**Evaluating Generative AI for Regulated Enterprise Environments**

Submitted to Northcentral University

School of Computer Science

in Partial Fulfillment of the

Requirements for the Degree of

DOCTOR OFPHILOSOPHY

by

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La Jolla, California

June 2023

Abstract

Begin writing here…

Checklist:

Briefly introduce the study topic, state the research problem, and describe who or what is impacted by this problem.

Clearly articulate the study purpose and guiding theoretical or conceptual framework of the study.

Provide details about the research methodology, participants, questions, design, procedures, and analysis.

Clearly present the results in relation to the research questions.

State the conclusions to include both the potential implications of the results on and the recommendations for future research and practice.

Do not include citations and abbreviations or acronyms, except those noted as exceptions by the American Psychological Association (APA).

Do not exceed 350 words. Strive for one page.

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# Chapter 1: Introduction

Generative AI (GAI) is a class of machine learning algorithms that can learn from and creates content such as text, images, video, audio, and code (Wu et al., 2023). GAI transforms documents into summarizations and user-defined classification labels (Pengfei et al., 2023). It also lowers the barrier to entry for software engineering tasks, increasing developer velocity (Ozkaya, 2023). Generative behaviors contrast with discriminative machine learning algorithms, which learn decision boundaries (Sun et al., 2022). For example, traditional logistical regression strategies are appropriate for predicting housing prices.

Implementations like Open AI’s ChatGPT capture the business community’s imagination and raise questions about its applications within regulated enterprises (Daugherty, Wilson, & Narain, 2023; Rozado, 2023). This combination necessitates research into the understanding of the technology and practical use cases. For instance, where are the delineations between what one can versus should do today? Equally important, how can developer operations (DevOps) teams leverage these capabilities securely, reliably, and safely? Since there are multiple technology choices, when should enterprises choose one over the other? How can enterprises methodically select the right option?

This chapter aims to frame these questions and establish the purpose of this constructive research project. It briefly describes the business context and essential drivers to assess the technical state of Generative AI and map this information to business architectures. Chapter 2, *Literature Review*, expands on core concept overviews and examines the academic perspective to leverage GAI successfully. Chapter 3, *Research Method*, documents the research approach and mechanisms for quantifying success. These instructions aim to be concise, specific, and reproducible by the broader engineering community. Chapter 4, *Findings*, contains an analysis of the study and observations regarding the research questions. Chapter 5, *Implications, Recommendations, and Conclusions*, interprets the data’s meaning and provides opinions for future implementation.

But first, what exactly is Generative AI, and where did it come from? 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 the 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.

Solutions like EMLo are Long-Term, Short-Term (LTSM) architectures that provide *context-sensitive* through self-attention mechanisms (Peters et al., 2017). Intuitively, this means that recently used words (tokens) should have a higher probability of reuse. Devlin et al. (2018) introduced the Bidirectional Encoder Representation from Transformers (BERT) architecture that *pre-trains* representations of data that maps left-to-right context (*inputs to outputs*) and vice versa (*outputs to inputs*). Their work fundamentally differs from decades of previous research into natural language processing (NLP) that follows the pattern of fine-tuned, purpose-built unidirectional task solvers. Specifically, BERT doesn’t require fine-tuning and labeled data for many scenarios because it learns these self-attentions through large cohorts of unstructured data.

The ubiquity of public cloud providers enables researchers to create 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 et al., 2022). This exponential parameter growth is likely to continue into the foreseeable future. As predictive capabilities mature, it democratizes machine learning by lowering the barrier to getting started and removing the need for extensive labeled training sets.

Businesses can consume and extend these *large language models* (LLMs) to solve unsupervised learning tasks. While the domain is rapidly maturing, numerous open research problems remain regarding prediction accuracy, explainability, suitability, safety, and security. These challenges become more pronounced in regulated enterprise settings such as financial, health care, and workplace safety. Suppose a generative response creates an insurance policy and offers it to end-users. In that case, the insurance provider becomes responsible for the terms of that policy. How can the insurer guarantee and represent its principles and business practices within that offering? Failures in this regard could hurt the business’s reputation, cause financial hardship, and alienate customers.

