ASSOCIATION BETWEEN TRADITIONAL AND GENERATIVE AI ENHANCED RESUMES ON INTERVIEW SELECTION RATES AMONG DIVERSE STEM EMPLOYMENT CANDIDATES: A QUANTITATIVE QUASI-EXPERIMENTAL STUDY

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# Abstract

Generative AI has recently become accessible to consumers at minimal or no cost. Early research indicates that Generative AI can assist in preparing employment documents, improving interview selection rates (ResumeBuilder.com, 2023). Existing literature highlights biases in pre-employment screening against marginalized groups, especially in STEM fields (West et al., 2019). However, there is a gap regarding the impact of Generative AI on preparing pre-employment documents for marginalized populations in STEM. Historically, these groups have faced exclusion from interview selections in STEM (Casad et al., 2021). This study explored this gap.

This quantitative, quasi-experimental design examined interview selection rates for statistically significant associations among diverse job seekers in STEM fields who utilize Generative AI for resume creation or enhancement and those who do not. The target population was college educated STEM job seekers. The target population was identified through social media snowball sampling. Data was collected through a survey examining pre-employment document preparation practices. The data analysis utilized Chi-squared and ANOVA to test hypotheses for statistically significant association between groups.

<ROOM to insert findings, significance and conclusion>

## Keywords

Generative AI, Employment, Applicant Tracking Systems, Diversity, Ethics, Artificial Intelligence, Interview, Algorithms, Selection, Transparency, Accountability, Self-Determination Theory, AI Ethical Principles, Imago Dei

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# Dedication

You may optionally dedicate your dissertation to an individual or organization.

# Epigraph

You may optionally include a quote or statement applicable to your dissertation.

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# Chapter 1: Introduction

There has been a global shift in using Artificial Intelligence (AI) to pre-screen applicants applying to positions in large companies (Holderman, 2014, p. 154). Research has also highlighted the bias affecting women and traditionally marginalized populations by being rejected during pre-screening with AI-enabled applicant tracking systems (ATS) (West et al., 2019, p. 7). ATS use pre-determined criteria to determine whether an applicant is a good fit for the position. The pre-determined criteria could be keywords in a job description, experience matching previously hired employees, or other criteria (Luo et al., 2018, p. 4). One of the most public descriptions is Amazon’s use of an ATS that rejected women for several years before being detected by a human observer (West et al., 2019, p. 7).

In 2022, Generative AI systems became broadly available to the population by releasing ChatGPT and other similar systems. This study will conduct research which examines the use of Generative AI to create or enhance pre-employment documentation, like resumes and cover letters, versus traditional pre-employment documentation development methods on the rate at which applicants are being pre-selected for interviews. The study will conduct research which will narrow the population focus to those working in Science, Technology, Engineering, and Math (STEM) because there is a well-documented shortage of talent in these fields (Horbach et al., 2020, p. 5; Nithithanatchinnapat et al., 2019, p. 61). Due to the shortfall in talent to fill open positions, applicants must be fairly evaluated and not prematurely eliminated from consideration. This study will further conduct research which narrows the population of interest to traditionally marginalized populations in the STEM field because ATS, much like human manual screening, has been found to have an exaggerated effect in eliminating diverse populations from interviews (Fuller et al., 2021, p. 5). Specifically, this study will conduct quasi-experimental research examining the association between interview selection rates among marginalized groups in STEM fields according to the use of Generative AI for resume creation or enhancement.

The study will be structured in five chapters. Chapter 1 will be the introduction, Chapter 2 will be the literature review, Chapter 3 will be a description of the methodology for experimentation and analysis, Chapter 4 will be an analysis of the experiment, and Chapter 5 will be the conclusion.

The Literature Review is conducted to research the gap between the available talent pool and the demand for STEM workers. It will analyze the gender and racial demographics of people graduating and available to work in STEM fields in the future. It will review the history of resume pre-screening and the impact of manual and ATS pre-screening. Chapter 2 will also review literature on the introduction of Generative AI tools available to all and the associated capability available using AI to help enhance or create pre-employment documentation. It further reviews literature on a case study where Generative AI is used to help during the pre-employment process. The case study will be analyzed from three viewpoints. The first will be the Self-Determination theoretical framework, the second will be the ethical principles governing the development and use of AI, and the third will be the theological perspective of common commands from Judeo-Christian, Muslim, and Jewish religions.

The Methodology chapter will describe the research purpose, significance, questions, and hypothesis. Additionally, it will explain the statistical analysis approach, including the dependent and independent variables associated with the survey-based data collection. It will describe the population and the methodology used to reach the population using Snowball sampling. It will describe the statistical analysis approach using the data collected. There will also be a description of methods to solicit and gain survey respondent approval. Finally, this section will describe data security measures to anonymize and protect the collected data.

# Statement of the Problem

The problem is marginalized groups have been historically excluded from interview selection in STEM fields (Casad et. al., 2021). Recently Generative AI has become widely available to consumers at little to no cost. Early studies have shown that Generative AI helped prepare employment documents, leading to greater success in interview selection rates (ResumeBuilder.com, 2023, p. 1-2). There is literature documenting bias in pre-employment screening of marginalized groups in all disciplines, particularly in STEM fields (West et al., 2019, p. 7). There is a gap in the literature related to the effect of Generative AI on preparing pre-employment documents for marginalized populations in STEM fields. This study conducts research that seeks to fill this gap.

# Purpose Statement

The purpose of this study is to examine the association in interview selection rates among marginalized groups in STEM fields according to the use of Generative AI for resume creation or enhancement.

According to Indeed.com, in April 2024, there were over 900,000 open STEM positions in the U.S. (Indeed.com, 2024, p. 1). According to Korhonen (2023), approximately 30% fewer graduates are at all levels than the number of open STEM positions (p. 1). The literature also documents through the survey of over 2400 companies worldwide where Artificial Intelligence driven Applicant Tracking Systems (ATS) are used to pre-screen resumes, of which 88% of those companies surveyed believe the ATSs are screening out qualified candidates (Fuller et al., 2021, p. 22). When large segments of the population are denied opportunity, it causes instability in the foundational fabric of society. Ensuring that all people qualified for positions are fairly evaluated and considered to fill those positions is foundational to societal economic stability and prosperity.

# Significance

The focus on STEM hiring in diversity is because research has shown a gap between the number of women, Black and Hispanic workers, and those working in the AI industry (West et al., 2019, p. 7). Specifically, research has shown through U.S. educational statistics that the number of women, Blacks, and Hispanic graduates in STEM is greater than those going into the field of mathematics and computer science (Kennedy, 2021, p. 1). These fields are particularly relevant because the AI development skillset is centered in this area. Research has shown that AI-enabled systems create bias in one population over another. Women and people of color are most likely to be disadvantaged by these systems. Research has shown that the companies that produce AI-enabled systems are in the West and have the lowest percentage of diverse staff in STEM fields ” (West et al., 2019, p. 7). Research has shown that companies increasingly use Applicant Tracking Systems (ATS) by companies to pre-screen resumes of ’employees’ resumes before being selected for an interview. Research has also shown that with the emergence of Generative AI, there is increasing success in the use of ChatGPT to help enhance or create resumes and cover letters to contain keywords searched for by ATS (ResumeBuilder.com, 2023, p. 1-2). While there has been research in the general population quantifying the benefit of using ChatGPT for resume enhancement and creation, no focus has been specifically on the diverse STEM population. West’s (2019) research states, “There is a close relationship between these workplaces with discriminatory practices and discriminatory tools (AI): a feedback loop that is shaping the AI industry and its tools. The products of the AI industry already influence the lives of millions. Addressing diversity issues is, therefore, not just in the interest of the tech industry but of everyone whose lives are affected by AI tools and services.“ (p. 7).

For this reason, this study conducts research to examine the association in interview selection rates among marginalized groups in STEM fields according to the use of Generative AI for resume creation or enhancement. If an association is found using Generative AI for pre-employment documentation creation or enhancement for diverse STEM jobseekers, then jobseekers may have more successful tools for job searches. Additionally, prospective employers may fill more open STEM positions with qualified, diverse applicants.

# Background of the Problem

In 1995, fewer than 300 companies (all major corporations) used applicant tracking software systems to store, organize, and search resumes, according to Training & Development magazine. Today, some industry experts estimate that 80 percent of all companies, large and small, rely on computerized ATS as the first reader for every resume received from any source. This evolution in hiring methodology has significant implications for clients since, for many candidates, the ATS is also the last reader – 75 percent of resumes in any company database are never seen by a human recruiter or hiring manager because they do not meet the employer’s pre-established criteria for a specific position.

The most common criteria ATS uses for screening resumes includes specific years of experience within an industry or job title. Some employers use ATS selective criteria only for currently employed candidates while rejecting all unemployed candidates. Others use the system to select candidates by location (zip code or area code), and some ask the ATS to identify candidates who have worked for (or are currently working for) specific companies or competitors. (Holderman, 2014). An explainable (X-AI) framework identifies criteria for resume evaluation as: Education level, number of working years, number of awards obtained, number of relevant skills and previous work positions (Luo, 2018).

The un- or under-employment of people due to the criteria used for AI-enabled pre-screening of resumes is a worldwide problem. “In February 2020, just before COVID-19 triggered global lockdowns, employers struggled to fill positions as the economy approached “full employment .”The number of unemployed persons per job posting in the United States stood at 0.8, with 7 million positions open in the U.S.. In contrast, 5.8 million people remained unemployed, and an equal number were underemployed. There were 721,000 job vacancies in the United Kingdom during the December 2019-February 2020 period, with 1.4 million unemployed people. Similarly, there were 712,000 job vacancies in Germany in February 2020, while 2.3 million people were unemployed (Fuller et al., 2021,p. 7). Given these developed countries have significant numbers of people who will be economically insecure, the countries themselves will suffer from economic growth and stability. History shows that when large segments of the population are denied opportunity, it causes instability in the foundational fabric of societies.

## AI Impact on Workforce Shortfall

A study by Accenture and the Harvard Business School showed that there are 27 million workers unemployed because of ATS, which uses artificial intelligence. They are unemployed because the ATS has eliminated their resumes from consideration (Fuller, 2021, p. 3). Additionally, of the more than 2400 companies interviewed worldwide for the Hidden Worker study, the majority understand that their ATSs are eliminating qualified workers from consideration. “They exclude from consideration viable candidates whose resumes do not match the [Applicant tracking system] criteria but who could perform at a high level with training. Most employers (88%) agree, telling us that qualified high-skills candidates are vetted out of the process because they do not match the exact criteria established by the job description. That number rose to 94% in the case of middle-skills workers.” (Fuller et al., 2021,p. 3). Empirical evidence suggests that ATS can eliminate even the most highly qualified candidates. Berin & Associates, a talent management research and consulting firm in Oakland, California, tested an ATS by writing a resume for a clinical scientist position. The firm used knowledge of the job requirements to craft the resume for a theoretical ideal candidate who met 100 percent of the desired qualifications. The ATS ranked this perfect candidate as meeting just 43 percent of the qualifications, a ranking far too low to merit an interview within most companies. The candidate was rejected as not meeting the minimum educational criteria, simply because of the way advanced degrees were formatted on the resume (Levinson, 2012); (Holderman, 2014).

Ensuring that all people qualified for positions are fairly evaluated and considered to fill those positions is foundational to societal economic stability and prosperity. This study will conduct research to evaluate the varied rate of interview selection with changes in resume generation method. The two methods are traditional resume development and AI-created or enhanced resume development.

Generative AI is potentially a way to create or enhance a person’s resume to be favorably viewed by the ATS. Generative AI refers to a type of artificial intelligence that when prompted with questions about content, can create answers to the questions by generating new content. Generative AI has trained on large volumes of sentence structures, so it becomes good at predicting the next words expected in a sentence. Examples of generative AI include models like GPT-3 and GPT-4, which can generate human-like linguistic pattern matching (Chat GPT-4, 2023). Generative AI models are now a technological tool available to all that can be used to create, revise or enhance resumes. The ChatGPT-3 model was released to the public in November 2022. The recent release of this technology to all at no cost to the consumer compels a study of the impact of diverse STEM job seekers on getting pre-selected for interviews.

# Research Questions

Seven research questions are being explored and described to support the study. There is one research qualifying question and six inquiry questions.

RQ1: What associations exist in interview selection rates between those who use Generative AI for resume creation or enhancement and those who do not among candidates in STEM fields?

RQ2: What association exists in interview selection rates between racial groups among candidates in STEM fields who use Generative AI for resume creation or enhancement?

RQ3: What association exists in interview selection rates between racial groups among candidates in STEM fields who do not use Generative AI for resume creation or enhancement?

RQ4: What association exists in interview selection rates between genders among candidates in STEM fields who do not use Generative AI for resume creation or enhancement?

RQ5: What association exists in interview selection rates between genders among candidates in STEM fields who use Generative AI for resume creation or enhancement?

RQ6: What differences exist in the perceived accuracy of AI-generated resume content between racial groups among candidates in STEM fields?

RQ7: What differences exist in the perceived accuracy of AI-generated resume content between genders among candidates in STEM fields?

A hypothesis tests each of these research questions.

# Hypotheses

Seven hypotheses are being tested and described to support the research study.

H01: No statistically significant association exists between interview selection rates of those who use Generative AI for resume creation or enhancement and those who do not among job seekers in STEM fields (RQ1).

Ha1: A statistically significant association exists between interview selection rates of those who use Generative AI for resume creation or enhancement and those who do not among job seekers in STEM fields (RQ1).

H02: No statistically significant association exists between interview selection rates and racial groups among candidates in STEM fields who use Generative AI for resume creation or enhancement. (RQ2).

Ha2: A statistically significant association exists between interview selection rates and racial groups among candidates in STEM fields who use Generative AI for resume creation or enhancement (RQ2).

Ha3: A statistically significant association exists between interview selection rates and racial groups among candidates in STEM fields who do not use Generative AI for resume creation or enhancement (RQ3).

Ha3: A statistically significant association exists between interview selection rates and racial groups among candidates in STEM fields who do not use Generative AI for resume creation or enhancement (RQ3).

H04: No statistically significant association exists between interview selection rates and genders among candidates in STEM fields who do not use Generative AI for resume creation or enhancement (RQ4).

Ha4: A statistically significant association exists between interview selection rates and genders among candidates in STEM fields who do not use Generative AI for resume creation or enhancement (RQ4).

H05: No statistically significant association exists between interview selection rates and genders among candidates in STEM fields who use Generative AI for resume creation or enhancement (RQ5).

Ha5: A statistically significant association exists between interview selection rates and genders among candidates in STEM fields who use Generative AI for resume creation or enhancement (RQ5).

H06: No statistically significant difference exists in the perceived accuracy of AI-generated resume content and racial groups among candidates in STEM fields? (RQ6).

Ha6: A statistically significant difference exists in the perceived accuracy of AI-generated resume content between racial groups among candidates in STEM fields? (RQ6).

H07: No statistically significant difference exists in the perceived accuracy of AI-generated resume content between genders among candidates in STEM fields (RQ7).

Ha7: A statistically significant difference exists in the perceived accuracy of AI-generated resume content between genders among candidates in STEM fields (RQ7).

Testing the hypotheses will require a rigorous research methodology and design.

# Research Methodology and Design

This quantitative, quasi-experimental design will examine interview selection rates for statistically significant associations among job seekers in STEM fields who utilize Generative AI for resume creation or enhancement and those who do not. This study will utilize chi-square analysis and ANOVA to test hypotheses for statistically significant association between groups.

A quasi-Experimental design is often used in social science research. It will be advantageous because it allows for real-world settings in which random group assignment is impractical. This Quasi-Experimental research design will compare differences in dependent variables between groups split on two independent variables from a validated quantitative instrument. The experimental design tests groups that are part of socially connected networks.

Chi-squared analysis will be used as a statistical method to determine if there is a significant association between two categorical variables. It will compare the observed frequency in each category to the frequencies one would expect to find if there were no causal associations between the variables. (Mac Farland et al., 2016, p. 77-78). Since the dependent variable is the interview selection rate, Chi-squared is appropriate for examining how the interview selection rates differ across expected rates in each category (Mac Farland et al., 2016, p. 77-78). The categorical independent variables are race, gender, and the accuracy of the resume. The data is organized in a matrix, referred to as a matrix representation. The interview selection rate is organized alongside the race, gender, and accuracy measures. The Chi-squared analysis assumes that the expected frequencies are sufficiently large for the Chi-squared approximation to be statistically valid. When the Chi-squared is less than 0.05, it will indicate there is a statistically significant difference between the observed and expected frequencies, indicating an association between the interview selection rate and race, gender, and use of Generative AI to create or enhance resumes or cover letters (MacFarland, 2016, p. 80; Creswell, 2023, p. 268).

The Analysis of Variance (ANOVA) test compares the means of two or more independent variables to determine if at least one dependent variable mean significantly differs from the others. In this analysis, the ANOVA test is used to determine if there is a significant difference between the dependent variable and rate of interview selection, and each independent variable, race, gender, or the use of Generative AI for resume creation or enhancement. This is especially helpful when analyzing multiple independent variables, which may each have different levels or categories.(Creswell et al., 2023, p. 268). The population and sampling rate are essential to the research design and methodology.

# Operational Definitions

The operational definitions for key terms are defined.

## Definition of Key Terms

Artificial Intelligence (AI) - Artificial Intelligence (AI) refers to developing computer systems capable of performing tasks that typically require human intelligence. These tasks include but are not limited to visual perception, speech recognition, decision-making, language translation, and problem-solving (McCarthy et al., 1955, p. 12-14).

Generative Artificial Intelligence (Generative AI) - Generative Artificial Intelligence (AI) refers to a subset of AI that often uses generative models to create new content, such as images, text, audio, and video. These models learn a given dataset's underlying patterns and structures and can then generate new data samples that resemble the original dataset (Vaswani et al., 2017, p5998-6008).

Gender - Gender refers to the social, cultural, and psychological attributes, roles, and behaviors a society considers appropriate for individuals based on their sex. It encompasses a range of identities, expressions, and experiences that may or may not align with the binary categorizations of male and female (West et al., 1987, p. 125-151).

