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COMMUNICATING THE BALANCING OF THE SCALES FOR GENDER EQUITY IN BUSINESS SCHOOLS: A MULTI-COUNTRY PERSPECTIVE

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ABSTRACT

This paper examines the relevance of gender equity to; faculty compensation, career advancement, and access to leadership roles in selected business schools in Finland, Jamaica, and the United States. These three countries reflect distinct cultural, political, economic, and societal structures and views regarding gender equity. Anchored by feminist, human capital, and socialization theories, we present the perspectives of both male and female business school faculty through cultural, economic, and societal constructs. A total of 410 business faculty members across 30 colleges in Finland, Jamaica, and the United States completed the modified Athena SWAN Gender Equity Survey. From this research, a conceptual framework was developed to help higher education administrators and faculty members contextualize the often-dissimilar experiences of business school faculty from a multi-cultural perspective. The findings confirm that female faculty in business colleges continue to lag in perceived and actual compensation and access to opportunities to succeed in business schools compared to males.

Additionally, the findings support the further examination of the dichotomous relationship between perceived and actual gender inequities encountered by female faculty in business schools. These inequitable treatments continue to reflect, even with positive societal shifts, a distinctly patriarchal leadership, career advancement, and compensation system in business schools, often regardless of cultural norms and mores. Our findings add to the organizational and gender studies literature by proposing a balancing of the scales for gender equity in business schools from a multi-country perspective.

Keywords: gender equity, business faculty, compensation, career advancement, leadership, organizational change

INTRODUCTION

The purpose of this research is to examine the relationship of gender equity to; faculty compensation, career advancement, and access to leadership roles in selected colleges of business in Finland, Jamaica, and the United States. Globally, women still exist in a world where parity is often not reflected in the four key measures of "…economic participation and opportunity, educational attainment, health and survival, and political empowerment" (World Economic Forum, Global Gender Gap Report, 2020, p.5). For example, according to Weinstein (2018), participation of women in the United States labor force ". . . nearly doubled, from 34% of working-age women (age 16 and older) in the labor force in 1950 to almost 57% in 2016," (p.1). Similarly, in Europe, the employment rate for women is 67% compared to 79% for men (Eurostat, 2020). Furthermore, according to the 2021 World Bank Data Report, the total labor participation rate for women in Jamaica is 60.28% compared to 71.05% for males. Thus, globally, there is a significant increase in women participating in the workforce. However, women still have a lower paid employment participation rate than their male counterparts (International Labour Organization, 2018).

In both developed and developing countries, equal opportunity and employment policies are being legislated and enacted to protect the rights of women and other marginalized populations (Bureau of Women's Affairs, 2011; Rose, 2015; Stromquist, 2013; United Nations (UN) Women, 2015). Furthermore, these disparities in the treatment of women are evident in higher education, specifically in traditionally male-dominated disciplines such as Science, Technology, Engineering, Math (STEM), and Business. Thus, the issue of gender equity is of interest to the researchers because this imbalance spreads throughout developed and developing societies, making this research very significant. For too long, women have been "left behind" regarding compensation, professional advancement, and leadership roles, especially in science and business. Hence, the authors address the following questions.

Research questions

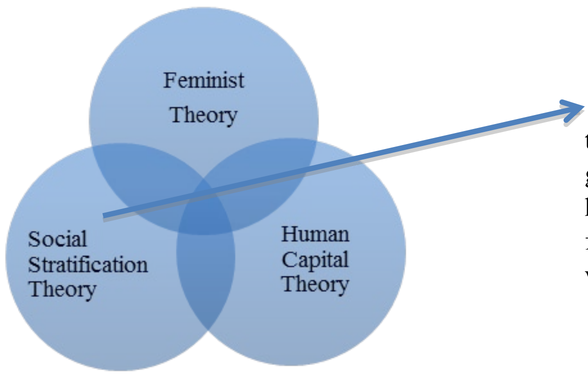
1. To what extent are female faculty members in business schools compensated differently than male counterparts?
2. What factors explain differences in the career advancement of female faculty in business schools?
3. To what extent are leadership positions in business schools determined by gender?

The authors answered each question in the context of the theoretical perspectives used to anchor this study.

THEORETICAL PERSPECTIVES

The three relevant theoretical perspectives that anchor this research are feminist socialist theory, socialization theory, and human capital theory. At the heart of these theories is gender equity, as shown in Figure 1.

Figure 1: Intersection of Gender Equity with Theoretical Perspectives



Gender equity is and has been the heart of these theories. However, gender equity is not only theoretical, but, has practical and procedural implications for improving the quality of life for women worldwide.

Figure 1 shows the intricate relationships among the three relevant theories guiding this research. Equity is at the center because it is a focal point of discovery and is directly and indirectly influenced by human capital assumptions, social and cultural norms, or mores. Gender equity impacts and is impacted by how females perceive themselves in their social and cultural norms. Furthermore, gendered socialization and the economic engine that drives human capital decisions in society continue to perpetuate systemic inequities toward females.

Feminist theory

Viewing inequity from a feminist socialist perspective suggests that established cultural norms and institutionalized and engrained economic and patriarchal systems influence how members of society are viewed and ultimately treated. Wharton (1991) postulates that how people are regarded and treated is based on how each individual sees themself and often how others view that individual based on established norms and institutionalized structures. According to Mundy, Bickmore, Hayhoe, Madden, and Madjidi (2008), ". . . feminist theory is based on people's own perceptions of their place in society, not only on what policymakers or bureaucrats may see as their path to progress" (p. 221). Thus, feminist theory suggests that how a female sees herself may be based on socialization, social strata, economic power, gender, race, or any other defining factor, which is very likely how she will construct her reality, resulting in how she is perceived and treated by others.

Powell (2013) suggests that the deconstruction and reconstruction of how members of society regard gender roles are crucial to recasting how men and women are essentially viewed and treated by members of society. Ledford (2012), Maitra (2013); Mundy, et al. (2008), and Nicholson (2013) advance that post-modernist feminist theorists have debunked gender essentialism, espoused by many early feminist theorists. It, therefore, suggests that women should not be viewed and ascribed expected behaviors based on specific roles they generally assume. These roles include but are not limited to child-rearing, caregiving, and other historically and culturally specific expectations.

Feminist theorists assert that if more women are in leadership roles and are perceived in a positive light by both men and women, then it is very likely that how other women and men view them will help in the deconstruction and reconstruction of how women are viewed and compensated in the society (Powell, 2013). Inequitable social and institutional structures form the nexus of inequities experienced by women and many marginalized groups (Gordon, 2016). The data from the 2011 American Association of University Professors (AAUP) report compiled by Curtis (2011) advances the notion that even though more women are graduating from institutions of higher education with advanced degrees when compared to males, there is still a disproportionate number of women (more women in part-time positions) who are employed as full-time faculty versus adjunct/part-time faculty. Feminist theorists purport that societal constructs, including social stratification, should no longer dictate the treatment of women in society.

Social stratification theory

According to Bowles (2013), social stratification is defined as ". . . the systematically unequal distribution of power, wealth, and status" within society (p. 33). Social stratification theory suggests that how men and women are treated in society indicates the power dynamics, wealth, and status of men versus women within a particular society (Acker, 1973; Bowles, 2013; Grusky, 2019; Kerbo, 2000; Kerbo 2006). How males and females are treated by the same and opposite sex within a society is crucial in assessing the impact of gender inequity and inequality within cultures (Carter, 2014; Verbos & Dykstra, 2014). Hence, many females may opt to leave a discipline because they do not feel they are treated equitably. For example, many female faculties are the minority in traditionally male-dominated disciplines of STEM and business. These faculties often feel 'out of place' because they do not experience what Maslow (1954) refers to as a sense of belongingness. Many eventually leave these traditionally male-dominated disciplines because they often feel like a misfit, coupled with the fact that they have few if any advocates. Hence, many women leave the organization or workforce for other lower-paying and more gender proportionate jobs (Grusky, 2019). Leaving their jobs for less paying jobs perpetuates inequities many women endure. The lower power positions ascribed to women in a male-dominated, historical, cultural, and social structure lead to women being seen and viewed as less valuable. These challenging inequities are persistent but less glaring in developed countries, where the gender gap is less when compared to many developing countries.

We found that social stratification through entrenched and inequitable institutional structures continues to influence gender equity negatively. Thus, the challenge that many female faculty members continue to encounter is defeating the entrenched patriarchal embedded societal system that has and continues to govern most societies. In these societies, there is generally powerful rhetoric of valuing human capital. However, upon a more in-depth examination of such rhetoric, one will find that human capital, as a vehicle of social and economic mobility, is not the same for both men and women.

Human capital theory

As is used in this paper, human capital theory refers to the epistemological framework that guides the understanding of the relationship between the expected positive impact of education and training on the explicit and implicit value an individual brings to the workforce. Hence, the more education and training an individual receives, they are perceived as more valuable to employers. Nafukho, Hairston, and Brooks (2004) suggest that "Human Capital Theory, the main outcome from investment in people, is the change that is manifested at the individual level in the form of improved performance, and at the organizational level in the form of improved productivity and profitability or at the societal level in the form of returns that benefit the entire society" (p. 549). This suggests that males are generally perceived as being more productive and profitable compared to many females. The Human Capital perspective in various societies generally guides how gender is perceived and treated in relation to power (Olson, 2013).

Human Capital models continue to be biased towards men at the economic expense of women. The languages and formulae used to craft benefit policies often favor males over females regarding resource access, training, family/childcare leave, health and wellness options (Bae & Patterson, 2014; Mundy et al., 2008; Olson, 2013). Additionally, Mundy et al. (2008) caution against the negative impact of popular views on human capital theory, as those espoused by noted human capital theorist Theodore Schultz. Views espoused by those who conform to Schultz's (1961) perspective on human capital continue to harm the treatment of women in the workplace. Mundy et al. (2008) quote Schultz as advancing the argument, "The distinctive part of human capital is that it is part of man. It is human, because it is embodied in man . . ." (p. 221). Human capital theorists such as Schultz do not account for women as essential to the economic wellbeing of a nation. Viewing women as an unimportant part of human capital arguably leads to the continued inequity in policies used by numerous institutions and organizations to manage their people.

The human capital disparity, as it relates to proportionate and equitable distribution of women in male-dominated disciplines in higher education, is a direct reflection of the global trends that exist (Lips, 2013; McKinsey & Company, 2014, 2015; Marginson, 2019; Schmitt, 2015; Zhou, 2015). Thus, human capital and socialization theories are the primary drivers for developing the proceeding conceptual framework, with feminist theory supporting both. Together all three theories provide a solid foundation on which this research is anchored and conceptualized.

GENDER EQUITY CONCEPTUAL FRAMEWORK

Incidences of gender inequities continue to exist in all facets of our society (European Institute for Gender Equality (EIGE) Report, 2017, 2020; World Economic Forum Global Gender Gap Report, 2018). For example, in the European Union (EU), a significant gender gap still exists for full-time employment of men and women. According to the European Institute for

Gender Equality (EIGE) Report (2017), "the gender gap in employment in the EU is wide and persistent, with the full-time equivalent (FTE) employment rate of 40 % for women and 56 % for men. Among couples with children, the FTE employment rate is 28 percentage points in favour of men" (p. 31). Higher education institutions are not immune to gender inequity's marginalizing impact on female faculty, especially regarding compensation, leadership, and upward mobility. In this research, the term framework is used because of its broad appeal and precise meaning. Hence, the framework in this research refers to ". . . methods of research and planning for assessing and promoting gender issues in institutions" (March, Smyth, & Mukhopadhyay, 2005, p. 11). Specifically, the two primary reasons for the framework were based on (1) the literature reviewed and (2) having a framework appropriate for the unit of research, gender equity, versus using other terminologies such as tools or methodology (March, Smyth, & Mukhopadhyay, 2005).

From the literature reviewed, it is observed that various frameworks have been advanced to explain and suggest policy and institutional changes to reduce and eliminate the differential treatment of males and females in public and private sector organizations, inclusive of higher education (Albertine, 2013; Daley & MacDonnell, 2011; Nielsen, 2014; Westring, McDonald, Carr & Grisso, 2016). However, from extant research, the limited focus has been placed on examining gender equity in colleges of business, a segment of higher education that has significant influence in developing human capital for the public and private sectors. The gender equity framework (Figure 2) developed from this study helps explain and link the differential treatment of males and females in business colleges to human capital perceptions based on gender, entrenched social stratification structures that reinforce patriarchy, and established cultural norms and mores.

Figure 2: Framework for Gender Equity in Colleges of Business

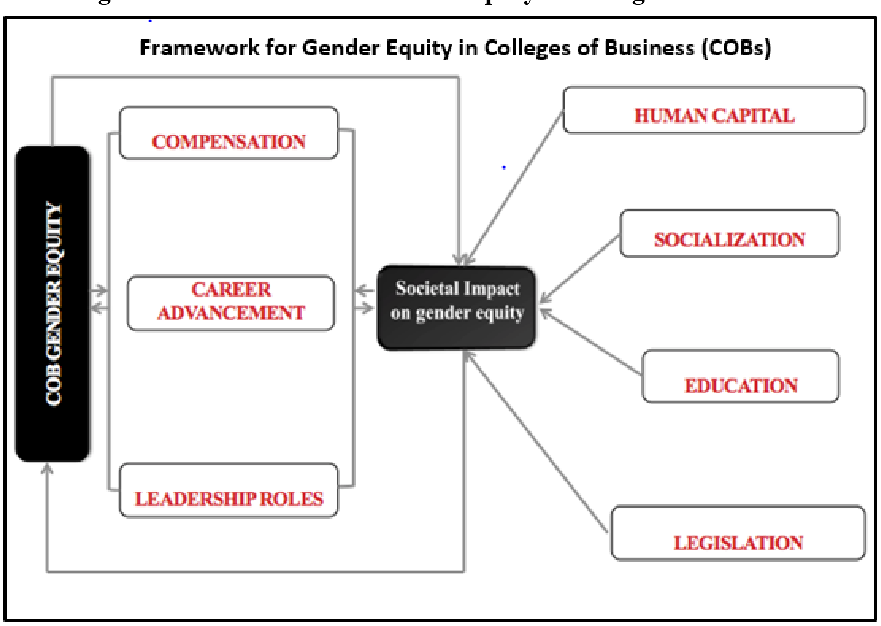


Figure 2 suggests societal gender inequity is at the heart of creating gender neutrality in all other facets of society. Therefore, societal gender equity is directly correlated to compensation, career advancement, and leadership. Furthermore, these three elements directly impact gender equity in colleges of business. On the other hand, societal gender equity is directly related to societal norms, culture, traditions, values, and symbols (Moss, 2002; Ramirez, 2010). In addition, education, human capital, laws, both enforced and unenforced, also impact societal gender equity.