## Statement of the Problem

The problem to be addressed in this study is an exploratory analysis of Generative AI use cases is the viability and practicality of mechanisms for ensuring norms and expectations of enterprise businesses within regulated environments. Researchers continuously discover new characteristics and challenges within LLMs that could misalign corporate standards. For instance, OpenAI’s ChatGPT-3.5 has safeguards and content moderation checks that ensure its responses are politically neutral. However, prompt engineering techniques bypass that validation and statistically demonstrate it’s broadly a left-leaning Libertarian (Rozado, 2023). While that’s appropriate for many settings, these implicit biases could be at odds with other organizations. Another set of challenges comes from international requirements, such as the European Union proposing copyright rules and China exploring a regulatory framework (International Business Times, 2023; Mondaq Business Briefing, 2023).

Technology hype cycles transition through five key phases: the innovation trigger, the peak of inflated expectations, the trough of disillusionment, the slope of enlightenment, and the plateau of productivity (Gartner, 2023). It can be challenging in the present to understand which stage enterprise businesses are experiencing, and that impacts their ability to prioritize today’s investments versus tomorrow’s.

## Purpose of the Study

The purpose of this constructive design study is to examine the state of Generative AI capabilities within enterprise businesses and create a framework for prioritizing use cases based on risk and practicality. For example, which business challenges are more economically solvable through statistical modeling and discriminative machine learning? Many organizations use automatic speech recognition (ASR) to transcribe audio-to-text economically. To what extent do LLMs enhance this performance? Since business and commercial communities operate at different speeds, defining the suitability of those performance gains is essential. These questions are not unique to audio use cases and span images, videos, rich text documents, and code scenarios. This research project will establish a multi-modal use case taxonomy as described in Chapter 3, *Research Method*.

## Introduction to Theoretical Framework

The 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 (Bryar & Carr, 2021; Peffers et al., 2007). 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, and adopts the following research questions. The overarching objective is identifying use cases, measuring suitability, and providing the next steps.

### RQ1

What is the taxonomy of use cases for Generative AI within regulated enterprises?

### RQ2

What is the effectiveness of Generative AI in learning and creating text, audio, image, video, and code?

### RQ2

What is the efficiency of Generative AI in learning and creating text, audio, image, video, and code?

### RQ4

What scenarios and use cases are most appropriate for using Generative AI within regulated enterprises?

## Significance of the Study

There has been an explosion of interest in Generative models like ChatGPT since December 2022 (see **Figure 1** *ChatGPT interest over the last 12 months*). This Google Trend represents a proxy for the public interest in these algorithms. While there have been significant advancements and recent publications on the topic, these tend to focus on consumer use cases. These challenges and opportunities overlap with enterprise requirements to a certain extent, necessitating an explicit and intentional exploration of the academic body of knowledge.

**Figure 1**   
*ChatGPT interest over the last 12 months*

A picture containing line, plot, text, screenshot

Description automatically generated

Within the business community, there is significant interest in Generative AI for solving unsupervised learning problems. However, a concise framework does not exist to enable the prioritization of use cases regarding audio, image, text, video, and code generation. This study uniquely brings these disappeared concepts into a taxonomy that helps regulated enterprises delight their customers through rich creative media. Businesses cannot efficiently invest in this transformative technology without understanding the practicality of use cases. Those missteps could impact brand reputation, cause economic hardship, and minimize effectively deploying capital to delight their end users. This scenario gives disruptive competitors an advantage.

## Definitions 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 essential activities are knowledge representation, reasoning, and learning (Whitson, 2020). Practitioners use AI/ML processes to implement “fuzzy rules” that rely on statistical probabilities.

### ChatGPT

### Discriminative Machine Learning

### Deep Learning Algorithms

### Explainability

### Generative AI

### Generative Pretrained Transformer

### Large Language Models (LLMs)

### Markov Process

### Neuro-symbolic Reasoning

### Neural Networks

### Prompting

### Recurrent Neural Network (RNN)

An RNN is an artificial neural network for sequential data sets like natural language processing and time series (Boorugu & Ramesh, 2020). HAR processes can combine CV and RNN to observe and predict workflows. For instance, CV can detect an agent’s performing a high-exertion activity and use that output as input to RNN for forecasting that person will injure themselves.