Race - Race is a socially constructed category used to classify people based on perceived physical or genetic characteristics, such as skin color, facial features, and hair texture. It is a fluid and contested concept that lacks biological validity but has profound social, cultural, and historical significance, shaping ’individuals’ experiences, identities, and opportunities within society (Omi et al., 2014, p. 23).

STEM - STEM (Science, Technology, Engineering, and Mathematics) refers to professions that require expertise in Science, Technology, Engineering, and Mathematics. These professions involve applying scientific and technical knowledge to solve problems, innovate, and advance knowledge across various industries and sectors (National Science Board,2018, p. 1).

AI Ethics Guidelines - AI Ethics Guidelines are a set of principles, standards, and recommendations that govern the development, deployment, and use of artificial intelligence (AI) technologies ethically and responsibly. These guidelines address fairness, transparency, accountability, privacy, bias, and societal impacts of AI systems, providing a framework for ensuring that AI technologies align with ethical principles and respect human rights (European Commission, 2019, p. 1).

Self-determination Theory - Self-Determination Theory (SDT) is a psychological framework that explores human motivation and personality development. It proposes that individuals have innate psychological needs for autonomy, competence, and relatedness, and when these needs are satisfied, individuals experience intrinsic motivation and psychological well-being. (Deci et al., 2002, p. 39)

Pre-employment screening - Pre-employment screening is the process of evaluating job ’applicants’ backgrounds, qualifications, and suitability for a particular position before they are hired (Collins, et al., 2004, p. 413-453).

Applicant Tracking Systems - Applicant Tracking Systems (ATS) are software applications organizations use to manage and streamline the recruitment and hiring process. These systems automate job posting, resume screening, candidate tracking, and communication with applicants, enabling employers to manage large volumes of job applications. (ATS Acute Market Reports, 2017, p. 112).

# Scope and Delimitations

The study will address diverse STEM job seekers seeking employment within the past twelve months. LinkedIn will be used to elicit survey participants. The platform used to elicit survey respondents is worldwide, but the method of soliciting participants is socially connected networks, which begin in US. Therefore, the participants will likely represent jobseekers’ experiences in the US. The study analysis will delineate job seeker experiences using AI in pre-employment document preparation by gender and race.

# Limitations

The field of AI is accelerating very quickly. The research regarding acceptable and ethical practices in employment pre-screening may mature to eliminate the same biases in current screening systems and perceptions of using Generative AI in employment. Because Chi-Square in a nonparametric procedure, the results cannot be generalized beyond the sample. The measured results will be a snapshot in time and may not be applicable as AI-enabled systems evolve. For example, the results of the Generative AI system may change over time to reflect the evolving corpus of data used to derive results. Subsequent adoption of AI Ethics principles by ATS system developers may change post-deployment system performance. There may be population selection bias using snowball sampling. It depends on the researcher’s social networks and those known by professional networks associated with the researcher. The population will predominantly come from the United States. While this is a global problem, cultural differences will influence Generative AI’s value, as most systems are developed in the US.

# Assumptions

Assumptions in the study are that ATS is used by the companies screening resumes and jobseeker resumes. Additionally, the job market conditions have not changed over 12 months to influence criteria for interview selection. The population sampling method produces sufficient respondents in each category to appropriately analyze the results using Chi-Square and ANOVA methodology. The Self-determination theory is assumed to be valid across populations of STEM-diverse job seekers and their prospective employers. The ethical principles analyzed are assumed to be relevant to the developers and users of the AI-enabled systems used. The theological framework is assumed to be relevant to 55% of the global population, Judeo-Christian, Jewish and Islam, but not the entire population.

# Summary and Conclusion

There is a shortfall in talent in STEM fields. Additionally, there is a long tradition of diverse talent being screened out before the interview process because bias will be demonstrated through research. Additionally, as AI-enabled systems replace human reviewers, research will be conducted to examine the persistence of bias in AI-enabled systems that pre-screen resumes for interview selection. Research will examine AI Ethical guidelines as a potential source to help minimize bias in developing and using AI-enabled systems like ATS. The theoretical framework analysis will explore the level of human autonomy or regulation that should govern the use of Generative AI in preparing pre-employment documentation. Additionally, research will show theologically a framework for evaluating the Christian, Muslim and Jewish religious perspectives in prospective employee, and employer social interaction as it relates to the call for one to Love God and love their neighbor as themselves. Bias against others would be inconsistent with the outcome of this kind of AI-enabled system, should either ethics or religious doctrine be followed.

As AI has become available to the general population through Generative AI, like ChatGPT, employment candidates are turning to AI to assist in resume creation or enhancement. This has been met with acceptance by some and rejection by other hiring managers. There is an under-representation of women and minorities in several STEM fields, but no research has been done to determine if using Generative AI will improve the outcome of resume screening by an AI-enabled ATS leading to being selected for an interview. The research problem is marginalized groups have been historically excluded at a higher rate from employment participation in STEM fields.

The quasi-experimental research design and methodology will examine the research questions and hypothesis to determine the association between using Generative AI vs traditional pre-employment document creation or enhancement method relationships to the rate of selection for interviews for job seekers in STEM fields. The methodology and statistical analysis methods will address the research questions and test the hypotheses. Further research will be presented regarding the method of sampling. Additionally, the study will conduct research to present data collection, processing, and analysis methodologies. Finally, the study will conduct research to present information regarding the protection of research survey respondents through a social science research questionnaire, IRB review process, and data protection provisions. This quantitative, quasi-experimental research design will inform employment seekers about the association between using Generative AI versus traditional methods and being pre-selected for an interview.

# Chapter 2: Literature Review

The purpose of this study is to examine the interview selection rate association between diverse candidates in STEM fields who do and not use Generative AI for resume creation or enhancement. With the increased use of AI-enabled systems to improve profitability in business operations, companies must also ensure they are not prematurely screening out candidates, particularly diverse candidates, in resume pre-screening to meet hiring demands.

The study frames the importance of understanding the relationship between traditional resume generation and AI-assisted resume generation in interview selection rates because of a persistent and well-documented talent shortage in STEM fields. The literature review researches the gap between open positions and the talent available to fill the open positions in STEM. The literature review further explores the demand for STEM talent exceeding the current supply, with particular emphasis on diverse candidates. Further, the literature review researches the relationship between using ATS to screen out qualified candidates prematurely and cites traditional resumes screened by humans and the human bias associated with that pre-screening method.

The literature review researches the ethical guidelines to ensure AI is used to help society, which can be applied to large corporate AI developers and individual candidates applying for employment. The literature review cites the relationship between AI ethical guidelines and the application of those guidelines in various cultures. The literature review compares AI ethical guidelines in resume development and pre-screening in STEM employment.

Further, the literature review researches STEM fields, including biological and biomedical sciences, computer and information sciences, engineering and engineering technologies, mathematics and statistics, and physical sciences and science technologies (U.S . Dept of Education, National Center for Education Statistics, 2022, p. 1).

The literature review researches the use of Generative AI as a method to assist applicants in developing resumes that may have a greater likelihood of meeting the search criteria for ATS. The literature review discusses disparate views on using Generative AI as potentially misrepresenting candidates’ qualifications. In the context of the self-determination theory, the study researches the motivation for the use of Generative AI as a tool to help applicants. Self-determination theory suggests people’s inherent growth tendencies and innate psychological needs that are the basis for their self-motivation and personality integration and the conditions that foster those positive processes. In the presence of technology evolution, such as ATS, to evaluate their qualifications, the self-determination theory literature review defines the need for candidates to grow and creatively adjust methods in their approach to meet the changing needs of our time. Finally, the literature review establishes the need for an increased supply of diverse STEM talent. It presents the impact innovation can have to address the need to improve society's long-term economic health.

# Workforce Shortage in STEM Fields

There is a shortage of workers in the STEM sector globally. This is especially apparent in the information technology sector (Nithithanatchinnapat et al., 2019, p. 61). The shortage is documented in developed countries around the globe (Horbach et al., 2020, p. 5; Nithithanatchinnapat et al., 2019, p. 61). A historical review of shortages in the technology sector reveals that a short-term fix to the technology sector labor shortage is higher salaries, but increasing supply is the longer-term solution (Arrow et al., 1959, p. 292). Current documented trends indicate the US is increasing the salaries of technology workers, but inadequate attention is being paid to increasing the supply of technology workers (Fuller et al., 2021, p. 3). The literature review presents the number of open STEM positions as over one million in the U.S. (Indeed, 2023, p. 1).

**Table 1**

Indeed, Open Technical Positions as of 04/2024

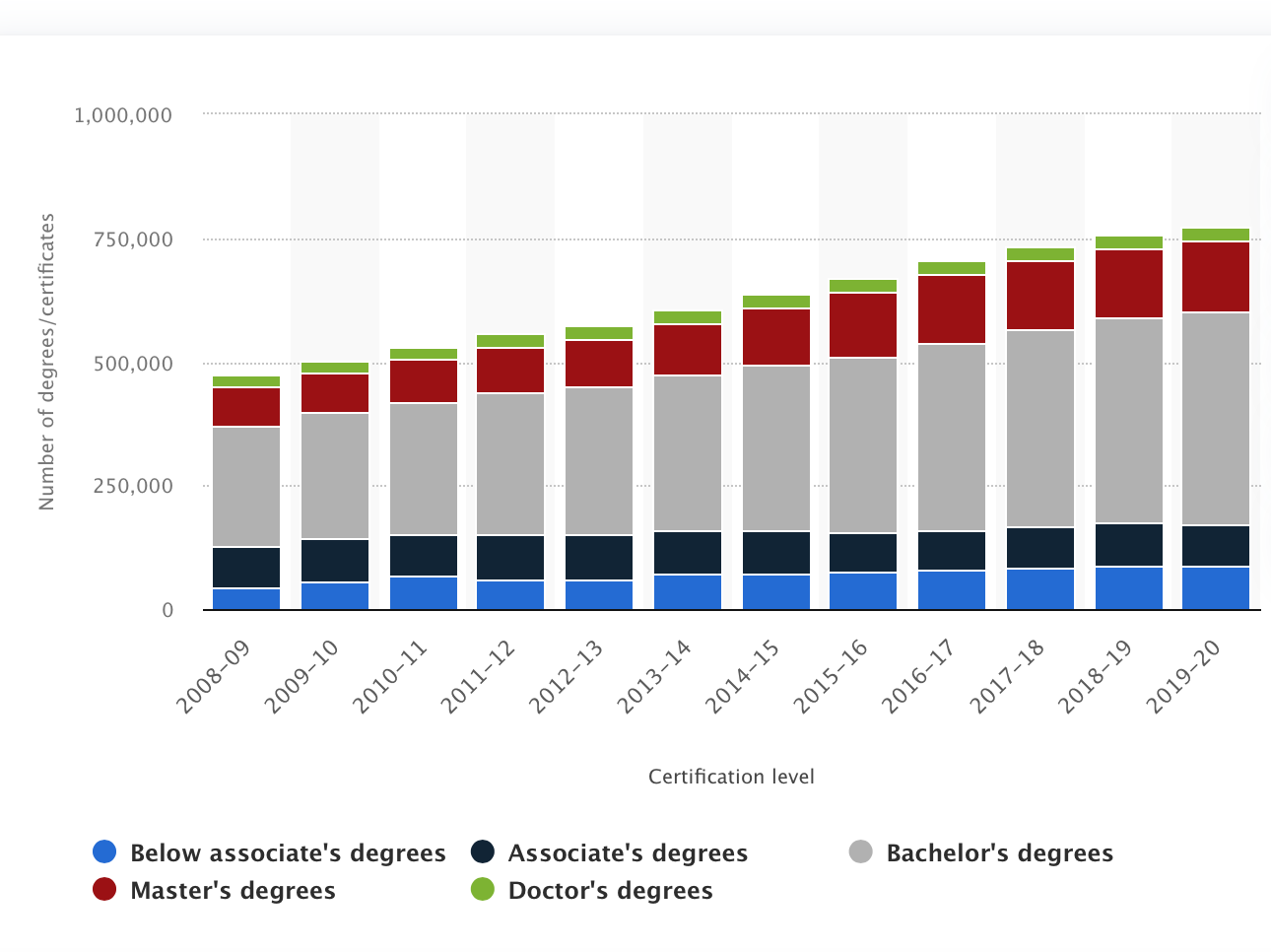
|  |  |  |
| --- | --- | --- |
| STEM Positions | | United States |
| Nursing |  | 405,952 |
| Nurse Practitioner | | 50,600 |
| Medical doctor | | 52,496 |
| Biological sciences | | 19,438 |
| Public health |  | 17,167 |
| Software Developer | | 67,151 |
| Software Architect | | 13,861 |
| Data Scientist |  | 12,247 |
| Hardware Engineer | | 44,610 |
| Cyber Security |  | 21,067 |
| IT |  | 157,729 |
| RF Engineer |  | 6, 219 |
| Cloud Engineer | | 8,570 |
| STEM Openings |  | 944,268 |

(Indeed.com, 2024, p. 1)

Research further shows the trend in new STEM degree awards between 2008 and 2020 (Korhonen, 2023, pg. 1). This research includes all degree categories, including Masters, Doctorate, Associate, and below Associate degrees. The overall number of STEM degrees awarded appears to be increasing overall. The STEM positions available in the U.S. are over 30% higher than the number of graduates available to fill the growing need for STEM talent. A graphical representation is shown in Figure 1:

Figure 1

*U.S. STEM Degree Trend from 2008-2020*



(Korhonen, 2023, pg. 1)

Since the number of degrees awarded is far short of the openings, it becomes even more imperative that each person who is evaluated for hire be evaluated fairly.

## Ethnic Diversity in STEM Fields

Black students are especially underrepresented in math, engineering, and physical science degree programs; they earned no more than 5% of master’s and research doctoral degrees in engineering or physical science during the 2017-2018 school year. Black students comprise just 3% to 4% of degree recipients in mathematics at the master’s level and above.

According to research, Black students earned 9% of bachelor’s degrees, 13% of master’s degrees, and 7% of all research doctorates in computer science fields during the 2017-2018 school year. Further, the survey showed that in the artificial intelligence field, a subset of computer science, only 2.4% of new US resident Ph.D. graduates were Black, and just 3.2% were Hispanic in 2019. This low level of diversity participation in the artificial intelligence field begs whether bias persists in AI algorithms due to lack of diversity (Kennedy, 2021, p. 1 ). This dissertation refers to the word “bias” throughout. It refers to “unintended bias” or bias that was not intentionally built into algorithms to achieve a desirable result.

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The research below further illuminates the percentage of minority population for Blacks and Hispanics being under-represented in these STEM fields (Kennedy, 2021, p. 1 )

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Figure 2

*STEM Job Type by Race/Ethnicity*

Diagram

Description automatically generated

(Kennedy, 2021, p. 1)

Figure 2 shows the ethnicity percentage working in all jobs compared to those in STEM. For example, in the Life Sciences, there are only 6% of Blacks working compared to 11% of Blacks working in all jobs. For Hispanics, the number working in STEM is 8%, which is 9% lower than the 17% working in all jobs. There is a significant under-representation. The percentage of Asians working in STEM is 10% compared to 6% in all other fields. In this case, the Asian population has a higher percentage of people working in STEM fields. The under-represented differences become even more pronounced when one compares the degree fields that drive the development of AI-enabled systems like Math and Computer Science. The number of Blacks and Hispanics working in Math are 9 and 8%, respectively. The number of Blacks and Hispanics working in all jobs is 11 and 17%, higher than those working in STEM. Comparatively, the number of Asians working in Math is 16% compared to 6% of Asians working in all jobs. The difference between Blacks and Hispanics working in computer science compared to all jobs becomes even more exaggerated. The number of Blacks is 7% vs 11% in all jobs. The number of Hispanics is still 8% compared to 17% in all jobs. Conversely, the number of Asians is at 20% compared to 6% in all fields. Mathematicians and Computer Scientists dominate the field of AI (Kennedy, 2021, p. 1). There may be various reasons driving the lower number of workers in STEM jobs than the percentage of graduates in the case of Blacks and Hispanics, but it is certainly an indication of under-employment in a field that has also shown unfavorable biases when AI algorithms are applied to diverse populations.

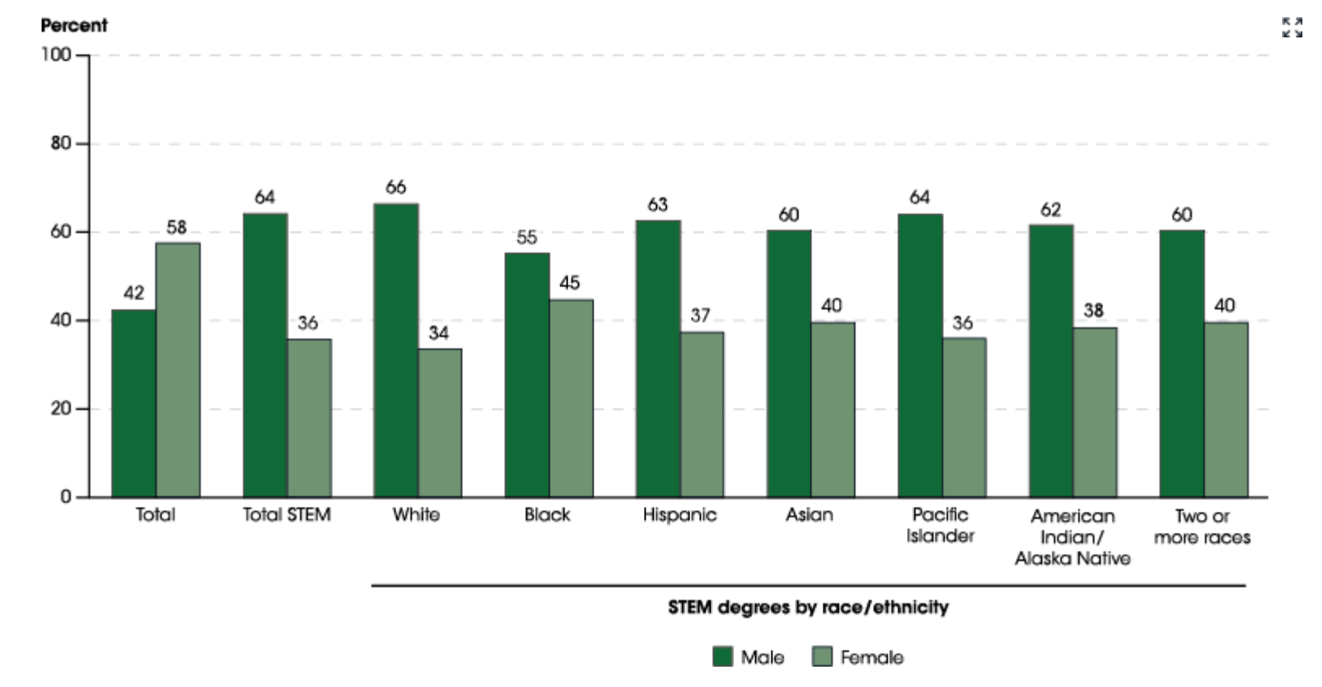
As the study more narrowly focuses on populations that could influence AI as domain experts, it will further examine the impact of ethnicity under-representation in software development, software engineering, software architecture, and IT-related fields on implementing AI-enabled systems using ethical guidelines**.**

## Gender Diversity in STEM Fields

The graph below shows the distribution of STEM degrees by race and gender. Overall, 64% of degrees in STEM-related fields are awarded to men and 36% to women. This is contrasted with the general degree distribution, where 42% of degrees awarded are to men, and 58% are awarded to women. The male-female distribution in STEM is consistently more men than women regardless of the racial group. However, the gap in percentage differs by racial group.