How far can this proposed framework for gender equity go towards helping to understand fair treatment for all members of our society? Gender inequities are mainstream concerns in the geopolitical arena of institutions and society as a whole (Wheeler 2016). However, issues surrounding gender equity also are complex, vexing, and challenging to unravel. These challenges are due to entrenched and learned socialization reflected in allocations of authority and resources, cultural norms, injustices, biases, and disparities relating to feminism (Jahan & Mumtaz, 1996; Moser, 1993; Razavi & Miller, 1995). In each culture, there are multiple perspectives and theories, such as feminist, human capital, and socialization theories, that influence and are influenced by gender equity in the wider society. This conceptual framework is vital in contextualizing the impact of societal inequities fueled and nurtured in the formative years in shaping policies and overall treatment of women in institutions of higher education, especially colleges of business, where there is limited research relating to gender equity.

METHODS, TECHNIQUES, AND MODES OF INQUIRY

This quantitative approach research utilized the modified Athena SWAN Gender Equity Survey to collect empirical data. The targeted population was 1, 500 faculty members and administrators from 30 colleges of business in Finland, Jamaica, and the United States. According to the National Center for Education Statistics (2019), 750 public 4-year colleges in the United States represent 26.5% of all 4-year higher education institutions. In addition, Finland has 35 public universities, and Jamaica has two public universities. The data for this study were collected in the fall of 2016.

Colleges of business are selected based on four inclusion criteria: (1) accreditation by a national, regional, or international board, such as the Association to Advance Collegiate Schools of Business (AACSB); and (2) masters granting or higher-level institutions; (3) public universities and (4) university full-time enrollment (FTE) of 10,000 or more students. The targeted population included: instructors, lecturers, senior lecturers, tenured or tenure-tracked faculty at the assistant; associate; and full rank professors to complete the surveys. A total of 1,500 surveys were electronically sent using SurveyMonkey to faculty members across 25 colleges of business in the United States and four colleges of business in Finland, and one college in Jamaica. The surveyed population included administrators (chairs, deans, directors, coordinators) to ascertain the relationship of gender equity to compensation, career advancement, and access to leadership roles for female faculty. To collect valid and reliable data, the UCL Athena SWAN Gender Equity Survey instrument was modified.

Instrumentation

The Athena SWAN Gender Equity Survey, developed by the University College of London (2015), was selected (and modified) because it addressed gender equity in STEM, a field with similar gender distribution characteristics as colleges of business. This instrument was used successfully to collect data regarding gender equity from science, technology, engineering, mathematics, and medicine (STEMM) professions (Munir, Mason, McDermott, Morris, Bagilhole & Nevill 2013; University College of London 2015). Written permission was obtained from the University College of London (UCL) to modify the Athena SWAN Gender Equity survey instrument.

The survey was divided into eight sections: workload; flexible working conditions/hours; appraisals; promotion; career development; workplace culture; maternity, paternity, adoption, and paternal leave; and demographic data. The demographic data addressed gender (male/female), job role; salary range; academic rank; duration in position; work hours (full/part-time); education level, and geographic location, including Jamaica, Finland, and United States regions.

A five-point Likert scale was used to measure the relationship of gender equity to; compensation, career advancement, and access to leadership roles in colleges of business. Values on the Likert scale range from 1–5 to assess the relationship of gender equity to compensation, career advancement, and leadership. The Likert scale indicated a value of 5 = Strongly Agree; 4 = Agree; 3 = Neutral; 2 = Disagree; 1 = Strongly Disagree. The sixth option of Not Applicable (NA) was added to the scale for relevance in a few cases. This modification was made based on feedback from faculty members who completed the pilot study.

Pilot study

Pilot research was conducted to increase the validity and reliability of the research and reduce the negative impact of an improperly designed survey instrument on the quality of the final survey results (Connelly, 2008; Johanson & Brooks 2010; Morse, Barrett, Mayan, Olson & Spiers, 2002). The pilot study was conducted with a representative population of faculty at the rank of instructor, lecturer/associate/senior lecturer, assistant, associate, and full professor. In addition to the UCL Athena SWAN Gender Equity survey, respondents provided feedback to 12 open-ended questions relating to survey content and face validity. The data from the pilot study questionnaire and the 12 open-ended questions were analyzed and used to improve the final survey's content and face validity (Aiken, 1980; Nevo, 1985).

Data collection and analysis

Data collected were analyzed using the IBM SPSS version 27.0 software. The data analysis includes descriptive statistics, exploratory factor analysis (EFA), independent samples t-test, and Pearson chi-square test of independence. In addition, internal consistency (Cronbach Alpha level of 0.6 or higher for statistical significance) of the survey items was conducted to improve the instrument's reliability (Bonett & Wright 2015).

RESULTS

This section of the paper provides the demographic results, followed by the outcomes aligned to the three research questions. In total, four hundred and sixty-six (466) of the one thousand five hundred (1,500) faculty members responded to the survey, for an overall response rate of 31%. From the 466 respondents in Finland, Jamaica, and the United States receiving the survey, 55 respondents started but did not complete the survey and were dropped from the study. This results in a final sample size of 410 and an effective response rate of 27.3%, as shown in Table 1.

Table 1: College of Business Faculty Count per Country (N=410)

Country	Frequency	Percent (%)	Response Rate (%) per Country
Finland	66	16.1	21
Jamaica	30	7.3	30
United States	264	64.4	21
^Not Identified/Reported	50	12.2	
Total			410/1,500 = 27.3%*

Not reported^ Country of origin not identified/reported
*Final response rate

As shown in Table 1, based on country, 16.1% of respondents were from Finland, 7.3% from Jamaica, and 64.4% of the respondents were from the United States. Furthermore, from this sample, 12.2% or 50 participants did not indicate the country location of their business school.

Across the three countries and two continents, the data revealed an almost equal number of females and males who responded to the modified Athena SWAN Gender Equity survey (see Table 2).

Table 2: Demographic Descriptors of Sample

Demographics/descriptors	Frequency	Percent %
Gender		
Woman	183	44.6
Man	182	44.4
Not reported^	45	11.0
Employment Type		
Full-Time	335	81.7
Part-Time	29	7.1
Not reported^	46	11.2
Position – Job Role		
Post Doc	13	3.2
Instructor	23	5.6
Lecturer/Senior Researcher Teaching Fellow	33	8.0
Senior Lecturer/Principle Researcher/Teaching Fellow	17	4.1
Assistant Professor	76	18.5
Associate Professor	64	15.6
Professor	84	20.5
Administrator and Faculty	41	10.0
Other Roles^^	16	3.9
Not reported^	43	10.5
Contract Types		
Permanent	203	49.5
Open-ended	41	10.0
Fixed term	103	25.1
Temporary	18	4.4
Not reported^	45	11.0

(N=410)
Not reported^ – respondents did not indicate the relevant category.
Other Roles^^ – comprised of doctoral candidates and full-time administrators

Noteworthy is that 45 faculty members chose not to indicate their gender on the survey, representing 10.98% of the total sample from Finland, Jamaica, and the United States. These faculty members were not included in any comparisons or analyses related to gender. As shown in Table 2, 44.6% of females and 44.4% males responded to the survey. The data points to assistant and associate professors making up approximately 34% of the overall participants in the study. Full professors and college administrators (Deans, Chairs, Directors, etc.) comprised approximately 31% of the respondents.

Furthermore, Table 2 indicates 66% of the college of business faculty in the sample indicated having permanent/open-ended contracts, compared with 29% employed under fixed-term/temporary employment contracts. As reflected in Table 2, the majority of respondents were full-time faculty, having a variety of job roles and contract type appointments. The time spent in the faculty role despite contract type is outlined in Table 3.

Table 3: Demographic Descriptors of Sample

Demographics/descriptors	Frequency	Percent %
Time in Position		
Less than 1 Yr. to 5 Years	182	44.4
5 to 10 Years	71	17.3
10 to 20 Years	67	16.3
More than 20 Years	47	11.5
Not reported^	43	10.5
Caring Responsibilities		
Yes	227	55.4
No	133	32.4
Prefer Not to Say	7	1.7
Not reported^	43	10.5
Age		
Under 25	2	0.5
26 – 35	71	17.3
36 – 45	85	20.7
46 – 55	80	19.5
56 – 65	95	23.2
66 and above	33	8.0
Not reported^	44	10.7

(N=410)
Not reported^ – respondents did not indicate the relevant category.
Other Roles^^ – comprised of doctoral candidates and full-time administrators

From the demographic data collected and presented in Table 3, we found that 44% of the respondents were in their position for less than five years. The data revealed 44% of the respondents were, on average, still relatively new to their positions. Additionally, over 33% of faculty members surveyed indicated they were between five and twenty years in their positions. The data collected also indicate that 43% of faculty members were between 46 and 65. Only 38% of respondents were between 26 and 45 years old. The demographic data examined provided a snapshot of the spread and impact of gender on various demographic descriptors such as contract type, job role, caring responsibilities, and years in current position.

The results based on the three research questions are presented in the next section.

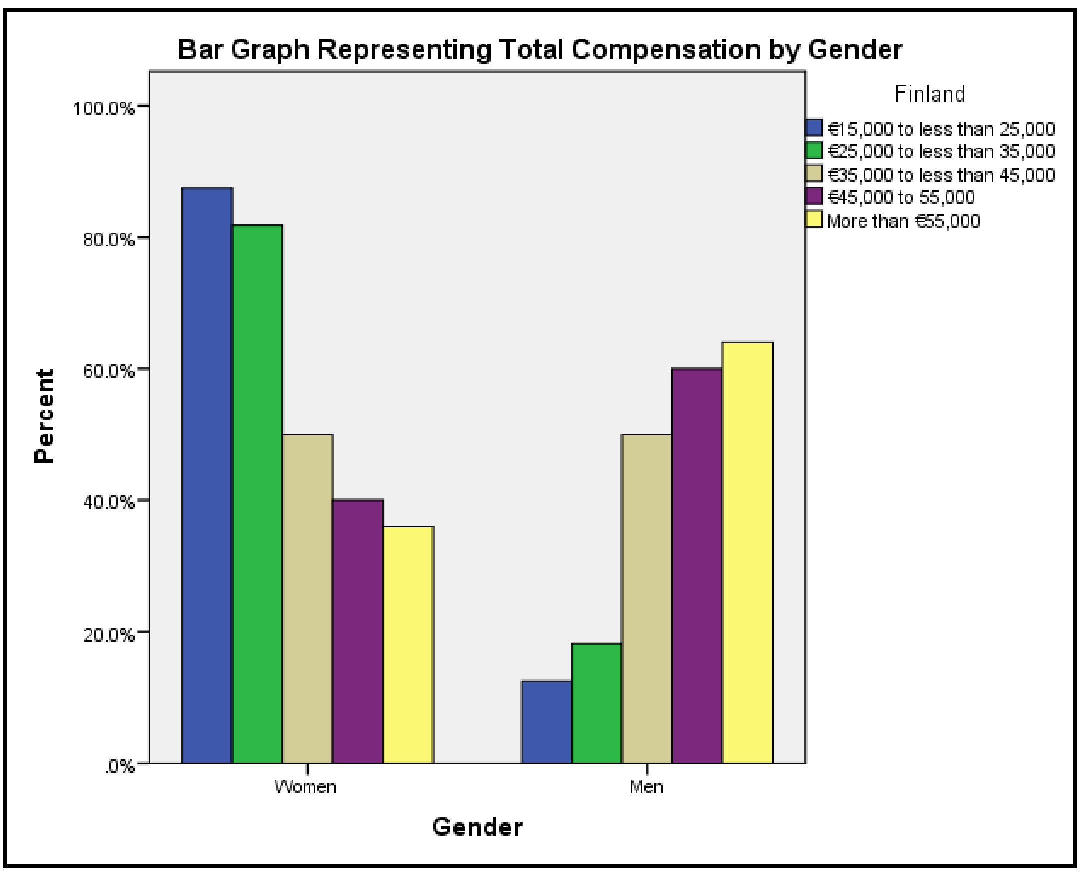
Research Question 1. To what extent are female faculty members in colleges of business compensated differently than male counterparts? For these results, compensation data are presented in Tables 4 & 5 and Figures 3 & 4, reflecting self-reported actual compensation earned by business school faculty by country and faculty members' perceptions regarding compensation.