### Reinforcement Learning

### Reinforcement Learning from Human Feedback (RLHF)

### Supervised Learning

### Unsupervised Learning

## Summary

Generative AI is lighting a fire under the business community and sparking their imagination of a world where unsupervised learning transforms every aspect of their customer experience. While this represents a transformative opportunity, it also comes with risks for highly regulated enterprises such as financial institutions, healthcare, and worker safety. In parallel, there are challenges and risks that the state-of-the-art doesn’t meet corporate standards and expectations. The actual state of technology is typically somewhere between the hype and the conservative perspective. This constructive research aims to explore these two extremes and present a logical use case-driven taxonomy that prioritizes safely meeting business expectations while minimizing the second-mover disadvantage.

This research project will achieve this objective through four research questions. First, it defines the taxonomy of use cases and potential opportunities. Generative AI features span text, audio, image, video, and code generation. Next, it examines the effectiveness and efficiency of implementing those techniques using state-of-the-art technologies. Fourth, it culminates these three research questions and asks what is most appropriate for regulated enterprises to adopt today versus tomorrow. Significant concerns and challenges exist within each of these steps as the consumer space exponentially processes. This research project aims to remain neutral and establish the most pragmatic model for businesses to allocate capital toward Generative AI features.

This study focuses on regulated businesses adopting Generative AI capabilities is unique. That makes its perspective unique over the growing interest in these capabilities. While the researchers stand committed to accelerating that adoption, it must occur responsibly, maximizing the end-user experience and minimizing any regulatory burden. Based on a cursory investigation, this perspective is under-represented, creating an opportunity for the constructive research project to differentiate itself.

Finally, a *Key Terms* list is available for establishing a baseline and helping the reader interpret the later chapters. In Chapter 2, *Literature Review*, the academic survey leverages these terms and definitions to explain foundational concepts. It represents an abridged list that later chapters will cover in-depth.

# Chapter 2: Literature Review

The problem to be addressed in this study is an exploratory analysis of Generative AI use cases is the viability and practicality of mechanisms for ensuring norms and expectations of enterprise businesses within regulated environments. The purpose of this constructive design study is to examine the state of Generative AI capabilities within enterprise businesses and create a framework for prioritizing use cases based on risk and practicality

## Literature Search Strategies

This literature review used the Northcentral University Library (NCUL) to identify relevant peer-reviewed articles and books published from 2019 to 2023. 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 2). 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 2.

**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~~ |

This chapter aims to frame the historical drivers and crucial decisions that shape state-of-the-art Generative AI. It approaches the problem starting with a low-level view of data mining and neural network technologies. Then it examines shortcomings across those areas driving deep neural networks (DNN) as the defacto solution. Next, it structures those results into a logical sequence of concepts that enables the reader to understand the breadth and depth of the body of knowledge.

## Theoretical Framework

A theoretical framework is a blueprint that communicates a natural progression of the phenomenon to be studied (Dickson et al., 2018). It is essential for quality research as it outlines a systematic structure of definitions, concepts, and relationships. Four core approaches exist for studying a business use case or phenomenon (see Table 3). 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 |

### Foundational 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) criticized 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 connecting artifacts with business needs and challenges.

### Central Concepts and Relationships

### Implementations and alternative frameworks

## How are LLMs influencing industries

This section analyzes success stories across multiple industries and examines the areas where practitioners apply Generative AI.

### Civil engineering

### Education

### Finance

### Health care

### Software engineering

## 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 give life. Ideas sprouted from mathematics, biology, and computer science before eventually producing modern artificial intelligence. While these domains have unique perspectives, they collectively land in four categories of intelligent systems (Lukac et al., 2018). The first division 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, laid 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 et al., 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 for 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 et al., 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***, emulating interpersonal experiences, and expressing 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 considering 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 et al., 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*.

### Rewarding choices

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 input 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 considering 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). The hypothetical purchasing model (see Figure 2) begins with a state diagram representing the available actions. 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) a 401k retirement account that only adds index funds versus (b) a delta-neutral (directionless) options trader. This trait is similar to other algorithms where efficient training requires relevant facts to specific questions.

**Figure 2**  
*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 (see Figure 3). 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 3***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 these connected graphs with an example of image classification passing through several 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 4). 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 4**  
*General Artificial Neural Network Architecture (de Waal & du Toit, 2011, p. 399)*

A picture containing sketch, diagram, drawing, line art

Description automatically generated

### 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 2**  
*TensorFlow Architecture for MNIST Analysis*

Diagram, schematic

Description automatically generated

### 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 will unlikely 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 must be 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 independent actions and 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 the 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 is available in Table 4. 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 have chosen 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.

