**Using AI/ML and simulation processes to improve elderly and special needs care**

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# Chapter 1: Introduction

A demographic change 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 (Mushsin et al., 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 continually 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 product selection and stifling creativity.

Technology within special needs and elderly care settings has unique challenges and requirements (Ferati et al., 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. This consistency enables artificial intelligence & machine learning (AI/ML) to respond through cyber-physical systems (CPS). 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 (Lei et al., 2021). Imagine 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 (Shirazi & Shekhani, 2021). 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.

## Statement of the Problem

The problem to be addressed in this study is the inability of elderly and special needs care organizations to capitalize on the effectiveness and efficiency of autonomous assistants for hemodialysis (Kim & Kim, 2021; Blackhurn, 2021). Multiple industry-wide trends create the need for this technology. First, the number of practicing nurses has declined for several years (Kim & Kim, 2021). This labor shortage increases hiring and employee retention costs that the patients and welfare programs must cover. The funding gap is a global problem that does not impact all communities equally. For instance, rural special needs communities in South Africa have 57% fewer nursing visits than their urban neighbors (Besada, 2020). Newly industrialized economies like Taiwan, South Korea, Thailand, and Malaysia are experiencing challenges maintaining their long-term care programs due to growing costs (Phua, 2021). Domestic programs like Veterans Health Administration (VHA) and Medicare are not immune to these economic limits (Lei et al., 2021). Businesses and governments must control these costs and replace human labor with less expensive automation.

Beyond human and process issues are technical complexities in configuring prototype autonomous assistants. It requires multiple domain specializations like computer networking, embedded technologies, AI/ML, and distributed computing (Tun, Madanian, & Mirza, 2021). Each cross-cutting concern adds complexity and reduces the probability that small teams can successfully provision their test environment. Furthermore, those difficulties limit other researchers from reproducing the results. These factors slow innovation and restrict the value researchers can contribute to the body of knowledge.

## Purpose of the Study

The purpose of this constructive research study is to provide an understanding of the effectiveness and efficiency of autonomous assistants for hemodialysis in elderly and special needs care organizations. Hemodialysis patients have a high risk of falling and becoming injured (Shirai et al., 2021). Similarly, early dementia patients need monitoring capabilities to assist with discovering objects and providing task management (Lei et al., 2021). It would be time-consuming and potentially dangerous to use humans, which invites the need for artificial agents. The research uses a virtual environment that divorces privacy and safety concerns from investigating autonomous assistants in elderly and special needs care. It aims to deliver this capability by utilizing artificial agents within a realistic physics simulation process like PhysX or Gazebo (Bipin, 2018; Unreal, 2021). These engines support replaying specific motion-capture animations (MoCAP) under varying character properties such as weight, flexibility, and dexterity. Next, positioning virtual cameras, instruments, and devices within the virtual world enables the study to collect experimentation data. Lastly, the automation can modify the environment using programmable interfaces such as raising the alarm or applying other mitigations.

The study focuses on a finite action space like hemodialysis because of its medical importance and access to training data (Shirai et al., 2021). This situation negatively impacts their quality of life by either remaining in bed or requiring more medical resources. The study explores this use case by virtualizing the patients and monitoring them with an AI/ML computer vision (CV) process to collect metadata and predict a fall in advance. Human trials prioritize safety, creating challenges to study metadata properties like floor slickness and character overexertion (Aihara et al., 2021). In contrast, humanoids are well-suited for these experiments.

## Introduction to Theoretical Framework

Design of experiments research creates purposeful artifacts and applies them to study a phenomenon (Hevner et al., 2004). Academic and business communities employ this method as a standard approach to Information Technology and Communication (IT&C) problems (Peffers et al., 2007; Bryar & Carr, 2021). It has well-defined guidelines (see Table 1) to implement a three-phased procedure. 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 Guidelines (Hevner et al. 2004)*

|  |  |
| --- | --- |
| Guideline | Description |
| Design as an Artifact | Design-science research must produce a viable artifact as 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 study uses these guidelines and conceptual steps to identify a research-worthy topic and an actionable aspect. Next, it defines an abstract approach and implements a concrete proof-of-concept, the simulation process, to assess patient monitoring (via CV) and remediation (via CPS) technologies. Third, the artifacts expand the body of knowledge through the research questions. See Chapter 3: Research Method for more information.

## Research Questions

In alignment with the purpose of this study, the following research questions (RQ) are adopted:

### RQ1

What is the effectiveness of autonomous assistants for hemodialysis in elderly and special needs care organizations**?**

### RQ2

What is the efficiency of autonomous assistances for hemodialysis in elderly and special needs care organizations?

## Significance of the Study

Human activity recognition (HAR) can improve elderly and special needs care by efficiently scaling out the visual coverage of medical facilities. Today, it is challenging to study HAR solutions within private residences. These issues stem from the system needing to record and share potentially privacy-sensitive situations, such as bathing or intimacy. Further complicating matters, the researchers must overcome the logistical challenges of finding representative samples, proving result reproducibility, and the economic overhead of multiple monitoring stations. Instead, this study proposes a research process using a physics simulator, animated actors, and virtual homes. The novel approach enables researchers to assess their CV algorithms across a repeatable configuration corpus. For instance, elderly patients falling is one of the most significant and avoidable reasons they need medical attention. This approach simulates this scenario, with each limb having distinct tensile strength, flexibility, and weight. When researchers can generate representative test cases economically, it unlocks the potential for faster product iterations and quickly expands the body of knowledge.

Cyber-physical systems (CPS) serve as a bridge between digital algorithms and the real world. These technologies need patterns and methodologies that react to intents discovered through HAR. Today, the fractured ecosystem spans multiple vendors, and it is cumbersome to assess holistic solutions. This research project aims to reduce this complexity with specific virtual health and safety devices compatible with the simulator. Future researchers can leverage these tools and services to introduce noise (e.g., camera distortion) into the virtual world. Further lowering the barrier to entry for study HAR within personal residences opens the door to future innovations not yet considered!

## Definition of Key Terms

### Artificial Intelligence/Machine Learning (AI/ML)

Artificial intelligence is the design, implementation, and use of programs, machines, and systems exhibiting human intelligence. Its most essential activities are knowledge representation, reasoning, and learning (Whitson, 2020).

### Computer Vision (CV)

Computer (or machine) vision is a capability that extracts information from 2D and 3D images (Hornberg, 2017).

### Convolutional Neural Network (CNN)

A CNN is an artificial neural network used in image recognition and processing domains (Nguyen, Huynh, Tran, & Ngo, 2019).

### Cyber-Physical Systems (CPS)

Cyber-Physical Systems are network-programmable devices that respond to digital messages through embedded capabilities (Aguida, Ouchani, & Benmalek, 2020). It is a subset of an Internet of Things (IoT) domain.

### Human activity recognition (HAR)

HAR is the process of identifying human behaviors from motion feeds (Gorgulu & Tasdelen, 2020).

### Internet of Things (IoT) device

The Internet of Things (IoT) attempts to widen the interconnectivity of computers by interconnecting objects (Commission of the European Communities, 2009).

### Motion capture (MoCap)

Motion capture is a process that digitizes structural body movements for film and television production (Gan, Li, Wang, & Zhang, 2020).

### Recurrent Neural Network (RNN)

An RNN is an artificial neural network used in sequential data sets like natural language processing and time series (Boorugu & Ramesh, 2020).

## Summary

The cost of healthcare is increasing, which creates the need for more automation. When patients cannot afford the required care, the quality decreases, or social programs must fund the difference. For many situations, like in-home monitoring of elderly and special needs patients, it is challenging to build that automation due to personal privacy and safety concerns. Researchers also encounter challenges spanning logistical, sufficient and diverse representation, and costs, among other entry barriers. After mitigating these issues, the research results are difficult and expensive to reproduce.

Implementing and verifying automation comes with a high barrier to entry, precisely due to personal privacy concerns, logistical complexity, ethical & cultural considerations, and procurement & configuration overhead. Researchers create frameworks to mitigate these privacy concerns (e.g., redaction), though these procedures are challenging in practice. Beyond human and process issues are technical complexities in configuring prototype autonomous assistants. It requires multiple domain specializations like computer networking, embedded technologies, AI/ML, and distributed computing. Each cross-cutting concern adds complexity and reduces the probability that small teams can successfully provision their test environment. Furthermore, those difficulties limit other researchers from reproducing the results. These factors slow innovation and restrict the value researchers can contribute to the body of knowledge.

This study aims to remove these barriers using artificial agents within a simulation process. It implements these capabilities using open-source software and existing MoCAP recordings. Next, virtual patients inside a physics simulator will perform animation sequences under differential physical configurations (e.g., weight and height). The study attempts to show this approach for detecting falling behaviors in hemodialysis patients. It will use AI/ML and the CV algorithm’s ability to perform HAR tasks. The project scope is constrained to specific real medical needs, though it is more broadly applicable. For example, similar experiments could exist for monitoring childcare. Regardless of the medical condition, the CV algorithm can learn HAR behaviors and control CPS systems worldwide.

# Chapter 2: Literature Review

The problem to be addressed in this study is the inability of elderly and special needs care organizations to capitalize on the effectiveness and efficiency of autonomous assistants for hemodialysis (Kim & Kim, 2021; Blackhurn, 2021). This research theorizes that computer vision (CV) can provide a consistent experience across a diverse global audience. Building autonomous assistants is challenging due to requiring multiple domain specializations like computer networking, embedded technologies, AI/ML, and distributed computing (Tun, Madanian, & Mirza, 2021). Beyond technical constraints, potential privacy and safety from video monitoring create barriers to locating volunteer patients. Furthermore, those difficulties limit other researchers from reproducing the results. These factors slow innovation and restrict the value researchers can contribute to the body of knowledge.

The purpose of this constructive research study is to provide an understanding of the effectiveness and efficiency of autonomous assistants for hemodialysis in elderly and special needs care organizations. Hemodialysis patients have a high risk of falling and injury (Shirai et al., 2021). It aims to deliver this capability by utilizing humanoid constructs within a realistic physics simulation process. Next, positioning virtual cameras, instruments, and devices within the virtual world enables researchers to collect their experimentation data. Lastly, the automation can modify the environment using programmable interfaces such as raising the alarm or applying other mitigations.

## 

## Search Method and Resources

This literature review used the Northcentral University Library (NCUL) to identify relevant peer-reviewed articles and books published from 2019 to 2022. It also includes foundational papers for historical context and generally accepted process standards outside this period. Students use NCUL’s Roadrunner search to aggregate results from industry-standard sources like the IEEE Xplore Digital Library, ACM Digital Library, and ProQuest.

A breath-first search scanned for surveys, challenges, and opportunities on the constructive research project’s core concepts (see Table 1). The breath-first search uncovered several themes that drove depth-first investigations. For instance, researchers are approaching hyper-scale ML training with custom hardware acceleration and continuous learning-at-the-edge methods (Plus Company Updates, 2021; Prapas et al., 2021). In other cases, themes like *Using Convolutional-Graph Neural Networks (C-GNN) for HAR* necessitate a sequential breadth-first search to contextualize supporting concepts. This search process continued until finding fifty unique documents. Next, bibliographical reviews for each publication extracted themes. Those sorted themes are available in the proceeding conceptual frame section, which presents each topic’s current state and direction from Table 1.

**Table 2**   
*Survey search terms*

|  |  |
| --- | --- |
| Concept | Example search queries |
| Elderly and special needs industry state | * (elderly care or special needs) and industry * (global or internal) and (disabled or medical) |
| Computer vision (CV) | * computer vision or CV * computer vision and (surveys or opportunities) |
| Human Activity Recognition (HAR) | * (human activity recognition or HAR) and (computer vision or CV) * HAR (state-of-the-art or challenges) |
| Machine Learning (ML) Training | * (ML or machine learning) training and scale * distributed ML training |
| Physics simulation | * (Unity or ROS or robotic operating system) and (process or environment) simulation * (dynamic or synthetic or virtual) environment testing |

## Conceptual Framework

A conceptual framework is a blueprint that communicates a natural progression of the phenomenon to be studied (Dickson, Emad, & Adu-Agyum, 2018). It is essential for quality research as it outlines a methodical structure of definitions, concepts, and relationships.

Four core approaches exist for studying a business use case or phenomena (see Table 2). This study’s blueprint derives from a constructive design science research (DSR) methodology.

DSR is one of the most common research methods for information systems and technology (Silvestrini & Sammito, 2012). These studies identify a problem, build 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. This methodology is appropriate for examining elderly and special needs care solutions. After creating the system, it can support a targeted case study that measures its ability to deliver value.