Figure 3

*U.S. Department of Education NCES STEM Degrees by Gender*



(USNCES, 2021, p1)

The research shows the number of women in STEM-related fields and associated trends. Interestingly, it appears that the number of women working in Computer Science has reduced from 32% down to 25% between 1990 and 2019. Computer Science has exploded in the number of jobs over this period. In the field of mathematics, the number of women increased slightly, by 4%, over the same period. Women seem to gravitate to the Life and Physical Sciences disciplines within STEM. The movement of women working in Life and Physical Sciences has been from 34 to 48% and 22 to 40%, respectively, over the same period, as shown in Figure 4(Kennedy, 2021, p. 1).

**Figure 4**

*The trend in women’s representation in STEM by discipline*

Histogram

Description automatically generated

(Kennedy, 2021, p. 1)

The data comparing the number of jobs available, and the production of new graduates shows a general deficiency in the number of STEM graduates. The percentage of diverse women working is small and sometimes shrinking. It points to the need to be sure we maximize the number of qualified STEM applicants considered for open positions. This research examines the impact of AI in resume enhancement vs traditional resume development on pre-screening candidates for interviews.

## Composition of Diverse Talent in AI Development

The literature review examines the demographics of those working in the AI field. As mentioned, the number of Blacks working in STEM is 9%, and in computer-related fields it is 7%. However, the number of Blacks working in companies developing AI products has significantly decreased, according to their self-reported diversity reports. The number of Blacks at Facebook, Google, and Microsoft is 4%, 2.5%, and 4%, respectively (West, 2019, p. 10). Similarly, the number of Hispanics working in STEM is 8%, and in computer-related fields is 8%. However, the Hispanic demographics of companies developing AI products are also significantly lower. The number of Hispanics working at Facebook, Google, and Microsoft are 5%, 3.6% and 6%, respectively (West et.al., 2019, p. 10).

Gender diversity in the computer-related field has decreased from 1990 at 32% to 2020 at 26%, while there has been significant growth in the number of positions available (Pew, 2020, p.1). At Facebook and Google, the number of women is 15% and 10% of their AI research staff, respectively, as reported on their websites (West, 2019, p. 11). “Large-scale AI systems are developed almost exclusively in a handful of technology companies and a small set of elite university laboratories, spaces that in the West tend to be extremely white, affluent, technically oriented, and male.” (West et al., 2019, p. 7).

The very limited number of Black, Hispanic, and women working on developing AI-enabled systems means there are far fewer people to recognize and challenge the resulting biased results. The bias shown in AI-enabled systems may directly be correlated with the lack of diverse representation in developing these products.

# Pre-employment Screening Methods in STEM Fields

Given the shortfall in overall candidates to fill jobs in computer-related STEM fields, and given the percentages of graduates are less than the demand for those needed in the field, literature examines comparatively the impact of screening with ATS and with and without the use of Generative AI by candidates in the development of their resumes and cover letters to increase the population of non-minorities working in STEM who are pre-selected for interviews.

## Applicant Tracking Systems

In 1995, fewer than 300 companies (all major corporations) used applicant tracking software to store, organize, and search resumes, according to Training & Development magazine (Holderman, 2014,p. 154). Today, some industry experts estimate that 80 percent of all companies, large and small, rely on computerized ATS as the first reader for every resume received from any source. This evolution in hiring methodology has significant implications for clients since, for many candidates, the ATS is also the last reader – 75 percent of applicant resumes in many company databases are never seen by a human recruiter or hiring manager because they do not meet the employer’s pre-established criteria for a specific position. (Financial Planning, 2023, p.3)

The most common criteria ATS uses for screening resumes include specific years of experience within an industry or job title. Some employers use ATS selective criteria to search only for currently employed candidates while rejecting all unemployed candidates. Others use the system to select candidates by location (zip code or area code). Some ask the ATS to identify candidates who have worked for (or are currently working for) specific companies or competitors. (Holderman, 2014, p. 160). An explainable (X-AI) framework identifies criteria for resume evaluation: Education level, number of working years, number of awards obtained, number of skills, and previous work positions. (Luo et. al., 2018, p. 4)

The unemployment or under-employment of people due to the criteria used for AI-enabled pre-screening of resumes is a worldwide problem. According to Fuller et al. (2021), “In February 2020, just before COVID-19 triggered global lockdowns, employers struggled to fill positions as the economy approached full employment. The number of unemployed persons per job posting in the United States stood at 0.8, with 7 million positions open in the US, while 5.8 million people remained unemployed, and an equal number were underemployed. There were 721,000 job vacancies in the United Kingdom during the December 2019-February 2020 period, with 1.4 million unemployed people. Similarly, there were 712,000 job vacancies in Germany in February 2020, while 2.3 million people were unemployed” (p. 6). Given these developed countries have significant numbers of people who will be economically insecure, the countries themselves will suffer from economic growth and stability. One can see through history that when large segments of the population are denied opportunity, it causes instability in the foundational fabric of society. Ensuring that all people qualified for positions are fairly evaluated and considered to fill those positions is foundational to societal economic stability and prosperity.

## Impact of Applicant Tracking Systems on Hiring

The literature also documents through the survey of over 2400 companies worldwide where Artificial Intelligence driven Applicant Tracking Systems (ATS) are used to pre-screen resumes. Also highlighted is that 88% of those companies surveyed believe the ATSs are screening out qualified candidates (Fuller et al., 2021, p. 22).

The literature documents that several factors contribute to the premature screening of qualified workers. For example, workers are excluded due to variables such as lack of a college degree or a gap in employment history. The literature asserts that applying “affirmative logic,” which would look for specific skills and experiences associated with fulfilling the role's core requirements, would be more efficient and inclusive {Fuller, 2021, p. 6). The assertion is based on the evidence that after each downturn in the market, the U.S., Germany, and UK labor markets take longer to recover. Specifically, after the 2001 and 2008 downturns, structural issues in the labor market created an imbalance. The number of working-age adults who remained outside the workforce increased post-recession. Those isolated workers have faced serious consequences. Extended gaps appear in their employment histories, which ATSs usually screen out. As time passes, those potential employees fall further and further behind in having the skills that are perceived as necessary by recruiters (Fuller, 2021, p. 6).

Additionally, the literature suggests new metrics for evaluating talent acquisition. The current system emphasizes and rewards expense minimization. Rather, it should maximize human asset maximization. This would measure the time it takes for a new employee to achieve expected levels of productivity, attrition, and advancement.

The literature reveals many studies showing that human resume screening creates a bias in pre-screening resumes (Derous, 2018, p. 234). AI technological evolution has attempted to remove human bias by using mathematical algorithms to make less biased decisions (Cowgill, 2020, p. 25); (Christian, 2021, p. 40). However, there is inherent variability in the characterization or algorithmic modeling of human experiences that lead to qualified employee selection (Christian, 2021, p. 48). There is literature arguing for and against the use of ATS systems that discusses the benefits and the risks (Cowgill, 2020, p. 25); (Christian, 2021, p. 40,48); (Ruehle, 2020, p. 107).

## The Case for Shifting to ATS: Impact of Human Screening on Hiring

The literature review examines the rationale for the chosen experimental design by evaluating a long history of field experiments measuring bias or discrimination experienced by minorities and women seeking employment. These experiments date back to periods before ATSs were used to evaluate candidate qualifications. According to Nunley (2015), “two types of field experiments were primarily used to study racial discrimination in the labor market: in-person and correspondence audits. For the in-person audits, white and black “actors” are recruited and trained to navigate the interview process as perfect substitutes. Such studies have been criticized because of the inability to assess unobservable attributes accurately. Additionally, the actors are aware of the experiment, which may skew their performance during the interview. Correspondence audits, which send resumes instead of actual people to apply for jobs, offer advantages over in-person audits because members of particular groups appear identical to employers in every respect other than variables such as race and gender. Correspondence studies are void of so-called experimenter effects, as the potential employers are unaware that they are part of an experiment, and the candidates for employment are fictitious. Because employers were unaware that they were the subjects of an experiment, correspondence tests likely to elicit the behavior employers exhibit in hiring decisions”. (p. 1097).

An extensive literature review was done on hiring decisions analyzing correspondence tests between 1990-2015 (Zschirnt et al., 2016, p. 37). Over 738 correspondence tests were analyzed in 43 separate studies conducted in OEDC countries. The findings of these experiments were analyzed. One employer is presented with two substantially identical job applications. The only difference is the characteristic of interest: the ethnic or racial group of the applicant. This resulted in controlled experiments on discrimination in hiring decisions in a real-world setting. It can plausibly be argued that differences in call-back rates of equally qualified minority and majority candidates can be attributed to discrimination (Zschirnt et al., 2016, p. 37). The results of these experiments show consistently reduced call-back rates for interviews for resume candidates with ethnic-sounding names versus those without ethnical-sounding names. There is no obvious difference in the experiences or qualifications of the candidates other than their names.

Similarly, Nunley’s (2015) study examined the employment prospects of recent college graduates in the context of a correspondence test experiment in which the races of job applicants are signaled with ethnic and non-ethnic sounding names. “Approximately 9,400 randomly generated resumes from fictitious, recently graduated job seekers were submitted to online job advertisements from January 2013 through the end of July 2013. They differentiate between statistical and taste-based discrimination, which could arise from perceived differences in the quality of training or job-skill match, by assigning approximately half of the applicant’s traditional business degrees. In contrast, the other applicants were assigned degrees from the arts and sciences. Additionally, they randomly assigned in-field internships to provide another source of experience gained before the applicant enters the job market. They then responded to job advertisements exclusively from the business sector so that they were able to examine how mismatches in qualification might affect the racial gap in employment opportunities. The results of these experiments offer strong evidence for discrimination in hiring decisions. There is a significant difference in interview call-back rates based on variation in ethnic-sounding names with no difference in experiences .”( p. 1097).

The experiments outlined in the correspondence test literature are conducted with human reviewers of resumes. There is strong evidence that when human reviewers are engaged in the process, fewer candidates with ethnic-sounding names are selected for interview callbacks. Given the consistency in fewer interview callbacks for ethnic vs. non-ethnic candidates with human resume reviewers, the case can be made that using ATSs, which replace human reviewers with AI-enabled decisions, could be a beneficial alternative to human reviewers.

# Generative AI: Potential Impact on Candidate Pre-screening

The literature discloses a shift in the methods used to create resumes. Manual creation of resumes is shifting to AI-enabled enhancement or creation of resumes. With the recent release of Generative AI models like ChatGPT, candidates for particular positions can use AI to tailor their resumes to align with the keywords sought in ATS. In effect, candidates can use AI to prepare their resumes to be screened by AI in ATS to increase their likelihood of being selected for an interview during the ATS pre-screening process.

In a 2023 study on how Generative AI would impact scientific management theory, according to Korzynski et al., many routine activities in human resource management (HRM) may need to be standardized and automated. These tasks can be performed by AI much faster and at greater volume than by humans. According to Kornzynski et al. (2023), “For instance, with the emergence of e-HRM, recruiters receive increasing numbers of applications per position and can no longer process the increased amounts of information and make decisions at the needed speed and volume (Black & van Esch, 2020, p. 223). ChatGPT takes this automation possibility to the next level because of the ability to learn and improve over time. With machine learning, ChatGPT can be trained on HR-related data, such as job descriptions, resumes, and HR guidelines, which can help perform routine activities.” (p46).

## The Case for Generative AI

ResumeBuilder.com (2023) conducted a study to determine if applicants who used ChatGPT to develop resumes or cover letters were more successful in interview pre-selection than those who did not use ChatGPT. “A population of 1000 respondents seeking jobs were evaluated, making it through pre-screening for interview selection. 46% used ChatGPT to write their resumes and/or cover letters. 72% reported using ChatGPT to write cover letters, which yielded high or very high quality. Of those respondents, 28% had to do little to no editing of the resumes and cover letters written by ChatGPT. 69% of those who used ChatGPT found they got a better employer response rate. Thus, 78% passed the pre-screening and were selected for interviews.” (p. 1-2) This indicates a strong relationship between Generative AI-enhanced or created resumes leading to pre-interview selection for the general job market.

## The Case Against Generative AI

Generative AI suffers from what is called “Hallucinations.” This means that one prompts a model, like ChatGPT, with a question. It returns what sounds like a very authoritative answer, which is incorrect. A study done by Elmohande et al. (2023) states, “Language models, such as ChatGPT, are dynamic, complex systems; thus, there is always room for improvement and expansion (Dwivedi, 2023). Improving the system will necessitate using more diverse training data, including text from various languages and cultures, comprehending a more diverse group of users, providing more precise fallback responses, increasing the depth of information provided, and avoiding disorganized or misleading responses (Eke, 2023). A challenge has recently been revealed regarding severe intellectual property and data ownership issues” (p. 21).

The policy risks are no less daunting than the technical ones. According to Illuminator (2023) in a 2023 study, “As a result, he said, companies that use AI often are regulating themselves: Unfortunately, I think what’s happened is a lot of AI developers and sales have been very effective at crowding out the conversation with policymakers around how to govern AI and to mitigate social consequences,” Okoh said. “And so, unfortunately, there’s a lot of interest in developing self-regulatory schemes. Some self-regulatory practices include audits or compliance that use general guidance such as the Blueprint for an AI Bill of Rights, Okoh said” (p. 4).

The results have sometimes raised concerns. Some organizations operating under their guidelines have used AI recruiting tools that showed bias, notably, Amazon’s hiring system, which the company’s developers found showed bias against women (West et al., 2019, p. 7). This weakness of using Generative AI requires further analysis of the self-governing principles discussed by companies developing and using AI for pre-employment screening.

There has been research on the shortfall of diversity and women in the STEM field relative to the number of open positions. Additionally, there has been research on the application of AI in the job search process prematurely screening out diverse women. There has also been research on the successful use of Generative AI in resume development and enhancement, which has successfully led to pre-selection for interviews in the job evaluation process. There has not been research specifically evaluating the interview selection rates between those who use Generative AI for resume creation or enhancement and those who do not among job seekers in STEM fields, particularly comparing the diverse and gender populations.

# Theoretical Framework

The theoretical framework through which the use of AI in employment pre-screening will be analyzed **is** the Self-Determination Theory.

## Self-Determination Theory: Changing Times Require Changing Methods

As applicants for positions grapple with being pre-screened for interview selection, assuming they would adjust to improve the likelihood of pre-selection is reasonable. Self-determination theory is a framework to evaluate the candidate’s behavior evolution in response to the use of ATS for candidate interview pre-selection. “Self-determination theory (SDT) is a theory of personality development and self-motivated behavior change. Fundamental to the theory is the principle that people have an innate organizational tendency toward growth, integration of the self, and the resolution of psychological inconsistency (Deci et al., 2002, p. 39). SDT was initially developed from experimental and field investigations of the effects of environmental events such as rewards, praise, or directives on intrinsic motivation (Ryan et al., 2022, p. 2). The interest in factors that facilitate or undermine intrinsic motivation subsequently led to theoretical and empirical investigations of volitional behavior more generally. Of particular interest is how people internalize and integrate extrinsic motivations and self-regulate their behaviors to engage autonomously in actions in their daily lives (Ryan et al., p. 2). SDT proposes that all behaviors can be understood as lying along a continuum ranging from heteronomy, external regulation, autonomy, or true self-regulation. SDT hypothesizes a variety of consequences associated with more controlled versus autonomous behavioral regulation, including effort, persistence, the quality of performance, and the quality of subjective experience. Autonomous regulation of behavior is held to be more stable and enduring and to have more positive effects on human well-being than controlled regulation (Ryan & Deci, 2000). SDT also specifies a number of factors that foster or undermine more autonomous styles of behavior regulation, including how parents, teachers, managers, and clinicians can either foster or forestall self-motivation for new behaviors.” (Markland et al., 2005, p. 26).

There have been varied positions relative to the use of Generative AI to assist candidates in aligning their qualifications with keywords searched for by ATS. The degree to which the use of Generative AI is viewed as an acceptable alternative is the degree to which it will continue to be used. Markland (2005) states in his description of self-determination theory motivation, “To the extent that the social environment provides for the nurturance of perceptions of competence, autonomy, and relatedness the person will move toward integration and a unified sense of self, and develop the personal resources for engaging in adaptive and autonomous self-regulation of behavior (Deci & Ryan, 1991, 2000)”. (p. 26). A discussion below will describe methods ChatGPT is used in job searches and reactions to its use.

## Self-Determination Theory Implications for Generative AI Use by Prospective Employees

There are several examples of people using ChatGPT in their job searches. Those who are laid off and searching can become drained emotionally. In the following case, the psychological stigma of being laid off and subsequent writer's block was overcome using ChatGPT. In case study number one, the subject laid off used ChatGPT to help write cover letters, including one that got him a foot in the door and later hired at a smart-tech company. The condition of being laid off and continually applying for jobs was very draining emotionally. ChatGPT was used to break writer's block, distilling the long-winded cover letter into four tight paragraphs. It was also used to help prepare for job interviews by suggesting new ways to ask about company culture and expectations for the role. Instead of asking a vague question about excelling in the prospective job, ChatGPT suggested more specific questions about the time frame and metrics for determining success. (Alcántara, 2023, p. 2). The self-determination theory driving the subject's desire to autonomously overcome the obstacle before them drove the use of ChatGPT as a newly available, creative solution.