Table 4: Finnish Faculty Members Analysis of Reported Actual Compensation by Gender

Survey Items – (See Appendix E)	Analysis	p-Value
1 – Perceived equality of work hours Compensated	χ^2 Test of Independence	.367
64b – Perception of equity in salary	χ^2 Test of Independence	.202
64c – Perception of equity in access to funding	χ^2 Test of Independence	.203
78 – Total compensation earned	χ^2 Test of Independence	.025*

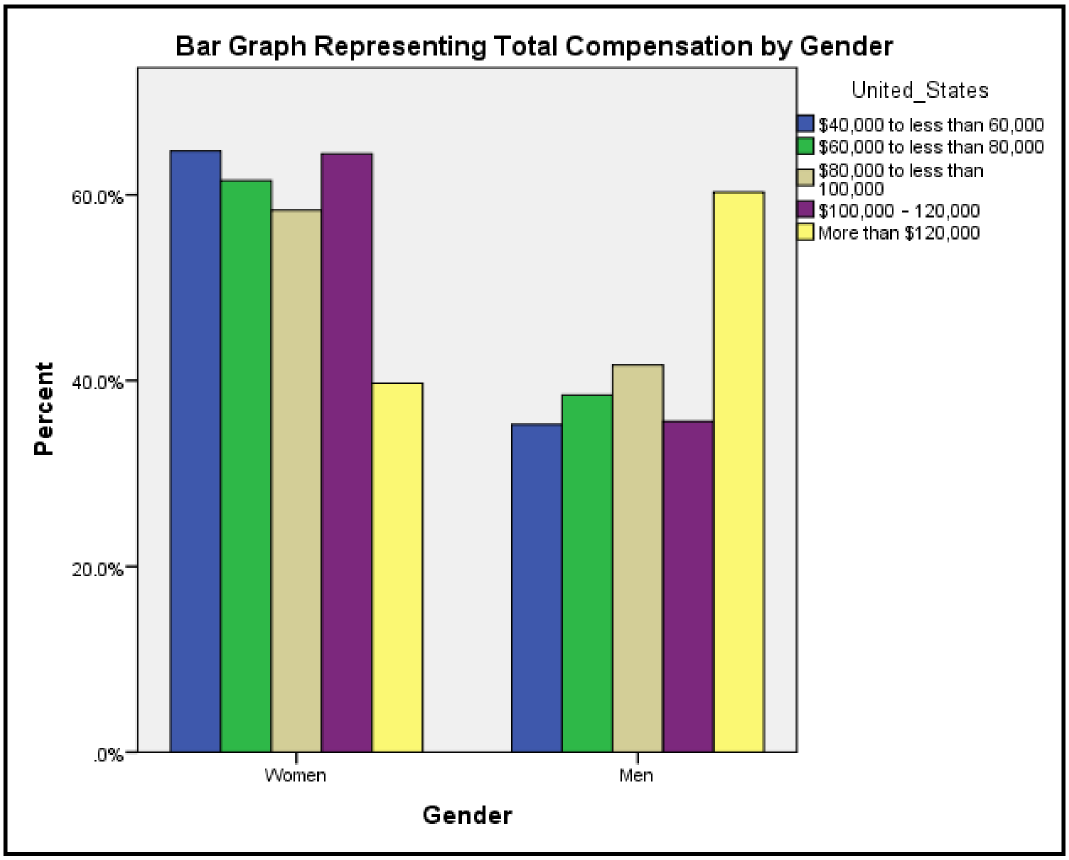
*Significant difference at the .05 level (p <.05)
**Significant difference at .01 level (p<.01)

Figure 3: Finnish Business Faculty Total Compensation by Gender



Our analysis indicates significant differences exist between how male and female business faculty members in Finland and the United States are compensated (see Tables 4 & 5; Figures 3 & 4). These research findings strongly support those female faculty members in Finland, and the United States earn less than males. However, our findings did not support any significant difference in the actual compensation of male and female business faculty members in Jamaica. The findings indicate that fewer Finnish females than male faculty members earned compensation of more than 55,000 Euros (Figure 3), the top of the salary scale used for comparison. Additionally, regarding female faculty members in the United States sample, we found only 22.2% earned more than $120,000/year (Figure 4).

Figure 4: United States Business Faculty Total Compensation by Gender



The data we present in Table 4 reveal the perceptions of Finnish faculty regarding compensation in direct contrast to the actual self-reported salaries of Finnish faculty members. Thus, the findings suggest, Finnish faculty are in effect being inequitably compensated based on self-reported actual salary earned. In addition, the findings did not support any significant difference between actual and perceived compensation of male and female faculty members in Jamaica by comparison to Finland. Hence, Jamaican business school faculty members' actual and perceived salary earned was equitable regardless of gender. Conversely, the data reveal that business school faculty members in the United States perceived inequitable treatment related to salary and access to funding sources for research/scholarship (see Tables 5 & 6).

Table 5: United States Faculty Members Analysis of Compensation with Gender

Survey Items (see Appendix E)	Analysis	p-Value
1 – Perceived equity of work hours compensated	χ^2 Test of Independence	.348
64b – Perception of equity in salary	χ^2 Test of Independence	.000**
64c – Perception of equity in access to funding	χ^2 Test of Independence	.000**
80 – Total compensation earned	χ^2 Test of Independence	.009**

*Significant difference at the .05 level (p <.05)
**Significant difference at .01 level (p<.01)

As shown in Table 5, the faculty in the United States perceived a difference in salary based on gender. This suggests that female faculty in the United States overwhelmingly believe that they are treated inequitably related to salary, access to funding for research/travel, and total compensation earned compared to their male counterparts. Table 6 further elucidates this difference in salary and access to funding for travel/research, based on gender in the United States.

Table 6: Perceptions Male and Female Faculty Regarding Salary and Access to Funding Independent Samples t-test in the USA

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Salary	Equal variances assumed	95.654	.000	8.974	254	.000	.74779	.08333	.58369	.91189
	Equal variances not assumed			8.938	199.301	.000	.74779	.08366	.58281	.91276
Access to funding	Equal variances assumed	91.135	.000	4.133	253	.000	.22632	.05476	.11847	.33416
	Equal variances not assumed			4.146	149.284	.000	.22632	.05458	.11847	.33417

*Significant difference at the .05 level (p <.05)
**Significant difference at .01 level (p<.01)

The data clearly show in Table 6 that females in the United States earn less than their male counterparts for doing the same job. Such inequities demoralize women in the workplace and continue the unfair treatment of faculty members based on gender.

Research question 2. What factors explain differences in the career advancement of female faculty in colleges of business? Table 7 summarizes the findings of research question two. Career advancement was measured using the sub-factors, recognition, tenure, promotion, work flexibility, and working part-time. Career advancement as an overall factor did not indicate any significant difference between male and female faculty members' perceived progress in their careers.

Table 7: Independent Samples T-test Summary Results of Career Advancement Perception

Country	p-Value		
Factor/Criteria	Finland	Jamaica	United States
Recognition	-.183	1.538	.193
Tenure & Promotion	.266	.180	.396
Work Flexibility	-.685	.690	.043*
Working Part-time	-.448	1.732	.411

*Significant difference at the .05 level (p <.05)
**Significant difference at .01 level (p<.01)

Additionally, sub-factors such as recognition, tenure and promotion, flexible working, and working part-time, derived from an exploratory factor analysis (EFA) using a varimax rotation (see Table 7), did not indicate significant differences, except for the United States sample, as it relates to flexible working hours. Female faculty in the United States business school indicated that flexible working conditions were inequitable based on gender (see Table 8).

Table 8: Rotated Component Matrix

*Items	Components								
	1	2	3	4	5	6	7	8	9
12	.891								
10	.816								
16	.807								
32	.789								
3	.708								
9	.699								
30	.659			.460					
35	.593		.425						-.395
28	.546			.504					-.333
14	.524	.396					.356	.308	
21		.857							
23	-.375	-.797							
8		.499				.402	.339		
7			.799						
13			-.667		.347				
11	.490		.529			-.448			
25				.871					
36		.422		.707				.460	
24					-.762				
22					-.747				
33						.882			
34					.336	.515			-.502
26							-.795		
15							.745		
27								.906	
31	.456				.352				.627

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization. [A]
a. Rotation converged in 21 iterations.

The findings from the Finnish business school sample in Table 8 did not indicate a statistically significant difference between career advancement variables, equality in treatment regarding; promotion, access to career development opportunities, office space, administrative support based on gender. Conversely, business school faculty members in the Jamaican sample perceived they were treated unequally/inequitably regarding promotion and receiving administrative support because of their gender (see Table 9). The data indicate a significant interaction between gender and the other perceived inequitable conditions faced by faculty in the United States sample (see Table 9).

Table 9: Pearson Chi-square Test of Independence Summary Results of Business Faculty Perceptions: Other Career Advancement Variables

	p-Value		
Factor/Criteria	Finland	Jamaica	United States
Access to Promotion	.190	.026*	.000**
Access to Career Development Opportunities	.564	.053	.000**
Access to equitable Office Space	.568	.364	.000**
Access to Administrative Support	.557	.008**	.000**

*Significant difference at the .05 level (p <.05)
**Significant difference at .01 level (p<.01)

Table 9 indicates that for career advancement variables such as access to promotion, career advancement opportunities, equitable office space, and administrative support, females in the United States sample continue to lag behind their male counterparts, irrespective of the number of years on the job. Only access to promotion and administrative support presented a significant interaction at p<.05 level in Jamaica. No significant difference was found between how male and female Finnish faculty access these career advancement variables.

Research question 3. To what extent are leadership positions in colleges of business determined by gender? Research question three focused on two sub-factors (1) gender-biased leadership and (2) equal access to leadership positions derived from an exploratory factor analysis (EFA) using a varimax rotation. This analysis found that gender-biased leadership represented a significant difference in how male and female faculty members in Finland, Jamaica, and the United States accessed leadership positions (see Table 10).

Table 10: Pearson Chi-square Test of Independence Summary Results of Business Faculty Leadership Factors

Factor/Criteria	Finland	Jamaica	United States
Gender-biased Leadership	10.299	.181	.000**
Equality of Access to Leadership	14.198	.243	.363

*Significant difference at the .05 level (p <.05)
**Significant difference at .01 level (p<.01)

As shown in Table 10, only findings from Finland and the United States sample indicated a statistically significant difference in equal access by male and female business faculty members to gender-biased leadership. The findings relating to perceptions of business faculty regarding other leadership variables are summarized in Table 11.

Table 11: Pearson Chi-square Test of Independence Summary Results of Business Faculty Perceptions: Other Leadership Variables

Factor/Criteria	Finland	Jamaica	United States
Leadership opportunities	.767	.602	.042*
Gender balance on committees	.048*	.084	.173
Decision making	.750	.498	.050*
Consulted on key decisions	.378	.105	.442

*Significant difference at the .05 level (p <.05)

**Significant difference at .01 level (p<.01)

Table 11 indicates that business school faculty members in Finland did not perceive that gender had any statistically significant role in how they accessed leadership opportunities and being involved in decision-making within their colleges. Conversely, Finnish business school faculty members did perceive that tenure/promotion committees lacked gender balance. From the data, female faculty perceived fewer females than males are represented on tenure/promotion committees.

DISCUSSION AND INTERPRETATION OF FINDINGS

The findings are presented and interpreted based on the three research questions that guided the study. Consistent with the findings regarding the extent to which female faculty members in colleges of business are compensated differently than their male counterparts, is borne out in existing literature regarding gender inequities in the United States and Finland (AAUW Report 2016-2017; European Commission 2016—2019; United Nations Women–Finland, 2015; World Economic Forum Global Gender Gap Report, 2020). The literature we reviewed revealed female faculty in academia continue to be compensated at a lower rate than their male counterparts. In Finland, the data revealed females were compensated at 87 cents to the dollar (European Institute for Gender Equality, 2020; Ministry of Social Affairs and Health, n.d.; Statistics Finland, 2014;) and in the United States, 82 cents to the dollar according to the American Association of University Women (AAUW) 2020 Report. According to the Statista Labor Market Gender Gap Index, 2021, females in Jamaica are compensated 63 cents to the dollar compared to their male counterparts (Romero, 2021).

Our findings for research question one confirmed what other researchers have advanced. That is, compensation remains a significant factor impacting gender equity in higher education. From this research, only data related to the total compensation of faculty members in Finland and the United States supported this significant relationship/interaction between gender and compensation earned. Conversely, the data from the Jamaican sample did not support a perceived or actual disparity related to compensation. The results from the Jamaican sample ran counter to the findings of the World Economic Forum Global Gender Gap Report (2018, p.137) findings that females are still being compensated at 61 cents to the dollar compared to their male counterparts.

The perceptions of business faculty members regarding equity in compensation were not explained in the literature reviewed. We found that perceptions of inequitable salaries based on gender confirmed the actual self-reported inequitable salary earned by female faculty members. In other cases, we did not support the findings. For example, even though Finnish faculty members were inequitably compensated based on the self-reported actual compensation, they did not perceive gender as having any impact on how they were compensated

Consequently, this research represents a fascinating and important extension based on anecdotal evidence that there is a disparity in how Finnish faculty members are compensated. This reality can lead to significant social, financial and political implications, especially for women in colleges of business. When compared to Jamaica, a small developing country, there was no statistical difference in the actual or perceived equity in compensation of male and female faculty members.

On the other hand, the findings indicate that faculty members in the United States perceive that gender plays a significant role in compensation. This finding was consistent with the literature and supported the actual self-reported compensation data collected in this study (Newman, 2014; World Economic Forum, Gender Gap Report, 2020, 2021). Current literature (International Labor Organization, 2018 and Grusky, 2019) placed significant focus on inequity in actual compensation and not on the impact of perceptions regarding compensation of business school faculty members. The findings from this research regarding perceptions of equity in compensation will expand earlier research regarding compensation and gender equity. Although no significant difference existed between compensation and gender for the Jamaican sample, the findings show that when salaries are negotiated in a highly-unionized system, issues of inequity are generally fewer.

All business faculty in the Jamaican sample, a public university, and the population for this study were compensated based on collective bargaining negotiations. Hence, compensation within Jamaica's highly unionized public university system makes it difficult for inequitable compensation to occur, at least when faculty are hired. Document analysis showed emphatically that the University of the West Indies, the largest public university in Jamaica, and by extension, Mona School of Business and Management, the sample for this study, hiring practices were guided by a gender mainstreaming policy. As a result, faculty compensation within the Jamaican system is part of collective bargaining and not decided within colleges. This collective bargaining practice reduces the likely impact of gender-based compensation at the time of hire.

These results are in keeping with the literature reviewed (UWI Statistical Report, 2016; UN Women, 2015; World Bank Data, 2020).