**Table 3**   
*Example Research Strategies for Classifying Movement in Video*

|  |  |  |
| --- | --- | --- |
| Approach | Description | Study Example |
| Quantitative | Studies the magnitude of a phenomena | Measure the resources necessary to classify movement with embedded systems |
| Qualitative | Explores a concept without a numerical basis | Exploration of reasons movement classification fails |
| Mixed-Method | Combines exploration and studying the magnitude of these issues | What preparation steps reduce the costs of movement classification |
| Constructive | Produce artifacts to study a scenario | Create an algorithm for classifying movements |

### Fundamental Approach

Constructive research practitioners gravitate toward either Design Science Research (DSR) or the Constructive Research Approach (CRA). One of the critical differences between them is that DSR relies more heavily on existing theories, versus CRA does not explicitly require a base theory (Piirainen & Gonzalez, 2013). More recently, Iivari (2020) criticizes the debate stating that constructive research must first and foremost produce high-quality artifacts. She advocates for “less theory, but better design theory (pg. 504),” especially within rapidly evolving industries like Information Technology and Communication. Zeller (2014) would agree with this position, adding success criteria that the artifacts are “challenging, elegant and useful.” This research project aligns with these requirements by focusing on connecting artifacts with patient needs and challenges.

### Central concepts and relationships

Here, the study presumes that CV and HAR can improve the livelihood of elderly and special needs patients. However, implementing those custom models is prohibitively expensive, and any research conclusions will be challenging to reproduce. This research project aims to mitigate these challenges by demonstrating CV and HAR methodology with simulated humanoids. It is beyond the scope of this dissertation to prove those methods are superior to existing and more laborious strategies.

There are multiple core concepts necessary to delivering this outcome. First, a literature review must examine the challenges and opportunities for elderly and special needs care. Quality research starts from customer challenges and works backward to find technological solutions (Bryar & Carr, 2021). In contrast, technology-first methodologies have a higher risk of not producing valuable outcomes.

Second, the central premise relies on exhibiting CV and HAR methodologies for predicting actions and behaviors. Computer vision (CV) is a process for extracting data from image sources. Next, human activity recognition (HAR) processes must classify that data into distinct actions and behaviors, such as the person is sitting or falling. Those requirements raise several questions within the literature review context. For example, what mechanisms are being built or deprecated? This research study does not aim to create a novel solution and plans to reuse existing methods.

Third, the research topic needs to train the ML model using a simulated environment with humanoid characters and virtual instruments. This situation raises implementation questions such as trade-offs between industry-standard tooling, design patterns, and configuration nuances. The literature review must identify strategies that are likely to produce high-quality results. It is beyond the scope of this dissertation to implement proof-of-concept (POC) solutions for every potential combination.

Fourth, the artifacts must be high-quality and functional within a noisy environment. Meeting these expectations raises questions regarding ML training strategies. For example, do other researchers remove (or add) randomness to their DNN architectures? Are there specific situations that are more applicable for improving model quality? This constructive research study aims to incorporate these recommendations but stops short of directly comparing algorithms or methods.

Fifth, the literature review must uncover strategies for scaling the ML training and inference to production scale. This sub-topic is crucial for bringing ML capabilities to public markets. However, it is also sufficiently complicated to populate multiple separate dissertations. Therefore, this dissertation only discusses literature trends for high-performance hardware, low-power hardware, and edge processing.

### Implementations and alternative framework

The proposed framework establishes capabilities that align with the business challenge of improving elderly care and special needs. It uses generalizable virtual camera instruments for CV and HAR experimentation with humanoid agents. Aspects of this framework appear in other publications (Gu et al., 2021; Banjarey et al., 2021). However, utilizing humanoid subjects with HAR and CV is not a mainstream topic in surveyed literature.

An evaluation of alternative conceptual frameworks also took place. First, would an alternative virtual instrument be more appropriate? Instead, this study could predict HAR with accelerometers and gyroscopes (Gu et al., 2021). Wearable sensors have several advantages, such as following the patient worldwide. Researchers have also demonstrated applying these sensors to predicting diverse action spaces (Nugroho et al., 2018). However, CV-based agents can extract more context from those same behaviors. For instance, a biosensor can predict that the patient is eating, but not the food type. Instead of directly competing technologies, future solutions must integrate these heterogeneous sources.

Second, an argument might exist that using humanoids is nonsensical and advocate for training the HAR models with public video repositories (e.g., YouTube). This approach has several benefits, such as realistic action depictions and freely available labeled data. However, it might be more challenging to train models on this real-world basis versus the controlled and sterile simulation process. Furthermore, researchers can dynamically scale humanoid properties (e.g., weight) to assess model performance across parameter gradients. Future research could combine the frameworks with the video repositories validating the laboratory environment’s usefulness.

## Challenges and opportunities for care providers

This section is a placeholder for compiling notes from the Industry state section. It attempts to frame the business environment and limitations that create the need for additional research.

## What is the role of data mining

The four data-mining categories are association rule mining, clustering, classification, and regression modeling (Barua & Mondal, 2019). Association rules are patterns like if *X then Y,* such as a person buying bread (X) is likely to purchase butter (Y). Clustering and classification are related strategies that attempt to group similar items into buckets. The critical difference is that classification knows the bucket labels ahead of time (supervised) while clustering does not (unsupervised). For instance, a teacher gives their class a quiz and then maps them into groups by their assessment score (e.g., A, B) is a classification problem. Suppose they mapped the students on their favorite color. In that case, the groups are not deterministic, which is a clustering scenario. Regression modeling tries to find a mathematical equation that explains the observations. A classic example estimates housing prices using square footage, house age, and room count, among other features.

Across these high-level categories, numerous scenario-specific algorithms are available for different data sets. For instance, Apriori-based algorithms rely on the concept that subsets of frequent itemsets must also be frequent itemsets to prune the search space and timely report recommendations (Mejia, Quintero, & Builes, 2017). Another use case comes from Self-Organizing Maps that cluster or categorize arbitrary data for anomaly detection (Sonmez et al., 2018). Then consider Ant Colony Optimization and Genetic Algorithms, which combine random guessing and regression modeling to iterate toward optimal solutions (Mirjaili et al., 2018; Leios, 2017). Other strategies exist to handle countless other challenges like dimension reduction (e.g., Principal Component Analysis) and brute force discovery (e.g., Parameter Sweeping) (Starmer, 2017).

### Organizational examples of data mining

Many financial investment firms rely on outcome-specific automated strategies to filter the sea of market data into a manageable number of options. For example, Fonskea and Liyange (2008) propose a data mining strategy that tracks related companies' correlation (e.g., FedEx and UPS) and profits from deviations. In this case, both shipping companies will likely experience similar political and economic headwinds. Bhoopathi and Rama (2017) propose an Apriori-like algorithm that attempts to derive trading signals based on implicit associations between instruments (e.g., X and Y are inversely correlated). Hargreaves and Yi (2012) use a decision tree model to filter the Australian index on fundamental data (e.g., return on equity) from 2000 companies down to a high-quality basket of the top six. Finally, George and Changat (2017) assess the market interdependencies by transforming daily quotes into connected graphs.

### Explain challenges experienced using data mining

There is a joke that ‘70% of all statistics are made-up,’ inferring that the model is unlikely to work in practice without properly evaluating correlation versus causation. Carver (2007) touches on this point with guidance that researchers focus on relevance, not “just seeing what we want to see.” Snee (2015) echoes that high-quality models are practical and explainable. Fonseka & Liyanage and George & Changat did not account for the contextually sensitive results of the Great Recession occurring in parallel. Bhoopathi and Rama’s association rules discovered tight relationships between Intuit (creator of TurboTax) and International Fragrance—with no economic justification. Aside from Hargreave and Yi, none of these approaches had a basis in modern market theory. For instance, correlations between price movements did not account for volume. The authors also limited their asset analysis to only primary assets instead of expanding into secondary assets. George & Changat determined that banks were the most critical aspect of their network but did not investigate interest rates, GDP, or consumer credit statistics. Bhoopathi and Rama could have transformed the data with a moving average to smooth out noise, decreasing false-positive rules.

### Enabling Machine Learning

Data mining enables transforming data into information. Researchers can build statistical models that predict outcomes when that information represents evidence for questions. Enabling this symbiosis requires well-defined objectives, or machine learning algorithms will lead to inaccurate solutions.

## What exactly is artificial intelligence

Dreams of artificial intelligence can trace back to philosophical debates in ancient Greece. Prometheus would mold handfuls of clay into images of the gods and later gave life. Ideas sprouted from mathematics, biology, and computer science before eventually producing modern artificial intelligence. While these different domains have unique perspectives, they collectively land in four categories of intelligent systems (Lukac, Milic, & Nikolic, 2018). The first divide asks if the system *thinks* or *acts*, or more precisely, can reason about the problem. These top-level categories contain subcategories of applications that mimic *humans* versus *rational* actors.

### Description of Technology

There are three high-level categories of artificial intelligence: rules and heuristics, machine learning, and deep understanding (Buchanan, 2005).

1. Before 1962, applications would rely on practical techniques for reducing the trial-and-error search space. This heuristic-centric approach is helpful for chess and other video game engines. Despite criticism for being naïve, many LOB (Line of Business) applications continue to leverage this technique successfully.
2. In 1963, Edward Feigenbaum and Julian Feldman’s *Computers and Thought* centralized many ideas across the computing industry. Their literature and new programming paradigms, such as McCarthy’s LISP, lay the foundation that became machine learning. Researchers use these tools to build statistical models that represent a situation. For instance, what else could you recommend if a customer purchases bread? Perhaps butter, jam, and deli meat.
3. In 1949, neural scientists found that the human brain transmits signals between a weighted graph of neurons (Lukac, Milic, & Nikolic, 2018). Despite unlocking the biological key to mimicking cognitive learning, the processing power was unavailable until the early 2000s. Researchers use neural networks to extract patterns to nebulous problems that meet or exceed human capacities.

### Purpose and Function

Traditional software follows the model of *data* plus *rules* equals *outcomes.* In contrast, intelligent systems use data and outcomes to derive rules. This distinction can be valuable when the *rules* are fuzzy or not entirely understood. After extracting those rules into a model, researchers and engineering teams can predict actions across mechanical, thinking, and feeling tasks (Huang, Rust, & Maksimovic, 2019).

* Mechanical tasks are actions that are highly repetitive and benefit from automation. These are operations like turning on lights or assembly-line construction.
* Thinking tasks are operations that require analysis and rationalization. For instance, “does this picture contain a hotdog,” or “is this sentence grammatically correct?”
* Feeling tasks, emulate interpersonal experiences, and express empathy toward the users. These autonomous systems might replace a call center or control support chatbots.

### Evolution of the problem

Numerous organizations begin their journey into intelligent systems with statistical modeling and variance analysis. These approaches work for many linear models but break down non-parametric functions (Waal & Toit, 2011). For example, a business wants to appraise houses given a collection of features about the home. Houses come in all shapes and sizes, making it challenging to compare those features directly. Instead, the appraiser must approximate a function that considers these characteristics and their weighted importance. Meanwhile, another company must classify handwritten digits by mapping a 32x32 pixel image to its numeric value. Both scenarios and countless more require a mechanism to translate these non-parametric functions into parametric approximations.

### Nature’s solution

In biology, animal brains accomplish these tasks through meshes of neurons that transmit signals across connected synaptic (transforming) and activation (filtering) links (Keller, Liu, & Fogel, 2016). Later, that animal sees an object, and its brain encodes the image into a feature map. These features traverse the brain’s neural pathways and output a collection of responses, such as “the object is food and ten feet away.” Over time, the creature *learns* if those responses are correct and revise network weights to encourage or avoid similar situations. Data scientists and mathematicians replicate these ideas by calibrating edge weights, through backpropagation, on connected graphs called *neural networks*.

## How does computer vision work

Modern CV-based methods emulate primate biology across three distinct subsystems: neural dynamics, embodiment, and awareness (Ballard & Zhang, 2021). Researchers expand on these different subsystems to implement their specific use cases.

### Neural dynamics

Primates use retinotopy to map visual input from their retina to neurons. This process incorporates a random sampling and batching procedure to activate those neurons, with different combinations producing unique classifications. Marr (1982) proposed that machines could emulate this behavior to extract intrinsic images and functional constraints. His research shows that for every point within an image , it is possible to calculate its information level. Then, a smoothing function can remove the noise and produce object detection masks! Marr’s paradigm remains foundational to modern CV methodologies even forty years later.

### Embodiment

Bajcsy (1988) proposed that vision is an active process, and a hierarchy of decisions must occur. Each layer within the hierarchical map must encode the likelihood of a prediction within the context of the previous layer. For instance, when a person sees a cat, their brain uses different neuron groups to identify edges-to-shapes, shapes-to-labels, and aggregate labels to object names. Today, AI/ML practitioners call this construct the “hidden layers” within neural network architectures.

### Awareness

Around the mid-90s, researchers began exploring the notion of gaze control and fixation (Ballard & Zhang, 2021). They discovered that at least six separate systems stabilize objects within primate vision and implement a sophisticated data inventory system. For instance, when primates search for *a blue ball in the image*, their brains cache metadata to accelerate the gaze. Another critical service called fixation only persists memories with an associated high reward. For example, people safely drive to work without recognizing the preceding events because the routine operation did not produce new information.

In 1996, Kaelbling et al. proposed encoding these systems as policy maps that activate through an abstract reward function. Their notion of *reinforcement learning* explains how primates program their brain using visual information. Researchers have formalized this approach into a multi-process model where “reinforcement threads” combine to produce sophisticated composite decisions. Consider the problem of “should I eat this food?” In this situation, parallel threads predict it is a hotdog, hunger level, and availability of mustard. Their aggregate response invokes an appropriate behavior based on the visual information.