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 5.

**Figure 3**  
*Multi-dimensional convergence (Kim & Cho, 2008, p. 1605)*

Chart

Description automatically generated

### Deep learning era

Object detection and labeling tasks were among 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 are particularly challenging to optimize because they contain high variability, multiple kernels, differing regularization scales, and untrained hyperparameters. 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 for this procedure (Ünal & Başçiftçi, 2021). Data scientists can represent multiple expert systems as a connected mesh of reinforcement models that search for ensemble methods, as Kim & Cho (2008) articulated. This mesh approach is standard for state-of-the-art architecture competitions like ImageNet Large Scale Visual Recognition Challenge (ILSVRC).

## What are Generative Adversarial Networks

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 Neural Network (GNN) and Discriminator Neural Network (DNN) (see ). 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 Freidman (2020), detecting Deep Fakes is an arms race because advances in DNN naturally improve GNN results.

**Figure 4***GAN Training Configuration*

Diagram, schematic

Description automatically generated

## What are Transformers

Over the past decades, there has been extensive research into RNN algorithms and their capabilities for handling NLP and time series modeling (Boorugu & Ramesh, 2020). Recurrent Neural Networks (RNN) algorithms like seq2seq and Long-Term, Short-Term Memory (LTSM) are classic examples of applying RNNs to natural language processing (NLP) tasks (see **Figure 5***Abstract Diagram of Differences*). The *What’s the Role of Markov Chains* section discusses a trivial Hello World implementation of this approach.

Through statistical modeling, these architectures predict the proceeding *log-likelihood* of a given token appearing next in a sequence. For example, suppose an RNN algorithm receives the input *Alice leaves her home at 8 AM and goes to…*? In that case, the system would review her historical routes to predict Starbucks for a double expresso before heading to the office. This response doesn’t need creativity, as the system merely weighs the statistical odds that she’ll follow her standard routine.

**Figure 5***Abstract Diagram of Differences*

Diagram

Description automatically generated

### Architecture

Transformers are state-of-the-art language models that excel at natural language processing (NLP) tasks (Penfei et al., 2023). Instead of predicting seasonality and relying on historical trends, GPT might creatively guess Alice goes to the mall, church, and dinner. But why? The reason derives from the transformer design, which leverages a stackable architect of *encoders* and *decoders* to convert the inputs into abstract representations (Cai et al., 2020). This approach fundamentally differs from RNN algorithms. Specifically, transformers can process data in parallel and rely solely on self-attention mechanisms (Vaswani et al., 2017).

### Encoders

Encoders have two constructs: the self-attention mechanism and positional encoding, enabling the model to accurately predict the masked token using recent words and the input sequence order. Suppose that model received *the* *quick brown fox jumped over the lazy log*. In that case, the self-attention mechanism might identify *fox* and *log* as relevant nouns for the response. The positional encoding would predict the foxis *brown* because it appears one versus six words away from the log.

The Bidirectional Encoder Representations from Transformers (BERT) advanced Vaswani et al.’s solution to incorporate “a pre-trained deep bidirectional representation of unlabeled text by joint conditioning on the left and right context in all layers (Devlin et al., 2018, p. 1).” The training process attempts to solve the Cloze task, which masks input or proceeding sentence segments. A trained model should reliably predict the masked tokens using the vocabulary and in-context state.

### Decoders

In contrast, GPT is a transformer decoder and implements autoregressive inference.

<insert more here>

Internally, the decoder doesn’t know that fox is a unique word, so it uses Multi-Head Self-Attention Mechanisms to identify the relationship between all tokens within the input sequence (Vaswani et al., 2017; Roisenzvit, 2023). The position-wise information utilizes a feed-forward network enabling fine-tuning and integration into subsequent decoders.

**Figure 6**  
*Transformer model architecture* (Vaswani et al., 2017, p. 3)

A picture containing text, diagram, screenshot, plan

Description automatically generated

### Tokenization

Before the input text can feed forward into the transformer, a process must break the text into bite-sized chunks (Roisenzvit, 2023). The naïve solution splits the sentence on every word, such as the brown fox equals nine tokens. However, this strategy has issues with international texts and can’t cleanly handle similar tokens like walk, walking, and walked. NLP researchers historically solve this with stemming and lemmatization (see ; Keller et al., 2016). State-of-the-art NLP models tokenize the input into sequences of two to five characters. In exchange for smaller tokens, the training process requires more examples to learn when its appropriate to predict partial word responses (Roisenzvit, 2023). For instance, English doesn’t have a word c*a* but does have call, cat, can’t, and cantaloupe.