In conjunction with research question two, the factors that explained the differences in the career advancement of female faculty in colleges of business were recognition, tenure and promotion, flexible working conditions, and working part-time. The literature reviewed pointed to gender inequities both in academia and the business world that negatively impacts career advancement of women related to these factors (Bilimoria & Liang 2011; Blättel-Mink, 2008; Doyle 2010; Mckinsey & Company 2014, 2015; McKinsey Quarterly 2015; Reilly, Jones, Vasquez & Krisjanous 2016; Tyer-Viola & Cesario 2010; Unterhalter et al. 2011; Sanders, Willemsen & Millar 2009; World Economic Forum Global Gender Gap Report 2020). The findings from this study do not support the premise that career advancement, on its own, was a significant factor being influenced by gender. Instead, the findings reveal that when career advancement sub-factors, recognition, tenure and promotion, flexible working hours, and working part-time were evaluated against gender, they contradicted existing literature. The literature indicated that these named factors were essential measures of career advancement that continue to be influenced by gender (Stromquist, 1990, 2013; Sanders, Willemsen, & Millar, 2009). We found the only exception was the sub-factor, flexible working hours, which presented a significant relationship with gender for the United States (see Table 7).

Furthermore, the results on gender perception indicate more females from the United States sample believed they were mistreated regarding issues related to workload. Perceptions tend to lead to behaviors that may impact an individual's overall performance on the job (Chang, Rosen, & Levy, 2009), in keeping with human capital theory. Hence, the findings from this research are essential, adding to and extending the body of literature regarding gender equity. Additionally, the findings indicate that male and female perceptions of inequitable treatment based on gender, as it relates to promotion and administrative support, were significant for some business faculty, but not for others, in accordance with both feminist and socialization theories. For example, female faculty members from the Jamaican and the United States samples were the only ones perceived to be treated inequitably related to promotion and getting administrative support (see Table 9). Thus, female faculty are still a marginalized population in the United States and Jamaica, and their perception of disproportionate treatment based on gender may result from their lived experiences. Again, this was in keeping with the tenets of feminist theory.

Additionally, perceived inequity by Jamaican business faculty may be based on the deep-rooted patriarchal culture and socialization patterns of women in the society who are still viewed as being inferior to men in many respects, inclusive but not limited to promotion and receiving administrative support (Bellony, Hoyos & Nopo, 2010; Thame & Thakur, 2014). The perceptions held of being mistreated in the areas of promotion and getting administrative support are critical components of career advancement that may also be further explained by feminist theory (Ledford, 2012; Powell, 2013) as well as by human capital theory (AAUP, 2018-2018; Bae & Patterson 2014; Mundy et al. 2008; Olson 2013). According to socialization and feminist theory, how individuals view themselves and others may directly result from the socialization process they have encountered from their formative years through adulthood. Hence, how each individual views themself continues to influence the expectations and their world view and perceptions.

Interestingly, for faculty in the United States sample, we found a significant relationship between gender and access to administrative support, equitable office space, career development opportunities, and access to promotion (see Table 9). Additionally, United States business school faculty members indicated that they felt unfairly burdened with low-level administrative and service work. These two factors have proven to be detrimental to their career. Analysis of survey data does not show a significant relationship between gender and inequities in career advancement for Finnish faculty members. However, according to the European Institute for Gender Equality report (2016, 2019, 2020), females in Finland lag behind their male counterparts regarding equitable access to healthcare, work, power, and shared time for caregiving. Notably, female faculty members from the United States and Jamaica perceived mistreatment compared to their male peers regarding promotion and administrative support access. Furthermore, female faculty members from the United States perceived they were treated inequitably regarding access to office space and career development opportunities.

Our findings to research question three examining the extent to which leadership positions in colleges of business were determined by gender is interpreted below. First, the findings indicate that significantly more female business faculty members in all three countries (Finland, Jamaica, and the United States) perceive that leadership positions in colleges of business are gender-biased. This finding supports both the literature in academia and the business world that gender inequity exists in business school leadership as well as leadership in corporate entities, respectively (Bilimoria, & Liang, 2011; Blättel-Mink, 2008; Doyle, 2010; Mckinsey, & Company, 2014, 2015; McKinsey Quarterly, 2015; Reilly, et al., 2016; Tyer-Viola & Cesario, 2010; Unterhalter et al., 2011; Sanders, Willemsen & Millar, 2009; World Economic Forum Global Gender Gap Report, 2014, 2015). Second, this study also confirmed findings in the literature that a significant relationship exists between gender and leadership opportunities. However, what is of interest, which deviates from the literature, is that significant interactions were not present between gender and equitable access to leadership (see Table 10).

Additionally, significantly more female faculty members in the United States sample indicated they noticed/observed others in their college being mistreated (gender-biased leadership) because of their gender (see Table 10). The fact that more females in the United States sample reported seeing inequitable treatment encountered by faculty because of gender may indicate different historical and social norms in the United States compared to Finland and Jamaica. Finally, with these strong findings come implications for policy and practice regarding reducing and ultimately eliminating gender inequity within business schools.

IMPLICATIONS OF THE FINDINGS FOR POLICY AND PRACTICE

Policy implications

We found that current literature on gender equity did not focus on business school faculty (Reilly, et al., 2016). Hence, this research sought to fill this gap in the literature. Additionally, examining issues of gender equity utilizing the perceptions of business faculty is not an area of focus in the literature. Therefore, we suggest that the findings from this study add to the general body of research literature on gender equity. More importantly, the findings of this study extend the discussion of gender equity by accounting for the impact of faculty perceptions of equity through a comparative and multicultural lens (U.S. Department of Education, National Center for Education Statistics, 2018). Using faculty members' perceptions of inequitable treatment helps understand why, as was found in this study, actual data sometimes runs counter to perceived inequities.

For example, even though female faculty members in Finland were compensated at lower rates than their male counterparts, they perceived no inequitable compensation between male and female faculty members. Because Finland, a Nordic Welfare State, is seemingly a more egalitarian society, likely, faculty would not have perceived any inequity in compensation. In contrast, faculty from the United States, a more individualistic/capitalistic society, perceived they are inequitably compensated, and in actuality, they are. Additionally, in a highly patriarchal society, faculty members from Jamaica did not perceive they were inequitably compensated. This finding was confirmed by self-reported actual salary data provided but contrasted with the World Economic Forum Global Gender Gap Report (2018) that indicates that on an overall country basis, females are inequitably compensated, 61 cents to the dollar compared to males.

Using Human Capital theory to examine the implications of perceptions regarding faculty compensation and the actual inequities between salaries of male and female faculty members is essential to gender equity research. From a human capital theory perspective, as Olson (2013) espoused, those who control the power and resources within societies determine how gender issues are viewed and treated. Therefore, if policymakers who make compensation decisions view females as less than males in their ability to get the job done, gender inequity will persist. Furthermore, even though females may come to the table with the same human capital, the compensation model valued by leadership will often favor male over female faculty.

According to Bowles (2013), those who control organization resources are typically those who control power. Therefore, policymakers, who more often than not are men, need to be educated to have a behavior change and to craft policies that equalize the playing field for females. From this study, we found that more males in the study sample earned higher compensation. This unequal distribution of compensation, based on the postulate of Bowles (2013) and Kerbo (2000), will likely lead to the unequal distribution of power and likely determine how females are treated, viewed, and positioned in society. To deconstruct the stereotypical view that men are generally destined to earn more than women based on expected societal norms, one must examine how men and women are socialized in their formative years (See Figure 2, Framework for Gender Equity in College of Businesses). This socialization process and practice generally decide how males and females perceive themselves and ultimately treat others.

Implications for practice

Except for working flexibly, an important practice impacting gender equity in the United States, career advancement was not deemed a significant factor explaining the differences in how male and female faculty members progress in their profession. Based on these results, we imply that generally, business faculty across these distinct cultures of Finland, Jamaica, and the United States, do not perceive their progression in their career being impacted by inequity in tenure and promotion, recognition for their work, and working part-time. The findings suggest that working flexibly is a significant factor impacting the career advancement of female faculty in the United States. These findings suggest that it is incumbent on legislators and policymakers at the national and university level to place more effort on eliminating perceived and actual inequities in compensation across these three countries. Additionally, accommodating working flexibility should become more equitable, especially as more females than males participate in caregiving roles.

Equitable access to leadership positions continues to be a critical factor advanced by many in the literature regarding male and female faculty (AAUW Report, 2016, 2018; AACSB Report, 2014; Curtis, 2011). The data obtained from business faculty in Finland, Jamaica, and the United States are emphatic that leadership positions in business schools are gendered in favor of males over females. Our findings further indicate that more male than female faculty members is in leadership positions in business schools across the three countries. The AACSB Report supports this finding (2014), Business School Data Guide Report (2018), and other literature reviewed. This finding implies that even though in Finland, Jamaica, and the United States, legislation and policies have been enacted to assure females have equitable access to jobs and opportunities, they still lag behind males based on their human capital.

We suggest that policy and practice implications implore policymakers/legislators at the country and university level to reexamine current Equal Employment Opportunity (EEO) mandates and determine necessary changes that will positively impact female business faculty access to leadership roles, equitable compensation, and particular career advancement opportunities. Crafting policies that lead to acceptable practices that focus on providing opportunities for more females to access leadership positions will be a step in the right direction. More females in leadership and policymaking positions provide both a real and psychological boost to females coming through the pipeline.

CONCLUSION

Conclusively, in this study, we set out to examine the relationship between gender equity and compensation, career advancement, and leadership. We found there were powerful connections between gender and actual compensation for Finland and the United States. However, no significant relationship existed between gender and compensation for Jamaica due to hiring policies guided by a collective bargaining unionized environment. In addition, there was no significant difference between gender and career advancement for all three countries.

Furthermore, our study confirmed gender-based leadership roles continue to significantly influence hiring practices in business schools where more males control senior leadership positions, are tenured or tenure-tracked full or part-time faculty and graduate teaching assistants compared to females (AACSB Business School Data Guide, 2021).

Gender inequity persists in the wider society. Its impact in businesses colleges is far-reaching as these business schools have the enviable task of preparing students who will likely be the business leaders of tomorrow or future faculty members. These research findings suggest the need for a strong focus in terms of policy and practice for fixing or providing equity for current gender inequities. This would require placing greater emphasis on societal norms, values, mores, and beliefs that shape each individual. Hence, the study posits a conceptual framework (see Figure 2) that places focus on deconstructing societal perceptions from the formative years (pre-school, kindergarten, elementary) that women are less than or unequal to men. However, trying to make meaningful change after the formative years where deeply rooted normed behaviors have been reinforced is difficult, if not impossible, in engendering sustainable changes in attitudes and behaviors by women about themselves and others regarding their place in society (Bicchieri & Mercier, 2014).

The deconstruction of entrenched societal and cultural norms must begin in the formative years for both males and females to assure that behavioral changes are sustained by accepting equity and equality for all members of society. Additionally, the findings of our study indicate actual and perceived unequal compensation by gender should inform legislation, educational policies, curricula, and other measures that seek to change cultural, institutional, and personal perceptions regarding gender equity. Finally, we want women worldwide to perceive and experience fairness in how they are compensated, promoted, and given access to leadership roles. This way, balancing the scale of gender equity will be achieved.

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ESTIMATING THE VALUE OF STATISTICAL LIFE (VSL) LOSSES FROM COVID-19 INFECTIONS IN THE UNITED STATES

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ABSTRACT

This paper uses the Value of Statistical Life (VSL) literature to weigh the costs and benefits of non-pharmaceutical interventions of the U.S. COVID-19 stay-at-home orders that affected 92 percent of the U.S. workforce at their peak in April 2020. We calculate the pre-vaccine COVID-19 infection fatality rate to have been 0.85 percent. We find that the stay-at-home orders saved most likely about 71,000 lives and led to a net benefit to the United States of 1.7 percent of GDP after accounting for lives saved and drops in workforce participation. Through October 31, 2021, the VSL of U.S. lives lost to COVID-19 was over $8.4 trillion.

Journal of Economic Literature Codes: G22, I1, I18, J31, J65, K32

Keywords: death rates, CFR, COVID-19, IFR, non-pharmaceutical intervention, NPI, SARS-CoV-2, social distancing, stay at home orders, VSL

INTRODUCTION

In this paper we model the benefits of social distancing measures in terms of the value of statistical lives (VSL) saved in the SARS-CoV-2 or COVID-19 pandemic. We find that the unprecedented state stay-at-home orders at their peak affected over 92 percent of the workforce. Those stay-at-home orders were likely economically justified in terms of the value of lives saved. Nevertheless, the cost benefit analysis is not positive in all scenarios. The U.S. state-level stay-at-home orders that stretched from March 11, 2020, to June 14, 2020, most likely led to net economic benefits of about 1.7 percent of 2019 U.S. GDP or $368 billion and saved over 71 thousand lives. The range of the net benefits was about $1.7 trillion to -$0.4 trillion.

Prior to pharmaceutical treatments becoming available, economically costly social distancing interventions as advocated by Ferguson *et al.* (2020) were one of the few tools available to suppress COVID-19. By the start of November 2021, COVID-19 had claimed the lives of over 745 thousand Americans or about 0.2 percent of the pre-pandemic population. There is some evidence that social distancing may be effective. RT is the number of additional persons that an infected person goes on to infect on average. Rocklöv *et al.* (2020) estimate that uncontrolled RT for COVID-19 on the Diamond Princess cruise ship was 14.8 before social isolation and 1.8 afterward. Chowell *et al.* (2011) argued that school closures in Mexico reduced

[1] The views expressed are of the author alone.

the RT of the H1N1 outbreak by more than 30 percent. Fowler *et al.* (2021) found that stay-at-home orders that lasted over three weeks suppressed COVID-19 cases by 48.6 percent.

By April 7, 2020, we found that 92 percent of the U.S. population was under a stay-at-home orders that meant that many businesses were shuddered. Morath and Chaney (2020) report that by April 16, 2020, 13 percent of the U.S. workforce or 22 million workers had filed unemployment insurance claims. The COVID-19 multi-state stay at home orders, and associated non-essential business shutdowns, began with Alaska, on March 11, 2020, and ended with New Hampshire on June 14, 2020. Before the SARS-CoV-2 disruptions, the U.S. unemployment rate stood at a record low 3.5 percent in February 2020, according to the Bureau of Labor Statistics.

