human Activity Recognition in Video Benchmarks: A Survey.* Springer.

Snee, R. (2015). A practical approach to data mining. *Quality Engineering, 27*(4), 477-487. doi:10.1080/08982112.2015.1065322

Stanford Artificial Intelligence Laboratory et al. (2018). *Robotic Operating System*. Retrieved from https://www.ros.org

US Bureau of Labor Statistics. (2020, May). *Registered Nurses*. Retrieved from US Bureau of Labor Statistics: https://www.bls.gov/ooh/healthcare/registered-nurses.htm

Wachter, S. (2018, June). Normative challenges of identification in the Internet of Things: privacy, profiling, discrimination, and the GDPR. *Computer Law & Security Review, 34*(3), 436-449. doi:https://doi.org/10.1016/j.clsr.2018.02.002

Wilson, C. (2017). *Caring for people with dementia: a shared approach.* Los Angeles, California: SAGE.

Wood, T. (n.d.). *What is the F-score*? Retrieved from Deep AI: https://deepai.org/machine-learning-glossary-and-terms/f-score

Yang, M., Min, G., Yang, G., & Li, Z. (2014). Software rejuvenation in cluster computing systems with dependency between nodes. *Computing, 96*, 503–526. doi:10.1007/s00607-014-0385-x

# Annotated Bibliography

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

## Human Activity Recognition

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.

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.

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 3D space plus time. Mechanisms exist for accelerating building custom datasets (e.g., transfer learning), though this is still an open research topic.

## Integrating IoT Systems

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 application profiles (e.g., heat management and fire detection). These abstract constructs 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).

## Enhancing Security

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 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., Alice versus Bob’s face). Ideally, the system minimizes the information that leaves the patient’s private network. However, these remote compute requirements are unavoidable in specific scenarios.

## Healthcare and Cloud

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 Raspberry-PIs. 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).

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 with various sensor readings (e.g., smoke detectors) into a secure private cloud. Unlike Das et al. (2019), the authors use Dynamic Time Warping (DTW) to compare and categorize 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).

Chen, Saiki & Nakamura (2020) state that monitoring low-intensity slow physical movements is challenging. These issues arise because training data is not broadly available due to researchers focusing on fast-paced sporting video by default. Their study uses PoseNet to track skeletal movements and predict activities. Additionally, they compare the resources necessary for Raspberry PI and a desktop computer to make those predictions. The researchers assess the model’s accuracy in delta changes in the bounding box. This approach is unique and comes with several limitations. For instance, a person laying on the couch versus standing will have different dimensions. While this methodology is not directly usable, it provides another measurement strategy.

Chaing et al. (2011) propose a Uniform Markup Language (UML) model for collecting health care metadata from video sources. Their solution focuses on physiological information, such as the patient’s movements. The model also describes a storage structure for persisting the recordings. There are specific aspects from this study that are reusable. For instance, the authors propose service interfaces to several patient monitoring components (e.g., heart rate and oxygen levels). However, the video monitoring system is critically dependent on wearable technologies.

Nugroho, Harmanto & Al-Absi (2018) propose a deep learning model to assess a patients’ pain level. Their solution uses facial expressions from fourteen people that train both OpenFace and FaceNet topologies. The researchers claim that they can predict with 93% accuracy a person’s level of pain. This capability is helpful within home monitoring systems to assess medication levels, improving patient care. For instance, the system could emit a pain frequency Key Performance Indicator (KPI) as part of the patient’s scorecard. The scorecard would then reassure family members that sufficient attention is available.