## What’s the role of Markov chains

A core challenge to applying basic statistics to real-world data is assuming that each action is independent. However, many scenarios contain a conditional state transition probability dependent on the current state. If the stock market falls 5%, should an investor buy? The binary question requires a contextually sensitive answer that considers their net position (short the market), outlook (2008 financial crisis versus 2017 Trump bump), and similar factors. Markov chains provide the mathematical basis for making statistical models incorporating these dependencies (Kahn Academy, 2014). Creating the hypothetical purchasing model (see Figure 1) begins with a state diagram representing the different actions available. Then Monte Carlo solutions can approximate each edge’s weight by random sampling and recording the decisions. At the same time, multiple use-cases can follow the same model, the scenario-specific decision weights. For instance, consider the differences between investing in (a) 401k retirement account that only adds index funds versus (b) delta-neutral (directionless) options trader. This trait is similar to other algorithms where efficient training requires relevant facts to specific questions.

**Figure 1**  
*Should you purchase more stocks model*

Diagram, schematic

Description automatically generated

### Markov Experiment

Many online tutorials recommend exploring Markov chains as a solution to predict the next token in a sequence. Mason (2020) maintains an open-source repository of Shakespeare plays, which is easy to mine for different related sentences. An experiment began with downloading each script and normalizing the text into a corpus of lowercase words. Next, an iterator constructs a word\_dictionary that maps n-gram tuples to a word bag to the immediately following values. Then traversal of the Markov model chooses a random starting point, then selects a random next word, iterating until a stop condition. Across the test iterations, tests of different n-gram sizes (degrees of freedom) ranged from one to six. The higher the count, the more natural the sentences sound due to overfitting. Even at low n-gram terms, a frequent challenge arose from many unique words causing long sequences of static choices.

**Figure 2**  
*n-gram Examples*

Graphical user interface, text, application

Description automatically generated

### Neural Networks

A Multi-Layer Perceptron (MLP) algorithm aims to map input features to a non-parametric function that approximates a set of outputs via an intermediary mapping function (the hidden layer). A fully connected graph can represent this structure. All inputs connect to the hidden layer, which connects to all outputs. Next, an iterative process forward-feeds examples through the network. Backpropagation updates the network weights and performs error corrections concerning the expected value (Ng, 2016).

According to Fridman (2017), backpropagation is a recursive process of taking the partial derivative of two logic gates and applying a weighted update. He expands on the idea of these connected graphs with an example of image classification passing through several three layers (extracting edges, corners, object parts, and object identities). While the mathematical basis and engineering steps are somewhat procedural, the network architecture's efficient design requires art and science.

Perhaps the artfulness comes from a lack of planning or awareness of how the *ensemble* of distinct training subsystems combines. There is no reason to assume that every node is fully connected or has an edge weight above zero (see Figure 3). A logical representation might consider feature ‘x1’ connected to N neurons that regress one output, with feature ‘x2’ implementing some classification pattern. These network segments produce collaborative signals to provide a more productive inference about the broader topology. These network segment microstructures remain present in more complex architectures. The solutions by both BellKor (2007) and Li et al. (2019) suggest that this assumption is generally accurate.

**Figure 3**  
*3 GANN Architecture (de Waal & du Toit, 2011, p. 399)*Diagram

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### Neural Network Experiment

Consider the scenario of mapping 28x28 images of clothing to ten categorical labels (e.g., hats versus coats). The number of input features (neurons) is 784, and there will be ten output neurons—how many neurons should exist in the middle? Rosebrock (2019) provides an example solution (see Figure 4) to Fashion MNIST that begins with feature reduction through two max-pooling hidden layers and batch normalization. After cleaning, the solution uses a single 512-neuron hidden layer to predict one of ten output categories (with softmax). Reducing the hidden layer's size to 128 or 256 has minimal impact on the cross-validation scores, though shallow values of 5 to 16 negatively impact accuracy. In this example, changing the activation functions (e.g., softmax to tan-h) creates more performance fluctuation than any other knob, with model accuracy ranging from 20 to 85%.

**Figure 4**  
*TensorFlow Architecture for MNIST Analysis*Diagram, schematic

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### Observations

The first and most critical step in any data mining exercise is determining the question and discovering supporting evidence. Until this action occurs, the business is unlikely to have a successful deliverable and will spend excessive resources investigating irrelevant materials. After clearly articulating the business value, the engineer teams can perform broad filtration of data sources based on their ability to address those questions. During filtration, having a logical framework can improve the search process through partition pruning for the relevant data stores. For instance, if the business operates in Michigan, there is potentially minimal value in exploring Texas-specific data. After coalescing the supporting facts into a central location, cleaning and curation processes must confirm that the data is complete and pristine. Perfect information needs to be both the right size and volume, or it might be incompatible with the analysis algorithms. For example, an instance learning algorithm expects individual records, not aggregate counts.

Markov Chains and Neural Networks are two strategies for making predictions on data through graph-like structures. Unlike basis statistics, Markov removes the need for actions to be independent and instead expresses them as weighted state machines. These state machines can improve workflow accuracy by guessing the next word in a sentence. Neural Networks and related MLP algorithms rely on weighted graphs and backpropagation to make predictions. While there is some artfulness, an alternative perspective asks if these are ensembles of small network segments. Evidence towards this interpretation exists in multiple advanced papers and helps to demystify the “machine learning black box.” It also means that several related concepts, patterns, and practices of data processing networks should also appear within more advanced neural network architectures.

## How are neural networks evolving

Frank Rosenblatt (1958) proposed the Mark I Perception as the first neural network architecture. This construct attempts to explain animals’ biological networks to *perceive* the world around them. The network consists of a collection of weighted sensors that converge into *one* learning circuit. Mechanical devices can replicate that implementation and train the connected weights to emulate animal intelligence with noisy data. Since this seminal paper, researchers have expanded deep neural networks to incorporate hundreds to thousands of connectivity layers. However, the specific configuration remains more art than science, with researchers manually iterating through trial and error experimentation (Ünal & Başçiftçi, 2021). The research field has two eras, with the first being evolution of the artificial neural network (ANN) from 1989 to 2015. Then, the deep neural network (DNN) evolution became the primary focus from 2015 to the present. The industry is moving so fast that information beyond two years is becoming outdated.

### Artificial neural networks era

Perceptron was revolutionary with its weighted signals triggering an activation function. This construct was insufficient for many scenarios and led to Multi-Layer Perceptron, which links a series of activation functions. Semantically, researchers can encode Boolean logic into these gates to derive more sophisticated insights. For instance, a network might contain two gates representing a person’s hunger level and food availability. Distinct signals can activate with each predicate to determine the overall scenario probability. That aggregate threshold can trigger an alarm or notification for the overarching decision to eat the food.

There are numerous activation functions, and a subset of the most common ones are available in Table 3. Originally researchers began with Sigmoid functions, which exponentially become a positive or negative one-value. However, this calculation is complex and slows down model convergence. A simple performance improvement came from using the tanh(x) function, similar to Sigmoid (Meta AI, n.a.). Now, researchers choose Rectified Linear Unit (ReLU) as the most preferred industry-standard algorithm (Ünal & Başçiftçi, 2021). Several scenario-specific variations like Leaky ReLU aim to scale and retain negative values versus truncating them entirely.

**Table 4**  
*Activation Functions*

|  |  |  |
| --- | --- | --- |
| Activation Function | Formula | Description |
| Sigmoid |  | Mathematical function having an S-shaped curve with asymptotes at -1 and 1 |
| Tanh |  | A hyperbolic function that’s a ratio of sinh and cosh |
| ReLU |  | The most popular activation function |
| Leaky ReLU |  | An enhanced ReLU for incorporating scaled negative values |

### Architecture generalization challenge

Simple networks have poor learning abilities and are challenging to generalize to more sophisticated scenarios. Meanwhile, deep neural networks can learn intricate and subtle patterns but require more data before converging (Ünal & Başçiftçi, 2021). This trade-off causes many researchers to follow the principles of Occam’s Razor, which “promotes minimizing complexity and defending reductionism where possible (Oxford, 2022).” Calculating the most efficient and minimal network is an open problem, so researchers approximate with genetic algorithms. These algorithms aim to converge to a decent local optimum, not the global one. Genetic programming is an essential tool and recipient of significant scientific investment. Multiple dissertations could cover this topic, which is full of open problems.

*Insert a sequence diagram or something demonstrating knowledge of this idea for interviews. That goes here.*

Modern network architectures aim to simultaneously solve multiple objectives regarding weight and structural parameters to maximize fitness with minimal design (Ünal & Başçiftçi, 2021). Researchers can optimize various problem dimensions concurrently using ensemble methods, provided those subtasks have similar but not overlapping objectives (Kim & Cho, 2008). These subtasks typically mutate the network architecture through additive and pruning strategies until convergence, as illustrated in Figure 1.

**Figure 5**  
*Multi-dimensional convergence (Kim & Cho, 2008, p. 1605)*

Chart

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### Deep learning era

Object detection and labeling tasks were some of the first problems leveraging deep neural networks. Notably, in 2006, separate work by Hinton and Li led to the creation of ImageNet, a CV model for detecting twenty thousand labels based on fourteen million images (Ünal & Başçiftçi, 2021). In 2012, AlexNet incorporated graphic processing units (GPUs), reducing the error rate by 50% over previous CV architectures. Today, using GPUs over CPUs is table stakes and has opened the door to training across big data sets.

DNN architectures contain multiple kernels, regularization, and hyperparameters. This variability makes them particularly challenging to optimize. Training hyperparameters control the model’s initial weights, learning rates, momentum factor, generalization, and the amount of training data (Jaisswal & Naik, 2021). These options influence several critical aspects of the final model, such as its sensitivity and degree of overfitting. Additionally, incorrect values can negatively impact training performance and defer model convergence.

Practitioners typically choose genetic programming or reinforcement learning (R.L.) for this procedure (Ünal & Başçiftçi, 2021). Data scientists can represent multiple expert systems as a connected mesh of R.L. models that search for ensemble methods like Kim & Cho (2008) articulate. This mesh approach is standard for state-of-the-art architecture competitions like ILSVRC (ImageNet Large Scale Visual Recognition Challenge).

## How does intelligent agent modeling work

Engineers consistently find that maintaining monolithic technologies requires substantial overhead. Alternatively, using microsystem architectures enables them to build and replace components rapidly in isolation. A similar idea exists with simulations that decompose the environment into multiple intelligent agents (see Table 4).

**Table 5***Principal Components*

|  |  |
| --- | --- |
| Aspect | Definition |
| Intelligence | The ability to reason about a problem |
| Simulation | An experiment that produces a statistical model |
| Environment | The universe contains the agents |
| Agent | An automaton that follows a predefined script |
| Objective | The goal of the agent |
| Tasks | The steps necessary to complete the objective |
| Notification | A collaborative or competing message between agents |
| Swarm | A group of agents |
| Choice | The random decision of an agent within its action space |
| Aggregate Choice | The net effect of multiple independent agent decisions |

A simulation experiment first identifies the environment, participants, and one or more objectives. Each participant, called an agent, attempts to complete their aim under guiding rules and principles. For instance, NetLogo’s BeeSmart environment contains multiple bees that try to maximize food production from various honey pots within a given scene (Wilensky, 2014). Initially, the swarm fumbles around until it discovers a food source. After some time, the colony will divide across multiple honey pots and compare site values with neighboring peers. Eventually, the bees converge to the optimal configuration that provides the maximum food for the hive.

**Figure 6**  
*BeeSmart Simulation (Wilensky, 2014)*

A screenshot of a computer

Description automatically generated with medium confidence

While no individual agent (bee) understands the ideal distribution across the environment, the aggregate of independent decisions enables analysts to extract sophisticated observations about the broader objectives. It is also possible to quickly expand upon this simulation by designing expert agents, such as communication specialists, that propagate messages twice as fast. After defining the role and its local rules, the existing simulation can immediately incorporate those customizations.

### Genetic Algorithms (G.A.)

The Traveling Salesman is a classical graph puzzle that attempts to find the most efficient route through N-cities. Even with ubiquitous access to cloud computing, enumerating through an exhaustive search is not practical due to the combinations growing at (Keller et al., 2016). As the simulation continues to scale out, it requires a mechanism to prune that search space and quickly discover the optimal answers. The Theory of Evolution states that biology weeds out inferior strains through the Natural Selection Process (Darwin, 1859). Computers can replicate this model through Genetic Algorithms to converge on optimal configurations (see Figure 2).

**Figure 7**  
*Genetic Algorithm Process*

Diagram

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The solution begins by modeling a potential answer as a vector of classification features. First, hundreds to thousands of randomly initialized instances run through the simulation to compute a per-instance score. Then a TOP-N ranking keeps the best instances, discarding the remainder. Next, a cross-breeding and mutation process mixes features from the fittest combinations to produce the offspring. Those offspring cycle through this system thousands of times until only superior specimens remain.

### Multi-Level Agent-Based Modeling (ML-ABM)

After decomposing complex models into individual agents, a mechanism must aggregate the independent decisions into more macro observations. Cellular Automata (C.A.) paints this picture by grouping related swarms into “a hierarchical series of discrete systems (Makarenko & Osaulenko, 2018).” Through multiple levels of aggregation, agents can feed into swarms and those individual swarms into swarm networks.