This experience using ChatGPT demonstrates how SDT on the autonomous behavior side of the continuum has positive effects on human well-being, particularly in providing intrinsic behavior to overcome obstacles. ChatGPT was used to break writer's block, create a more concise cover letter, and create questions for the interviewer.

In use case number two, after being let go by a previous employer, subject two started job hunting for roles in software engineering -- alongside thousands of laid-off tech workers. The subject turned to ChatGPT for help, first sharing job descriptions and resumé with the chatbot to see what it would tweak. Then, the subject asked ChatGPT to write a recommendation letter for a coveted role. The chatbot assessed the subject was perfect for the job, as his technical skill set "aligns well with the requirements." The subject told the recruiter of the bot’s assessment. The disclosure intrigued the recruiter, who liked the creativity, but ultimately, the subject was hired at another company without ChatGPT's help” (Alcántara, 2023, p. 3). While it wasn’t immediately helpful, perhaps the creative approach, a self-determined approach, gave the momentum to keep pursuing other options.

Similarly, this experience using ChatGPT demonstrates how SDT autonomy positively affects human well-being. ChatGPT was used as a tool to align the resume with the job description and write a recommendation letter.

## Self-Determination Theory Implications for Generative AI Use by Prospective Employers

In a third use case, the hiring manager requires the candidates to write a tweet and press release to communicate the presence of a new microwave tower. Most candidates fail the test because it requires research about the geographic area and the industry. The hiring manager noticed an anomaly when five applicants passed the test with similar language in the press release. The hiring manager then used ChatGPT to create the press release and got the same answer that all five candidates had produced on the test. This was viewed as a problem initially. After grappling with the change in approaches by candidates, the hiring manager augmented the assessment to require additional research and edits to illuminate the candidate’s true skills. (Alcántara, 2023, p. 4). In this case, the SDT on the side of autonomy prevailed for the candidates by allowing them to continue to take advantage of the new Generative AI capability, but the new assessment and a subsequently installed bot detector regulated the degree to which their creativity could be applied to the responses without transparency. The ethical principle of transparency suggests that users and developers of AI should be transparent about the use and application of AI, which should be disclosed willingly.

In the use cases, managers have had positive and negative reactions to using and accepting Generative AI in the employment pre-selection process. The SDT theory and ethical principles provide important and nuanced factors to consider when evaluating the appropriate use of Generative AI.

# Sociological Perspectives

The use of AI-enabled systems in many areas has demonstrated biased results that unfairly cause harm to minorities and women. Several noteworthy examples are facial recognition, which has a high error rate when facial matching women of color compared to facial matching for white men (Raji et al., 2020, p. 34). Additionally, the COMPAS prison sentencing system over-predicts repeat offenses for African American men compared to white men (Angwin, 2016, p. 18 ). The most relevant example to this study is Amazon's recruitment tool, which screened out references to women during the AI-enabled resume screening process (Illuminator, 2023, p. 4). Companies and governments' response to the widespread problem of bias against segments of society has been to issue self-governing guidelines without necessarily the social sensitivity to how these guidelines impact cultures worldwide differently.

## Ethical Guidelines in AI

This consistency in racial and gender-based bias for AI-enabled systems has led to the development of many published AI Ethical guidelines or principles. In Hagerty’s (2018) review of AI's social impacts and ethical implications, “Rather than offering a simple set of solutions, situating AI ethics within heterogeneous and malleable cultural milieus complicates the way AI technologies interface with global populations. Technology companies and governments are increasingly developing ethical principles to address questions of the social impacts and ethical implications of artificial intelligence technologies. In 2018, sixteen countries released national AI strategies, including at least some stated ethical principles.” (p. 18)

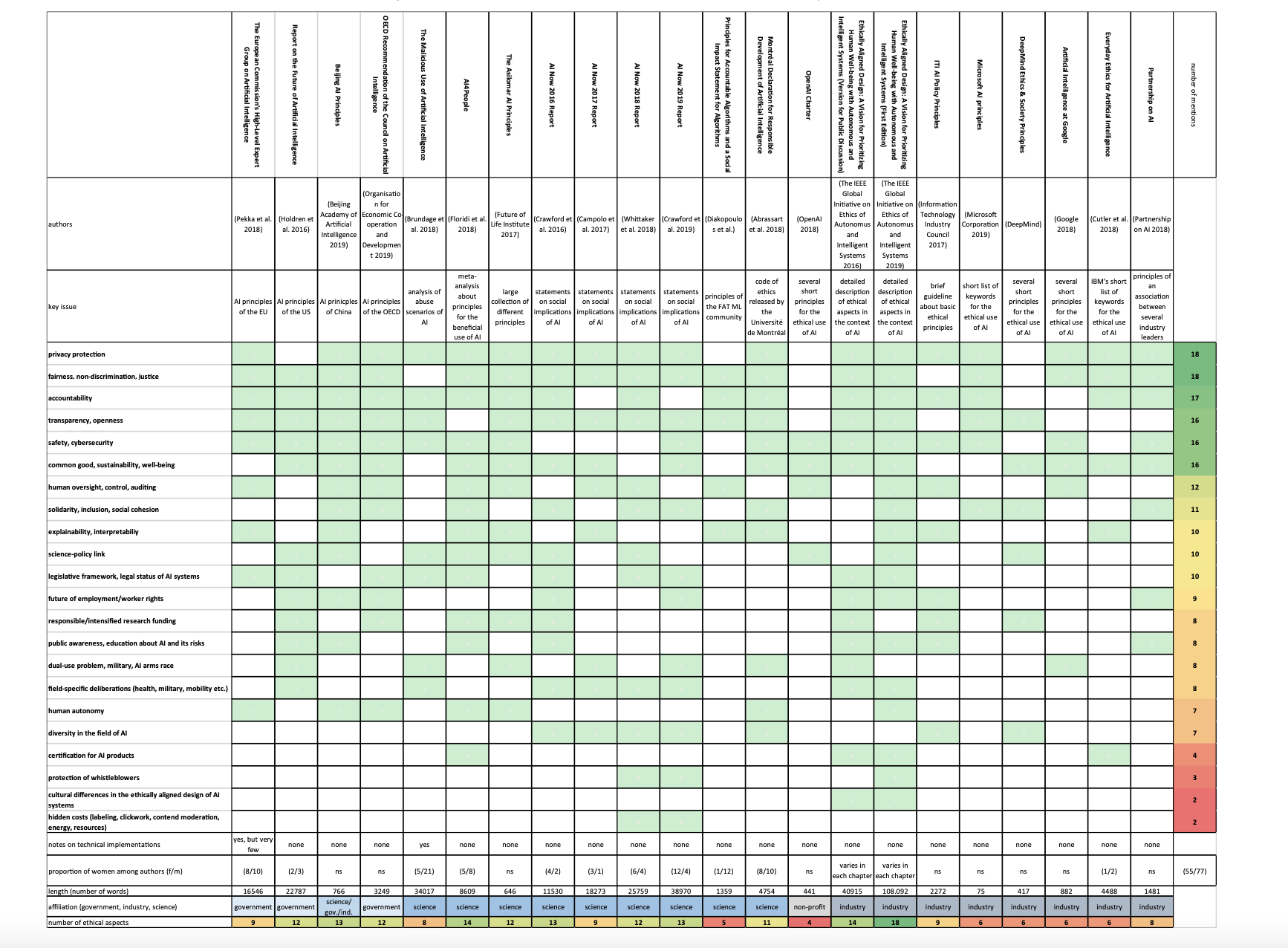
These principles increase the awareness of developers and users that resulting algorithms have the potential to disadvantage one group over another. The principles are not regulated by policy but are guidelines to be followed at will for a wide array of AI uses by companies and prospective employees. Through the development of AI Ethics guidelines, several AI ethics researchers have defined AI Ethics as virtue ethics. These AI researchers define the ethics of what is called an agent. The agent simply refers to the AI software or algorithm making decisions. The ethical definition accepted by the AI researchers is as follows:

Ethics is a normative, practical philosophical discipline of how one should act towards others. Virtue ethics: an agent is ethical if and only if it acts and thinks according to some moral values (Yu et al. 2018, p. 5527).

The ethical implications of AI used in resume pre-screening are considered, and the moral values are defined by the public or private institution to which the AI-enabled system is applied. Therefore, it is imperative to examine the principles of AI ethics established by the public and private sectors. Figure 5 is an analysis of 21 documents released over the period of 2016-2020 that were based on ethical guidelines and principles. A heat map was created for the prevalence of the dominant principles (Hagendorff, 2019, p. 102).

**Figure 5**

*Heatmap of AI Ethical Guidelines*



(Hagendorff, 2019, p. 102)

## Public Sector Ethical Guidelines

The public sector AI ethical guidelines represent the EU AI Ethical guidelines developed by a European Commission High-Level Expert Group on AI, called Ethics Guidelines for Trustworthy AI. The objective of the guidelines was to create a framework that led to Trustworthy AI. The central concerns for AI ethics guidelines were the good life of individuals, whether in terms of quality of life or human autonomy and freedom necessary for a democratic society. The resulting principles in the context of AI-enabled systems are:

### Respect for Human Autonomy.

This principle is defined as ensuring respect for the freedom and autonomy of human beings. Humans interacting with AI systems must be able to maintain full and effective self-determination over themselves and partake in the democratic process. AI systems should not unjustifiably subordinate, coerce, deceive, manipulate, condition, or herd humans. Instead, they should be designed to augment, complement, and empower human cognitive, social, and cultural skills. The allocation of function between human and AI systems should follow human-centric design principles and leave meaningful opportunities for human choice. This means securing human oversight over work processes in AI systems. AI systems may also fundamentally change the work sphere. It should support humans in the working environment and aim for the creation of meaningful work.”

### Prevention of Harm**.**

AI systems should neither cause nor exacerbate harm or adversely affect human beings. This entails the protection of human dignity as well as mental and physical integrity. AI Systems and the environments in which they operate must be safe and secure. They must be technically robust, and they should be ensured that they are not open to malicious use. Vulnerable persons should receive greater attention and be included in developing, deploying, and using AI systems. Particular attention must also be paid to situations where SI systems can cause or exacerbate adverse impacts due to asymmetries of power or information, such as between employers and employees, businesses and consumers, and governments. Preventing harm also entails consideration of the natural environment and all living beings.

### Fairness.

The development, deployment, and use of AI systems must be fair. While we acknowledge many different interpretations of fairness, we believe that fairness has both a substantive and a procedural dimension. The substantive dimension implies a commitment to ensuring equal and just distribution of both benefits and costs and ensuring that individuals and groups are free from unfair bias, discrimination, and stigmatization. AI systems could even increase societal fairness if unfair biases can be avoided. Equal opportunity in terms of access to education, goods, services, and technology should also be fostered. Moreover, the use of AI systems should never lead to people being deceived or unjustifiably impaired in their freedom of choice. Additionally, fairness implies that AI practitioners should respect the principle of proportionality between means and ends and consider carefully how to balance competing interests and objectives. The procedural dimension of fairness entails the ability to contest and seek effective redress against decisions made by AI systems and by the humans operating them. To do so, the entity accountable for the decision must be identifiable, and the decision-making process should be explicable.

### Explicability.

Explicability is crucial for building and maintaining users’ trust in AI systems that are openly communicated and decisions – to the extent possible -explainable to those directly and indirectly affected. Without such information, a decision cannot be duly contested. It is not always possible to explain how a model has generated a particular output or decision (and what combination of input factors contributed to that). These cases are referred to as black box algorithms and require special attention. In those circumstances, other explicability measures (e.g., traceability, auditability, and transparent communication or system capabilities) may be required, provided the system respects fundamental rights. The degree to which explicability is needed depends on the context and severity of the consequences if that output is erroneous or otherwise inaccurate” (Rotenberg, 2020, p. 44-60).

Following the release of the EU AI Principles, they devised the AI Act. “The AI Act aims to establish a cohesive legal framework governing AI systems within the EU. A prominent feature of this framework is the introduction of a “risk-based approach,” which entails the categorization of AI systems into four distinct groups based on risk assessment: namely, unacceptable risk, high risk, limited risk, and low/minimal risk. This stratification allows for tailored regulations that seek to tailor future regulations according to the four potential risk classes associated with different AI applications“ (Celsi, 2023, p. 3). For the literature review and subsequent analysis, the use cases of using ChatGPT for cover letter and resume creation or enhancement is considered an acceptable risk because the prospective employee is the final decision-maker for the content recommended by ChatGPT.

## Ethical Implications of Generative AI Use by Prospective Employees

The central concerns for AI ethics established by the EU were the good life of individuals, whether in terms of quality of life or human autonomy and freedom necessary for a democratic society as we examine the application of the ethical principle of respect for Human autonomy, which foremost encourages freedom and autonomy of human beings (Rotenberg, 2020, p. 50). Interestingly, it requires humans to interact with the AI-enabled technology similarly to the SDT on the autonomy side of the continuum. The respect for human autonomy principle also requires that humans interacting with AI systems be able to maintain full and effective self-determination over themselves and partake in the democratic process. (Rotenberg, 2020, p. 50). As a reminder, case study number one described a subject who was laid off and used ChatGPT to help write cover letters, including one that got him a foot in the door and later hired at a smart-tech company. The condition of being laid off and continually applying for jobs is emotionally draining to the subject. ChatGPT was used to break writer's block, distilling the long-winded cover letter into four tight paragraphs. It was also used to help prepare for job interviews by suggesting new ways to ask about company culture and expectations for the role. (Alcántara, 2023, p. 1). Innovatively applying ChatGPT to both the cover letter and developing interview questions was instrumental in creating a higher quality cover letter and interview. The freedom to choose a new method, ChatGPT, to prepare for employment application was aligned with the EU ethics description of respect for human autonomy. Clearly, the applicant used ChatGPT to write the cover letter to interact with the system in a way that allowed him to address his need for a more condensed version of his cover letter autonomously (Alcántara, 2023, p. 1). In the user’s interaction with this AI-enabled system, it did not subordinate, coerce, deceive, manipulate, or condition his response (Rotenberg, 2020, p. 50) because the user has the final responsibility to verify the information the systems give him in response to prompting is not deceptive or inaccurate. It appears the user felt empowered cognitively and socially (Alcántara, 2023, p. 1). The allocation of function between human and AI systems should follow human-centric design principles and leave meaningful opportunities for human choice (Rotenberg, 2020, p. 50). The users' experience did not obligate them to use the output. Instead, the results were evaluated, and a decision was made to use the condensed version of the cover letter and additional questions for the interviewer (Alcántara, 2023, p. 1).

As we explore the quality of life, particularly for public sector governance over individuals, working is foundational to individual and societal well-being. According to Fuller, in the use of ATSs, qualified workers are removed from employment consideration (Fuller, 2021,p. 6). If using ChatGPT increases the likelihood of finding employment, as in this case, it appears so, then the quality of life was improved for the subject. According to Horbach, productivity for society will be reduced, and innovation will be stifled with a gap between available positions and workers who can fill those positions. (Horbach et. al., 2020, p. 6). Thus, the ethical guidelines support not only individual autonomy and quality of life, which is necessary for societal well-being, but also improve overall societal productivity.

As we examine the ethical principle of Prevention of Harm, as the job seeker used ChatGPT to condense the cover letter, it requires that the AI-enabled system should neither cause nor exacerbate harm or otherwise adversely affect human beings. The use of ChatGPT did not cause harm to the user. Conversely, it helped the user. Thus, human dignity was protected, and mental and physical integrity was maintained. Additionally, the AI-enabled system was safe and secure based on the reporting in the use case experience. While not explicitly obvious from this use case, if the person were vulnerable (e.g., visually or hearing impaired), the AI-enabled system should still allow persons to interact with the system. The prevention of harm principle also requires particular attention to be paid to situations where AI systems can cause or exacerbate adverse impacts due to asymmetries of power or information, such as between employers and employees, businesses and consumers, or governments and citizens. The user of ChatGPT was not directly connected to the employer or governmental entity. So, it appears there was no asymmetric power imbalance. If the employer or government had shared the results prior to condensing them using the tool, there may have been undue harm. The tool was analogous to using Microsoft Word in this case to check grammar and condense writing for more concise wording. Finally, prevention of harm requires consideration of the natural environment and all living beings. AI-enabled systems, particularly Generative AI models, require a great deal of energy to run. The extent to which the environment is harmed through excessive power generation is beyond the scope of this research.

As the principle of fairness is examined, it intends to ensure equal and just distribution of benefits and costs and ensure that individuals and groups are free from unfair bias, discrimination, and stigmatization. The use of ChatGPT is open to the public. It is free to use. A tool such as Microsoft Word is not as accessible to the public as ChatGPT. On the surface, there is no appearance of unfair or discriminative bias in the use of this tool.

However, there have been reports of bias in the results produced by ChatGPT. An AI algorithm is only as unbiased as the underlying training data. There have been studies on the accuracy of language translation across the globe using Generative AI. If the training data for a particular region is not as dense in the model, the resulting recommendations from Generative AI will be less accurate and more likely to contain bias. A study of ChatGPT’s performance relative to language resources demonstrates a considerable gap between its performance on low-resource and high-resource languages. Specifically, performance in English, Japanese. Russian, German, French, and Chinese showed acceptable accuracy. However, Akan, Samoan, and Southern Sotho showed very poor results. The results were tied to the underlying training data in the ChatGPT model. (Zhuo et. al., 2023, p. 4)

Another factor that might lead to bias or discrimination is hallucinations. According to Zhuo, these hallucinations require the final decision-maker from the results of ChatGPT to be a human. Specifically, the reliability of generative language models may be compromised by the phenomenon of hallucination. Hallucination refers to the generation of false or misleading information by such models. This problem is prevalent in natural language generation, and the distribution of misinformation and disinformation is a common manifestation. However, measuring the prevalence of hallucination in natural language generation is challenging, as it typically necessitates using human judgment” (Zhuo, 2023, p. 6).