Eichenbaum *et al.* (2021) estimate that containing COVID-19 "optimally" with social distancing will lead to consumption dropping by 22 percent versus 7 percent without containment of the virus. Since consumption is about 68.1 percent of GDP, according to the St. Louis Fed, and 2019 GDP was $21.43 trillion, they are arguing macroeconomic consumption losses are about (0.22 – .07)*$21.43 trillion = $3.2 trillion. We find more modest losses from the March to June 2020 stay-at-home orders, which were relatively short in duration. Without considering the benefits in terms of lives saved, the ninety-six days of stay-at-home orders cost about $0.4 trillion according to our calculations.

Yale News (2020) estimated the daily losses of shutdowns at $19 billion per day or about $7 trillion per year. Our estimates of the daily costs of stay-at-home orders were less. We find in this paper that, on a workforce weighted average basis, the U.S.A. had about 44.1 days of stay-at-home orders, which cost U.S. output worth $4.7 to $14.8 billion per day.

We also find that the number of deaths and value of statistical life (VSL) losses are extremely high from high rates of COVID-19 infection in the range of $5.2 to $11.5 trillion by October 31, 2021. Thus, major economic disruptions from social distancing, stay at home orders, and school closures could be justified if they in fact prevent illness and death. Nevertheless, the emergency approval of the first COVID-19 vaccine in the U.S.A. on December 11, 2020, has likely made more costly social distancing interventions harder to justify economically.

In section 2, we discuss how to value human life with the value of statistical life (VSL) literature and estimate the economic cost of the COVID-19 pandemic. In section 3, we estimate the infection fatality rate (IFR) of the SARS-CoV-2 virus from the U.S. Centers for Disease Control's (CDC's) large serology studies. In section 4, we weigh the expected VSL of lives saved from the March to June 2020 stay-at-home orders against the lost economic output from those partial economic shutdowns. Finally, in section 5 we conclude.

VALUE OF STATISTICAL LIFE LOSSES

To weigh the costs of social distancing measures, we need to be able to estimate the value of human life. Clearly, we cannot stomach sacrificing all of society's resources to save one life and let 99.99999 percent of the world starve to death. There must be some price at which saving a human life is too dear. The value of statistical life (VSL) literature says we should value human life at the rate that individuals value their own life. An individual chooses between a risky job and a safe job or a risky product and a safer product. This choice trades money for a small probability of death. VSL = (extra money gained)/(extra probability of death). For example if an individual gains $4,000 from a 1 in 2,000 probability of death, then VSL = $4,000/(1/2000) = $8 million.

This is a large literature that O'Brien (2018) does a good job of introducing the reader to. We selected the studies that looked at a range of ages at least as large as 18 to 62. Selected studies reviewed by O'Brien (2018) are in table 1. We only selected studies with a minimum age of persons studied of 18 or lower. All selected studies had to have a maximum age of 62 or higher. In addition, we only selected studies that had a range of VSL estimates. The upper and lower bound estimates of the selected studies Johannesson *et al.* (1997), Aldy and Viscusi (2003), Viscusi and Aldy (2007), Aldy and Viscusi (2008), and Kneisner, Viscusi, and Ziliak (2006) are in table 1. Our lower bound estimate is the average of those studies' lower bound, $5.75 million. The upper bound average VSL estimate is $12.57 million. The average of the upper and lower bound is $9.16 million. The inflation multiple from the Bureau of Labor Statistics from 2009 to 2020 is 1.2218. Thus, in 2020 dollars our low, expected, and high VSL estimates are $7.0 million, $11.2 million, and $15.4 million.

Table 1: Value of statistical life (VSL) studies upper and lower estimates in 2009 U.S. dollars

Study	**Lower VSL in 2009 US Dollars**	**Upper VSL in 2009 US Dollars**	**Age Range Studied**
Johannesson et al. (1997)	$4.83	$7.48	18-74
Aldy and Viscusi (2003)	$4.00	$10.42	18-62
Viscusy and Aldy (2007)	$7.30	$15.35	18-62
Aldy and Viscusi (2008)	$4.22	$9.70	18-62
Kneisner, Viscusi, and Ziliak (2006)	$8.42	$19.92	18-65
Average	**$5.75**	**$12.57**	

Source: O'Brian (2018)

This is a subset of the studies of the value of statistical lives (VSL) in O'Brien (2018)'s Table 1 which are in 2009 prices. We selected the studies that at least looked at an age range that started no higher than 18 years old and had a top age no lower than 62 years old. There had to be an upper and lower bound to the VSL estimates cited in O'Brian for a study to be selected. A simple average of the five studies lower and upper bounds were taken. The average of the average upper and lower bound was calculated as our VSL expected estimate.

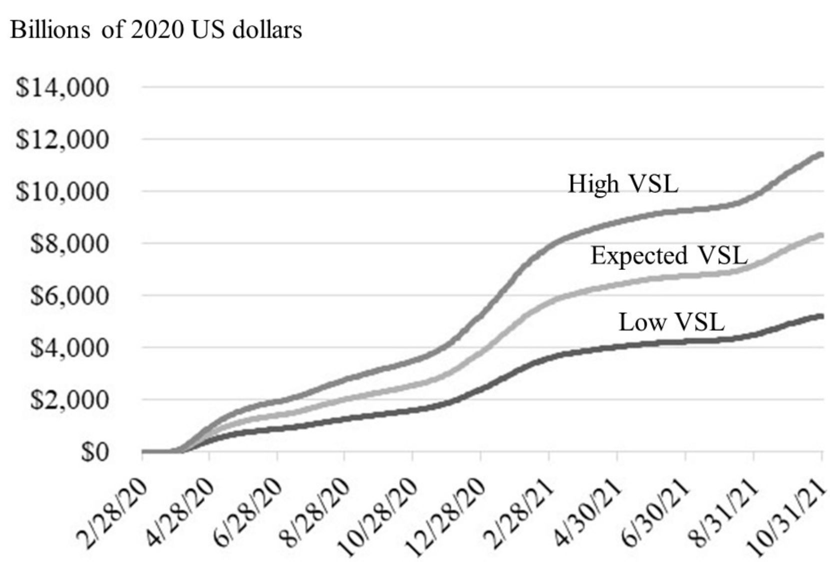
O'Brien (2018) points out that many studies, including O'Brien (2018), find an inverted U-shape that seems to conform to people's valuations of their lives depends on their current income. The young and post-retirement persons have lower VSL's than persons in their peak earning years. Unfortunately, most studies do not track VSL into the 70s, 80s, and 90s because employment choices are the most common method of calculating VSL. Thus, we don't have a good idea of how much the VSL of a person in their 50s differs from someone in their 90s. Nevertheless, VSL does not track closely with life expectancy because we see VSL increasing from the 20s to the 50s while life expectancy declines.

For simplicity, we do not distinguish between age and VSL. Our low, expected, and high estimates do not differ between age categories. Thus, a 90-year-old man with a life expectancy of 4.1 years has the same VSL as a 1-year-old girl with a life expectancy of 80.4 years in our analysis. Porter and Tankersley (2020) argue that the U.S. Environmental Protection Agency (EPA) under the George W. Bush administration abandoned attempts to discount VSL for seniors by 33 percent after a political backlash. Eichenbaum *et al.* (2021) use the $9.5 million VSL which the EPA uses. $9.5 million is between our lower end expected VSL estimates of $7 million and $11 million.

After adjusting Merrill (2017) for inflation, the median wrongful death jury award was only $2.6 million, the median 9/11 compensation was $2.4 million, and the average lifetime earnings of college graduates was $2.8 million in 2020 U.S. dollars. Thus, both the EPA and our VSL range place a much higher value on American lives than juries have done or the 9/11 commission did.

By October 31, 2020, Ritchie *et al.* (2021) tabulated over 745 thousand COVID-19 deaths in the United States. The first recorded COVID-19 death in the U.S. was on February 29, 2020. By comparison, heart disease has been the number one killer of Americans, and it results in 647 thousand deaths per year according to Bacon and Yomtov (2020).

Figure 1: The Cost of COVID-19 Deaths in the United States Over Time. The Value of Statistical Lives (VSL) Lost from SARS-COV-2 in the USA.



By the end of October 2021, the United States had over 745 thousand COVID-19 deaths that amounted to 0.23 percent of its February 28, 2020, population of 331,331,747 estimated by the U.S. Census at https://www.census.gov/popclock/. That economic cost of those lost lives is estimated at between $5.2 and $11.5 trillion dollars with an expected total VSL of $8.4 trillion. The high, expected, and low value of statistical lives (VSL) per COVID-19 death is from table 1. According to the Bureau of Labor Statistics 2009 U.S. dollars are worth

1.2218 times 2020 U.S. dollars. The figure is in 2020 U.S. dollars. The per death expected VSL of $11.2 million is the average of the averages of the upper and lower VSL from the surveys studied adjusted for inflation. The per death high VSL estimate of $15.4 million is from the average of the upper VSL estimates adjusted for inflation. The low VSL per death of $7.0 million is the average of the lower estimates in table 1 adjusted for inflation. Per person VSL is multiplied by the cumulative number of COVID-19 deaths reported by Ritchie *et al.* (2021).

The deaths calculated for the low, expected, and high estimates in figure 1 are multiplied by the low. midpoint, and high VSL estimates of $7.0 million, $11.2 million, and $15.4 million per death, respectively. Those estimates are plotted in figure 1. Our midpoint VSL estimate produces losses of $8.351 trillion with a high and low range of $11.458 and low of $5.235. Scaling those numbers by pre-pandemic 2019 U.S. GDP of $21.43 trillion from Mataloni and Aversa (2020), those costs through October 31, 2021, are equal 39.0 percent of the U.S. annual output with a range 53.5 to 24.5 percent of U.S. GDP.

INFECTION FATALITY RATES

The economic losses from COVID-19 depend on the disease's infection fatality rate (IFR). IFR is the rate at which infected persons die. Ferguson *et al.* (2020) uses Verity *et al.* (2020)'s overall IFR estimate of 0.9 percent with a 95 percent confidence interval of 0.4 and 1.4 percent. Ferguson *et al.* (2020) is in line with the IFR estimate by Wilson (2020) of 0.850 percent using New York City data.

Case fatality rates (CFRs) measure death rates of persons tested. The IFR is meant to measure the death rates of all persons infected. A significant portion of COVID-19-positive persons might not be tested. For example, in part, early on in the pandemic that may have been due to testing shortages and testing protocols in many states that require symptoms. Moreover, persons with asymptomatic COVID-19 cases may have failed to seek out testing regardless of testing availability. Sutton *et al.* (2020), tested all women admitted to deliver a baby at New York Presbyterian Hospital. That study found that over eighty percent of COVID-19-positive pregnant women were asymptomatic at the time of their test. Only about ten percent of the asymptomatic women developed any symptoms during their three-day stay at the hospital. Gudbjartsson *et al.* (2020) conducted a randomized test of persons in Iceland. 54 percent of the persons testing COVID-19-positive had no symptoms.

The Centers for Disease Control conducted twenty nationwide serology studies to detect the incidence of COVID-19 antibodies from July 27, 2020, to July 11, 2021. Bajema *et al.* (2021) summarizes the results of the first four of these serology surveys. In these large studies, which all had over 38,000 observations, the percent of the U.S. population that had been infected by COVID-19 grew from 5.9 percent in July and August of 2020, to 22.1 percent by June and July of 2021. The seroprevalance surveys by the CDC seem in line with the estimates reported in Henderson (2021) from the study of Noh and Danuser (2021). In February 2021, the CDC estimated that 20.0 percent of U.S. population had been infected with COVID-19. Noh and Danuser (2021) found 21.5 percent had likely been infected with the virus.

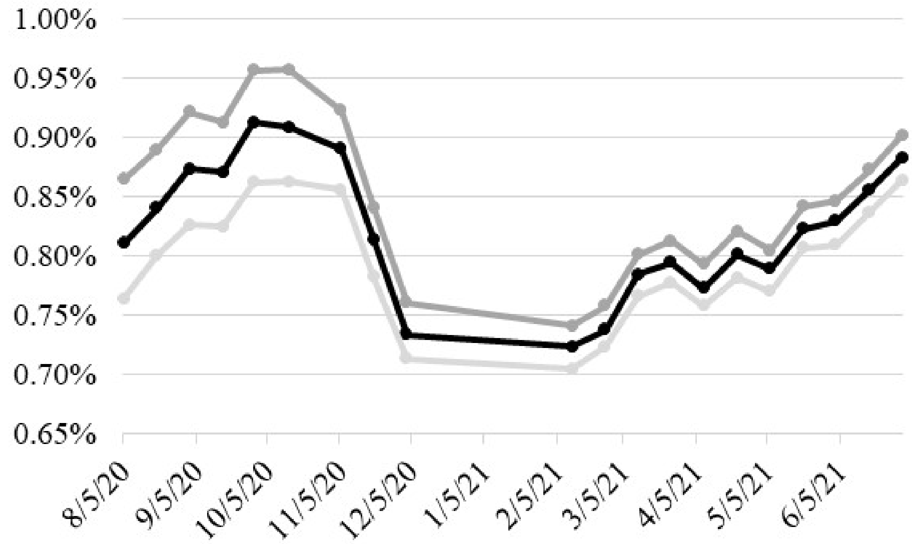
Table 2: Summary Statistics of the CDC's Serology Surveys and the Implied Infection Fatality Rate

	Min	Max	Median	Average	St Dev
Serology Study Start Date	7/27/20	6/21/21	2/8/21	1/11/21	111
Serology Study End Date	8/13/20	7/11/21	2/28/21	1/30/21	112
Length in Days of Serology Survey	18	22	21	20	1
Observations in Serology Survey	38,776	64,717	59,427	56,164	7,811
Median Date of Serology Survey	8/5/20	7/1/21	2/18/21	1/21/21	111.53
% U.S. Infected with COVID-19	5.90%	22.10%	20.20%	15.01%	7.01%
% U.S. Infected Lower Estimate	5.53%	21.67%	19.75%	14.60%	6.94%
% U.S. Infected Upper Estimate	6.26%	22.64%	20.72%	15.44%	7.07%
U.S. COVID-19 Deaths	158,626	604,533	494,964	403,550	182,089
Confirmed Cases	4,828,127	33,750,712	28,019,431	20,961,387	12,093,805
Case Fatality Rate (CFR)	1.746%	3.285%	1.812%	2.209%	0.564%
Estimated Population of the U.S.	331,030,119	332,475,723	332,141,912	332,040,304	345,626
Total U.S. Cases Implied by Serology	19,567,521	73,439,542	67,095,549	49,856,468	23,322,048
% of U.S. Cases Unreported	50.722%	75.326%	58.646%	61.040%	7.510%
Infection Fatality Rate (IFR)	0.723%	0.913%	0.818%	0.822%	0.057%
Infection Fatality Rate (IFR) low	0.704%	0.864%	0.791%	0.794%	0.049%
Infection Fatality Rate (IFR) high	0.741%	0.957%	0.844%	0.851%	0.065%

These are the summary statistics of the twenty nationwide serology studies conducted by the CDC from July 27, 2020, to July 11, 2021. Those COVID-19 antibody studies were available at https://covid.cdc.gov/covid-data-tracker/#national-lab. Confirmed cases and U.S. COVID-19 deaths are from Ritchie *et al.* (2021). The estimated U.S. Population for the median day of each survey is from the U.S. Census' population clock at https://www.census.gov/popclock/. Case fatality rates (CFR) are U.S. deaths over confirmed cases in Ritchie *et al.* (2021) on the median day of each of the twenty serology surveys. Total U.S. cases implied by serology is the estimated population on the median day of the survey times estimate of the percent of the U.S. infected by the serology survey. Percent of cases unreported is the difference between total cases implied by serology and the confirmed cases. That number is divided by total cases implied by serology. The serology studies indicate that only fifty to twenty-five percent of all COVID-19 cases were confirmed over this period. Infection Fatality Rate (IFR) is the total deaths on the median day of the study divided by the total number of people infected. Infected persons are the U.S. population estimate on the median day of the survey times the serology surveys' point, upper, and lower estimate.