For instance, a financial market environment has individual buy-and-sell participants who react to supply-and-demand fluctuations (see Figure 3). This specific example simulation contains thousands of personal portfolio accounts (agents) that frequently make rational transactions. An analysis could apply C.A. across these portfolios by aggregating many data points to improve the data’s usability for professional traders. However, an inefficiency exists within this design because some individual portfolios (agent states) are nearly identical. Like the risk-free rate, other aspects do not require the fidelity that swarms of agents produce. These situations can rely on ML-ABM to approximate irrelevant details (e.g., with caches) and enable fine-grained influence over critical decisions (e.g., with swarms of agents) (Hijorth et al., 2020).

## How does neural network training work

Model training aims to estimate the weights and connectivity structure for mapping a set of inputs to prediction outputs. This process requires optimizing a cost function using a series of forward-feeding data operations followed by backpropagation (Fridman, 2020). Backpropagation is a mathematical procedure that compares the expected versus actual outputs. Next, it calculates each parameter's partial derivatives and cascades updates to adjust the input weights accordingly (Lee & Yoo, 2021). Finally, after sufficient iterations, the network converges, which means that the difference between expected and actual outputs is within an acceptable margin of error.

### How are they scaling to millions of parameters

Recently, titans of the industry like Google Brain Team, OpenAI, and Uber Labs are scaling their evolutionary algorithms to millions of parameters without human intervention. Discovering the optimal architecture for CV and NLP problems at this scale is improbable due to its combinatorial nature and high costs per iteration (Lui, K, Fernando, & Kavukcuoglu, 2018). Instead, automation must represent the network as a traditional graph G consisting of nodes and weighted edges. Next, multi-level motifs augment the connectivity hierarchy to discover the impact of broad and narrow changes. For instance, these mutations might inject high-level filters or split the N-th hidden layer. In many ways, this is analogous to traditional fuzz testing, which exploits software through bit flipping.

Google DeepMind (2018) implements its search algorithm based on tournament selection. Each round begins by selecting the top 5% of the population and applying permutations from a discrete action space. After mutating the networks, only the superior offspring survive to the next round. This random search process is a genetic algorithm with an R.L. model steering its evolution to deliver the best of the breed through a simple search model.

### Modern scalability challenges

The sheer volume of matrix-based computations introduces challenges in scaling the training systems. Around 2012, researchers began using Graphical Processing Units (GPUs) over Central Processing Units (CPUs) to expedite model convergence significantly (Krizhevshy, Sutskever, & Hinton, 2012). According to some estimates, this hardware change leaped the state-of-the-art Deep Learning a decade (Ünal & Başçiftçi, 2021). However, researchers continue to require more extensive and sophisticated models. For example, GPT-3, an autoregressive language model, has over 175 billion parameters, a 10x increase over GPT-2 (Brown et al., 2020). More recently, Google Brain demonstrated an NLP translation model with over a trillion parameters (Fedus, Zoph, & Shazeer, 2022). This exponential parameter growth is likely to continue into the foreseeable future.

Several practical limitations exist to *scaling up* an individual server to support training a billion parameters. Instead, researchers turn to distributed systems patterns for horizontally *scaling-out* across hundreds to thousands of commodity servers (Langer, He, Rahayu, & Xue, 2020). The orchestrator, parameter server, and the worker node are three essential roles within these compute clusters. Worker nodes communicate with the orchestration process to determine the next training operation in the queue. Then, it fetches the shared parameter state and performs its work. Eventually, the operation completes, and the calculated gradients push to the parameter server. The parameter server is responsible for merging worker node updates into the shared state. This cycle repeats until the orchestrator determines that no more work is necessary.

### Fault-tolerant design requirements

The exponential growth in parameters and data volumes forces the training process to execute for days or weeks. That process must be highly reliable to withstand random errors during this period.

**Influence of Hierarchy.** Generally speaking, there are two mechanisms for modeling distributed systems, lists, and trees. A list can efficiently manage small groups of related nodes; however, it can become cumbersome with more massive sets. Trees allow for more expansive designs as the system can hierarchically describe the problem through multiple levels of control. Consider the difference between Domain Name Services (DNS, tree) and NetBIOS (list). NetBIOS can easily manage a small branch office, not the Internet because its simple flat list structure is *globalized*. In contrast, DNS has multiple subdomains, with each subdomain owned by heterogeneous service providers. Since each subdomain holds a specific set of children, read and write operations can be *localized*.

**Influence of Partitioning**. Localized designs are inherently more performant and fault-tolerant because of the containment of both scale and blast radius (Vosshall, 2018). Imagine a scientific dataset that has grown to several petabytes in size. The storage network would need to decompose this logical file system into multiple blocks and replicate it across multiple physical servers. These physical servers will run into mechanical failures, such as disk corruption or power outages.

When these outages occur, other nodes must efficiently Set up, Challenge, and Repair (SCR) the missing data (Chen & Curtmola, 2017). The time necessary to perform that repair operation is proportional to the size of each block and the system’s ability to scale the reconstruction over multiple peers horizontally. Assume that 1TB of the dataset has entered a failed state and needs to recover across a 10GB/s network (see Table 5). If only one virtual peer has a copy of the data, the system will heal in 102.4 seconds. Then contrast that with the smaller block size of 128GB, which can economically be sprawled across many servers, reaching an MTTR of under a second.

**Table 6**   
*Mean Time to Recover*

|  |  |  |  |
| --- | --- | --- | --- |
|  | Repair 1TB of Data | | |
| Block Size | Virtual Peers | Num Blocks | MTTR (seconds) |
| 1024 GB | 1 | 1024 | 102.4 |
| 8 | 1024 | 12.8 |
| 16 | 1024 | 6.4 |
| 512 | 2 | 2048 | 51.2 |
| 16 | 2048 | 6.4 |
| 32 | 2048 | 3.2 |
| 256 | 4 | 4096 | 25.6 |
| 32 | 4096 | 3.2 |
| 64 | 4096 | 1.6 |
| 128 | 8 | 8192 | 12.8 |
| 64 | 8192 | 1.6 |
| 128 | 8192 | 0.8 |

**Influence of Fail-Over Groups.** Proxy servers and similar brokers operate on ephemeral requests and need fault tolerance to come from a different source. One strategy is maintaining a target group of service instances and monitoring their availability (see Figure 1). The monitoring can come from at least three reference points: (1) the network operating system, (2) the observed traffic of the broker itself, and (3) a local health agent on the service instance. The broker can use the Observed Health State Store (OHSS) to select the most appropriate receiver as new requests arrive. A recovery policy could also exist to manage any Service Level Objectives (SLO) of the backend application. For instance, if the backend application needs to be highly available, the broker could be augmented to trap specific exceptions and automatically route to another node. Other systems must optimize scenario-specific goals and metrics, such as more consistent response time, and choose completely different behaviors.

**Influence of Geo-Redundancy**. Cloud Service Providers (CSP) allows fault tolerance across multiple physical regions, so that entire data centers can fail without impacting uptime (see Figure 2). The scheme starts with deploying the service stack into two or more locations like Seattle and New York. Next, data store replication enables the sites to be kept in sync. Finally, the user can discover the most performant service stack instance from a location-aware Canolical Naming Service (CNAME). That system can consider latency and other metrics, like the proposed Fail-Over Group solution.

**Figure 8**  
*Multi-Region Deployment*A picture containing text, map, table, indoor

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**Influence of Consensus.** The physical distance between the sites forces the need for eventual consistency protocols that range in complexity from (a) the latest timestamp wins, (b) Paxos algorithms, and (c) Byzantine General’s solutions (Zhao, 2014). The latest timestamp wins are easy to understand. Still, they need to rely on highly reliable distributed clock synchronization, an open research problem in itself (Ting, Chun-Yang, Di, Xiao-ming, & Heng, 2014). Under Paxos (see Figure 3), multiple rounds of preparation, acceptance, and learning phases occur to gain consensus. This elegant protocol can efficiently reconcile a single systems image, provided none of the nodes are malicious. If malicious or erroneous nodes exist, 3f +1 cross-validations must occur (Zhao, 2014).

**Figure 9***Paxos Consensus (Zhao, 2014, p. 196)*Diagram

Description automatically generated

**Influence of Protocol.** Message passing between components can either use reliable or unreliable communication. Unreliable handoff can be helpful for best-effort or performance-critical systems, such as real-time video or sampled telemetry reporting. Reliable handoff is crucial for scenarios that mandate full and consistent accounting, such as user data or financial records. These fault tolerance decisions are not limited to the low-level transport protocol differences between User Datagram Protocol (UDP) and Transmission Control Protocol (TCP). They also appear at higher application levels (see Figure 4). The actor can notify the Alice service directly; however, the message could become lost due to a network failure. Instead, they can first place the payload into a command queue and remove it only after the server-side acknowledgment. When Alice accepts the event, she needs to receive confirmation from Bob and Charlie before returning success. Bob stores the event in a durable command queue, whereas Charlie executes it directly. In either scenario, the client can reliably infer that handoff has occurred.

**Figure 10**  
*Durable Command Queue Pattern*

Diagram

Description automatically generated

### Scheduling-specific design requirements

The training process must also choose an asynchronous or synchronous scheduling architecture (Langer, He, Rahayu, & Xue, 2020). Synchronous systems partition the training iteration (epoch) across the worker nodes and merge all responses before starting the next round. This approach has several advantages, such as simplicity regarding the design and maintenance. However, as the total worker nodes increase, so do the idle cycles from waiting on the slowest tasks to complete. Asynchronous systems aim to eliminate these idle cycles by prematurely starting the next training round. Since each worker node owns an isolated job, this technique is highly effective. However, the parameter server and orchestration processes must assume more complexity for this time-optimization. For instance, what should the parameter server do when task outputs (gradients) are late or never arrive?

Langer et al. (2020) propose a collection of boundary conditions for asynchronous architectures. For example, the parameter server system should disregard any gradient exceeding K-epochs latency or changing an individual parameter by X-threshold delta. They also advise using priority queuing over FIFO queuing for the incoming responses. Another solution is to use multiple parameter servers and periodically reconcile the differences between their local states.

### Continuous learning techniques

Countless researchers and product teams periodically retrain their models from scratch as they iteratively add more example data. This approach is intuitive to design but wasteful and could become impractical as model parameter counts continue exponentially growing. Instead, researchers are proposing training architectures that support *continuous learning*.

**On-device training architectures.** On-device training architectures aim to fine-tune generalized machine learning models using local sensor data (Lee & Yoo, 2021). This design begins with a cloud training process that consumes a public data set to produce a shared model. Next, a second training process will download the shared dataset and fine-tune it to include personal data (e.g., a smartphone’s photo album). Lastly, an inference process uses the private model to deliver a personalized experience.

There are several essential advantages to this design pattern. First, the cloud-based training process does most calculations and has significantly more resources than an individual device. Next, the device-based training process can maintain data privacy and residency requirements because the personal data doesn’t need to be in the public data set. This characteristic could help overcome specific privacy concerns in regulated industries like healthcare. Third, the decoupled training processes refresh both models at a higher frequency.

**Figure 11**  
*On-device training architectures*  
Diagram

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**Stream-based training architectures.** This section is a placeholder for futureliterature review topics that may expand upon this point.

## What is autoencoding

In its simplest form, “an autoencoder learns the representation or code by trying to copy the input to the output by encoding the input’s distribution into a low-dimensional vector (Atienza, 2018, p. 78).” Figure 2 contains an example architecture illustration with three features compressed into one parameter before expanding into three new features. The precise connectivity graph depends on the specific situation. For instance, researchers can use this process for scenarios such as colorizing images, denoising, replicating artistic styles, and intrusion detection, among other conditions.

**Figure 12**  
*Autoencoding architecture*

Diagram

Description automatically generated

### Example usages

Include a summary of the art stylizer paper

Include the summary of DACNN here from the intrusion detection paper.

## How does sequence analysis work

Natural Language Processing (NLP) sits at the intersection of artificial intelligence, human language, and computer science.

### Language Parsing

NLP systems typically begin with sentence normalization, combining and annotating tokens, and finally performing custom business logic (see Figure 13) (Edureka, 2018). Using Lemmatiziation and Stemming strategies enables the parsers to reduce the variability between sentences, such as removing verb-tensing. Next, annotations are associated with the words by subsystems like Named Entity Recognition (NER) that discover the sentence’s critical components. After chunking related tokens together, the scenario-specific business logic can operate on a semantic representation of the text. Depending on the use case, these steps could be massive subsystems or single lines of code.

**Figure 13**  
*NLP Analysis Procedure*

Diagram

Description automatically generated with medium confidence

### Deep Learning

NLP appears across various use cases like language translation, speech-to-text, and sentiment analysis. In biology, animal brains accomplish these tasks through meshes of neurons that transmit signals across connected synaptic (transforming) and activation (filtering) links (Keller, Liu, & Fogel, 2016). Computer scientists mimic this behavior with Deep Learning on Neural Networks, essentially weighted graphs. Generally, NLP architectures use Recurrent Neural Network (RNN) structures containing connectivity loops to previous layers (see Figure 14). More advanced designs include subnets for memory retention (see Table 6), encoding and decoding segments, and greater parallelization from attention vectors (Fu, 2019). Researchers and engineers can add or remove these subsystems to optimize a specific use case.