**Figure 7***NLP Analysis Procedure*

Diagram

Description automatically generated with medium confidence

### Embeddings

Which word’s meaning is closest to kitten: cat, dog, or tree? Embedding is a technique for quantifying token similarity regarding meaning and properties (Roisenzvit, 2023). Embedding is a powerful construct within the model, as it permits the model to reason about interchangeable terms (e.g., unhappy versus sad), analogies (e.g., a king is to man; as a queen is to woman), and contextual information (e.g., a bank is the side of river and institution).

First, language models choose if a token represents an individual word, sentence, or paragraph of text. Next, a vectorization process, like Word2vec, encodes the vocabulary into numerical representations. For a naïve model, this means replacing each word with a scalar identifier, such as *Have a great day and great night* equals 1, 2, 3, 4, 3, 5. More sophisticated algorithms like Doc2vec maintain contexts, such as positional encoding and related metadata (Hendrawan, Utami, & Hartanto, 2022). Third, given a sufficiently large corpus of documents, the model will learn the Euclidean distance between the vectors. Finally, when the model needs to generate a response, it finds the closest tokens and semi-randomly selects one. This behavior is what humans perceive as creativity.

## How do you talk to language models

The Structured Query Language (SQL) defines a ridged syntax for retrieving information from a data store. Language models use *prompt engineering* and natural language to guide the transformers and generate appropriate responses. Three of the most common query types are Generation, Ranking, and Top-K for use cases like document classification, multi-choice answering, and sentence similarity scoring (Strobelt et al., 2023).

For example, suppose that a banking system receives an email from its depositor (see **Figure 7** *Example prompt use case*). In that case, the language model could predict that the message asks about opening an account, transferring funds, or disputing a charge. Development teams can use the response to initialize appropriate workflows, which recursively invokes more prompts to classify natural language input further. This approach simplifies the user experience by permitting them to ask questions most intuitively. It also constrains the response to something easily parsed by code.

**Figure 8**  
*Example prompt use case*

class OperationType(Enum):

OPEN\_BANK\_ACCOUNT

TRANSFER\_FUNDS  
 DISPUTE\_CHARGE

def classify\_input(input)  
 response = prompt('''

return (A) open bank account, (B) transfer funds, or (C) dispute charge as the classification of this document: {input}

'''.format(input=input))

return OPEN\_BANK\_ACCOUNT if '(A) open bank account' in response  
 return TRANSFER\_FUNDS if '(B) transfer funds' in response

return DISPUTE\_CHARGE if '(C) dispute charge' in response

def main():

operation = classify\_input('Why did you bill me $3.50')

if operation is OPEN\_BANK\_ACCOUNT:

start\_open\_account\_workflow(...)

else if operation is TRANSFER\_FUNDS:

start\_transfer\_funds\_workflow(...)

else if operation is DISPUTE\_CHARGE:

start\_dispute\_workflow(...)

### Prompt Templates

Traditional supervised NLP tasks rely extensively on feature engineering and heuristics to predict the best response. Large language models (LLMs) fundamentally differ regarding their data structure and self-attention mechanism that control data retrieval (see the proceeding figure).

**Figure 9**  
*Four Paradigms of NLP (Pengfei et al., 2023, p. 195)*

A picture containing text, screenshot, font, number

Description automatically generated

Their design necessitates encapsulating context, questions, examples, and response formatting into prompt templates (Pengfei et al., 2023; Strobelt et al., 2023). For example, suppose a financial broker or stock trading application wants to provide personalized guidance using a language model (**Figure 9** *Prompt template*). A conservative investor named Alice comes to the support interface and asks: *Hi, should I trade oil futures*? The prompt template can start with Alice’s properties, such as her investment style and account balance. Next, append the prompt to include her natural language question. Third, specify the response classifications like the previous example.