Table 2 shows that the numbers of infected Americans was grossly understated by official case counts. 51 to 75 percent of infections were not reported in official cases counts according to these antibody studies sponsored by the CDC. We can used the number of infections implied by these studies to get twenty observations for the infection fatality rate. Deaths are taken from Ritchie *et al.* (2021) and the estimated U.S. population is from the U.S. Census. The average COVID-19 infection fatality rate across the studies was 0.822 percent. In figure 2, we plot the point estimate and the 95 percent confidence interval of the IFR for each of the twenty nationwide antibody studies.

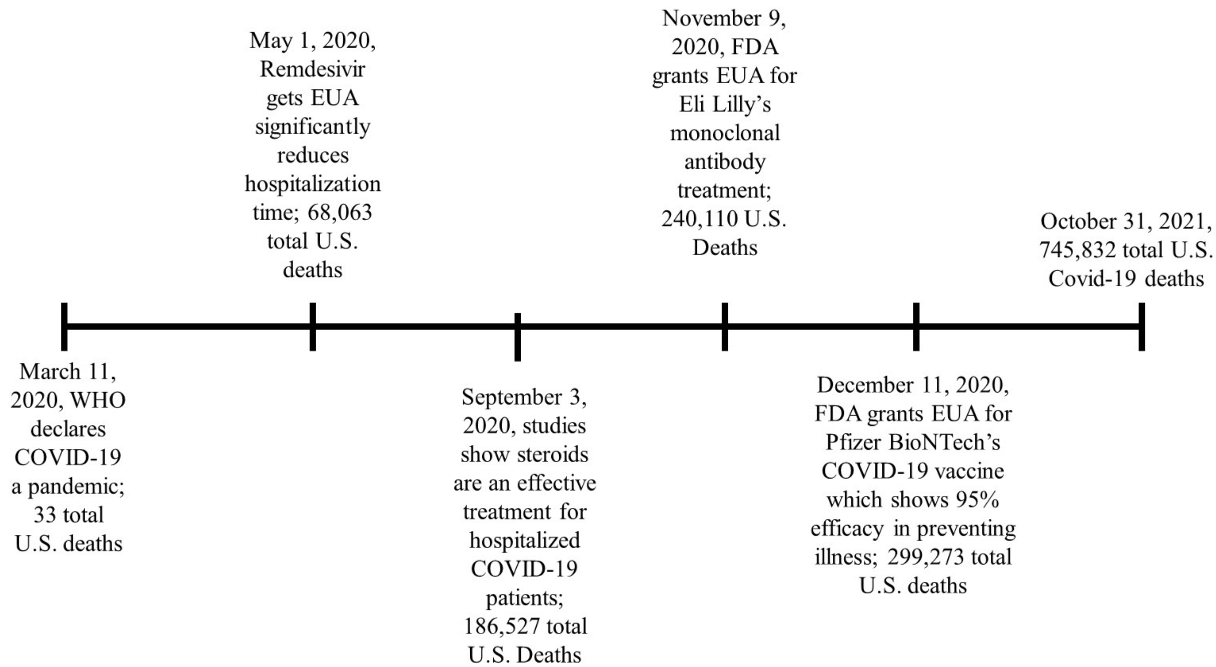
Figure 2: SARS-CoV-2 Infection Fatality Rate in the United States Implied by the CDC's Serology Surveys



The U.S. Centers for Disease Control (CDC) conducted large COVID-19 serology surveillance from July 27, 2020, to July 11, 2021, called the Nationwide Commercial Laboratory Seroprevalence Survey, at https://covid.cdc.gov/covid-data-tracker/#national-lab. There were twenty surveys conducted. The point estimate and 95 percent confidence interval of COVID-19 infections are used to calculate the infection fatality rate. U.S. COVID-19 deaths are from Ritchie *et al.* (2021).

For most of 2020, the pharmaceutical treatments for COVID-19 were modest according to AJMC Staff (2020). Figure 3 gives a timeline of select pharmaceutical breakthroughs throughout the pandemic. Remdesivir was not shown to reduce death, but it reduced hospitalization times. The efficacy of steroid treatments for moderate to severe cases of COVID-19 was demonstrated in studies appearing in September 2020. Monoclonal antibody treatments received an emergency use authorization (EUA) on November 8, 2020. Nevertheless, the most significant breakthrough was not available until after December 11, 2020, when the first COVID-19 vaccine was approved for an EUA in the United States. The Pfizer BioNTech SARS-CoV-2 vaccine received an EUA after showing 95 percent efficacy in preventing infection.

Figure 3: Timeline of Select Pharmaceutical Breakthroughs in the COVID-19 Pandemic through October 31, 2021



The dates of pharmaceutical breakthroughs are from AJMC Staff (2020). U.S. Covid-19 deaths are from Ritchie *et al.* (2021).

We might suspect that the increasing number of preventative and treatment measures available by the end of 2020, would have made COVID-19 less deadly in 2021 than in 2020. That is what we find looking at the implied infection fatality rates from studies conducted in 2020 versus 2021. The average IFR in 2020 was 0.850 percent versus 0.799 percent in 2021. The 2020 IFR was significantly higher than the 2021 IFR with over 95 percent confidence according to table 3.

Table 3: T-test of Means of U.S. Infection Fatality Rates (IFR) Implied by the CDC Serology Studies in 2020 and 2021

Year	2020	2021
Mean	0.850%	0.799%
Observations	9	11
df	15	
t-statistic	2.139	
P(T<=t) two-tail	0.049	
P(T<=t) one-tail	0.025	

This is a two-sample t-test with unequal variances assumed. With over 95 percent confidence, the COVID-19 IFR was significantly lower in 2021 after the COVID-19 vaccine began to be administered in the United States than in the serology surveys in 2020, which were conducted prior to Emergency Use Authorization (EUA) of the first COVID-19 vaccine in the U.S. on December 11, 2020. The last of nine seroprevalence studies by the CDC in 2021 was conducted between November 23, 2020, to December 12, 2020. The first study in 2021, was conducted from February 1, 2020, to February 21, 2021. Deaths are for the median date in the studies and are taken from Ritchie *et al.* (2021).

THE BENEFITS AND COSTS OF STATE STAY-AT-HOME ORDERS

To estimate the benefits in terms of lives saved by the stay-at-home orders, we use the estimate of Fowler *et al.* (2021). Fowler *et al.* (2021) found that cases declined by 48.6 percent during U.S. stay-at-home orders which were 22-days and longer with a 95 percent confidence interval of 31.1 to 61.7 percent.

Theoretically, deaths, d, are a linear function of cases, c, and IFR. $d = cIFR$. IFR can be estimated as in table 3. Backing out cases from death, we believe the cases are better estimated from the pre-COVID-19 vaccine serology estimates in 2020 table 3, because in table 4 we find that infections are significantly understated relative to the CDC's serology estimates.

Table 4: Paired T-test of Total U.S. Cases Implied by the CDC's Serology Surveys and Total U.S. Confirmed Cases

	Total U.S. Cases Implied by Serology	Confirmed Cases	Difference
Mean	49,856,468	20,961,387	28,895,081
Observations	20	20	
df	19		
t-statistic	11.363		
P(T<=t) one-tail	0.000		
P(T<=t) two-tail	0.000		

This is a paired t-test of the estimated cases from the CDC's twenty nation-wide serology surveys and the confirmed cases on the median date of those surveys from Ritchie *et al.* (2021). With over 99 percent confidence, confirmed cases understated actual COVID-19 infections. The average number of confirmed cases understated the actual number of infected Americans by 28.9 million on average. The CDC's COVID-19 antibody studies were available at https://covid.cdc.gov/covid-data-tracker/#national-lab. The estimated U.S. Population for the median day of each survey is from the U.S. Census' population clock at https://www.census.gov/popclock/. Total U.S. cases implied by serology is the estimated population on the median day of the survey times estimate of the percent of the U.S. infected by the point estimate of the serology survey.

Marschner (2021) estimates that deaths lag confirmed cases by eighteen days on average. Thus, cases are best approximated by 18-day forward deaths divided by *IFR*. The infection fatality rate (IFR) for 2020 was 0.850 percent with 8 degrees of freedom and a 95 percent confidence interval of 0.895 to 0.806. Let $d_{t,i}$ equal deaths at time t where t takes on the value zero 18-days after the start of the stay-at-home order and one 18-days after the end of the stay-at-home order. i is an index for all fifty U.S. states and the District of Columbia. Let infections be $c_{t,i}$ where $t = 0$ at the start of the stay at home order and $t = 1$ at the end of the stay at home order. $c_{t,i} = d_{t,i}/IFR$. Given that a state or the District of Columbia had a stay-at-home order, we find that all those state stay-at-home orders exceeded 21-days. Let r_j = reduction in cases estimated by Fowler *et al.* (2021) where $j = L, E,$ or H corresponding to the 95 percent confidence interval and point estimate of case reductions of $\{r_L, r_E, r_H\} = \{0.311, 0.486, 0.617\}$. The lives saved, $s_{j,i}$, in scenario j in a state or the District of Columbia i from its stay-at-home order are as follows:

$$s_{j,i} = [r_j/(1- r_j)](d_{1,i} - d_{0,i}) \quad (1)$$

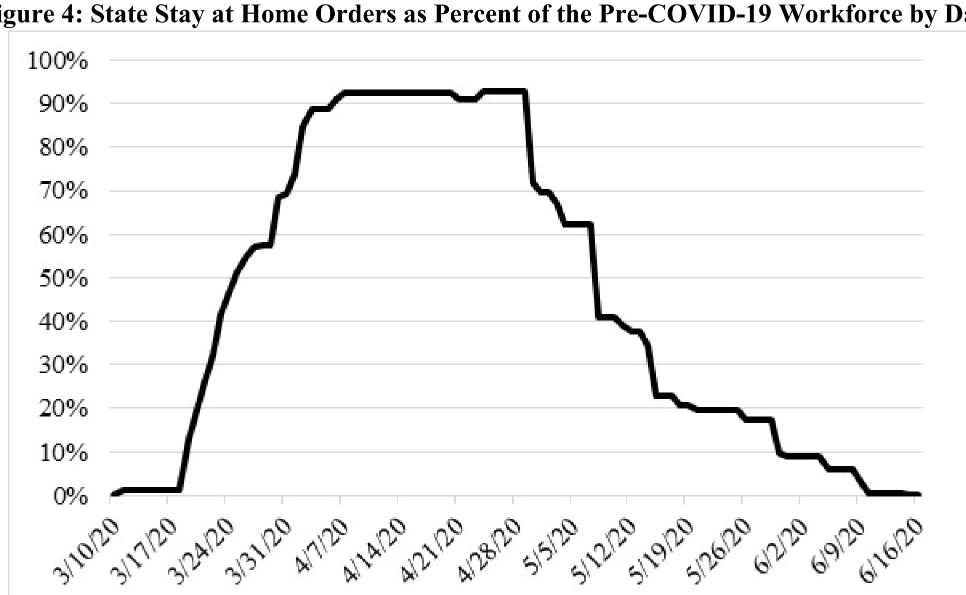
Total lives saved for our low, expected, and high estimates are as follows:

$$s_j = \sum_{i=1}^{51} s_{i,j} \tag{2}$$

We find that stay-at-home orders saved between 35,701 and 121,657 lives with a point estimate of 71,404 lives. We use the VSL estimates of VSL_j = {\$7.0 million, \$11.2 million, and \$15.4 million} per death, respectively, which was discussed in section 2. $s_j VSL_j$ is equal to the economic benefits, B_j, from the stay-at-home orders. We estimate the economic benefit in terms of lives saved from the stay-at-home orders are B_L = \$0.251 trillion to B_H = \$1.869 trillion with a point estimate of B_E = \$0.799 trillion.

Stay-at-home orders began in the fifty states and district of Columbia with Alaska on March 11, 2020, and ended with New Hampshire on June 15, 2020, according to USA Today (2021), Levin (2020), Arco (2020), Oregonian (2020), and Kentucky Governor's Office (2020). We use the seasonally adjusted non-farm payroll data from the Bureau of Labor Statistics at https://www.bls.gov/web/laus/ststdsadata.txt in February 2020 to calculate the percent of the U.S. workforce subject to stay-at-home orders. The end of a stay-at-home order was defined as a "Phase 1" re-opening of a majority of non-essential retail stores. Most non-essential stores had to be open for business in some capacity for us to designate the stay-at-home order over. Seven states never had a stay at home order. The percent of the workforce covered by stay-at-home orders peaked at 92.3 percent of the pre-pandemic, February 2020, workforce between April 7, 2020, and April 20, 2020.