**Table 7**  
*Example progressions of N.N. architecture complexity*

|  |  |
| --- | --- |
| Algorithm | Description |
| seq2seq | Simple Recurrent N.N. (RNN) for a token sequence to sequence prediction. These systems are easy to implement but lack memory |
| Long Short Term Memory | Extends the seq2seq by including a “long term” cache to hold context information |
| Transformers | State-of-the-art solution for massively parallel NLP through attention vectors and position encoding |

**Figure 14***Abstract Diagram of Differences*Diagram

Description automatically generated

### Feature Extraction Process

The first steps to any business intelligence problem are identifying the specific questions and locating facts to support answers (Snee, 2015). When researchers ignore this preparation, it produces garbage-in/garbage-out results. For instance, Alsudias et al. (2014) built an NLP system for predicting where the user was during the submission (e.g., restaurant or nightclub). Their approach extracts keywords from Yelp reviews (using term frequency), business metadata (e.g., name and location), and tweet metadata (e.g., timestamp). These features flow into a random forest classifier that determines the user’s location with a 74% accuracy. However, using only the business metadata produces an 88% accuracy, indicating that these additional details provide negative value.

Researchers might have specific requirements to model social media users’ speech patterns and create new content in their voices. The Feature Extraction Process must therefore consider the user’s metadata (e.g., age and locale), the online community properties (e.g., forum name), the posted content, and any quality ratings (e.g., Facebook Likes). There are several considerations to augment this process. For instance, adding a filtration step to remove comments with negative ratings might create more well-liked personalities. However, it could also be advantageous to generate trolls that argue an alternative position, reinforcing the political situation that the other side is illegitimate or less sophisticated.

### Training Process

Around 2014, GAN (Generative Adversarial) Networks became the state-of-the-art approach to producing high-quality fabricated content (Fridman, 2020). These systems utilize a feedback loop between a Generative N.N. (GNN) and Discriminator N.N. (DNN). Each iteration outputs a ‘Deep-Fake’ asset and assesses its likelihood of being legitimate. This process enables both systems to learn from one another, continuously improving. According to Fridman (2020), detecting Deep Fakes is an arms race because advances in DNN naturally improve GNN results. NPAC leverages this methodology for self-teaching its systems to deliver more accurate content (see Figure 4). The organization’s solution uses the NLP transformer to improve parallelization over LSTM and a second RNN classification network. Periodic snapshots archive the content and model state for offline troubleshooting use cases during the training process.

**Figure 15**  
*GAN Training Configuration*Diagram, schematic

Description automatically generated

## How does recognizing human activities work

One critical application of CV is to detect human activities from photos, images, and video streams. This capability is essential for personalizing systems across the healthcare, smart home, and safety industries (Gu et al., 2021). Adapting traditional ML tactics to human activity recognition (HAR) is laborious, error-prone, and challenging. Researchers mitigate these issues with deep learning models (Gu et al., 2021; Banjarey et al., 2021). There are several algorithm families used to model these predictions.

### Restricted Boltzmann Machine (RBM)

The first HAR implementations used Deep Belief Networks as their prediction basis. Training this solution was extraordinarily challenging and deprecated (Gu et al., 2021).

### Convolutional Neural Networks (CNN)

A preceding section examined the biological constructs that enable primates’ vision and nature’s solution.

A neural network consists of three building blocks' input, hidden, and output layers. For instance, an animal image classification system might assign 64x64 pixel images into ten predetermined categories. This example requires an input layer with 4096 neurons, an output layer of ten neurons, and some hidden layers in the middle. Adding more hidden layers enables extracting more details from the image, similar to object edges (layer-1), ears (layer-2), cat’s ears (layer-3), and a tiger’s ears (layer-4) (Fridman, MIT 6.S094: Introduction to Deep Learning and Self-Driving Cars, 2017). While more complex networks can extract more insights, it comes with the cost of needing exponentially more data to train the model.

Experts suggest that a fully trained model requires at least ten observations per parameter (Snee, 2015). This situation can become too expensive and require model compression strategies (Cheng, Wang, Zhou, & Zhang, 2018). For instance, the input layer could feed into a series of pooling transforms that downgrade the resolution by averaging every 2x2 pixels. Another tactic might focus on connecting and evaluating local segments of neurons before outputting into global join constructs and prognostication output (see Figure 16). Meanwhile, other situations like estimating housing prices perform better with fully connected shallow pipelines. While standard architectures exist for many classes of predictions, some experimentation is necessary.

**Figure 16**  
*Network Structure*

Diagram

Description automatically generated

## How do dynamic environment simulations work

This is a placeholder for literature review material during the Unity versus ROS selection process. An initial proof-of-concept suggests that both solutions meet the requirements. Future investigation maybe necessary during the fourth chapter

### Methods

Place holder for future investigation into best practices

### Unity-based

Placeholder for anything Unity-specific.

## Computer vision and autonomous driving

Researchers are applying CV to many health and safety system like autonomous driving. Investigating these related use cases can uncover best practices and reusable patterns for this elderly and special needs care study.

Machine learning can enhance every aspect of the drive, from extending the physical parts’ lifespan to increasing the driver’s overall satisfaction. Figure 1 contains a non-exhaustive taxonomy of uses-cases for artificial intelligence in motor vehicles, such as reducing wear and tear and object detection. The central application topic is the primary deciding factor for item assignment within the tree. Many items, such as Voice Assistance (V.A.), could arguably live under a different pillar, safety. However, safety systems could exist in the same capacity using more traditional input interfaces, making this example fall under convenience.

**Figure 17**  
*Taxonomy of Example Use-Cases*

### Data collection process

Since covering each use case in full detail would fill multiple books, this section reviews these user scenarios’ commonality. The lifeblood of these systems is data, and only through synthesizing information into knowledge can they be more adaptive. These processes require collecting telemetry, mining data, and modeling the interactions (see Figure 18). As simulations run across that model, statistical distributions form, leading to predictive capabilities. When the model’s complexity grows or the required accuracy increases, the learning system also needs more examples to cover each scenario.

Consider the analogy of building an All-Wheel-Drive (AWD) feature that only knows about Florida’s flat tropical roads. Despite the engineers' best efforts, the vehicle will encounter challenges on Colorado’s ice-covered mountainous climbs. Similar behaviors exist across the autonomous vehicle supply chain, demanding either (a) more data or (b) more erroneous assumptions. This trade-off introduces acceptable feature risks in specific situations (e.g., entertainment modules) and undesirable consequences for others (e.g., safety modules).

**Figure 18**  
*System Design*

A picture containing text, map, indoor

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Around 2014, GAN (Generative Adversarial Networks) became the state-of-the-art approach for constructing high-quality detectors and fabricated content (Fridman, Deep Learning State of the Art, 2020). These systems utilize a feedback loop between a Generative Neural Network (GNN) and Discriminator Neural Network (DNN). Each iteration outputs a ‘Deep-Fake’ asset and assesses its validity (see Figure 3). Under this process, both systems learn from one another, continuously improving their expertise.

**Figure 19***Training Configuration*

Diagram

Description automatically generated

Automotive companies like Formula One use this methodology to synthesize more efficient race cars that can safely operate at high speeds (Smedley, 2019). First, a collection of features (e.g., car shape and weather data) load into the GNN and its simulation environment. Next, the output flows into a DNN, assessing the solution’s feasibility (e.g., wind drag and safety requirements). Then, the GNN modifies the solution’s parameters to search for a higher score (e.g., faster car). After executing thousands of cycles, both networks converge with optimal solutions to deliver innovation (GNN) or detect problems (DNN).

### Safety Control Systems

Annually, 32,000 Americans die from automotive accidents, and another 2 million are injured (CDC, 2016). These statistics are unacceptably high and require innovations that increase all participants’ safety on the road (see Figure 20). Artificial intelligence can assist in these scenarios by collecting sensor data and predicting risks and opportunities. However, numerous open problems exist throughout the safety domain. These challenges should not discourage investments in these areas as they are essential to public safety.

**Figure 20**  
*Taxonomy of Participants and Example Challenges*

For example, manufacturers like Subaru and Lexus include audible collision alerts during lane changes or reversing. While these capabilities exist today, they are often incomplete models due to the high volume of edge cases, such as children fetching a ball from the street. Even after detecting the example child, several open problems span ethical and philosophical debates. Lex (2017) asksif avoiding the pedestrian requires killing the driver— what calculus dictates that autonomous decision? These situations might play out in fractions of a second, limiting the value of human intuition. Since concrete answers do not exist, machines must resort to static guardrails (e.g., slamming on the breaks or swerving) that could risk a multi-vehicle accident.

### Convenience Systems

Long monotonous segments are often necessary to arrive at the destination during a road trip. This requirement forces the driver to expel significant concentration relative to the mundane task. Instead, auto-pilot systems can take the wheel and allow the motorist to relax and participate in leisure activities (e.g., conversing with passengers). Some manufacturers tackle these needs with adaptive cruise control technologies. This approach is helpful in static environments (e.g., open highways) but encounters limitations in more dynamic environments (e.g., urban cities). Researchers are closing this gap by including more sensors that feed into sophisticated reinforcement learning algorithms (Fridman, 2020). However, continuing to scale these monolithic expert systems is challenging.

**Figure 21**  
*Example Microservice Architecture*

Diagram

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V-TORCS (Virtual the Open Racing Car Simulation) and other modern architectures address these issues using ensemble and multi-task learning methods (Li et al., 2019). Consider a decision process that feeds camera frames into an image classification Convolutional Neural Network (CNN) to extract objects and contextualize the environment (see Figure 21). CNN algorithms mimic an eye’s biological structures by normalizing neighboring pixel blocks to derive structure (Keller et al., 2016). These results flow into expert subsystems controlling the car, such as turning the wheel or accelerating. An ensemble of subsystem observations merges into a broader system-wide decision model that contains one or more I/O (Input/Output) controllers. Like other microsystem architectures, each subsystem’s implementation can evolve independently of peer components—enabling greater agility and innovation.

### Optimization Systems

Modern personal vehicles have a lifespan of over 200,000 miles and often travel 24,000 miles per year (Ford, 2012). Assuming a driver purchases a $25,000 car and keeps it that entire usable period, they will likely spend at least that much on fuel and repairs (see Table 7). Data scientists can improve this situation by introducing micro-optimization systems across the automobile. For instance, traditional cruise control maintains a specific speed (e.g., 70mph) without considering any environmental context. Meanwhile, a more intelligent system can factor in the road’s incline, the driver’s profile, and metrics about the trip to create a dynamic profile ranging from, e.g., 65-70mph. As this idea expands outward, it collects micro-optimizers that monitor all aspects of the driving experience, potentially saving hundreds of dollars in costs.

**Table 8**  
*Ongoing Fees*

|  |  |
| --- | --- |
| Line Item | Total |
| 200,000 miles @ 30 miles/gallon | 6,667 gallons |
| x $2.50/gallon | $16,700 |
| + Typical Repairs | $10,000 |
|  |  |
| Total Costs | $26,700 |

When the driver has advance notice that a component is likely to fail, they can schedule the maintenance and minimize costs. The Preventative Maintenance System (PMS) provides this capability by collecting component-level telemetry and looking for anomalous metrics (see Figure 4). For instance, an engine monitoring solution might observe the RPMs (Revolutions per Minute) and the electrical output. Sensor time series data are noisy and require a curation process (e.g., Kalman filter) to derive a stable moving average signal (Jackson & Rege, 2019). Next, the curated call flows into a Recurrent Neural Network (RNN), which uses sequences of previous tokens to predict future values (Keller et al., 2016). An anomaly exists when new observations deviate from these predictions and needs to surface in a decision control process.

**Figure 22**  
*Preventative Maintenance System*Diagram, schematic

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### Smart City Integration

The future evolution of city planning makes urban areas highly connected with fast wireless networking and intelligent machines emitting enormous telemetry data volumes (Balduccini et al., 2018). The autonomous vehicle is a central participant in this ecosystem, as it transmits metrics to infrastructure (V2I) and other vehicles (V2V). These metadata feeds will enable more efficient traffic shaping, alertness to potential risks, and insights into driver patterns (Tong et al., 2019). For instance, each driver inputs their GPS destination and follows the route in an isolated silo. Tomorrow, aspects of those routing decisions can become centralized, resulting in less route congestion. While ideas of this ideal state are already coming to life in major cities like Seattle, Boston, and New York, the large-scale implementation is still years out (Cohen, 2013). Modernizing these areas will require significant infrastructure investments, consensus on V2X communication protocols, and machines implementing those standards. Machine learning technologies will need to synthesize those capabilities by making predictions by pairing vehicle-local sensors with ubiquitous cloud services.

### Observations

Three takeaways of this paper are (1) that artificial systems need to augment human processes; (2) a suitable starting place is safety and cost optimization; and (3) intelligent cities are several years away, requiring cloud services to fill that void.