**Figure 10**  
*Prompt template*

Alice: a conservative investor   
Account Balance: $1000   
Approved For: Buying stocks and options   
Cannot: Short stocks   
  
Hi, should I trade oil futures?   
return (A) if this aligns with her strategy (B) this is not a good idea

Semantically, the template warms up the transformer with hints that influence the positional encoders and activate the embeddings, leading to creativity (see the *What are Transformers* section). In this case, the Euclidian distance between *trading oil futures* (high-risk strategy) and a *conservative investor* is closest to the token (B) this is not a good idea. It’s possible to inspect the distance further by changing the response format to *return the distance to* and reissuing the prompt.

**Figure 11**  
*Response to prompt template*

Based on the given information, the distance to (A) if trading oil futures aligns with Alice's strategy and (B) if it is not a good idea can be evaluated as follows:

(A) If this aligns with her strategy: Medium distance. Oil futures trading is typically considered more speculative and carries higher risks. As a conservative investor, Alice may prefer investment options with lower risk profiles.

(B) This is not a good idea: Short distance. Trading oil futures may not align with Alice's conservative investment approach, as it involves higher risks and volatility.

Considering both factors, the recommendation would lean towards (B) as it is generally not advisable for Alice, a conservative investor, to trade oil futures due to the higher risk involved.

### Multi-shot Processing

## What is Symbolic Reasoning

*This section discusses what neuro-symbolic reasoning is and how it influences LLMs.*

### Drivers for multi-shot

*In this section discuss one, few, and langchain value-prop*

## How do LLMs handle multi-modal content

This section discusses LLMs’ capabilities, strengths, and weaknesses based on the media type.

### Images

### Audio

### Video

### Code

## How are industry leaders inventing and simplifying

### Amazon

### Google

### Hugging Face

### Microsoft

### Open AI

## How are researchers customizing LLMs

### Embedding

### Fine-tuning

## Are models explainable

*This section discusses the protections to ensure the models are not racist, etc.*

### Examining Beliefs

*In this section talk about the Socratic Method and Political bystep.*

### The DAN Attack

*It’d be good to bring up the DAN attack*

### Strategies for XAI

## How are governments approaching regulations

### America

### China

### European Union

## Summary

Begin writing here…

Checklist:

Briefly restate the key points discussed in the chapter. Review the headings and/or table of contents to ensure all key points are covered.

Highlight areas of convergence and divergence as well as gaps in the literature that support the need for the study. This discussion should logically lead to Chapter 3, where the research methodology and design will be discussed.

# Chapter 3: Research Method

The problem to be addressed in this study is an exploratory analysis of Generative AI use cases is the viability and practicality of mechanisms for ensuring norms and expectations of enterprise businesses within regulated environments. The purpose of this constructive design study is to examine the state of Generative AI capabilities within enterprise businesses and create a framework for prioritizing use cases based on risk and practicality

This chapter examines

Provide a brief overview of the contents of this chapter, including a statement that identifies the research methodology and design.

## 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 (Bryar & Carr, 2021; Peffers et al., 2007). The methodology 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.

Many people erroneously believe one method is superior to another (Creswell, 2014; Jason & Glenwick, 2016; McCusker & Gunaydin, 2015). Instead, researchers must align the method with the research problem and purpose. Design science is appropriate for understanding the effectiveness and efficiency of autonomous assistants for creating an extensible human behavior classification model for elderly and special needs care organizations. The study considered and declined alternative quantitative, qualitative, and mixed methods. These approaches best align with problem and purpose statement variations (see Table 10). Suppose the objective is to compare treatment effectiveness or aggregate patient monitoring implementations. In that case, respectably, quantitative and qualitative methods are a better fit.

**Table 4**  
*Alternative 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 * Exploring a scientific idea and then mapping it to use cases |

## Population and Sample

Begin writing here…

Checklist:

Describe the population, including the estimated size and relevant characteristics.

Explain why the population is appropriate, given the study problem, purpose, and research questions.

Describe the sample that will be (proposal) or was (manuscript) obtained.

Explain why the sample is appropriate, given the study problem, purpose, and research questions.

Explain the type of sampling used and why it is appropriate for the dissertation proposal methodology and design. For qualitative studies, evidence must be presented that saturation will be (proposal) or was (manuscript) reached. For quantitative studies, a power analysis must be reported to include the parameters (e.g., effect size, alpha, beta, and number of groups) included, and evidence must be presented that the minimum required sample size will be (proposal) or was (manuscript) reached.