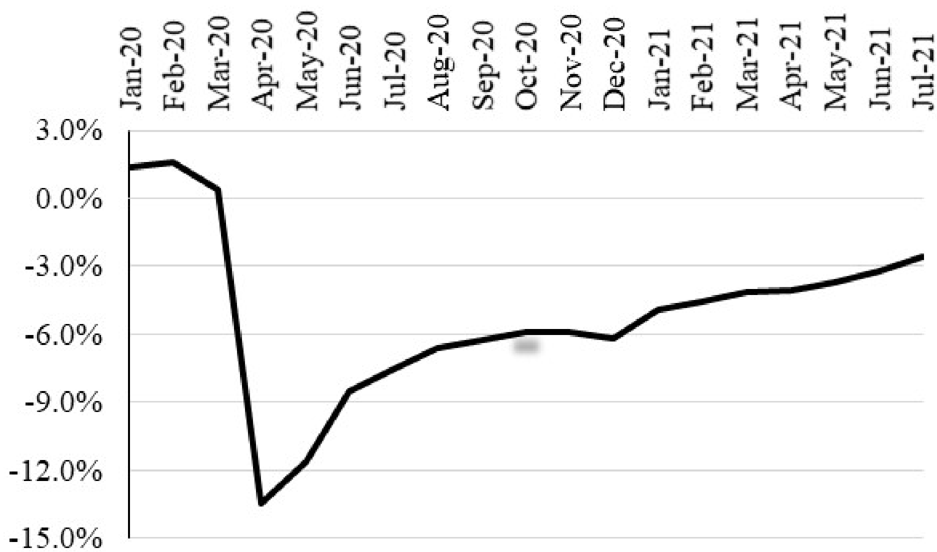
Figure 4: State Stay at Home Orders as Percent of the Pre-COVID-19 Workforce by Date



The figure tracks the percent of the February 2020 seasonally-adjusted, non-farm payroll workers who resided in one of the 50 states or District of Columbia which had active stay at home orders from March 10, 2020, to June 16, 2020. The first stay-at-home order was enacted on March 11, 2020, in Alaska. New Hampshire was the last state in this period to end its state-wide stay-at-home order on June 15, 2021. The seasonally adjusted non-farm payroll data was from the Bureau of Labor Statistics at https://www.bls.gov/web/laus/ststdsadata.txt. State stay-at-home orders beginning and ending dates were from USA Today (2021), Levin (2020), Arco (2020), Oregonian (2020), and Kentucky Governor's Office (2020). A "Phase 1" re-opening which allowed the majority of non-essential retail stores to conduct business was treated as the end of the stay-at-home order. Seven states had no stay-at-home orders over this period.

On the cost side of the ledger, stay-at-home orders reduced labor force participation. We look at seasonally adjusted labor force participation. It fell from a high of 100.4 percent of the pre-pandemic March 2019 level in March 2020 to 86.5 percent of the April 2019 level in April 2020. After the last stay-at-home order ended in June, workforce participation only rebounded to 92.5 percent of its June 2019 level and stayed down below 2019 levels through July 2021.

Figure 5: Change in the Labor Force Participation Rate from that Month in 2019



The plot shows the change in the U.S. seasonally adjusted non-farm labor force participation rate from 2019 levels. The labor force participation rate was the lowest down 13.5 and 11.7 percent, respectively, from pre-pandemic 2019 levels in April and May of 2020, when most workers were affected by stay-at-home orders as plotted in figure 4. The seasonally adjusted non-farm workers data was from the Bureau of Labor Statistics at https://www.bls.gov/web/laus/ststdsadata.txt. Labor force participation did not reach 95 percent of 2019 levels until January 2021 after the first COVID-19 vaccine was approved by the FDA on December 11, 2021, according to figure 3.

We believe the unprecedented intertemporal transfers make GDP changes misleading metrics of the economic impacts of stay-at-home orders. According to Snell (2020) and Taylor *et al.* (2020) the Coronavirus Aid, Relief, and Economic Security Act (CARES) Act signed into law on March 27, 2020, had a $2.2 trillion price tag. It included $300 billion in cash payments to most households, $260 billion in generous unemployment benefits, and $300 billion in *de facto* grants to businesses to not lay off workers with its Paycheck Protection Program (PPP). Individuals were paid an unprecedented sum for not working. Because of these huge transfer payments, we cannot expect GDP and consumption to dip to fully reflect the lost productive opportunities due to government prohibitions on economic activity within the COVID-19 stay-at-home orders. For this reason, we measure the economic losses in terms of the decline in workforce participation.

Let n_i be the seasonally adjusted non-farm payroll number in February 2020 of the i-th state or District of Columbia. Total non-farm payroll workers in February 2020 sum to $N = \sum_{i=1}^{51} n_i$. T_i is the days that that the i-th state (or DC) was under a stay-at-home order. Thus, $T_i/366$ is the fraction of the year that the stay-at-home order was in effect in the i-th state (or DC). This ranged from zero to 80 days in the sample. We find that the weighted average days, $\frac{\sum_{i=1}^{51} n_i T_i}{N}$, in which were covered by stay-at-home orders was 44.1 or about 12.1 percent of 2020.

The 2019 Q4 GDP was \$21.43 trillion according Mataloni and Aversa (2020). The monthly average non-farm payroll for 2019, according to the Bureau of Labor Statistics was just over 150 million workers. GDP divided by the average seasonally adjusted non-farm workers was \$143,767, which we will denote as w. In the three months after stay-at-home orders took effect beginning in March 2020, April 2020, May 2020, and June 2020, workforce participation dipped on average 11.2 percent from the seasonally adjusted levels for those months in 2019. In March 2020, workforce participation was up 0.4 percent from March 2019. 0.38% – (-11.24%) = 11.62%. That is our upper bound estimate for the percent of the workforce lost due to the stay-at-home orders. Some of the dip in workforce participation may have been due to worker hesitancy to work and not just the Governors' mandates. In July 2020, after all the stay-at-home orders ended, workforce participation was still down 7.5 percent from 2019. Thus, our lower bound estimate for the drop in workforce participation was –7.52% – (-11.24%) = 3.72%. The middle estimate was a simple average of the two estimates or 7.67%. Let k = 1, 2, or 3 where d_1 = 0.1162, d_2 = 0.0767, and d_3 = 0.0372. The monthly national labor force participation numbers reflect stay-at-home orders affecting only parts of the country. Workforce participation was only partially prohibited between March 11, 2021, and June 15, 2021, when the orders were in effect. That was 96 days or 96/366 = 26.2 percent of the year. C_k is the cost of the stay-at-home order in scenario k.

$$C_k = \frac{w d_k 96}{366} \tag{3}$$

C_1 = \$0.653 trillion, C_2 = \$0.431 trillion, and C_3 = \$0.209 trillion. Thus, the benefits are VSL of lives saved minus the costs of lost output. We will look at three scenarios. The scenario of the least VSL benefit, B_L, and the most economic cost, C_1, has the stay-at-home orders being a net economic loss of \$402 billion. That is, $B_L - C_1$ = \$(0.251 – 0.653) trillion = -\$0.402 trillion. The scenario of the most lives saved, B_H, and the least economic cost, C_3, has a net economic benefit of \$1,660 billion. That is, $B_H - C_3$ = \$(1.869 – 0.209) trillion = +\$1.660 trillion. Finally, the most likely scenario is that the stay-at-home orders generated B_E and cost C_2 and lead to a net economic benefit to the U.S. economy of \$368 billion. That is, $B_E - C_2$ = \$(0.799 – 0.431) trillion

= +$0.368 trillion. The actual net benefits of the stay-at-home orders depend on the lives saved and the costs in terms of declines in workforce participation. On balance, the stay-at-home orders led to a large-to-modest benefit in the order of -1.9 to 7.7 percent of 2019 GDP. We expect that the state stay-at-home orders increased national well-being by about 1.7 percent of the previous year's GDP.

CONCLUSION

In this paper, we attempt to weigh the costs and the benefits of the non-pharmaceutical interventions (NPIs) of the United States' state-level stay-at-home orders which were in force from March 11, 2020, to June 15, 2020. Our review of the Value of Statistical Life (VSL) literature weighs each life saved from NPIs at $7.0 million to $15.4 million with a mean estimate of $11.2 million in 2020 U.S. dollars. Using the CDC's pre-COVID-19 vaccine serology studies conducted in 2020, we estimate that the SARS-CoV-2 infection fatality rate (IFR) was 0.850 percent with a 95 percent confidence interval of 0.895 percent to 0.806 percent. We calculate that state stay-at-home orders from March 11, 2020, to June 15, 2020, saved between 35,701 and 121,657 lives with a point estimate of 71,404 lives. That economic benefit in terms of lives saved from the stay-at-home orders was $0.251 trillion to $1.869 trillion with a point estimate of $0.799 trillion. We estimate that the stay-at-home orders cost the U.S. economy between $0.209 trillion and $0.653 trillion with a point estimate of $0.431 trillion. That put the net benefits from stay-at-home orders at -$0.402 trillion to $1.660 trillion with a point estimate of $0.368 trillion.

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UNDERSTANDING THE RELATIONSHIP AMONG INTERNET ANXIETY, INTERNET IDENTIFICATION AND INTERNET SELF – EFFICACY IN THE PHILIPPINES

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ABSTRACT

The study aims to examine the relationship among three key factors related to Internet usage and experience in the Philippines: Internet anxiety, Internet identification and Internet self - efficacy. Confirmatory factor analysis and regression analysis were used to analyze the data from 820 respondents focusing on three subgroups (gender (male or female), age groups and occupation (college student, employees and entrepreneurs)). The results indicate that Internet anxiety is negatively related to Internet self – efficacy which is positively related to Internet identification. The results also indicate that, although Internet anxiety may not be negatively related to Internet identification in general, there is a significant and negative relationship between Internet anxiety and Internet identification among the respondents in the 18 – 25 year - old age group. This is most likely explained by the fact that most of the respondents in this group were born after the introduction of the Internet in the Philippines in 1994 and do not remember a time without the Internet.

Since Internet self – efficacy is a strong predictor of Internet identification, it is imperative that opportunities to build Internet self – efficacy in schools, workplaces and in the business environment here in the Philippines such as trainings in using Internet technologies for coursework, workplace productivity and streamlining business transactions and interactions should be provided to help Filipinos reap the benefit of the Internet. To help ensure this, internet infrastructure must be enhanced and prioritized through the leadership of the Department of Information and Communications Technology in cooperation with Internet technology providers in the private sector.

Keywords: Internet anxiety, Internet identification, Internet self – efficacy, Internet usage and experience

INTRODUCTION

We live in a digital world where we spend a lot of time on the Internet, whether it is for academic, work or personal reasons. Because an increasing number of people access the Internet regularly for different types of information – from academic (especially for research related requirements in school) to personal (such as health and wellness or restaurant choices) to financial and investment related, do different types of searches – from job opportunities to scholarships to staycation or vacation packages and watch videos and other forms of entertainment on top of their messaging and posting on Facebook, Twitter and Instagram (Howard, Rainie, and Jones, 2002; Fallows, 2004; Hargittai and Shafer, 2006), their information creation and sharing capabilities as well as data mining and interaction facilitation have rapidly increased and developed.

We are able to recognize the importance of being able to leverage Internet technologies and applications. However, especially in a third world country like the Philippines where being digitally connected may only be fully experienced by those in cities or places where the telecommunications infrastructure is sound, it is important that opportunities for Filipinos across all walks of life to reap the benefits of the Internet whether it be in at home, in school or in the workplace or any business environment be provided and taken advantage of.

In order for such opportunities to harness Internet technologies and applications to be effective, more research has to be done to look into the factors that affect a person's use of the Internet. There has been previous research into different factors that impact on a person's Internet usage including gender differences in psychological influences of Internet usage (Teo and Lim, 2000; Whitty and McLaughlin, 2007; Vekiri and Chronaki, 2008; Madu, Otuka and Adebayo, 2011; Powell, 2013), gender and Internet anxiety (Cazan, Cocorada and Maican, 2015) gender, Internet anxiety and Internet identification (Joiner, Brosnan, Duffield, Gavin, and Maras, 2007; Joiner et al., 2012), perceived usefulness and ease of use (Teo, 2001; Hanson, 2010) and Internet self-efficacy (Hsu and Chiu, 2004; Tsai, Chuang, Liang and Tsai, 2011; Tsai and Tsai, 2003). There are three factors that can be considered as important determinants of Internet usage and experience: Internet anxiety, i.e., the trepidation or apprehension that individuals undergo when using the Internet (Presno, 1998), Internet identification, the degree to which an individual's self-concept is connected with his or her perceived ability to use the Internet (Cooper and Weaver, 2003; Joiner et al., 2007, 2012) and Internet self – efficacy, an individual's self-perceived confidence and expectation of using the Internet (Tsai and Tsai, 2003) or the beliefs in one's capabilities to organize and execute courses of Internet actions required to produce given attainments (Hsu and Chiu, 2004).

Despite the fact that we are living in a digitally connected world, as experienced even to a certain extent in countries like the Philippines, Internet anxiety can still be considered as one of the major obstacles in effective Internet usage (Kalwar, Heikkinen, and Porras, 2011, 2013). Anxiety and other similar emotional states affect not only interaction but also performance, productivity, social relationships, learning, health and overall well-being (Saadé and Kira, 2009). A significant number of research studies have discovered that Internet anxiety is negatively related to Internet use and experience (Cooper and Weaver, 2003; Joiner et al., 2012), while Internet identification, on the other hand, impacts positively on Internet use and experience (Cooper and Weaver, 2003; Joiner et al., 2012). Someone possessing a high degree of Internet identification is most likely to be characterized as having extensive experience using the Internet, motivated to allocate time to learn how to fully use the Internet by either enrolling in courses or watching different media sources on expertly navigating the Internet and thus demonstrating a positive attitude toward the Internet (Joiner et al., 2007).