The principle of Explicability was created to maintain users’ trust in AI systems recommendations and decisions, as much as possible, to users directly and indirectly affected. Explicability, sometimes called explain-ability, is required for a decision to be contested. For the system to respect fundamental rights, traceability, auditability, and transparent communication or system capabilities may be required. The degree to which explicability is needed is dependent on the risk associated with the recommendation or decision. (Rotenberg, 2020, p. 44-60). As previously mentioned, the use of ChatGPT to create a cover letter and develop interview questions is considered low because the job candidate can have the final authority to use the recommendations coming from ChatGPT.

The ChatGPT model does not provide the rationale as to why it makes recommendations. There is little to no transparency into the underlying algorithm. For the reasons mentioned above, the system user has an obligation to ensure the resulting cover letter being presented regarding qualifications is accurate. Similarly, the questions suggested for the interview should also be vetted against independent sources to ensure an accurate representation of the company’s facts. There is a direct correlation between trust in an AI system and the provenance of information from which decisions are derived. Without addressing the need for provenance, the proliferation of misinformation could erode societal trust in the system (Zhuo, 2023, p. 6). The user is the final decision maker, so the explicability principle is not as consequential as respect for human autonomy, prevention of harm, and fairness in this use case.

## Ethical Implications of Generative AI Use by Prospective Employers

In a third use case, the hiring manager requires the candidates to write a tweet and press release to communicate the presence of a new microwave tower. This requires research about the state of microwave systems in the geographic area and the industry. The hiring manager noticed an anomaly when five applicants passed the test with similar language in the press release. The hiring manager then used ChatGPT to create the press release and got the same answer that all five candidates had produced on the test. This was viewed as a problem initially. After grappling with the change in approach by candidates, the hiring manager augmented the assessment to require additional research and edits to illuminate the candidate’s true skills. The new assessment PR test and a subsequently installed bot detector regulated the degree to which the candidates could use ChatGPT responses without transparency. (Alcántara, 2023).

From the perspective of respect for human autonomy, the manager maintained the user’s ability to work autonomously but increased the regulation of responses with a bot detector. A bot detector would identify ChatGPT-driven responses not as a disqualifier but to allow the employer to distinguish between ChatGPT-derived content and the candidates’ unique skills. The manager adjusted to the new approach, and it became an enabler to increase the type of skills evaluated by the candidate.

From the perspective of prevention of harm, in a low-risk application such as those in use case three, there is little to no harm that could be inflicted on either party. However, the prevention of harm principle also requires particular attention to be paid to situations where AI systems can cause or exacerbate adverse impacts due to asymmetries of power or information, such as between employers and employees, businesses and consumers, or governments and citizens. The employer employed Generative AI detection as part of the employment assessment process, ensuring the assessment evaluation is fairly applied across demographic groups and individuals. The fairness principle requires no bias or discrimination to be present in the use of Generative AI. There is insufficient information about the modified assessment test to assess bias in applying the new approach.

## Private Sector Ethical Guidelines

The literature review research for private sector ethical guidelines considers the environments in which AI-enabled systems are both developed and operationalized. In a one-year study by West et al. on this discriminatory impact on races and gender of these systems, it is stated, “But as the focus on AI bias and ethics grows, the scope of inquiry should expand to consider not only how AI tools can be biased technically, but how they are shaped by the environments in which they are built and the people that build them. By integrating these concerns, we can develop a more accurate understanding of how AI can be developed and employed in ways that are fair and just, and how we might be able to ensure both” (West et al., 2019, p. 7).

Large-scale AI systems are developed almost exclusively in a handful of technology companies and a small set of elite university laboratories, spaces that in the West tend to be extremely white, affluent, technically oriented, and male. These are also spaces that have a history of problems of discrimination, exclusion, and sexual harassment. As Melinda Gates describes, “Men who demean, degrade or disrespect women have been able to operate with such impunity—not just in Hollywood, but in tech, venture capital, and other spaces where their influence and investment can make or break a career” (West et al., 2019, p. 7).

The most prevalent AI Ethics principles in the private sector are similar but not the same as those in the public sector. Each of the principles is written with very broad “Ethical” language, leaving interpretation open and implementation very fuzzy. The terms for some of the principles have similar meanings, so they are clustered together. The five most prevalent principles or categories of principles are:

1. Privacy
2. Fairness, Non-discrimination, Justice
3. Transparency and Openness
4. Accountability
5. Safety and Cyber Security (Hagendorff, 2019, p. 102)

The two ethical principles that seem unique to the private sector are privacy and accountability. The private sector companies engaged in the development of ethical principles are developing AI-enabled systems and applying these systems globally. Cross-cultural factors are associated with the impact of the private sector. This is also why having a diverse STEM workforce can minimize bias and discrimination during the development lifecycle. Privacy and Accountability will be discussed further in the context of the use cases. The other principles will be considered as they relate to the cultural influences of AI-enabled system development and operation.

### Privacy.

The private sector definition of Privacy for Microsoft focuses on secure systems that respect people's privacy (Rotenberg, 2020, p. 197; Hagendorff, 2018, p. 104). IBM's expressed values around privacy involve protecting the rights of the user’s data and preserving the user's access and use of their data” (Rotenberg, 2020, p. 195). This is increasingly more important as the UK has made protecting users’ data a legal requirement under GDPR, General Data Protection Rights (Hagerty et al., 2023, p. 10). The state of California enacted a similar law protecting user data called CCPA, or the California Consumer Privacy Act (Barrett, 2019, p. 25). The CCPA was amended with a provision weakening consumer rights, requiring the California Privacy Protection Agency to issue “regulations governing access and opt‐out rights concerning businesses’ use of automated decision-making technology, including profiling and requiring businesses’ response to access requests to include meaningful information about the logic involved in those decision-making processes, as well as a description of the likely outcome of the process concerning the consumer.” (Kaminski,2021,p. 1962). Private sector companies seem to be preparing for a greater policy-based focus on protecting users’ data, giving them greater flexibility than the consumers.

Perspectives on privacy vary widely depending on culture and social norms. Depending on the culture, the ethical interpretations of privacy are different. Hagerty writes, “Conceptions of privacy differ by culture. An American visiting the Netherlands is likely to be struck by the lack of curtains on windows, with families eating dinner and watching TV in clear view of the street. Americans are likely to have been raised with the idea that privacy is a natural right of the individual. In contrast, someone who grew up in China is more likely to have absorbed a notion of privacy as something that pertains to the family rather than the individual. In China, the concept of privacy appears to be shifting. In contrast, it was once seen in primarily negative terms, often closely related to selfishness that has softened (Hagerty et al., 2023, p. 10). Hagerty (2023) also states, “Conceptions of privacy are shaped by culture and intersect with our understandings of the nature of personhood and the relationship between the individual and society. The ethical ideas informing AI principles do not travel light, but come encumbered with social histories and cultural assumptions” (p. 11). The concept of privacy varies widely depending on the culture where AI is being used to pre-screen candidates' resumes for interview selection. The use of ChatGPT for resume creation or enhancement may also differ widely depending on the culture in which the resume is being developed.

### Fairness, Non-discrimination, Justice.

Similarly, in fairness, non-discrimination, and justice, depending on the company or region, there are different expressions of ethical values. In a case study in Brazil, the use of facial recognition in COMPAS prison sentencing systems, which have been proven to show bias in African American populations, was viewed to be adequate for use in policing. (Hillman, 2019, p. 37). Beyond the social difference in interpretation variability, there are design considerations in AI development and use.

It is critical to understand how AI disadvantages some and how it works to the advantage of others, reinforcing a narrow idea of the ‘normal’ person in the classification of data. By tracing the way in which race, gender, and other identities are understood, represented, and reflected, both within AI systems and in the contexts where they are applied, one can begin to see the bigger picture, which acknowledges power relationships, and leans toward equity and justice (West et al., 2019, p. 7).

In autocratic regimes, AI-enabled systems can become an enabler for disadvantaging large segments of their societies and favorably viewing very few. The development and user community must understand in the design and development process in democratic societies that the training data includes representation from the entire population on which it operates. This will minimize unintentional bias against one population or another. One important way to ensure a diverse representation of training data is to have a diverse representation of employees during the design and development life cycle. This includes testing the systems before deployment and over time. The guideline for fairness is that AI should treat all people fairly or that AI must minimize unintentional bias and promote inclusive representation.

### Transparency and Openness.

Of all the AI Ethics principles, Transparency and Openness have had the most enduring discussions. It encompasses making sure the AI is explainable, meaning one can explain why every outcome occurs and that those outcomes align with the original design intent. The range of considerations here for transparency and openness ranges from having an open discussion during the design process with experts in all areas to explaining decisions made years after the systems are deployed. The beauty of AI is it learns. The challenge of AI is understanding over time if the learning aligns with the ethical values one sets out to accomplish. Microsoft simply states, “Transparent AI systems should be understandable” (Rotenberg, 2020, p. 197). IBM states, “AI should be designed for humans to easily perceive, detect, and understand its decision process” (Rotenberg, 2020, p. 193-194). So, the ethical values around transparency and openness all point to understanding the rationale for decisions made by the system. In many cultures, a small group of leaders closely determine how decisions are made. This is certainly true in the Brazilian example of the continued use of facial recognition and COMPAS prison sentencing software after the software's discriminatory biases were part of the public discourse.

### Accountability.

Accountability's ethical value is a culmination of compliance with all the other principles. Microsoft states AI systems should have algorithmic accountability (Rotenberg, 2020, p. 197). IBM states “All designers and developers are responsible for considering AI design development, decision processes, and outcomes” (Rotenberg, 2020, p. 192). “Microsoft points to the algorithm accountability, and IBM points to understanding end to end from development to use to outcomes of AI systems. Regardless of the ethical principal definition, it points to being accountable or responsible for fully understanding the AI-enabled system's performance. However, as previously mentioned, these systems have very few regulations to hold private companies accountable.

### Safety and Cyber Security.

Finally, the fifth and most prevalent AI Ethical principle is that AI is Safe and builds on cybersecurity. As discussed, Microsoft combines the safety and security discussion with privacy”.(Rotenberg, 2020, p. 197). This principle applies to companies that develop and operate AI-enabled systems.

## Ethical Implications of Generative AI Use by Prospective Employees

As a reminder, case study number one described a subject who was laid off and used ChatGPT to help write cover letters, including one that got him a foot in the door and later hired at a smart-tech company. The condition of being laid off and continually applying for jobs was very draining emotionally to the subject. ChatGPT was used to break writer's block, distilling the long-winded cover letter into four tight paragraphs. It was also used to help prepare for job interviews by suggesting new ways to ask about company culture and expectations for the role. (Alcántara, 2023, p. 1). Innovatively applying ChatGPT to both the cover letter and developing interview questions was instrumental in creating a higher quality cover letter and interview questions.

Concerning the ethical principle of Privacy, the prospective employee put his personal qualifications in ChatGPT. Once one puts information into ChatGPT, it becomes public domain information. The ethical principle of privacy no longer applies to this information. The risk of losing the right to privacy over unique qualifications is low as most people’s professional information is already in the public domain in Western countries. The loss of privacy of information in some countries or in some Western countries’ professions may be of greater concern. The prospective employee must be aware of the loss of privacy before entering their information into such a system. Concerning the Accountability principle, the private sector's view is primarily on algorithmic accountability, which applies to the system development lifecycle. (Rothenberg, 2020, p. 192) not the user or employee,

## Ethical Implications of Generative AI Use by Prospective Employers

As a reminder, in the third use case, the hiring manager requires the candidates to write a tweet and press release to communicate the presence of a new microwave tower. This requires research about the state of microwave systems in the geographic area and the industry. The hiring manager noticed an anomaly when five applicants passed the test with similar language in the press release. The hiring manager then used ChatGPT to create the press release and got the same answer that all five candidates produced on the test. This was viewed as a problem initially. After grappling with the change in approach by candidates, the hiring manager augmented the assessment to require additional research and edits, which would illuminate the candidate’s true skills. The new assessment PR test and a subsequently installed bot detector regulated the degree to which the candidates could use ChatGPT responses without transparency. (Alcántara, 2023).

Examining the assessment of employees using an assessment test against the privacy principle. The employer is advised to protect the privacy of the information the prospective employee provided on the assessment test. The assessment test and bot detector employed must also be non-biased and without discrimination. One important consideration, according to a study by Zhuo et al., is that “Social bias may occur when the data used to train a language model includes biased representations of specific groups of individuals, social stereotypes and unfair discrimination may result. This may cause the model to provide unfair or discriminatory predictions towards those groups. For example, a language technology that analyzes curricula vitae for recruitment or career guidance may be less likely to recommend historically discriminated groups to recruiters or more likely to offer lower-paying occupations to marginalized groups. To prevent this, it is essential to ensure that the training data is diverse and representative of the population for which it will be used and to actively discover and eradicate any potential biases in the data.” (Zhuo, 2023, p. 4). This is a critical responsibility of the employer that applies to this use case and to the use of ATSs writ large. Another form of employee assessment is AI analysis of micro-expressions. According to West et al. (2019), assessing worker competence via visual ‘micro-expressions.’ are deeply flawed, replicating patterns of racial and gender bias in ways that can deepen and justify historical inequality (West et al.,2019, p. 3). Micro-expressions and other visual clues can often be steeped in culture. As stated by Hagerty (2023), “To understand ethics, we must understand culture, and vice versa. Ethics and culture must be considered together as interlocking strands of social DNA. These twin helices constitute each other. To understand any culture, we must consider its values; to understand values, we must understand their cultural context. Because ethics and culture are joined, we cannot study ethics solely as a philosophical abstraction. Ethics must be studied in everyday cultural contexts to be fully understood. In other words, it is not enough to know the “rules of the game” we must also understand how people play. Up-close and on-the-ground research is vital” (Hagerty, 2023, p. 9). It becomes very important that cultural context be considered in the development and use of AI.

The unintended consequences of the AI-enabled system's effect on racial and gender disparity in outcomes are pervasive, so it does not appear that the designers follow these ethical principles. The operational reality of AI on diverse populations in the U.S. indicates limited adherence to ethical principles without regulation or consequence.

# Faith Perspectives

The literature review researches the theological perspectives on the development and use of AI in the evaluation of candidates in resume pre-screening. There are two perspectives considered: Imago Dei, all people are made in the image of God, and God’s commandment to love Him and love others. The literature research examines the religious texts of the Christian, Muslim, and Jewish communities, which comprise 55% of the world's population. The dominant consideration in AI showing bias against one population or another is insufficient inclusion of the machine-readable differences in various populations over which the AI is applied. Much of the development of AI is done in a small segment of Western companies, which white male developers dominate. According to West et al. (2019), this results in algorithms developed with data on a much narrower population than it is applied operationally. This is certainly true with the Amazon employment process, which screened out women.

## Imago Dei

The first theological lens through which AI development and use will be researched is found in the Judeo-Christian Bible. From Genesis to Revelation, there has been an emphasis on cross-cultural unity. A consistent message conveys God’s story of redemption for every nation and tribe and that regardless of culture, God’s people are all one in Christ. Specifically, in Genesis 1:27, God says, “So God created mankind in his own image, in the image of God he created them; male and female he created them” (Biblica, 1984, p. 7). All people, regardless of gender, race, creed, economic status, etc.., are made in the image of God and should, therefore, treat one another equally. A description of people created in God’s image is called “Imago Dei” (Pelikan, 2011, p. 23). Every group of people, beginning with Adam and Eve, were reflections of the very image of God himself. We are, therefore, to view one another as children of God without distinction. After the fall of humanity in Genesis 3, sin created division and disunity among people. This is evident in Genesis 11 when God confused the language as the people tried to build the tower of Babel. At that point, humanity was scattered, and the division of language gave way to different cultures and ethnicities. The final book of the Bible, Revelation, is a vision from God of what the world will look like when redeemed humanity is reunited with God in heaven. Revelation 7:9 says there will be a reunification of all people. Specifically, it says: “Here before me was a great multitude that no one could count, from every nation, tribe, people, and language, standing before the throne and before the Lamb” (Biblica, 1984, p. 1974). God intended at creation, and he revealed from Genesis 1 through Revelation 7:9 that all people were to be drawn to him without regard to cultural or ethnic background” (Pelikan, 2011, p. 23). People were intended to treat one another equally as all are made in God’s image, *Imago Dei*. The Judeo-Christian moral standard for behavior or ethical standards is based on treating one another equally.

## Love God and Love your Neighbor as Yourself

Theologically, the text for Christians, Muslims, and Jews requires everyone to “Love God and love your neighbor as yourself.” The literature research points to this common vision across all three religions. “First, “A Common Word” points both Muslims and Christians to what is undeniably essential in each faith and common to both – love of God and love of neighbor. Second, it shows how that which is essential in each faith and common to both has the power to bind them together because it encourages – indeed, demands – that their adherents seed the good of others, not just their own good. If it is true that the dual command of love binds the faiths together, the consequences are revolutionary in the best sense of the word. We no longer have to say, “The deeper your faith is, the more at odds with others you will be!” (provided, of course, that “deep faith” means not just emotionally strong faith but also intelligent and informed faith). To the contrary, we must say” “The deeper your faith is, the more in harmony with others you will live!” A deep faith no longer leads to clashes – it fosters peaceful coexistence.” (Volf et al., 2010,p. 24). The Pentateuch followed by Jewish tradition also commands in Leviticus 19:18.,“‘Do not seek revenge or bear a grudge against anyone among your people, but love your neighbor as yourself. I am the Lord.” (Biblica, 1984, 173). It also says in Deuteronomy 10:19 that you are to love those who are foreigners, for you were foreigners in Egypt (Biblica, 1984, 258).

Further, in a historic teaching on the Torah conducted by Professor Harvey from McGill. He taught the summation of the Torah in two important points, which are very much aligned with Christian and Muslim teachings.