Describe how the participants will be (proposal) or were (manuscript) recruited (e.g., email lists from professional organizations, flyers) and/or the data will be (proposal) or were (manuscript) obtained (e.g., archived data, public records) with sufficient detail so the study could be replicated.

## Materials or Instrumentation

Begin writing here…

Checklist:

Describe the instruments (e.g., tests, questionnaires, observation protocols) that will be (proposal) or were (manuscript) used, including information on their origin and evidence of their reliability and validity. OR as applicable, describe the materials to be used (e.g., lesson plans for interventions, webinars, or archived data, etc.).

Describe in detail any field testing or pilot testing of instruments to include their results and any subsequent modifications.

If instruments or materials are used that were developed by another researcher, include evidence in the appendix that permission was granted to use the instrument(s) and/or material(s) and refer to that fact and the appendix in this section.

## Operational Definitions of Variables

Begin writing here...

### XXX

Text…

Checklist:

For quantitative and mixed methods studies, identify how each variable will be (proposal) or was (manuscript) used in the study. Use terminology appropriate for the selected statistical test (e.g., independent/dependent, predictor/criterion, mediator, moderator).

Base the operational definitions on published research and valid and reliable instruments.

Identify the specific instrument that will be (proposal) or was (manuscript) used to measure each variable.

Describe the level of measurement of each variable (e.g., nominal, ordinal, interval, ratio), potential scores for each variable (e.g., the range [0–100] or levels [low, medium, high]), and data sources. If appropriate, identify what specific scores (e.g., subscale scores, total scores) will be (proposal) or were (manuscript) included in the analysis and how they will be (proposal) or were (manuscript) derived (e.g., calculating the sum, difference, average).

## Study Procedures

Begin writing here…

Checklist:

Describe the exact steps that will be (proposal) or were (manuscript) followed to collect the data, addressing what data as well as how, when, from where, and from whom those data will be (proposal) or were (manuscript) collected in enough detail the study can be replicated.

## Data Analysis

Begin writing here…

Checklist:

Describe the strategies that will be (proposal) or were (manuscript) used to code and/or analyze the data, and any software that will be (proposal) or was (manuscript) used.

Ensure the data that will be (proposal) or were (manuscript) analyzed can be used to answer the research questions and/or test the hypotheses with the ultimate goal of addressing the identified problem.

Use proper terminology in association with each design/analysis (e.g., independent variable and dependent variable for an experimental design, predictor and criterion variables for regression).

For quantitative studies, describe the analysis that will be (proposal) or was (manuscript) used to test each hypothesis. Provide evidence the statistical test chosen is appropriate to test the hypotheses and the data meet the assumptions of the statistical tests.

For qualitative studies, describe how the data will be (proposal) or were (manuscript) processed and analyzed, including any triangulation efforts. Explain the role of the researcher.

For mixed methods studies, include all of the above.

## Assumptions

Begin writing here…

Checklist:

Discuss the assumptions along with the corresponding rationale underlying them.

## Limitations

Begin writing here…

Checklist:

Describe the study limitations.

Discuss the measures taken to mitigate these limitations.

## Delimitations

Begin writing here…

Checklist:

Describe the study delimitations along with the corresponding rationale underlying them. An example of delimitations are the conditions and parameters set intentionally by the researcher or by selection of the population and sample.

Explain how these research decisions relate to the existing literature and theoretical/conceptual framework, problem statement, purpose statement, and research questions.

## Ethical Assurances

Begin writing here…

Checklist:

Confirm in a statement the study will (proposal) or did (manuscript) receive approval from Northcentral University’s Institutional Review Board (IRB) prior to data collection.

If the risk to participants is greater than minimal, discuss the relevant ethical issues and how they will be (proposal) or were (manuscript) addressed.

Describe how confidentiality or anonymity will be (proposal) or was (manuscript) achieved.

Identify how the data will be (proposal) or were (manuscript) securely stored in accordance with IRB requirements.

Describe the role of the researcher in the study. Discuss relevant issues, including biases as well as personal and professional experiences with the topic, problem, or context. Present the strategies that will be (proposal) or were (manuscript) used to prevent these biases and experiences from influencing the analysis or findings.

In the dissertation manuscript only, include the IRB approval letter in an appendix.

## Summary

Begin writing here…

Checklist:

Summarize the key points presented in the chapter.

Logically lead the reader to the next chapter on the findings of the study.