The most powerful artificial intelligence applications use machines to enhance human capabilities rather than replace them. Motor vehicles contain many integration points. Machine learning can handle tedious aspects of the journey with greater precision and accuracy than humans. After freeing the driver from the burden of mundane work, she can focus on value-differentiating traveling qualities, such as talking with passengers and thinking about the day ahead. Meanwhile, intelligent systems remain vigilant in the background looking for risks like a child running into the road. Another collection of machine learning tasks revolves around cruise control capabilities. These systems keep us out of harm’s way and reduce wear-and-tear on internal parts. Looking further into the future, integrating intelligent vehicles within smart cities promises more efficient traffic shaping and risk awareness. However, the necessary infrastructure investments will unlikely arise in the next decade. Instead, machine learning will pair vehicular telemetry into ubiquitous cloud computing to provide a similar experience.

## How does the reproducibility crisis impact ML design

There is an abundance of non-reproducible experiments because researchers do not account for nuances in the data collection (Rivera-Landos, Khomh, & Nikanjam, 2021). These challenges originate from *Non-Determinism Introducing Factors* (NDIF), such as software updates and defects, hardware-specific differences, data uniqueness, randomization seeding, and dropout rates, among other reasons.

### Sources of Non-Determinism Introducing Factors

NDIF issues also originate from incorrect industry assumptions and unknown unknowns. For instance, software taint analysis is a process for discovering security-critical variables and parameters within an application. Generally, these tools parse the underlying bytecode through language-specific Reflection APIs. Next, they build call trees and use graph analysis methodologies to discover vulnerable code paths (Kilgallon, De la Rosa, & Cavazos, 2017). Researchers publish new techniques and present their findings using open-source products like FlowDroid, AmanDroid, and DroidSafe. However, the detection rate for those tools is highly dependent on configuration-specific settings (Qiu, Wang, & Rubin, 2018). This subtle dependency can be problematic for researchers and small businesses that lack the technical expertise necessary to support multiple competing toolchains.

It’s challenging and expensive to recreate many foundational experiments, so researchers must assume that previous authors are correct. Unverified facts present a significant risk that can have cascading ramifications. Consider Majoranas, an extremely sensitive nanowire that operates at absolute zero temperatures and in extreme magnetic fields, to measure individual electrons within quantum computers. This precision “plays an important role in protecting quantum information and enabling reliable computation (Langston, 2022).” Limited access to equipment forces many researchers to rely on computerized physics simulation processes. Recently, Pennsylvania State University could not reproduce several foundational studies and received opposite results (Frolov, 2021). After disproving basic expectations, researchers revisited other assumptions and found that at least six other core tenants were false. This situation highlights the criticality of revalidating technological assumptions. The body of knowledge is never precise and continually evolving with new facts.

Negligence and maliciousness also create reproducibility challenges. Miyakawa has handled 180 manuscripts since early 2017 and identified 41 potentially fabricated experiments. When he requested raw for these studies, “more than 97% [(40 of 41)] pulled their publication request, suggesting a possibility that the data didn’t exist from the beginning (Miyakawa, 2020, p. 1).” The editor claims to spot these situations by looking for data too perfect, error rates improbable, and study impact too significant. It’s relatively easy to catch blatant lies, though humans commonly only cheat a little (Ariely, 2009). Behavioral economists consistently demonstrate that people mispresent small details that lead to a better story with believably exaggerated results (e.g., an 75% accurate score becomes 82%).

### Influence of societal norms and ethical design

Hudson (2021) argues that researchers should focus on replicability over reproducibility. He identifies incorrect study design, not disproving the null hypothesis, wrong statistical methods, societal norms, and publication bias, among other factors. These factors impact research reproducibility. Therefore, researchers should accept that incorrect facts exist, and that’s because humans aim to prove what they believe. Douglas & Elliott (2022) responds to Hudson’s article, asserting it conflates value-ladenness with bias and mispresents values as evidential factors. They state that researchers are generally well-intentioned and aim to make reliable, repeatable studies. However, it is impractical for those practitioners to wait for results to be flawless, as this means science no longer evolves. Put another way, “all models are wrong, but some are useful (Denis, 2015, p. 3).” The quote infers that it can be challenging to include all aspects of the environment. These external factors can create deltas between expectations and reality. Academics should perceive the book of knowledge as continually developing principles and tenants, where more precise instruments will eventually supersede those ideas.

### Role of ethical design

Researchers need to manage ethical challenges that arise from their work. These issues originate from societal norms and internal biases. While several frameworks exist to guide the conversation, they can be ambiguous or focus on a subset of the problem.

Ethics are a system of moral principles that dictate the norms of a group. Societies implement these systems through social constructivism, enabling and constraining the group’s actions (Burr, 2015). Communities leverage this mechanism to assign truths and infer values about concepts (Gergen, 2010). Consider a project that seeks to prove that men are superior to women. Within a chauvinistic cohort, these results align with their worldview and are ethical. However, a diverse group would chastise the very idea, regardless of methodology. Further complicating the matter, ethical identities are dynamic and evolve (or regress) over time.

Scholars need to understand their audience and the group’s customs. These social contracts limit the researcher’s influence and ability to solicit their work. These implicit rule sets vary between cohorts, making it impossible to remove these subtle biases entirely.

### Threats to validity

Four major categorical threats exist to making statistically accurate conclusions, leading to false, erroneous results (Parker, 1993). When designing high-quality experiments, the designers must be cognizant of these issues and their sources (see Table 1). Fundamentally, these challenges represent a degradation of the experiment’s confidentiality, integrity, and availability. These limitations prevent the generalization and reproducibility of research, resulting in the discrediting of publications and professional embarrassment (García-Pérez, 2012). Instead, researchers must decide on controls and procedures before even beginning data collection.

**Table 9**  
*Threat Sources*

|  |  |
| --- | --- |
| Source | Description |
| Internal Threat | Contamination by the research team |
| External Threat | Contamination outside of the study’s controls |
| Statistical Conclusion Validity | Results are arbitrary or non-reproducible |
| Construct Validity | Controls are not enforceable or consistent |

For example, if a participant needs to provide personally sensitive information, the data collection must convey trustworthiness (construct validity). Otherwise, the candidate will likely hold back data like side-effects that are highly relevant to the research project. Without trust, the contributor might engage in activities that directly go at odds with the study (external threats). The research team might lack a plan to deal with these confounding variables and deviate arbitrarily exclude group members (internal threats). Since these results are now arbitrary, shoehorning outcomes into various statistical models until it lines up (statistical conclusion validity). An unlimited number of these permutations exist, and it is impossible to remove all of them (Parker, 1993). However, any procedure that reduces the influence of garbage-in/garbage-out experimentation is ideal.

### Internal biases

Researchers need to understand their internal biases. Everyone has historical and cultural defaults that lead to prejudices. These subtle classification differences influence language and construct our reality (Owen, 2017). Words matter, and one needs to choose them carefully. These biases sneak into our written and verbal communication. They cause us to gloss over issues of Diversity, Equity, and Inclusion (DEI). For instance, the terms such as whitelist and blacklist have a racial connotation. These modifiers become a sub-conscience reinforcement that one’s worldview is the only perspective.

### Sources of ethical frameworks

Numerous professional, regulatory, and advisory groups create frameworks that outline strategies for approaching ethical designs. These professional standards can contain conflicts of interest, hidden agendas, and inconsistent moral standards (Tan, 2021). The Belmont Report (1979) famously defines three core principles: respect for persons, beneficence, and justice. These tenants ask researchers to treat everyone fairly and avoid harm. However, even this simple statement has ambiguity.

After forty years, the ethical code requires modernization to align with the evolving worldviews. Adashi et al. (2018, p. 1347) argue that the Belmont Report’s “distinction between research and practice is disappearing within the commercialization of present-day research.” Businesses actively debate the definition of “harm” and propose a notion of “harm versus setback.” This worldview states that any action that is not directly harmful is, at worse, an indirect setback. Roberts (2021, p. 15) proposes that researchers “must focus on risks of the research process itself, not outcome-related risks as downstream consequences are beyond the purview of ethical gatekeeping.” Facebook has a moral (and potentially legal) mandate to protect its user’s privacy. Under Robert’s definition, the social-media juggernaut can ethically track relationships between billions of people. However, it is not bound to prevent malicious auxiliary use-cases (e.g., election interference). While this position resonates with specific cohorts, it faces fierce opposition from others.

### Controversial Subjects

Many academic and business communities embrace Diversity, Equity, and Inclusion (DEI) concepts. These ideas are becoming mainstream, and that will cause them to become shared truths and social norms. Researchers that fight against this force are likely to find exclusion and isolation (Owen, 2017; Adashi et al., 2018). Instead, they should adopt the social standards and assume “people are people.” However, this is often easier said than done. Human data sets contain numerous highly correlated variables (e.g., race and income). These statical properties prevent merely dropping an individual column and making the results racially neutral. Researchers can explicitly call out the risk in their findings, but fully addressing this situation is an open problem.

## Ethical considerations of A.I.

Artificial intelligence is a scary black box that spreads malicious propaganda, destroys jobs, and seeks to destabilize honest citizens’ values. This statement is intentionally farcical, yet it also touches on fundamental concerns of ethical A.I. designs. People fear what they do not understand and use science-fiction to fill these gaps. Within those futuristic worlds, machines become the dominant species that control every decision of an enslaved human population. However, several challenges prevent this transition of power from becoming a reality, such as intelligent systems that lack actual *intelligence* (Wildberger, 1996; Hole & Ahmad, 2019; Upchurch, 2018). Instead, organizations need to assess these tools rationally, explore applications that enhance human capabilities, and remove undifferentiating overhead.

### Roles of Artificial Intelligence

Despite artificial intelligence already being well-entrenched in everyday life, there are concerns about its role. First, does the advancement of machine learning mean fewer jobs? Second, of those remaining jobs, are humans giving away control unnecessarily? Third, are those machines capable of manipulating the public to steal dominion?

**Role in Employment.** Before 1949, digging a ditch would take hours or even days with a crew of manual workers. After the invention of the backhoe, these jobs required less time with fewer employees. From the organization’s perspective, these efficiencies translate into faster time to market at lower costs. Meanwhile, the former diggers became displaced into new roles, repairing, operating, and supervising the machinery. Each of these positions requires entire supply chains of support. For instance, it takes factories to produce the backhoe parts, each staffed with hundreds of blue-collar jobs. Cities must also build universities and technical schools to train team members to fill these roles, expanding the job market.

Similarly, modern businesses actively seek methods to reduce costs and improve efficiencies through automation. The most powerful artificial intelligence applications use machines to enhance human capabilities rather than replace them (Heer, 2019; Boire, 2017). For instance, a person can write a more profound business case than a machine; however, the same device will have fewer grammatical errors. This dichotomy exists because humans specialize in contextualizing thought versus using patterns to make predictions (Schleer et al., 2019). Many professions exist as a combination of decision-making, pattern recognition, and mechanical tasks. Expert systems address specific aspects of the job requirements; however, superseding the soft skills that unify these role components is challenging (Huang et al., 2019).

Specific low-skilled jobs, such as bank tellers and office clerical staff, are at risk of being replaced (Hamid et al., 2017). Similarly, expert pattern matching tasks like identifying tumors in MRI (Magnetic Resonance Imaging) becomes commoditized through A.I. systems. Given the lower entry barrier, some low-skilled workers will transition to better-paying jobs operating sophisticated and commoditized systems. For instance, many workers cannot access foreign markets due to language and communication limitations. Artificial intelligence can aid these in these translation scenarios while leaving control with humans.

**Role in Decision Making.** Many decision-making processes can benefit from machines providing recommendations and validations. For instance, a court judge could use an intelligent system to assess how their sentencing aligns with existing norms. Perhaps the device predicts the defendant should receive five years of probation, while a judge considers fifteen years in prison. When the validation check expresses such a difference in opinions, it could suggest that unconscious bias is taking place and warrants additional considerations. That bias either provides ammunition for appeals processes or incarcerates people unjustifiably long.

While this approach has much potential, there are concerns that professionals arbitrarily accept recommendations. However, these challenges occur everywhere that automation controls the ‘last mile’ of decision making. If the suggestion comes from a machine or peer, the person in charge of the process must be accountable for the final call. Blindly delegating control to machines is dangerous because learning algorithms are greedy, brittle, rigid, and opaque (Hole & Ahmad, 2019). Until artificial brains can rationalize abstract thought, humans must perform this task.

**Role in Manipulation.** Modern censorship does not restrict free speech; instead, it increases the noise and drowns the signal (Thomas, 2019). Fundamentally, marketing campaigns and propaganda machines follow the same process of Segmentation, Targeting, and Positioning (STP) (Kane, 2019). Delivering on this objective requires pattern matching, content delivery, and human intuition. Automation is well-suited for these tasks and can use social media channels, like Facebook and Twitter, to connect with billions of people and manage significant portions of those interactions.

Congressional and media sources raise ethical questions around the ease of access to these capabilities for political manipulation. Unfortunately, these questions are mostly talking points rather than a call for action. Artificial intelligence has many abstract concepts that do not fit within the complex and opaque legal language (Guiffrida et al., 2018). For instance, machines cannot reason about their instructions, so can the courts hold *them* accountable? Perhaps the system designers should be responsible for their creations. However, the algorithms are primarily algebraic formulas controlled by end-users. Without a mechanism to define and enforce a standard operating behavior, it is impossible to expect a different outcome.