“There is, of course, in Judaism no official list of dogmas. But there have been many attempts to sum up the spirit of Judaism in one general principle, one concept, sometimes in one Biblical verse or in one commandment - to teach the whole Torah while standing on one foot. I intend to discuss two such general principles which overlap as we shall see. The two principles are (1) love of neighbor and (2) imitatio Dei. The area in which they overlap is gemilut hasadim, acts of love. Let us begin with the main Biblical source texts of the two principles. (1) "Thou shalt love thy neighbor as thyself: I am the Lord" (Lev. 19:18). When the Gentile in the famous aggadah challenged impatient Shammai, "Convert me on the condition that you teach me the whole Torah in its entirety while I stand on one foot!', he was chased away with a builder's cubit, but when he similarly challenged kindly Hillel, he was converted and told, "What is hateful to you, do not do to your comrade; this the whole Torah in its entirety; the rest is its commentary: go learn! In his negative formula, Hillel may be understood as rephrasing our affirmative verse, "Thou shalt love thy neighbor as thyself"; that is, he may be understood as saying that "Love thy neighbor as thyself' is the whole Torah in its entirety? Finally, Rabbi Akiva that hero of love who taught "that the whole world in its entirety is not as much worth as the day on which the Song of Songs was given to Israel"- stated explicitly that the affirmative commandment "Love thy neighbor as thyself" is Torah” (Harvey, 1976, p. 16).

Harvey’s teaching pulls the concepts of Imago Dei and Love for God and loving your neighbor as yourself. As technology is developed and applied against populations, to disadvantage one population over another does not reflect the command to love your neighbor as yourself. Nor does it recognize that all people were created in the image of God and, therefore, should be created equally. It would require consideration of the entire sphere where technology is applied to ensure equality in the application. One might consider the concept of love being applied to technology development as too soft a consideration. However, Volf makes clear in his literature, “love is not a soft and a nebulous emotion but a tough, practical virtue of benevolence and beneficence, a virtue of which justice is an absolutely integral part.” – that love demands an acknowledgment of the inherent value of each person, and a corresponding commitment to help those in need, regardless of their religious affiliation. (Volf, 2010, Forward). Treating anyone less than one would treat themselves is an ideal Biblical text supports.

There is a call for justice from the social, ethical, and theological perspectives on the development and use of AI. Careful attention to the effect AI-enabled systems has on populations to which the technology is applied. In the case of AI, there is gross misalignment between the application of AI and societal justice for all.

## Theological Implications of Generative AI Use by Prospective Employees

As a reminder, case study number one described a subject who was laid off and used ChatGPT to help write cover letters, including one that got him a foot in the door and later hired at a smart-tech company. The condition of being laid off and continually applying for jobs is emotionally draining to the subject. ChatGPT was used to break writer's block, distilling the long-winded cover letter into four tight paragraphs. It was also used to help prepare for job interviews by suggesting new ways to ask about company culture and expectations for the role. (Alcántara, 2023, p. 1). Innovatively applying ChatGPT to the cover letter and developing interview questions were instrumental in creating a higher quality cover letter and interview.

The theological ideology of Imago dei espouses that we are all created in the image of God. Does our relationship with machine learning tools like ChatGPT diminish one’s image? The intentional use of this to help enhance one's resume to find work is consistent with God’s call to pursue work. Exodus 23:12 says, “Six days you are to work, but on the seventh day do not work.” (Biblica, 1984, p. 121).

In research on Faith and Work integration, Buszka (2020) credits Bill Talcott, an organizer, thinking on the nature of work, who said, “History is a lot of people getting together to work deciding they want a better life for themselves and their kids” (Buszka, 2020, p. 9). Work provides deep meaning for those who pursue it, which is why the subject of this use case was so cognitively stressed when they were laid off. If ChatGPT is viewed as a tool to reduce cognitive stress and enable work, there are many examples in historical text where tools were used successfully to accomplish a task. No dimension in using ChatGPT requires interaction with another person. As previously mentioned, the final decision on the use of ChatGPT content rests on the prospective employee. The second question presents the theological question of whether using ChatGPT to create more thoughtful and specific interview questions violates Imago Dei or loving God and neighbors. ChatGPT, in this case, was used as a resource for conducting research. Again, the final decision to use or not use the information derived from ChatGPT rests with the prospective employee. It does not appear using ChatGPT as a tool or resource is inconsistent with theology.

## Theological Implications of Generative AI Use by Prospective Employers

As a reminder, in the third use case, the hiring manager requires the candidates to write a tweet and press release to communicate the presence of a new microwave tower. This requires research about the state of microwave systems in the geographic area and the industry. The hiring manager noticed an anomaly when five of five applicants passed the test with very similar language in the press release. The hiring manager then used ChatGPT to create the press release and got the same answer that all five candidates produced on the test. This was viewed as a problem initially. After grappling with the change in approach by candidates, the hiring manager augmented the assessment to require additional research and edits to illuminate the candidate’s true skills. The new assessment PR test and a subsequently installed bot detector regulated the degree to which the candidates could use ChatGPT responses without disclosing their use to the interviewer (Alcántara, 2023, p. 1).

A theological examination of this use case in the context of Imago Dei and loving God and your neighbor as yourself views ChatGPT as a resource ultimately used to help assess a candidate’s skills. After initially struggling with the prospect, the manager demonstrated care for the prospective employee to allow a new approach to conduct research. The hiring manager also employed a new approach to adjust the assessment of the candidates. There was no apparent discord between the manager and the prospective employees. It appears that mutual respect prevailed in the resolution of a new Generative AI approach between the employee and the employer (Alcántara, 2023, p. 1)..

However, the employee needs to be fully transparent about the method used to devise the tweet and PR statement (Rotenberg, 2020, p. 197). In a loving environment, information is shared without fear of reproach. Similarly, the employer should disclose their methods for detecting the use of Generative AI, so the regulation is not a surprise to the prospective employee. In so doing, full openness and trust were established between the two subjects in use case three.

There are many theological ideals that would usher in the new wave of AI to enable prospective employees of any color to find work. AI being used to bias one population over another also requires examination. There is historical precedence that demonstrates the church's tolerance of racial division.

According to Wiley-Blackwell (2012), “In the midst of the struggle against apartheid, for example, South African theologian John de Gruchy protested against the churches’ complicity with the apartheid government. De Gruchy put the blame in part on a dangerously individualistic and otherworldly spirituality, an “unbiblical privatization of piety which has separated prayer and the struggle for justice” (1986: 33). This critique needs serious attention from practical theologians and scholars of spirituality.

Christian spirituality is ambivalent on this point. Many traditions of Christian spirituality prioritize the contemplative over the active life and remain silent about politics. Yet, Christian spirituality also offers resources for a more engaged spirituality. Scholars have begun to uncover the interconnections between mysticism and social transformation, exploring the dynamic relationship between contemplation and action.” (p. 331).

# Synthesis of Current Literature

The purpose of this study is to examine the association in interview selection rates among marginalized groups in STEM fields according to the use of Generative AI for resume creation or enhancement. The focus on STEM hiring in diversity is because research has shown that there is a gap between the number of women, Black and Hispanic workers, and those working in the AI industry. Specifically, research has shown through US educational statistics that the number of women, Blacks and Hispanic graduates in STEM is greater than those going into the field of mathematics and computer science. These fields are particularly interesting because the AI development skillset is centered in this area. Research has shown that AI-enabled systems create bias in one population over another. Women, and people of color are most likely to be disadvantaged by these systems. Research has shown that the companies that produce AI-enabled systems are in the West and have the lowest percentage of diverse staff in STEM fields. Research has shown that companies increasingly use Applicant Tracking Systems (ATS) by companies to pre-screen resumes of employees' resumes before being selected for an interview. Research has also shown that with the emergence of Generative A, there is increasing success in the use of ChatGPT to help enhance or create resumes and cover letters to contain keywords searched for by ATS. While there has been research in the general population quantifying the benefit of using ChatGPT for resume enhancement and creation, there has been no focus specifically on the diverse STEM population. As stated in West’s research, “There is a close relationship between these workplaces with discriminatory practices and discriminatory tools (AI): a feedback loop that is shaping the AI industry and its tools. The products of the AI industry already influence the lives of millions. Addressing diversity issues is, therefore, not just in the interest of the tech industry but of everyone whose lives are affected by AI tools and services.“(West et al., 2019, p. 7). For this reason, this research is necessary to examine the association in interview selection rates among marginalized groups in STEM fields according to the use of Generative AI for resume creation or enhancement.

The literature review research has shown through the analysis of Self-determination Theory as a theoretical framework for analysis that autonomy is a strong motivator for overcoming obstacles like being laid off from work and seeking employment. (Ryan et. al., 2022, p. 2), Research has also shown that ethical principles that the public sector has created encourage AI system developers and users to seek the highest levels of respect for human autonomy (Rotenberg, 2020, p. 44-60). Both the public and private sectors encourage AI system developers and users to seek fairness in the outcomes of these systems for the users. However, significant and consistent research points to bias in marginalized populations when AI makes recommendations affecting their lives. Research has shown that AI-enabled systems should have explicable or explainable results, but they often do not. Therefore, the risk level introduced with the decisions made by these systems must be assessed to determine if the lack of transparency in decisions is worth the possibility of being a poor decision.

In the case of Generative AI being used to create or enhance resume development, three use cases were analyzed against the Self-determination theory, the ethical principles, and a theological doctrine of imago dei and love. In each of the cases, the low risk of using Generative AI to create or enhance pre-interview selection material is considered viable for different reasons. In the case of SDT, using Generative AI is desirable because of explicit experimentation and the promotion of autonomy, which helps overcome cognitive blocks in creativity. In the case of ethical principles, it is viable as a user of Generative AI because the final arbiter of what to put in the resume or cover letter is the person creating the pre-employment selection documents. In the case of theological doctrine, the use of Generative AI for creating pre-employment documents is acceptable, provided they accurately represent the person. The weight or pressure associated with working and the cognitive block that is sometimes created is easier to overcome using a tool like ChatGPT. Throughout biblical history, tools have been creatively used to complete tasks.

**Table 2**

*Synthesis of Varied Perspectives on the use of Generative AI for Pre-employment screening*

**Table 2**

Crosswalk View of AI, Human Intelligence, and Spiritual Intelligence

|  |  |  |  |
| --- | --- | --- | --- |
|  | Artificial Intelligence | Human Intelligence | Spiritual Intelligence |
| Technical View | New and very fast, not self-aware, leads to bias in resume screening | Humans traditionally do the job slower, which also leads to bias in resume screening | If the doctrine of love is practiced, justice in the use of AI would improve |
| Social View | Ethical principles were created to minimize bias in AI-enabled systems, but the use is not yet supported by policy, so injustice persists | Humans are predisposed to bias based on their own cultural experiences, so bias in resume pre-screening against women and minorities persists. | Equal treatment of all people would minimize bias. Lead to greater diversity in employment and societal growth |
| Theological View | God created all people in his image with the command to love Him and one another. It is antithetical to Judeo-Christian, Islam, and Jewish Doctrine to unjustly deny people the right to work. | God's word, when corrected, studied, and applied in the development and use of AI-enabled systems, would eliminate bias in resume pre-screening. Humanizing | The highest level of human treatment is we love God and others as ourselves. Develop systems that reflect no bias. Supported by the doctrine of 55% of the world’s population. |

The table was created to crosswalk the varied perspectives from the technical, social, and theological views compared to the varied levels of intelligence. Artificial intelligence is defined as machine-readable, trained data systems that make decisions for humans at superhuman speed. Its attributes are very fast but not necessarily very accurate. Human intelligence is defined by traditional thought that a human might apply in making decisions that are limited by the life, cultural, and social experiences that shape one’s opinion. Spiritual Intelligence is defined as the highest level of intelligence that comes through listening to the voice of God. In Judeo-Christian religion the voice is from the Holy Spirit. Spiritual Intelligence has attributes of being more profoundly future-focused but not as quick to manifest as AI or HI. As various communities are assessing their position on using Generative AI in the employment process, the crosswalk provides a quick reference of considerations.

# Variant Perspectives

The variant perspectives on the use of Generative AI in pre-employment document development for SDT theory social and theological views are discussed in this section.

## Variant Theoretical Framework Perspectives

The variant perspective on the use of Generative AI in the pre-employment development of documents using Generative AI for the SDT is there is little regulation on the kind of recommendations these tools provide to the user (Illuminator, 2023, p. 4). SDT proposes that all behaviors can be understood as lying along a continuum ranging from heteronomy, or external regulation, to autonomy, or true self-regulation. SDT hypothesizes a variety of consequences associated with more controlled versus autonomous behavioral regulation .” (Markland et al., 2005, p. 26). The variant perspectives support the need to have more regulation over the use of AI. AI decisions or recommendations strongly correlate with the social or cultural backgrounds where the AI is being applied. Regulatory policy is behind the innovative development and use of AI in all cultures. AI algorithms being used must be designed for the region or culture in which it is being applied (Hagerty et al., 2023, p. 10). Without regulatory proof that there is transparency in AI-enabled decision-making, AI use is not recommended. Consequently, the variant perspective is more external regulation, and inspection of compliance with those regulations should be enacted in policy. In fact, Celsi (2023) states the swift progression of AI technologies, exemplified by ChatGPT, has ignited debates on the appropriateness of its rapid deployment. The open letter from the Future of Life Institute, signed by prominent technologists and evangelists including Nell Watson and Grady Booch, emphasizes the lack of transparency in AI models and the need for a pause in research” (p. 2.). The rapid use of AI without regulation or social impact analysis is viewed as extremely risky.

### SDT Variant Views of Generative AI Use by Prospective Employees

As a reminder, case study number one described a subject who was laid off and used ChatGPT to help write cover letters, including one that got him a foot in the door and later hired at a smart-tech company. The condition of being laid off and continually applying for jobs is emotionally draining to the subject. ChatGPT was used to break writer's block, distilling the long-winded cover letter into four tight paragraphs. It was also used to help prepare for job interviews by suggesting new ways to ask about company culture and expectations for the role. (Alcántara, 2023, p. 1). Innovatively applying ChatGPT to the cover letter and developing interview questions were instrumental in creating a higher quality cover letter and interview.

The use of Generative AI for creating documents should be regulated. According to Lima (2024), in an interview with House Member Yvette D. Clarke (D-NY), “Generative tools can be of benefit to our society. I don't want it to seem as though it's a doomsday [scenario]. However, like so much in the tech space, there needs to be some regulatory regime to protect consumers from misinformation weaponization of the tool. (p. 1). This idea was written into draft legislation in 2019, HR 2231, The Algorithm Accountability Act. It is a concept which is not yet law but has been gaining momentum.

### SDT Variant Views of Generative AI Use by Prospective Employers

Another variant perspective for assessing potential employees using AI from the SDT view is that the assessments created or detectors for detecting the use of AI by potential employers themselves could be biased. The onus is on the employer to verify that these tools are not creating a skewed pool that passes the assessment, such as in the case of Amazon's recruitment tool (West et al., 2019, p. 7).

The regulatory perspective for employers using AI is discussed in a March 28, 2024, announcement of a new U.S. Federal AI Act. From the Executive Office of the President, the AI Act announcement was made by VP Kamala Harris. The VP stated,

“First, we are announcing new standards to protect rights and safety. When government agencies use AI tools, we will now require them to verify that those tools do not endanger the rights and safety of the American people.  
I'll give you an example. If the Veterans Administration wants to use AI in VA hospitals to help doctors diagnose patients, they would first have to demonstrate that AI does not produce racially biased diagnoses. So, that I offer as an example.  
The second requirement -- binding requirement relates to transparency. The American people have a right to know that when and how their government is using AI it is being used in a responsible way. And we want to do it in a way that holds leaders accountable for the responsible use of AI. Transparency often, and we believe, should facilitate accountability.  
And so, today, President Biden and I are requiring that every year, U.S. government agencies publish online a list of their AI systems, an assessment of the risks those systems might pose, and how those risks are being managed. Third and finally, a requirement that relates to internal oversight. We have directed all federal agencies to designate a chief AI officer with the experience, expertise, and authority to oversee all -- I'm going to emphasize that -- all AI technologies used by that agency. And this is to make sure that AI is used responsibly, understanding that we must have senior leaders across our government who are specifically tasked with overseeing AI adoption and use.”(p. 1).

The SDT states that autonomous decision-making by individuals, whether within or outside of an organization, leads to higher levels of motivation and performance. However, AI has been deemed to have sufficient risk in areas such as bot detectors being applied to applicants that within the Federal Government, senior leadership accountability and full disclosure are required before and during its operational use to guarantee civil rights and the safety of citizens. This is a variant perspective to SDT, helping innovative technology be embraced autonomously to help increase productivity. Rather, external regulation is viewed as more appropriate due to the increased risk associated with AI-enabled systems.

Additionally, employers must maintain the privacy of the data collected on potential employees. Cybersecurity measures need to be improved, according to Celsi (2023). “Organizations may need to allocate more resources to enhance cybersecurity measures, including encryption, access controls, and regular security audits, to safeguard the data used in AI projects. Organizations might also establish closer collaborations between AI experts and cybersecurity professionals to ensure a comprehensive approach to data protection in AI projects.” (p. 17). Maintaining privacy and security over those systems is an additional enterprise burden that must be weighed against the benefits it offers.

The variant perspective for using Generative AI in developing pre-employment documents or processes is tied to the theological practice of tolerating bias over social justice all too often. This is less important in using AI to create documents which are is inspected by the user and more important to ensure there is an unbiased assessment of potential employees by the potential employer.

History has shown religions can lean toward supporting the dominant political power structure, like in the case of Apartheid in South Africa (Wiley-Blackwell, 2012, p. 331).

In the Judeo-Christian Bible, the Jewish leaders accused Jesus of blasphemy for saying he was a King, but for trial and conviction they depended on the regulatory authority of the dominate political power structure of the day, Pilate, to carry out injustice against Jesus (Biblica, 1984, p. Luke 23:1-25). Through the injustice of sending Jesus to death on the cross, they brought justice to all people through Christ’s redemption. In this case, the variant view is in God’s sovereignty. The Jewish leaders in leaning on the political power of the day brought fulfillment of prophesy and justice to all. (Biblica, 1984, p. Luke 24:46-47).

AI-enabled systems have already been proven to show bias affecting underserved millions. The religious community needs to value social justice action over contemplative prayer while tolerating injustice (Wiley-Blackwell, 2012, p. 331).