# Chapter 4: Findings

Begin writing here…

Checklist:

Begin with an introduction and restatement of the problem and purpose sentences verbatim and the organization of the chapter.

Organize the entire chapter around the research questions/hypotheses.

## XXX of the Data

Begin writing here…

Checklist:

For qualitative studies, clearly identify the means by which the trustworthiness of the data was established. Discuss credibility (e.g., triangulation, member checks), transferability (e.g., the extent to which the findings are generalizable to other situations), dependability (e.g., an in-depth description of the methodology and design to allow the study to be repeated), and confirmability (e.g., the steps to ensure the data and findings are not due to participant and/or researcher bias).

For quantitative studies, explain the extent to which the data meet the assumptions of the statistical test and identify any potential factors that might impact the interpretation of the findings. Provide evidence of the psychometric soundness (i.e., adequate validity and reliability) of the instruments from the literature as well as in this study (as appropriate). Do not merely list and describe all the measures of validity and reliability.

Mixed methods studies should include discussions of the trustworthiness of the data as well as validity and reliability.

## Results

Begin writing here…

Checklist:

Briefly discuss the overall study. Organize the presentation of the results by the research questions/hypotheses.

Objectively report the results of the analysis without discussion, interpretation, or speculation.

Provide an overview of the demographic information collected. It can be presented in a table. Ensure no potentially identifying information is reported.

### Research Question 1/Hypothesis

Text…

Report all the results (without discussion) salient to the research question/hypothesis. Identify common themes or patterns.

Use tables and/or figures to report the results as appropriate.

For quantitative studies, report any additional descriptive information as appropriate. Identify the assumptions of the statistical test and explain how the extent to which the data met these assumptions was tested. Report any violations and describe how they were managed as appropriate. Make decisions based on the results of the statistical analysis. Include relevant test statistics, *p* values, and effect sizes in accordance with APA requirements.

For qualitative studies,describe the steps taken to analyze the data to explain how the themes and categories were generated. Include thick descriptions of the participants’ experiences. Provide a comprehensive and coherent reconstruction of the information obtained from all the participants.

For mixed methods studies,include all of the above.

## Evaluation of the Findings

Begin writing here…

Checklist:

Interpret the results in light of the existing research and theoretical or conceptual framework (as discussed in Chapters 1 and 2). Briefly indicate the extent to which the results were consistent with existing research and theory.

Organize this discussion by research question/hypothesis.

Do not draw conclusions beyond what can be interpreted directly from the results.

Devote approximately one to two pages to this section.

## Summary

Begin writing here…

Checklist:

Summarize the key points presented in the chapter.

# Chapter 5: Implications, Recommendations, and Conclusions

Begin writing here…

Checklist:

Begin with an introduction and restatement of the problem and purpose sentences verbatim, and a brief review of methodology, design, results, and limitations.

Conclude with a brief overview of the chapter.

## Implications

Begin writing here…

Checklist:

Organize the discussion around each research question and (when appropriate) hypothesis individually. Support all the conclusions with one or more findings from the study.

Discuss any factors that might have influenced the interpretation of the results.

Present the results in the context of the study by describing the extent to which they address the study problem and purpose and contribute to the existing literature and framework described in Chapter 2.

Describe the extent to which the results are consistent with existing research and theory and provide potential explanations for unexpected or divergent results.

Identify the most significant implications and consequences of the dissertation (whether positive and/or negative) to society/desired societal outcomes and distinguish probable from improbable implications.

### Research Question 1/Hypothesis

Text…

## Recommendations for Practice

Begin writing here…

Checklist:

Discuss recommendations for how the findings of the study can be applied to practice and/or theory. Support all the recommendations with at least one finding from the study and frame them in the literature from Chapter 2.

Do not overstate the applicability of the findings.

## Recommendations for Future Research

Begin writing here…

Checklist:

Based on the framework, findings, and implications, explain what future researchers might do to learn from and build upon this study. Justify these explanations.

Discuss how future researchers can improve upon this study, given its limitations.

Explain what the next logical step is in this line of research.

## Conclusions

Begin writing here…

Checklist:

Provide a strong, concise conclusion to include a summary of the study, the problem addressed, and the importance of the study.

Present the “take-home message” of the entire study.

Emphasize what the results of the study mean with respect to previous research and either theory (PhD studies) or practice (applied studies).

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