### Design Considerations

Two recent attempts to define this process for ensuring ethical A.I. are the European Union’s Ethics Guidelines for Trustworthy A.I. and the OECD’s Principals of Ethical A.I. (E.U., 2019; OECD, 2019). Both documents describe the need for artificially intelligent systems to be human-centric, transparent, explainable, robust, and secure.

### Human-Centric

Robotics’s Three Law states that automation should not injure humans, ignore people’s commands, and protect their existence (Asimov, 1942). These rules lay a foundation for the idea that devices exist to cooperate and enhance humanity. Unfortunately, the machines cannot reason and are bound to their program designs. Since machines cannot devise these criteria independently, it becomes the system engineers’ responsibility to enforce these requirements. Those decisions are predominately a matter of business priorities and vary across different use-cases. For instance, Lockheed Martin, a military weapons designer, views its human-centric role as protecting American interests at foreign nations’ expense. This perspective is radically different from other organizations yet equally valid.

### Transparent and Explainable

Artificial brains often rely on deep learning techniques through neural network solutions. These networks approximate a function that maps inputs and outputs through multiple non-parametric transforms. While data scientists can perform experiments to verify the model’s accuracy, they often cannot explain it (Gilpin et al., 2018). This limitation prevents broader adoption in places like the European Union, where the General Data Protection Regulation (GDPR) grants citizens a Right to Explanation.

Further complicating matters, neural networks learn the patterns we *ask*, not necessarily the ones we *mean*. For instance, Beauty.ai, an algorithm for rating female attractiveness, lost credibility due to only giving high scores to light-skinned candidates (Upchurch, 2018). This outcome was not intentionally malicious but the byproduct of not sufficiently representing minorities in the training set. Similar imbalanced issues occur across many real-world domains and require sophisticated data handling strategies (Kaur et al., 2019). Even with expert data scientists, it is possible to miss these edge cases and produce invalid predictions.

### Robust and Secure

Engineers who become data scientists follow a different curriculum than their peers who become security specialists. This distinction in training is most evident in the lack of controls across artificially intelligent solutions (Lin et al., 2018; Sethi & Kantardzic, 2018). Malicious actors can influence these predicted decisions by inserting erroneous samples into the training set or directly attacking the probability distributions. For instance, researchers have shown that applying tiny amounts of distortion to images can change the graphic’s predicted class (e.g., cat versus dog) (Sethi & Kantardzic, 2018). If people cannot trust the classification algorithms’ integrity, how can mission-critical environments effectively use them?

### Observations

Artificial intelligence is a tool that can automate mechanical tasks, pattern match data, and enhance human capabilities. Organizations can use these means to improve efficiency and reduce wastefulness. These innovations deprecate the need for specific skill sets and lower the entry barrier into other expert systems. While this causes an initial decrease in jobs necessary, entirely new industries follow shortly afterward. This promotion justifies the short-term pain when a society can replace low-paying jobs with high-paying alternatives.

Machine learning technology is too immature to delegate business-critical decisions. Instead, professionals should consider these technologies for initial recommendations and verify that their choices are free of unconscious biases. For example, a court judge should assess their sentencing aligning with a regression algorithm’s prediction and not blindly issue that verdict. Humans must maintain control of our actions and consequences. However, preventing machines from manipulating our free will can be challenging.

Laws cannot keep up with technology’s high-velocity innovation, causing businesses to define and self-regulate their ethical behavior. Without an official solution for maintaining accountability, this moral desire must compete against existing business priorities. Those priorities will vary significantly between organizations, as defining ‘human-centric systems’ is ambiguous. Moving past those challenges are issues with the fundamental integrity of neural network technologies. Implementing transparency and explainability are open research problems for all but the most trivial systems. After solving those issues, ensuring only inclusive training data use requires significant investments into unverifiable results.

These limitations bring the discussion around full circle to the beginning. Artificial intelligent systems are not ethical, evil, or corrupt. They are tools that automate everyday tasks and lower the barrier to entry. Users of that tool must know what these predictions mean and how they influence decisions. However, that is not the same thing as delegating control with impunity.

## Summary

This chapter contains the study’s literature review on modern AI/ML concepts. It began with foundational concepts like data mining and multi-level perceptron techniques that form the statistical basis for CV. These statistical models aim to emulate biological structures found in primates. However, primates have very sophisticated subsystems for embodiment and awareness that grant them contextually sensitive information beyond these simple models. Researchers use reinforcement learning to approximate Markov chains as decision policies. This technique has enabled machines to solve more complex use cases than ever.

Next, the era of deep learning utilizes ubiquitous access to cloud resources and specialized hardware. Researchers can train models with nearly one trillion parameters to gain extreme prediction to challenging problems like natural language processing. They approach these state-of-the-art designs by ensembling multiple reinforcement algorithms to mutate the model’s architecture. Like traditional generic algorithms, these expert systems cross-breed random model network connectivity until they discover the most efficient combinations.

There are several significant ramifications to this evolution. For instance, the computing resources necessary for training are growing exponentially, but the per-unit capacity is linearly increasing. This situation means that ML training must operate in high distributed runtimes. Within these environments, failures are likely to occur, and the orchestration system must account for error conditions. Consider the influence of discrete processors merging calculated gradients and the impact of network latencies. The processors began with relatively similar policy maps, mutated with an ensemble of RL updates, and must reconcile the changes. One could quickly fill several dissertations on this topic alone.

Third, this chapter examines the reproducibility crisis and ethical considerations arising from these steps’ sheer complexity. AI/ML is a tool for enhancing productivity, and humans must remain cognizant that biases will creep into the design. These issues stem from systemic data correlations that are not always obvious (e.g., race and income). Controls and procedures must limit these factors and promote explainable AI.

# Chapter 3: Research Method

The problem to be addressed in this study is the inability of elderly and special needs care organizations to capitalize on the effectiveness and efficiency of autonomous assistants for hemodialysis (Kim & Kim, 2021; Blackhurn, 2021). The purpose of this constructive research study is to provide an understanding of the effectiveness and efficiency of autonomous assistants for hemodialysis in elderly and special needs care organizations. Hemodialysis patients have a high risk of falling and injury (Shirai et al., 2021). Like other projects, a high-quality research effort begins with a well-defined plan and stated outcomes. This chapter aims to meet these requirements by detailing the research methodology and its appropriateness. Next, it documents mechanisms for collecting data and analyzing that information. The chapter concludes by enumerating known assumptions, limitations, delimitations, and ethical assurances.

## Research Methodology and Design

Design science is a research methodology that creates and uses purposeful artifacts to study a phenomenon (Hevner et al., 2004). Academic and business communities employ this method as a standard approach to Information Technology and Communication (IT&C) problems (Peffers et al., 2007; Bryar & Carr, 2021). It comes with well-defined guidelines to implement a three-phased procedure. 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.

### Study Appropriateness

It is challenging to study humans in privacy-sensitive situations like home monitoring situations. This study proposes a research method for simulating those humanoids and having them perform realistic behaviors. Within the simulation process, the humanoids will perform MoCAP sequences like falling, and virtual cameras can extract that metadata for an ML model. Using a design science research method is appropriate to explore this technique as it explores the phenomenon directly.

### Alternative Methodologies

Quality research begins with a well-defined set of questions, such as ‘can an autonomous vehicle safely navigate city streets?’ Next, the researcher needs a plan to answer the question by collecting evidence and observations. Executing that plan requires a collection of quantitive and qualitative methods. Each of these methods is a tool with its inherent strengths and weaknesses (Jason & Glenwick, 2016). These attributes necessitate researchers to understand when a hammer is more appropriate than a screwdriver (see Table 1). Many people erroneously believe that quantitative methods are superior to qualitative alternatives (McCusker & Gunaydin, 2015; Creswell, 2014; Jason & Glenwick, 2016). This naïve perspective incorrectly assumes that a hammer is always the right tool. When researchers treat screws like nails, it results in erroneous publication claims.

**Table 10**  
*Research Approaches*

|  |  |  |
| --- | --- | --- |
| Approach | Description | Example Use Case |
| Quantitative | Statistical modeling of a scenario | * Estimate the probability of an event * Stating a broad generalization * Cause and effect analysis |
| Qualitative | Non-numerical representation of a scenario | * Open-ended surveys * Exploration of needs * Investigating a local issue |
| Mixed-Method | Combination of both quantitative and qualitative | * Examining the breadth and depth of a topic * Examining a scientific idea and then mapping it to use cases |

Consider the difference when the vehicle study’s objective is (a) to identify safety requirements versus (b) modeling the limitations of the braking system. Under (a), qualitative methods best support the open exploratory nature of the problem. With (b), the answer needs a quantitative approach that describes the relationship of multiple variables, such as the car’s speed and the number of objects on the road. However, a more comprehensive study could answer both (a) and (b) by uncovering the importance of braking enhancements and then describing the limitations in greater detail.

This study’s objective is to demonstrate a research method. It does not aim to prove that method is superior to existing techniques through quantitative or qualitative measurements. These design constraints make the constructive research approach more appropriate. Future research should expand on the study and assess optimizations and enhancements through quantitative and qualitative questions. For instance, an example-derived quantitative study could examine different ML algorithms and measure the accuracy against real humans. Meanwhile, another example-derived qualitative study might consider the influence of humanoid character properties (e.g., gender and weight).

## Population and Sample

This study aims to demonstrate predicting HAR behaviors within a simulated process. It would be impractical to test every possible behavior; instead, a sampling procedure is required. The sampling will combine MoCAP sequences with different physical properties in a noisy simulated world. No biological humans are subjects within this constructive design project.

For an experiment to be successful, it needs to have sufficient *power* to measure the *effect* in question. Several knobs feed into the power of an experiment, such as relaxing the confidence interval, using parametric statistics, converting to a one-tail model, increasing the samples, or adjusting the sensitivity (Donovan, 2016). Choosing which value to tweak and optimize is scenario-specific and can be somewhat of an art form.

### Determining Power

There are unlimited human behavior permutations, and it is impractical to examine each combination. Instead, a reasonable cross-section is appropriate for demonstrating the simulation technique. Given the relatively small sample count, adjusting the confidence intervals to meet acceptable power requirements might be necessary. Another option might be to reduce the number of physical categories and degree of dynamic environmental changes. These data tweaks might detect high-level trends that future research could tease further.

### Determining Effect

Effect size measures the strength of a phenomenon (Donovan, 2016). While calculating the difference between the two distributions is relatively straightforward, it can be difficult to predict ahead of time. This bittersweet relationship introduces challenges when determining the appropriate sample size. One potential solution is to use an iterative sequential sampling policy instead of a fixed size upfront (García-Pérez, 2012). In this situation, that would mean first choosing two similar humanoid populations (e.g., age of 50 and 200LB weight) and comparing *noise level* and *HAR prediction accuracy* as independent variables. While this small group would have a reasonably low confidence interval, it could qualitatively hint at the overall sample size needing to be minor, medium, or large. There are potential risks that the random-initial sample produces an invalid seed in the study.

### Potential Sample Sizes

Despite the effect size being unknown potential, it is possible to determine the range of sample sizes for the experiment (see Table 2). G\*Power version 3.1.9.7 projects that t-tests of the “difference between two independent means (two groups)” for a one-tail model will need somewhere from 4 to 1580 examples. Since the available MoCAP sequences and simulator configuration options are virtually unlimited, there should be sufficient coverage assuming the specific measurements are kept simple. Therefore, a high probability exists that adequate data production can occur to measure the phenomenon.

**Table 11***Data sampling requirements*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Power | Effect Size | Confidence – 50% | Confidence – 80% | Confidence – 95% | Confidence – 99% |
| 70% Adequate | 0.20 – Small | 28 | 188 | 472 | 816 |
| 0.50 – Medium | 6 | 32 | 78 | 134 |
| 0.80 – Large | 4 | 14 | 32 | 54 |
| 95% Excellent | 0.20 – Small | 272 | 620 | 1084 | 1580 |
| 0.50 – Medium | 44 | 100 | 176 | 256 |
| 0.80 – Large | 18 | 40 | 70 | 102 |

### Acquiring the Sample

This study aims to demonstrate a research methodology for using humanoids in simulation processes to assess machine learning models. It presents an example of employing computer vision (CV) to detect falling patients. The research project will generate different humanoid configurations and have them perform MoCAP sequences. For instance, one experiment would provide a thirty-year-old actor that’s one hundred pounds (forty-five kilograms). Another one could have a sixty-year-old actor that weighs three hundred pounds. The simulation software will use these variables to influence movement speed and flexibility.

Using this approach is appropriate for the dissertation proposal methodology and design. It has several core strengths, such as avoiding a cumbersome human recruiting process and concerns that the selection procedure is unfair. This method examines the generalization and usefulness of the research technique. Furthermore, the experiments automated nature makes reproducing the results straightforward and economical. This design choice means that future researchers have sufficient information to replicate the study.

## Instrumentation

There are three aspects to the study that require data collection. These aspects include ML training performance, model accuracy, and inference performance. It is within the project’s scope to use instruments to confirm that correct procedures occur. However, this study does not aim to demonstrate extreme precision or the superiority of the research technique over existing patterns.