# Literature Gap

The literature review presented research on the shortfall in STEM talent, particularly regarding women and minorities. The literature review examined the demographics of those working in the AI field. As mentioned the number of Blacks working in STEM is 9%, and in computer-related fields are 7%. However, the number of Blacks working in companies developing AI products has significantly decreased, according to their self-reported diversity reports. The number of Blacks at Facebook, Google, and Microsoft are 4%, 2.5% and 4%, respectively (West, 2019, p. 10). Similarly, the number of Hispanics working in STEM is 8%, and in computer-related fields is 8%. However, the Hispanic demographics of companies developing AI products are also significantly lower. The number of Hispanics working at Facebook, Google, and Microsoft are 5%, 3.6% and 6%, respectively (West et.al., 2019, p. 10). Companies that develop AI-enabled systems also have many discriminatory complaints against them.

Research was presented on the bias from both traditional resume screening and AI resume screening by applicant screeners. Research has been presented that shows the AI ethical guidelines that have been created to counter the bias found in AI-enabled systems. Further research was presented on the societal impact of applying AI ethical principles in different cultures worldwide. Research was presented on the theological principles that could be applied to developing less biased AI-enabled systems. Research that describes the application of the Self-Determination Theory on individuals who apply for positions was presented. Research has been presented on the improvements found when applicants use ChatGPT to create or enhance their resumes as a general population. This study will determine if the pipeline of diverse populations can be increased for interview selection in STEM fields in general and AI-enabled system development companies in particular. Given that the lower percentage of representation has led to significant bias in production systems, increasing diverse representation in employment is expected to improve the focus on bias in the AI development life cycle. No research has been done on the impact of using Generative AI in STEM fields on resume creation or enhancement and the association with being pre-selected for interviews. This research fills that gap.

# Summary and Conclusion

The literature review has shown a shortfall in talent in STEM fields. Further societies with a demand for talent that exceeds the supply can no longer grow economically. The research has shown that a long tradition of diverse talent is being screened out before the interview process because of bias. As AI-enabled systems replace human reviewers, bias also continues in AI-enabled systems that pre-screen resumes for interview selection. The societal impact of this bias was a catalyst for the creation of AI Ethical guidelines to help minimize bias. Additionally, the Christian, Muslim and Jewish religions all call for one to Love God and love their neighbor as themselves. Bias against others would be inconsistent with the outcome of this kind of AI-enabled system, should either ethics or religious doctrine be followed.

As AI has become available to the general population through Generative AI, like ChatGPT, employment candidates are turning to AI to assist in resume creation or enhancement. This has been met with acceptance by some and rejection by other hiring managers. The SDT of human behavior indicates that candidates want autonomy in their approach to applying for positions, which includes adjusting to new methods like ChatGPT. Because of the shortfall of talent, where women and diverse talent are concerned, there may be people fully qualified to do work who are prematurely screened out of the interview process. There is an under-representation of women and minorities in several STEM fields, but no research has been done to determine if using Generative AI will improve the outcome of resume screening by an AI-enabled ATS leading to being selected for an interview. This study will examine the extent to which interview selection rates are associated with AI-created or enhanced resumes for diverse candidates in STEM fields.

# Chapter 3 Methodology

This section contains the research study methodology. It describes the research questions and hypothesis being explored to determine the association between using Generative AI vs. traditional pre-employment document creation or enhancement methods as it relates to the rate of selection for interviews for job seekers in STEM fields. The research design is a quantitative, quasi-experimental design. The information describes how the research methodology and the statistical analysis methods will address the research questions and test the hypotheses. Further information is provided to explain details about the survey population, the sampling method, and instrumentation. Additionally, it describes the data collection, processing, and analysis methodologies. Finally, it includes information regarding the protection of research survey respondents through a social science research questionnaire, IRB review process, and data protection provisions.

# Research Questions

There are seven research questions being explored which are described to support the research study. There is one research qualifying question, and six inquiry questions.

RQ1: What associations exist in interview selection rates between those who use Generative AI for resume creation or enhancement and those who do not among candidates in STEM fields?

RQ2: What association exists in interview selection rates between racial groups among candidates in STEM fields who use Generative AI for resume creation or enhancement?

RQ3: What association exists in interview selection rates between racial groups among candidates in STEM fields who do not use Generative AI for resume creation or enhancement?

RQ4: What association exists in interview selection rates between genders among candidates in STEM fields who do not use Generative AI for resume creation or enhancement?

RQ5: What association exists in interview selection rates between genders among candidates in STEM fields who use Generative AI for resume creation or enhancement?

RQ6: What differences exist in the perceived accuracy of AI-generated resume content between racial groups among candidates in STEM fields?

RQ7: What differences exist in the perceived accuracy of AI-generated resume content between genders among candidates in STEM fields?

# Hypotheses

Seven hypotheses are being tested in support of the research study.

Quasi-Experimental:

H01: No statistically significant association exists between interview selection rates of those who use Generative AI for resume creation or enhancement and those who do not among job seekers in STEM fields (RQ1).

Ha1: A statistically significant association exists between interview selection rates of those who use Generative AI for resume creation or enhancement and those who do not among job seekers in STEM fields (RQ1).

H02: No statistically significant association exists between interview selection rates and racial groups among candidates in STEM fields who use Generative AI for resume creation or enhancement. (RQ2).

Ha2: A statistically significant association exists between interview selection rates and racial groups among candidates in STEM fields who use Generative AI for resume creation or enhancement (RQ2).

Ha3: A statistically significant association exists between interview selection rates and racial groups among candidates in STEM fields who do not use Generative AI for resume creation or enhancement (RQ3).

Ha3: A statistically significant association exists between interview selection rates and racial groups among candidates in STEM fields who do not use Generative AI for resume creation or enhancement (RQ3).

H04: No statistically significant association exists between interview selection rates and genders among candidates in STEM fields who do not use Generative AI for resume creation or enhancement (RQ4).

Ha4: A statistically significant association exists between interview selection rates and genders among candidates in STEM fields who do not use Generative AI for resume creation or enhancement (RQ4).

H05: No statistically significant association exists between interview selection rates and genders among candidates in STEM fields who use Generative AI for resume creation or enhancement (RQ5).

Ha5: A statistically significant difference association exists between interview selection rates and genders among candidates in STEM fields who use Generative AI for resume creation or enhancement (RQ5).

H06: No statistically significant difference exists in the perceived accuracy of AI-generated resume content and racial groups among candidates in STEM fields? (RQ6).

Ha6: A statistically significant difference exists in the perceived accuracy of AI-generated resume content between racial groups among candidates in STEM fields? (RQ6).

H07: No statistically significant difference exists in the perceived accuracy of AI-generated resume content between genders among candidates in STEM fields (RQ7).

Ha7: A statistically significant difference exists in the perceived accuracy of AI-generated resume content between genders among candidates in STEM fields (RQ7).

Testing the hypotheses will require a rigorous research methodology and design.

# Research Methodology and Design

This quantitative study will utilize a quasi-experimental design because it will examine interview selection rates for statistically significant associations among job seekers in STEM fields who utilize Generative AI for resume creation or enhancement and those who do not. This study will utilize chi-squared analysis and ANOVA to test hypotheses for statistically significant association between groups.

Quasi-Experimental design is often used in social science research. It is advantageous because it allows for real-world settings where random assignment of group membership is impractical. Quasi-Experimental research designs compare differences in a continuous dependent variable between groups split on one or more independent variables from a validated instrument (quantitative, deductive).Quasi-Experimental is used in the experimental design due to the groups not being randomly assigned instead, groups are connected in social relationships. The group membership has pre-existing connections through professional relationships on LinkedIn. The LinkedIn member is sharing the survey with those with whom they have a professional relationship. The limitation is that it increases the risk of confounding variables, making it more difficult to assert causal relationships with the same confidence as randomized controlled trials (Terrell, 2023, p. 119).

Chi-squared analysis is a statistical method used to determine if there is a significant association between two categorical variables. It compares the observed frequency in each category to the frequencies one would expect to find if there were no causal associations between the variables. (Mac Farland et al., 2016, p. 77-78). Since the dependent variable is the interview selection rate, Chi-square is appropriate for examining how the interview selection rates differ across expected rates in each category (Mac Farland et al., 2016, p. 77-78). The categorical independent variables are race, gender, and the use of Generative AI for resume creation or enhancement. The data is organized in a matrix, referred to as a matrix representation. The interview selection rate is organized alongside the race, gender and use of Generative AI. The Chi-square test will analyze the data organized in the matrix. The Chi-square analysis assumes that the expected frequencies are sufficiently large for the Chi-square approximation to be statistically valid. Usually, this means each cell count will have a value of 5 or more. When the Chi-square is less than 0.05, it indicates there is a statistically significant difference between the observed and expected frequencies, indicating an association between the independent and dependent variables (MacFarland et al., 2016; p. 80, Creswell et al., 2023, p. 268).

The Analysis of Variance (ANOVA) test compares the means of two or more independent variables to determine if at least one dependent variable mean is significantly different from the others. In this analysis, the ANOVA test is used to determine if there is a significant difference between the dependent variable, rate of interview selection, and each independent variable, race, gender or the use of Generative AI for resume creation or enhancement. This is especially helpful when analyzing multiple independent variables, which may each have different levels or categories.(Creswell et al., 2023, p. 268). Factorial ANOVA, which can analyze the effects of each independent variable and their interactions on a dependent variable. (Mac Farland et al., 2016, p. 177). The t-test was not used for this analysis because there are multiple independent variables, race, gender and the varied use of Generative AI. T-tests are designed to compare the means of only two groups. Since there are more than two groups to compare, multiple t-tests would increase the likelihood of rejecting a true null hypothesis, a Type 1 error. ANOVA is the better choice because the analyzed data contains multiple independent variables. The population and sampling are important to the research design and methodology.

# Population and Sampling

The target population for this study will be diverse STEM college or university-educated job seekers from socially connected networks. The size of the target population is unknown because snowball sampling via social media will be utilized. However, based on Indeed.com, in April 2024, approximately 944,000 open positions were active in the job market for STEM-related fields. There are approximately 500,000 diverse and female graduates seeking employment. Approximately 39% of these job seekers are diverse, and approximately 40% are female candidates (NCES, 2024, p. 322.20, 322.30). The distribution is not mutually exclusive.

Snowball sampling will be utilized to encourage broader participation on social media for a period of four weeks. A recruitment request, informed consent, and instrument will be posted to the researcher’s social media platforms (LinkedIn) and relevant social media groups (with permission from the group administrators), with a request for others to share the post. The sample size will be a convenience sample based on the responses received during the recruitment period. Snowball sampling is a process by which participants are recruited for a study by sharing recruitment information with other potentially eligible participants until a specific target sample size is reached (Goodman, 1961, p. 148-150). In a study by Kozowski (2021), a similar method was used. One of the possible solutions to this problem is the selection of respondents via LinkedIn, which is the world’s largest platform for employees from various industries. LinkedIn, like other large Internet platforms, has a network structure, i.e., each user is “connected’’ to a certain group of people, each with their own group of connections, and so on, very quickly creating a vast network of potential respondents. The sampling procedure consists of four steps:

1. Building a list of potential respondents belonging to the study population  
2. Acquiring respondents from the created list as direct contacts of the researcher

3. Distributing invitations to participate in the study ” (p. 2)

4. Allowing those invited to share the invitation with others in their professional network.

The desired sample size is a minimum of 30. If a minimum sample size of 30 is not reached within the recruitment period, the recruitment period will be extended. If more than 30 eligible participants are recruited during the study, all participants will be utilized. A sample size calculator will not be utilized for this study because normality of the sample is not anticipated. The chi-square and ANOVA analyses will be treated as nonparametric procedures with no expectation of generalizability to the entire sample. Inclusion and exclusion criteria will be used to determine eligibility.

The inclusion criteria for research participants are their perceived qualification based on applying for a job in a STEM field. Secondarily, the survey participant must have been looking for a job in the past 12 months. The exclusion criteria are not having applied for work in a STEM field in the past 12 months.

## Instrumentation

This study will utilize a researcher-developed survey instrument comprised of eight questions: two demographic screening questions, five binary (Yes/No) questions, and a single Likert-style question. The instrument will be validated through field testing by a panel of 3 subject matter experts (SMEs).

## Variables

Table 1 demonstrates the alignment of research questions and the variables measured by the instruments to establish clear organization and structure.

**Table 1***Alignment of Variables to Research Questions*

|  |  |  |
| --- | --- | --- |
| Quantitative Variable(s) | Research Question | Theory or Literature Support |
| Interview Selection Rates (dependent)  Ratio Scale as Percentage | RQ1, RQ2,RQ3,RQ4, RQ5 | MacFarland et al., 2016, p. 178 |
| Racial Groups (Independent)  Categorical/Nominal | RQ2,RQ3 | MacFarland et al., 2016, p. 178 |
| Gender (independent)  Categorical/Nominal | RQ4,RQ5 | MacFarland et al., 2016, p. 178 |
| Accuracy of resume content (independent)  Categorical/Nominal | RQ6, RQ7 | MacFarland et al., 2016, p. 178 |
| Traditional versus AI-assisted (independent)Categorical/Nominal | RQ1,RQ2,RQ3, RQ4, RQ5, RQ6, RQ7 | MacFarland et al., 2016, p. 177-178 |
| Traditional versus Professional Resume Service (independent)  Categorical/Nominal | RQ1,RQ2,RQ3, RQ4, RQ5, RQ6, RQ7 | MacFarland et al., 2016, p. 177-178 |
| Improvement in resume content (dependent)  Ordinal/Likert Scale |  | Sideridis et al., 2023, p. 886 |

The interview selection rate as the dependent variable is analyzed relative to the independent variables of race, gender, use of Generative AI, as well as the accuracy of the results from the use of Generative AI. Additionally, the degree of improvement from using Generative AI for pre-employment document preparation is measured on a Likert scale. The Likert scale has five measurement options, where the distance between options is equidistant, as Sideridis (2023) recommended. The Likert question is analyzed only if the survey respondent used Generative AI to create or enhance their pre-employment documents.

## Validity and Reliability

Because the instrument is primarily binary, interrater reliability or construct validity is unnecessary. Subject matter experts will review the single Likert-style question on an ordinal scale for alignment and appropriateness to the intended research questions.

## Instrument Validation

Two subject matter experts in the fields of artificial intelligence and STEM professions were solicited to review the instrument and provide feedback. Feedback is included in Appendix 2. The following revisions were made based on expert feedback on the subject matter. An additional question was added to determine whether a professional resume writing service was sought to create or enhance the pre-employment document creation. The relative improvement of AI-assisted vs. professional services will also be compared from the analysis of survey results.

All experts were PhD mathematicians working in AI applied research. They reviewed the alignment of the research questions and the variables and agreed that the instrument was sufficient for the research study.

# Data Collection and Analysis

The social science research data collection and analysis will consist of an on-line survey through Survey Monkey, LLC. A detailed description of the data preparation, storage, protection and analysis method is provided.

## Data Collection

The AI Ethics Foundation, LLC will be the conduit for a research participant to access both the research consent form and the survey. The survey can be found on [AIEthicsFoundation.org](http://aiethicsfoundation.org/). The principal investigator owns the AI Ethics Foundation, LLC. A URL to the AI Ethics Foundation, LLC will direct the potential research participant to a description of the purpose for the survey. If the potential participant consents to the research agreement, they digitally sign the document and are then advanced to the advanced to the survey. The survey questions are on the Survey Monkey platform. All the data will be collected on this platform for consistency. After sufficient samples of the population are collected for the nonparametric study, the data will be downloaded in aggregate from Survey Monkey to a CSV file and sent to an encrypted computer. The data will be kept in a password protected file for no more than eighteen months.

## Data Preparation

The data preparation contains three stages. First, the data will be exported in a CSV file with delimited data by question. Next, the data will be put into an Excel file, cleaned, and curated for analysis. Extraneous data or incomplete survey data will be eliminated through the cleaning process. There will be an inspection to ensure alignment of answers to every relevant question. A theoretical sample of the cleaned and curated data can be found in Appendix 1. Finally, the curated data will be imported into PSPP for analysis.

## Data Analysis

This study will test data for normality and relevant assumptions of appropriate statistical procedures. If data do not meet assumptions for parametric procedures (results apply to the population), nonparametric procedures (results apply only to the sample) will be utilized. The types of test to be used to test normality of the data are visual inspection using a histograms, Q-Q plots, or box plots to assess the shape and symmetry of the distribution. An alternative to just visual inspection for normality is the Anderson-Darling Test. The Anderson-Darling test calculates a test statistic based on the differences between the observed and expected cumulative distribution function. If the calculated statistic exceeds the critical value for a chosen significance level, the null hypothesis will be rejected, indicating a departure from normality. The final alternative for normal distribution testing is the Lilliefors Test. The Lilliefors test is specifically designed for small sample sizes. It assesses the difference between the empirical cumulative distribution function of the data and the theoretical normal distribution. The null hypothesis is that the sample is drawn from a normal distribution and rejecting this hypothesis suggests non-normality (Ewens et al., 2023, p. 205).

This study will utilize a Chi-Squared analysis and an ANOVA to test the hypotheses for statistically significant associations. The details of these two approaches are described in the research design and methodology section.

This study will include post-hoc statistical procedures such as power and effect size to aid the interpretation of the results. The power analysis will examine the effect size or the magnitude of the difference or relationship between variables in the population. Larger effect sizes will make it easier to detect with higher power. The sample size will also be examined to determine effect on power. The significance level () will be set at 0.05. the probability of correctly rejecting the null hypothesis when it is false or ( will be analyzed additionally. A Type I Error (or false positive rate) is the probability of rejecting the null hypothesis when it is true, and the Type II Error (false negative rate) is the probability of failing to reject the null hypothesis when it is actually false. In addition to aiding in the data analysis, the power analysis will guide the direction for planning future studies (Trenkler, 1994, p. 396).

# Ethical Considerations

The nature of the study requires human subject data collection. The participants will be given a Social Research consent form before participation. Participation in the survey is completely voluntary. Should they choose to participate, they will also be given contact information to withdraw from participation before the publication of the results. Their data will be anonymized when stored on in an encrypted file and kept no longer than eighteen months. The consent form outlines this information and can be found in Appendix B.