### ML Training Instruments

First, telemetry must report that the ML training process is performant and converging. This information is available through Amazon SageMaker, Tensorflow 2.0, and Keras metrics. Keras is a high-level framework that standardizes building ML architectures and can generate low-level Tensorflow operations. The study does not plan to build custom metrics beyond the standard reports.

### ML Model Instruments

Next, the study must confirm that the ML model accurately predicts humanoid behaviors. In a physics simulation process, humanoid actors perform behaviors in a highly controlled environment. This feature allows the study always to know the current world state and quickly assess any CV model prediction’s accuracy.

### ML Inference Instruments

Third, an ML inference process will host the model and return predictions. Amazon SageMaker offers several core capabilities to streamline this process as model endpoints. An endpoint consists of computing and storage constructs that autoscale ML model predictions in response to network traffic patterns. It collects statistics during these operations and reports on the resource’s performance. The study will use this built-in information to confirm that the inference follows industry standards.

### Field Testing

The study will create a highly-simplified example to confirm that the instruments function expectedly. This stable configuration might consist of a 2-D humanoid performing two MoCAP sequences for a binary classification problem. After validating the expected results, the field test will increase complexity through higher dimensionality.

## Study Procedures

The research project aims to build a CV model that can accurately predict human activity recognition (HAR). Model training will initialize a random experiment configuration and perform an appropriate MoCAP sequence. During the performance, a virtual camera will collect changes in joint positionings. This delta stream will serve as input feature parameters to the classification process (e.g., sitting versus falling).

### Building the Model

A distributed training service can horizontally scale and assess these different humanoid permutations in isolation. Amazon SageMaker offers these capabilities through its “bring your own container” design. Researchers essentially bundle custom automation and open-source tooling into a virtualized process. SageMaker uses public cloud resources like compute and storage to execute the experiment hundreds or thousands of times. It also integrates into TensorFlow 2 for collecting accuracy and performance metrics. These features reduce the complexity of building boilerplate instruments for many standard requirements.

Future researchers can replicate this experiment by deploying the same container images into their Amazon SageMaker and TensorFlow 2 environments. The humanoid automation will be versioned using GitHub. GitHub simplifies sharing open-source code and identifying specific point-in-time versions (called a commit SHA). Since those researchers can synchronize the repository to a particular commit and rerun the automation using industry-standard tooling, they have sufficient capabilities to reproduce the experiment.

### Implementing the Simulation Process

A critical component of the design is the simulation environment. This research project uses Unity 4 for modeling physical interactions and humanoid behaviors. Unity 5 is generally available (G.A.) but does not yet support Linux, a requirement for model training with Amazon SageMaker. An alternative design could use Robot Operating System (ROS) and its Gazebo-based ecosystem. ROS and Unity share similar feature sets and are semantically equivalent within this study’s context.

The world and relevant artifacts will publish to Amazon Elastic Compute Cloud (EC2) resources. While Unity offers numerous features for modeling incredibly realistic and complex situations, many of those capabilities are outside this project’s scope.

### Recording Results

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 monitor and react 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 23**  
*Experiment Design*

Diagram, schematic

Description automatically generated

### Test Case Definition

A test case encapsulates a specific experiment. An arbitrary number of subjects will perform pre-configured animation sequences during the investigation, 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 and move furniture but not modify the floor plan.

### Data Generation Process

ROS actors represent the patients within the simulation environment, which perform 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 a 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 24**   
*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 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 24). Next, A.I. 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 specifications (AWS, 2021). This capability allows the researchers to create custom sensors and algorithms, not position furniture. This dissertation also 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 agent 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 26). 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 computing (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 26**  
*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 designing 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

### 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 live outside the time-series database for troubleshooting requirements.

### 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 by modifying the actors’ flexibility, weight, and other variables through a randomization process. 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 industry-standard tooling (e.g., Apache Spark).

### Evaluation Process

Creating high-quality software requires quality assurance procedures. Several defects categories exist 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 requires a report generation process that collects and visualizes the evaluation assessments. Building a custom Business Intelligence (B.I.) 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.

## Data Analysis

There are two phases to implementing an AI/ML process: training the model and operationalizing the capability. The analysis must confirm that these phases meet acceptable quality standards. Additionally, it must succinctly address the research questions from chapter 1.

### Addressing the research questions

This research project attempts to demonstrate extracting *intents* from dynamic and noisy video streams (see RQ1). There must exist measurements of the inference accuracy and the extent to which the scene contains noise. Unity offers several rendering effects for smoke, fog, reflections, and lighting. Controls exist for adjusting these effects and their enablement strength between zero to one hundred percent. This analysis is appropriate as it assesses the research questions directly.

### Model Training Analysis

Tensor Flow 2 generates statistical information regarding the model training performance. These Key Performance Indicators (KPIs) describe gradient convergence, model accuracy, and various troubleshooting metrics. An analysis must confirm that the training configuration occurs efficiently. Suppose the performance is substandard. In that case, this research plans to investigate the defects and reconfigure the training service (e.g., Amazon SageMaker). It is beyond this study’s scope to create “a perfect model” and only seeks to demonstrate the research technique’s viability. However, this study will validate that training is reliable and reproducible across positive and negative test cases.

### Model Inference Analysis

An analysis of the model inference must confirm that it is usable. This phase requires provisioning a model endpoint and posting experimental data. A simple approach could be using RGB+D cameras to record a small human group repeating the humanoid behaviors. There are several core advantages to this solution. First, it demonstrates bringing the simulation process into the real world. Next, these volunteers are readily available through work and social gatherings. It is beyond this study’s scope to “perfectly predict” every behavior. Instead, the goal is to collect and evaluate operationalizing the research technique.

## Assumptions

Research projects must be cognizant of the internal and external factors influencing their research. Making an assumptions inventory is essential to quality research because it communicates the implicit drivers in the design.

### CV Models can Predict HAR

This dissertation aims to demonstrate a research technique using computer vision to predict human activity recognition. Several researchers are documenting their successful experiments within the field. However, this is a state-of-the-art topic, and the underlying example might not work. The study aims to communicate the open problems and potential next steps in this case. While this study makes every effort to mitigate critical blocks efficiently, it is beyond the scope of the core research.

### Simulation Processes and MoCAP are Compatible

There is an assumption that open-source motion capture (MoCAP) files are compatible with industry-standard physics simulation processes. The test cases aim to use virtual cameras to capture this information in 3-D open worlds. Suppose it is not possible to reuse that footage. In that case, the study can flatten the MoCAP to 2-D and present the findings. This approach is not as impressive but would complete the dissertation requirements.

### Adequate Funding Exists

The current plan also assumes access to a highly discounted rate for cloud computing resources. Amazon Web Services (AWS) has several programs for aiding researchers, like AWS Cloud Credit for Research and AWS Educate. Presently this study has funding through one or more of these programs and can pursue the entire project’s scope. Suppose that Amazon discontinued funding. In that case, the study would reduce the scale and focus on fewer test cases and humanoid configuration combinations.

### Quality Tooling Exists

This study makes several assumptions about the current industry state. It assumes that mainstream solutions like Amazon SageMaker, Robotic Operating System, Docker, OpenAI’s Gym, and Unity’s PhysX deliver the capabilities necessary to build the core artifacts. This situation would allow the experiment to focus on the AI/ML components, not rewriting boilerplate infrastructure. Suppose the toolsets haven’t matured to an acceptable level. In that case, the study will simplify the training subsystem. Similarly, these can be simplifications for hosting ML inference endpoints if they are overly cumbersome.

## Limitations

Limitations are internal and external factors that *implicitly* restrict the study from exploring all aspects of the problem.

### Range of Motion

This study aims to build a HAR classification model that supports a predefined set of activities. These limitations exist due to challenges in finding sufficient example data. In this case, expanding the sample to contain open-source repositories will become necessary. These repositories could include YouTube, among other sites.

## Delimitations

Deliminiations are internal and external factors that *explicitly* restrict the study from exploring all aspects of the problem.

### Humanoids are not Humans

There is an implicit assumption that humanoids can substitute humans in semantically similar configurations. This study does not have sufficient resources to evaluate the validity of that assumption. Future research could exist to compare real cameras against the MoCAP footage.

### Humanoid Constraints

Humanoid actors initialize with a configuration that controls their mechanical movement. There are virtually unlimited permutations for these characters and their weight, height, dexterity, and flexibility, among other properties. The distributed training process must set value bounds to learn the problem space efficiently. For instance, there’s only one person over a 635KG weight (Guinness World Records, 2022). Therefore, it does not make sense for test cases to exceed this extreme limit. Similar practical constraints also exist for other properties. It is beyond the scope and budget of this study to examine outliers.

## Ethical Assurances

Northcentral University’s Institutional Review Board (IRB) must issue a statement covering ethical concerns, privacy violations, or undue harm risks.

### Human Subject Concerns

This study uses humanoids in a physics simulation process as a research technique that mitigates ethical concerns and personal privacy risks. Since a humanoid is a virtual construct, it intentionally and explicitly divorces any moral hazards. Furthermore, the simulation has no right or assumption to privacy, as it does not exist in the real world. To verify the model training, a small cohort of volunteers will re-enact safe behaviors that do not risk personal privacy or harm. For instance, the falling behavior can be onto a padded surface.

### Secure Data Storage

Medical facilities have a business requirement to collect private information from patients. While building a system that stores and retrieves this data is relatively trivial, several specific considerations influence the final implementation. Which users can issue queries against the datastore? What maintains the confidentiality of these records? How will auditing and compliance reporting work? Does this data have legal or regulatory implications? Answering these questions produces a model of acceptable risks and identifies business policies requiring cybersecurity enforcement. These enforcements protect the business against negligent and malicious attacks that could harm the integrity or reputation of the brand.

The principal objective of any business is to execute its mission in the most efficient manner possible. Delivering on that mission requires choosing between acceptable risks and desirable conveniences (Mickens, 2018; Dai Zovi, 2019). For instance, many small to midsized business owners lack the expertise to run a domain controller or email service. Employing dedicated staff retracts from resources that could provide value differentiation towards its core competencies. Contracting a consulting firm would be less expensive but lacks the deep economy of scale discounts available from Microsoft Office365. While financial factors influence many decisions, the security and compliance teams need to assess the risks to privacy and availability. Not all decisions originate from the leadership and often come from internal department requests. For instance, a data science team might require a Juypter Notebook server with access to a production database. While that team has enough knowledge to be dangerous and deploy an operational instance, they might lack a broader understanding of business continuity requirements (Brown, 2015). What physical host controls this instance? Does the database connection use encryption? How are backup and restore scenarios handled? Until understanding these subtle decisions, it is impossible to determine if a failed server hard drive will lose three minutes or years of productivity.

These decisions must influence the study’s data storage design to be secure, reliable, and durable. In this context, the *seed* data is not confidential and comes from public repositories. However, there are risks that the *result* data can become corrupted or destroyed. That situation would risk the dissertation process completing on time. This constructive research project mitigates those scenarios using automated backup into Amazon Simple Scalable Storage (S3) storage and frequent commits to GitHub. Both services offer industry-standard durability, versioning capabilities, encryption at rest, and authentication controls.

### Researchers Role

The researcher is responsible for building the artifacts, measuring their accuracy, and reporting the results. There is the potential for biases impacting the study due to resource constraints. For instance, the project might plan four different MoCAP sequences but only three work successfully. In that case, the results should not ignore the failure and instead discuss potential reasons for the issue. It is beyond this project’s scope to validate every situation though it should make reasonable attempts. Additionally, controls are in place to limit cheating or deceiving the results. For example, the result data originates through an automated process.

## Summary

Like many situations, elderly and special needs care can use AI/ML processes to improve the patient’s quality of life. However, it’s difficult for researchers to experiment within these contexts due to personal privacy, safety concerns, and reproducible result challenges. This study aims to mitigate these issues through a simulation technique demonstrating the approach for training and deploying a CV model.

Through an analogy of studying car-breaking systems, this chapter discusses the differences between research methodologies and designs. Each method is a specialized tool that aids the discovery of specific question types. For instance, one could quantitatively measure the lifespan of a particular part. Meanwhile, another study might qualitatively assess failure categories. Neither method is superior to the other than a hammer versus a wrench. However, this study chose constructive research because it’s the right tool for the research questions (see Chapter 1).

Within a methodology’s framework exists several crucial project planning steps. Projects that haphazardly proceed are unlikely to conclude with a compelling case. These challenges stem from inadequate data, measurement capabilities, operational and analytical procedures, and inaccurate assumptions. Researchers should formally declare these constructs to mitigate these risks. Here, the objective is to place humanoid characters within a virtual environment and extract HAR data in noisy configurations. This deliverable requires instruments that collect telemetry across training convergence, inference performance, and model accuracy.

This chapter reviewed assumptions, limitations, delimitations, and ethical assurances. It is essential to enumerate these aspects upfront to identify undue project risk. For example, the study assumes that adequate tooling exists. If that is not the case, cascading changes are necessary to revise the demonstration. Similarly, the project doesn’t consider several stretch goals, secondary considerations, and other delimitations due to finite resources and budgeting.

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