## Participant Consent

The human participants in the study will be presented with a Consent form for social science research that explains the protection of their information and their rights as a participants. Specifically, the consent for describes the purposes of the study. It also describes the method of recruitment of participants, procedures which generally describes the seven questions which will be asked during the survey. Additionally, it describes the risks and benefits of the study. The methods used to protect the participants data are described, including it never being sold, shared or disclosed to anyone without their consent. The information will be kept confidential and encoded with a unique identifier for storage and analysis. It also describes that the research is voluntary and provides contact information should the participant want to withdraw from the study later. No compensation will be provided for any of the participants. The procedure is described for reporting any adverse effects experienced by participants taking the study. Digitally signed consent forms are emailed to the AI Ethics Foundation, LLC. A copy of the Social Science Research Consent Form can be found in Appendix C.Bias Acknowledgment and Mitigation

Research biases may come from population selection bias using snowball sampling. It depends on the researcher’s social networks and those known by professional networks associated with the researcher. To mitigate this bias, an initial list for distribution of the survey on linked in will come from at least 5 associates. Additionally, snowball sampling to the second and third degree of distance from the researcher will reduce the likelihood of bias in the population.

# Summary and Conclusion

The quasi-experimental research design and methodology was described in detail. It contained the research questions and hypothesis being explored to determine the association between using Generative AI vs traditional pre-employment document creation or enhancement method relationships to the selection rate for interviews for job seekers in STEM fields. The information described how the research methodology and a description of the statistical analysis methods will address the research questions and test the hypotheses. Further information was provided to describe details about the survey population, the method of Snowball sampling, and distribution of the survey questions through LinkedIn professional associations. Additionally, it described the data collection, processing and analysis methodologies. Finally, it included information regarding the protection of research survey respondents through a social science research questionnaire, IRB review process and data protection provisions. This quantitative, quasi-experimental research design will inform employment seekers on the association between using Generative AI and being pre-selected for an interview.

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WORKS CITED

# Appendix A: Informed Consent: Social Science Research Consent Form

Consent Form for Social Science Research Study

**Interview Selection Rate Association Between Traditional and Generative AI Enhanced Resumes Among Diverse STEM Employment Candidates: A Quantitative Quasi-Experimental Study**

AI Enhanced Resumes Among Diverse STEM Employment Candidates: A Quantitative

Quasi-Experimental Study

Dear Volunteer,

Thank you for your interest in participating in our social science research in the title above. This study is being conducted on behalf of the AI Ethics Foundation, LLC. The purpose of this consent form is to give you the information you will need to help you decide whether to be in the study or not. Please read the form carefully. You may direct questions about this research to ??@OGS.edu. This process is called “informed consent.” You may download a copy of this form for your records.

Principal Investigator: Gina Marshall-Johnson.

Purpose of the Study

The purpose of this study is to examine associations between interview selection rates among underserved groups in Science Technology Engineering and Math (STEM) fields according to the use of Generative AI for resume creation or enhancement. Many companies use AI to pre-screen resumes prior to interview selection. Participation in this study will help quantify the impact of Generative AI in interview selection rates.

Participant Recruitment

The target population for this study will be diverse STEM college or university-educated job seekers from socially connected networks. Participants must be 18 years or older to participate in this study. Snowball sampling will be utilized to encourage broader participation on social media for a period of four weeks until the end of the recruitment period.

Study Procedures

The study consists of a researcher-developed and validated, survey instrument comprised of seven questions: two demographic screening questions, four binary (Yes/No) questions, and a single Likert-style question. The commitment of time is minimal. The entire survey will take three to five minutes to complete.

Risks and Benefits of the Study

There are no foreseeable risks with this study. The findings from the study may help private and public businesses meet their technology sector hiring needs, and adhere to AI ethics principles established to ensure equity across all populations regardless of race, ethnicity or gender.

Confidentiality and Privacy of Research Information

The Research Committee understands and respects the privacy of each participant. The researcher guarantees that the information gathered through this research will never be sold, shared, or disclosed to anyone without their consent. All the information you provide will be confidential. All data is coded by a unique identifier associated with your answer. The researcher has no access to identifiable data. The researcher may share the overall findings based on the participant’s information. The researcher respects the rights and privacy of the participant.

Procedures for Withdraw

Given this research is voluntary in nature, the participant may withdraw from the research at any time. If you have filled out the survey and wish to withdraw your submission please email [survey@aiethicsfoundation.org](mailto:survey@aiethicsfoundation.org) along with a PDF of your responses.

Compensation

There will be no compensation provided for participants in this study.

Data Monitoring and Safety

If you experience any adverse events or unanticipated problems by participating in this survey, please email survey@aiethicsfoundation.org. All participants that experience such events will be reported to the Oversight Institutional Review Board at Omega Graduate School.

Questions

You may direct questions about this research to [???@OGS.edu](mailto:???@OGS.edu)

# Appendix B: Recruitment Letter

**Invitation to Participate in Research Study**

**Study Title: Interview Selection Rate Association Between Traditional and Generative AI Enhanced Resumes Among Diverse STEM Employment Candidates: A Quantitative Quasi-Experimental Study**

Dear [Participant's Name],

We are excited to invite you to participate in a groundbreaking research study exploring the impact of traditional versus generative AI-enhanced resumes on interview selection rates for STEM employment candidates. This study aims to understand how advanced technologies are influencing the hiring process, especially for diverse candidates in the STEM fields.

**Purpose of the Study**

The goal of this research is to evaluate the association between AI-enhanced resumes compared to traditional resumes in securing interview opportunities. By participating, you will contribute valuable insights into how modern resume-enhancing technologies can potentially level the playing field for diverse job seekers in the STEM industry.

**Who Can Participate?**

We are seeking individuals who:

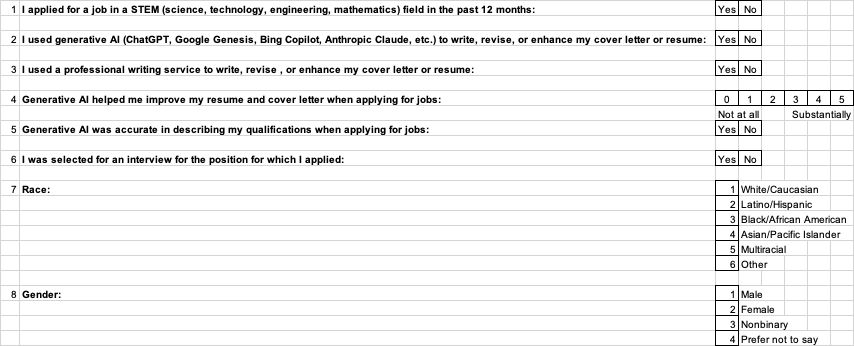
Are currently seeking employment or who have sought employment in the past 12 months in Science, Technology, Engineering and Math (STEM) fields.

**What Does Participation Involve?**

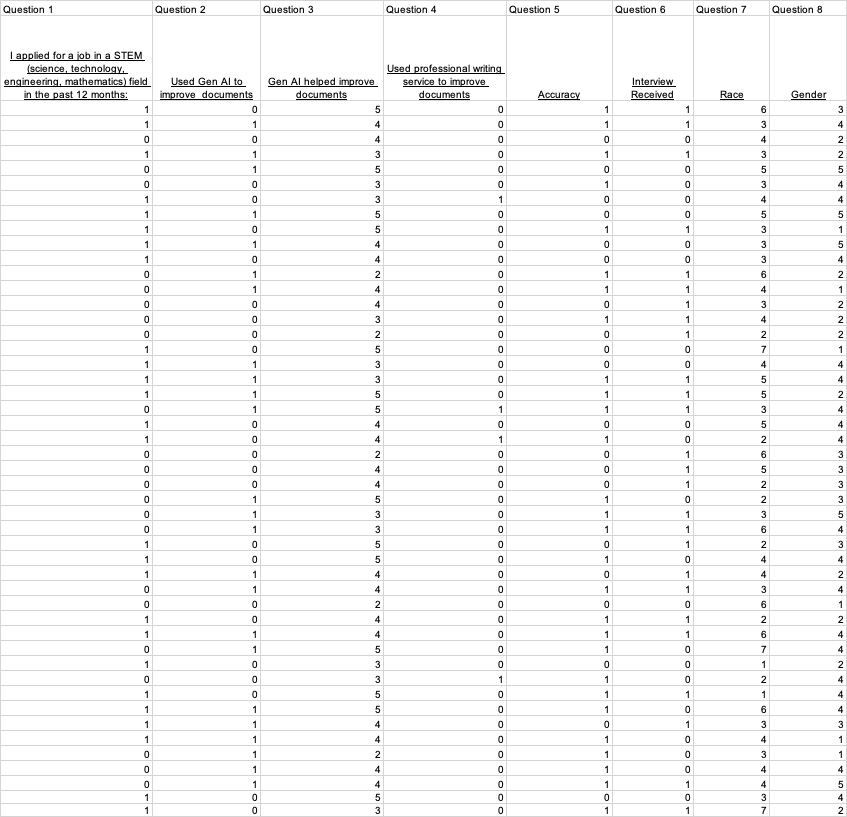
Go to AIEthicsFoundation.org and click on [Survey](https://www.aiethicsfoundation.org/our-survey). You will be led to an Informed Consent form and then an 8 question survey. The commitment in time is less than 5 minutes.

Principal Investigator: Gina Marshall-Johnson.

# Appendix C: Instrument



# Appendix D: Sample Data Collection Excel File



# Appendix E: Validity Documentation

SME #1 – Shelby Wilson, PhD Mathematics, University of Maryland College Park

Shelby,

As part of my tribe, I am sharing my research questions and asking if you can take a look and let me know if you think the variables for data collection are sufficiently aligned with the search questions.  I also have one survey question that is not covered with a research question.  Should I add one?

Thanks for sharing your PhD brilliance.

Gina

**Research questions**

RQ1: What associations exist in interview selection rates between those who use Generative AI for resume creation or enhancement and those who do not among candidates in STEM fields?

RQ2: What association exists in interview selection rates between racial groups among candidates in STEM fields who use Generative AI for resume creation or enhancement?

RQ3: What association exists in interview selection rates between racial groups among candidates in STEM fields who do not use Generative AI for resume creation or enhancement?

RQ4: What association exists in interview selection rates between genders among candidates in STEM fields who do not use Generative AI for resume creation or enhancement?

RQ5: What association exists in interview selection rates between genders among candidates in STEM fields who use Generative AI for resume creation or enhancement?

RQ6: What association exists in accuracy of resume content between traditionally generated resumes or those who use Generative AI for creation or enhancement?

Table 1 demonstrates alignment of research questions and the variables measured by the instruments to establish clear organization and structure.

**Table 1***Alignment of Variables to Research Questions*

|  |  |  |
| --- | --- | --- |
| Quantitative Variable(s) | Research Question | Theory or Literature Support |
| Interview Selection Rates (dependent)  Ratio Scale as Percentage | RQ1, RQ2,RQ3,RQ4, RQ5 | MacFarland et al., 2016, p. 178 |
| Racial Groups (independent)  Categorical/Nominal | RQ2,RQ3 | MacFarland et al., 2016, p. 178 |
| Gender (independent)  Categorical/Nominal | RQ4,RQ5 | MacFarland et al., 2016, p. 178 |
| Accuracy of resume content (independent)  Categorical/Nominal | RQ6 | MacFarland et al., 2016, p. 178 |
| Traditional versus AI-generated (independent)  Categorical/Nominal | RQ1,RQ2,RQ3, RQ4, RQ5, RQ6 | MacFarland et al., 2016, p. 177-178 |

|  |  |  |
| --- | --- | --- |
| Improvement in resume content (independent)  Ordinal/Likert Scale |  | Sideridis [et al](http://et.al)., 2023, p. 886 |
|  |  |  |

Because hallucinations are such a prevalent attribute of Generative AI inquiries, I am wondering if I should explicitly report on this part of the analysis as part of my findings.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| |  | | --- | | Gina Marshall-Johnson | | Mon, Apr 8, 7:54 AM (9 days ago) |  |  |
| |  | | --- | | to Shelby.wilson | | | |

There is a figure missing below.  Please use this version.

Thanks for being part of my tribe.  I am wondering if you can review my research questions to be sure they are aligned with the variables for data collection.  Also, I realized there is one survey question that is not covered by a research question. Do you think I should add an additional question to cover it?

Thanks for sharing your PhD brilliance!  I am open to any and all suggestions.

Thanks,

Gina

Because hallucinations are such a prevalent attribute of Generative AI inquiries, I am wondering if I should explicitly report on this part of the analysis as part of my findings.



|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| |  | | --- | | Wilson, Shelby N. | | Wed, Apr 10, 11:48 AM (7 days ago) |  |  |
| |  | | --- | | to me | | | |

Hi Gina,

Thanks for sharing.  I was out on Monday to go see the eclipse.  It was amazing!

The “*Variable relationships to research questions*”image didn’t render in the email.  It seems like this image likely shows similar information to what’s in the table?  So I think I get the idea.  But let me know if I’m wrong.

Otherwise, I like the research questions and look forward to hearing what you find during your research.

I have a couple of suggestions/comments:

Consider Swapping RQ4 and RQ5.  This is so that the “does use GAI” falls on evens RQ2, RQ4… and “does not use GAI” falls on the odds RQ3 and RQ5.  (It took me a few minutes to realize this was “off” during reading.  It doesn’t change the science at all, but it’s the type of silly thing that reviewers of manuscripts don’t take the time to disambiguate).

To your question about adding a RQ leading towards improvement, I think it’d be an interesting question to see whether the use of GAI actually improves the resumes. I would imagine that GAI might make women’s resume’s look a lot better because we tend to undersell ourselves.  But this is just a hypotheses   I don’t think you actually need to necessarily need to break out by race/gender.  But if you add this analysis, then you have both RQ1 “who selects to use GAI” and RQ7 “Does the use of GAI improve resume content”

I like the idea of reporting on hallucinations.  Any findings you have here don’t necessarily have to be a part of your “research” but I could definitely see this being a part of your literature review and how hallucinations (and trust of AI) might impact people’s willingness to use GAI for their resumes as well as their ability to catch errors/hallucinations generated in their resumes (You could nod to RQ6 here!)

The thing that is not mentioned here, and might impact your results is whether or not an individual used a non-AI resource to generate/improve their resume (I’m thinking a resume writing service or a recruiting service).  I think whether or not this is a factor might originate from who you’re surveying.  I could imagine more senior/corporate people being more apt to use a human to help with their resume generation.  Again, I wouldn’t modify your survey/research questions, but something to consider whether it will impact your findings and should be included in the background/discussion.

This is exciting work and I hope this feedback helps.  Happy to have more in depth discussion!

Cheers,

Shelby

SME #2 Tamara Goyea, PhD Mathematics, University of Maryland College Park

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| |  | | --- | | Gina Marshall-Johnson | | Mon, Apr 8, 7:48 AM (9 days ago) |  |  |
| |  | | --- | | to Tamara.goyea | | | |

Tamara,

Thanks for being part of my tribe.  I am wondering if you can review my research questions to be sure they are aligned with the variables for data collection.  Also, I realized there is one survey question that is not covered by a research question. Do you think I should add an additional question to cover it?

Thanks for sharing your PhD brilliance!  I am open to any and all suggestions.

Thanks,

Gina

**Research questions**

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RQ2: What association exists in interview selection rates between racial groups among candidates in STEM fields who use Generative AI for resume creation or enhancement?

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|  |  |  |
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| Racial Groups (independent)  Categorical/Nominal | RQ2,RQ3 | MacFarland et al., 2016, p. 178 |
| Gender (independent)  Categorical/Nominal | RQ4,RQ5 | MacFarland et al., 2016, p. 178 |
| Accuracy of resume content (independent)  Categorical/Nominal | RQ6 | MacFarland et al., 2016, p. 178 |
| Traditional versus AI-generated (independent)  Categorical/Nominal | RQ1,RQ2,RQ3, RQ4, RQ5, RQ6 | MacFarland et al., 2016, p. 177-178 |

|  |  |  |
| --- | --- | --- |
| Improvement in resume content (independent)  Ordinal/Likert Scale |  | Sideridis [et al](http://et.al)., 2023, p. 886 |
|  |  |  |

Because hallucinations are such a prevalent attribute of Generative AI inquiries, I am wondering if I should explicitly report on this part of the analysis as part of my findings.

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| --- | --- | --- | --- | --- |
| |  | | --- | | Goyea, Tamara D. | | Wed, Apr 10, 5:07 PM (7 days ago) |  |  |
| |  | | --- | | to me | | | |

Hi Gina,

I took a look at the research questions and believe that they are aligned with the variables for data collection.

I do think it may be good to add a research question to cover the survey question to ensure completeness and consistency.

Hope this helps and very excited about the work!!!! Please let me know if you need help with anything.

All the best,

Tamara

-----  
Tamara Goyea, Ph.D.

# Appendix F: OGS IRB Approval Letter (Pending)

Dissertation Title: Association Between Traditional and Generative AI Enhanced Resume Interview Selection Rates Among Diverse STEM Employment Candidates: A Quantitative Quasi-Experimental Study

Candidate’s Name: Gina Marshall-Johnson

Candidate’s Email Address: gina@aiethicsfoundation.net

**Recruitment Method**

☐ In-person recruitment at a research site

☐ Electronic recruitment requiring permission (ie, email to a specific organization/group)

**X** Social media snowball sampling

☐ Other \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

**X** I have secured permission to conduct my study from my research site (if applicable).

**Verification of Ethical Procedures**

I assure the Institutional Review Board of the following:

**X** I have discussed the ethical considerations of my study with my chair.

**X** I will protect the confidentiality and rights of participants.

**X** My study does not involve vulnerable populations such as minors or the incarcerated.

**X** I will uphold the ethical standards of the Belmont Report (Justice, Beneficence, and Respect for Persons) and OGS’s policies.

**X** I have completed the NIH/CITI certificate for protecting human subjects in research.

**X** I will ensure data are kept securely for up to three years and then destroyed.

**Attachments**

**X** Research Proposal (Chapters 1-3)

**X** Completed Informed Consent Document

**X** Recruitment Letter or Email

**X** Site Permission (if applicable)

**Researcher’s Statement**

I hereby confirm that the information provided is accurate and that I will conduct the research following the ethical guidelines and policies of Omega Graduate School, including adherence to the details outlined in the attached informed consent document.

Researcher’s Signature: \_Gina Marshall-Johnson\_\_\_\_\_\_

Date: \_\_\_\_\_\_June 12, 2024\_\_\_\_\_\_\_

# Appendix G: NIH/CITI Human Subject Research Certification