Although the significance of Internet anxiety, Internet identification and Internet self – efficacy to Internet use and experience has been established, little is known about the relationships that exist, if any, among the three of them (e.g. how are Internet anxiety and Internet identification related to one another, how is Internet self – efficacy related to Internet anxiety and Internet identification, etc.) Delving into these relationships will allow us to: 1) get a better understanding of how to deal with the impact of these factors on a person's Internet use and experience; 2) more clearly grasp the interactions manifested in the relationship between Internet anxiety and Internet identification, Internet self – efficacy and Internet anxiety and

Internet self – efficacy and Internet identification and 3) equip decision – makers (i.e., educators, industry leaders, government officials, etc.) in making decisions related to providing opportunities to leverage Internet technologies and applications in different environments (e.g., schools, workplaces, government offices, etc.) so that Filipinos will be better prepared to use the Internet in a more effective and efficient manner.

LITERATURE REVIEW

Knowing that a number of previous research studies have looked into the relationship between factors such as Internet anxiety and Internet identification (Joiner et al, 2007; Rezaei and Shams, 2011) and the importance of Internet self – efficacy in determining how a person uses and experiences the Internet and related technologies and applications (Hsu and Chiu, 2004; Tsai and Tsai, 2003), it would be advantageous to investigate how these three important factors interact with one another and impact on a person's Internet usage and experience.

Previous research studies have identified that Internet anxiety, an emotional state, serves as an important source of information in making judgments and decisions, and in liking, efficacy belief and importance evaluation (Hsiao, Zhu and Chen, 2017; Clore, Gaspar and Garvin, 2001; Clore and Storbeck, 2006). In order to get a better understanding on how the hypotheses in this research study were developed, it would be good to look at related literature on the three factors.

Internet Anxiety

When people observe intimidating, hostile or even frightening or menacing circumstances in their surroundings or in the situations they face day to day, these people can suffer from anxiety. Anxiety is defined as worry, stress, fright, the feeling of being unsuccessful, inability, not knowing the result and criticism type of excitement or almost all is included (Cuceloglu, 2008). When the situation involves the Internet, people experience Internet anxiety, which is defined as the fear or trepidation that people experience when they use the Internet (Presno, 1998). Internet anxiety is said to be an anxiety that is situation – specific as it is brought about by the distress of danger and powerlessness when interacting with others on the Internet which leads to mental anguish (Joiner et al., 2007). Thus, Internet anxiety is considered an impediment or hindrance to the effective and efficient use or experience of Internet technologies and applications (Hsiao, Zhu and Chen, 2017) which are considered staple fare in today's digitally connected world such as email, social media (e.g., Facebook, Twitter, Instagram, etc.), information searches (e.g., Google, etc.) and other online activities.

Earlier research studies have discovered that Internet usefulness, enjoyment and efficacy as observed by people in their Internet experience are negatively related to Internet anxiety (Zhang, 2005). Relatedly, an individual's awareness that there is are resources that provide a more positive Internet experience and the trust of such Internet technologies that result can lead to Internet anxiety being reduced (Thatcher, Loughry, Lim, and McKnight, 2007). The characteristics of Internet anxiety are derived from computer self-efficacy; thus, Internet self-efficacy is also a concept-specific form of anxiety because it is a feeling that is associated with a person's interaction with the Internet (Hsiao, Zhu and Chen, 2017). Individuals need to understand the new applications that seem strange for them and learn the new technologies. This then creates new anxieties upon users (Thatcher, Loughry, Lim, & McKnight, 2007). It also brings along with it most of the risks of internet usage such as viruses, spyware/malware or invasion of privacy (Thatcher, Loughry, Lim, & McKnight, 2007).

Internet Identification

Another significant factor that impacts an individual's use and experience of the Internet is Internet identification (Cooper and Weaver, 2003; Facer, Furlong, Furlong and Sutherland, 2003; Holloway and Valentine, 2003). Identification with a domain (e.g., mathematics, sports, songwriting, technology, etc.) connects an individual's self-esteem with his or her ability to perform successfully in that domain (Cooper and Weaver, 2003; Shen and Chiou, 2009). Internet identification is a type of domain identification inherently attached with images of those who use the Internet, a type of visual connection by a person to those he or she sees as most likely to be using the Internet for different purposes (Gavin et al., 2007). Consequently, Internet identification can be defined as the extent to which an individual's self-concept is bound with his or her manifest ability to use the Internet or the importance of an individual's ability to use the Internet for their self-concept (Joiner et al., 2007). An individual with a high degree of Internet identification is able to use the Internet effectively to maintain his or her sense of self-worth. It can also be argued that identification is an important factor in understanding people's attitudes towards and uses of technology (Cooper and Weaver, 2003). Consequently, they are likely to have a high degree of experience using the Internet; will have positive attitudes towards the Internet; will be motivated to spend time learning how to use it; and may take courses on using the Internet. If they perform badly using the Internet, this is likely to make them feel anxious because it threatens their self-esteem. (Joiner et al., 2007)

According to affect-as-information theory, people attend to their feelings as a source of information. Affect such as Internet anxiety can serve as important sources of information and knowledge not only in making judgments and decisions, but also in liking, efficacy belief and importance evaluation (Hsiao, Zhu and Chen, 2017; Clore, Gaspar and Garvin, 2001; Clore and Storbeck, 2006). If people feel anxious, uncomfortable or perturbed about using the Internet, they will justify their behavior by saying that the Internet may not be good for them, and, as a result, they may decide that they do not want to belong to the community of digital natives on the Internet (Hsaio, Zhu and Chen, 2017). Hence, it would be logical to propose as the first hypothesis to be tested and explored:

Hypothesis 1: *Internet anxiety will be negatively related to Internet identification.*

Internet Self – Efficacy

In order to enhance self-efficacy or one's ability to undertake different opportunities or face different challenges with the end goal of succeeding in general, one should focus on making sure that such opportunities are available for people to master a variety of challenging tasks in many different domains and finding positive role models such as people in different circles that individuals find themselves in who will encourage, inspire and motivate them to rise up to the challenge and succeed. Research findings suggest that the predictive capability of a self-efficacy estimate is most accurate when determined by specific domain-related measures rather than with general measures (Bandura, 1989). Computer self – efficacy research served as the takeoff point for research initiatives into Internet self – efficacy. This was a result of Internet self – efficacy being distinguished from computer self – efficacy as the belief that one can successfully perform a distinct set of behaviors required to establish, maintain and utilize effectively the Internet over and above basic personal computer skills (Eastin and LaRose, 2000).

Previous research has looked into the impact of Internet self-efficacy on Internet use (Hsu and Chiu, 2004; Tsai and Tsai, 2003). Students with high Internet self-efficacy have better information searching strategies and learn faster than students with low Internet self-efficacy when given Web – based learning tasks (Tsai and Tsai, 2003). People with high Internet self-efficacy are more likely to use e-services and implied that the increasing Internet self-efficacy of customers is extremely important to an e-service's successful operation (Hsu and Chiu, 2004). Thus, it is important to recognize that efficacy belief is a significant factor in investigating activities, emotions, and perceptions related to the use of the Internet in various milieus or domains.

Since state anxiety (more specifically, Internet anxiety) and specific self-efficacy (in this case, Internet self-efficacy) are elements in the self-efficacy framework of Bandura (1997), it can be surmised that anxiety, which is an affective response, has a direct influence on self-efficacy beliefs. Relatedly, a significant relationship among state anxiety, specific self-efficacy and performance can be demonstrated (Chen, Gully, Whiteman, and Kilcullen, 2000). Anxiety can also have an effect on computer-based learning by affecting the levels of self-efficacy (Saadé and Kira, 2009). Thus, a relationship between Internet anxiety and Internet self-efficacy can be established which ultimately influences Internet-related behavior, use and experience. This leads to the proposition of the following hypotheses:

Hypothesis 2*: Internet anxiety is negatively related to Internet self - efficacy.*
Hypothesis 3*: Internet self-efficacy is positively related to Internet identification.*

METHODOLOGY

The Instrument

The questionnaire used three scales from different studies related to the three factors being investigated: 1) Internet anxiety scale (Joiner et al, 2007) where respondents were asked to answer a 6 item scale using a five-point Likert scale ranging from "never" to "always" (1=never, 2=rarely, 3=sometimes, 4=often, and 5=always); 2) Internet identification scale (Joiner et al, 2007 based on the work of Maras, 2002) where respondents were asked to answer a 10 item scale using a five-point Likert scale ranging from "definitely/totally disagree" to "definitely/totally agree" (1=definitely/totally disagree, 2=sometimes disagree, 3=neither agree nor disagree, 4= sometimes agree, and 5= definitely/totally agree); 3) Internet self – efficacy scale (Tsai and Tsai, 2003) where respondents were asked to answer a 6 item scale using a five-point Likert scale ranging from "never" to "always" (1=never, 2=rarely, 3=sometimes, 4=often, and 5=always).

Sample and Procedures

A mix of random sampling and purposive sampling (i.e., to ensure more or less a balance of male and female respondents and a mix of students, employees or working people and entrepreneurs) was conducted in the identified location of Metro Manila and a respondent base of 820 resulted consisting of 383 males (46.71%) and 437 females (53.21%) who were either students (303 or 36.95%), employees or working people (375 or 45.73%) or entrepreneurs (142 or 17.32%). The ages of the respondents ranged from 18 – 55 and they came from SECs A, B, broad C and D.

Factor loading was done in order to determine which components of each scale should not be included (because they had factor loading values of less than 0.6) and the Chronbach's alpha of the resulting scales were determined to establish the reliability of the scales.

Correlation analysis (Hypothesis 1) and Regression Analysis (Hypothesis 2 and 3) were conducted to determine if a relationship, if any, existed between Internet anxiety and Internet identification (Hypothesis 1), Internet anxiety and Internet self – efficacy (Hypothesis 2) and Internet identification and Internet self – efficacy (Hypothesis 3).

RESULTS AND DISCUSSION

The reliability (internal consistency) of items in the three scales used was examined using Cronbach's alpha to confirm the adequacy of the measures for testing the hypotheses.

One item ("I usually fee lost or confused when I am seeking information on the World Wide Web (WWW)) was deleted from the Internet self – efficacy scale because it's loading was below 0.6. The Chronbach's alpha of the resulting five – item scale is 0.84 and reliability was found to be accurate on this measure.

Two items ("It is easy for me to use the Internet" and "It is important for me to be able to use the Internet") were deleted from the Internet anxiety scale because their loading was below 0.6. The Chronbach's alpha of the resulting four – item scale is 0.78 and reliability was found to be accurate on this measure.

Two items ("I am very different from Internet users" and "I feel very emotionally attached to Internet users in general") were deleted from the Internet identification scale because their loading was below 0.6. The Chronbach's alpha of the resulting eight – item scale is 0.837 and reliability was found to be accurate on this measure.

For Hypothesis 1, correlation analysis was done for the different subgroups (Occupation, Gender and Age). For Occupation, a significant and negative correlation (-.102) was established for Occupation category 1 which was Students. Looking at cross – tabulation results, it can be seen that a majority of the 303 student respondents were in the age bracket 18 – 25 years old (74.6%) and almost all the respondents who were 18 – 25 years old were students (98.7%). For the other two categories, Occupation category 2 (Employees) and Occupation category 3 (Entrepreneurs), insignificant correlations were established and the correlation, in fact, for Occupation category 3 was positive on top of being insignificant. Thus, it can be said that there is support for Hypothesis 1 only in one Occupation category and that is Students.

For Gender, a significant and negative correlation was found in both males (-0.094) and females (-0.138). Since the sample was more or less balanced across the two gender categories, it was significant to note that respondents aged 18 – 25 years old comprised almost half of the male respondents (48.8%) and also almost half of the female respondents (49%). This led to exploring the third subgroup to see how this subgroup impacted on Hypothesis 1.

For Age Groups, it could be seen that Age Group 1 (18 – 25 year olds) answered more towards the poles of the scale than any other age group, and had less variation. They also answered exactly in the expected manner, reporting higher internet identification and lower internet anxiety scores than other groups. This leads to the belief that a significant and negative correlation was established because it can be surmised that the respondents in this age group had very similar, leaning towards the more positive, Internet experiences.

Overall, although Internet anxiety may not be negatively related to Internet identification in general, there is a significant and negative relationship between Internet anxiety and Internet identification among the respondents in the 18 – 25 year - old age group. This is most likely explained by the fact that most of the respondents in this group were born after the introduction of the Internet in the Philippines in 1994 and do not remember a time without the Internet.

For Hypothesis 2, regression analysis on the different subgroups (Occupation, Gender and Age) was performed with Internet self – efficacy as the dependent variable and Internet anxiety as the independent variable. The following table summarizes the different regression equations of the subgroup categories (Occupation (Student, Employee, Entrepreneur); Gender (Male, Female); Age Groups (18 – 25, 26 – 30, 31 – 35, 36 – 40, 41 – 45, 46 – 50, 51 – 55).

Table 1
Hypothesis 2
Summary of Regression Equations of Subgroup Categories under Occupation, Gender and Age

SUBGROUP CATEGORY	REGRESSION EQUATION
Student	Efficacy = -0.7015Anxiety + 2.5915
Employee	Efficacy = -0.4003Anxiety + 3.9203
Entrepreneur	Efficacy = -0.0715Anxiety + 2.5912
Male	Efficacy = -0.3826Anxiety + 3.8601
Female	Efficacy = -0.2663Anxiety + 3.3474
18 – 25	Efficacy = -0.7505Anxiety + 5.4857
26 – 30	Efficacy = -0.2663Anxiety + 3.3651
31 – 35	Efficacy = -0.4778Anxiety + 4.1856
36 – 40	Efficacy = -0.0321Anxiety + 2.5353
41 – 45	Efficacy = -0.4316Anxiety + 4.0449
46 – 50	Efficacy = -0.5113Anxiety + 4.3033
51 – 55	Efficacy = -0.015Anxiety + 2.2252

As can be seen from the table, all subgroup categories exhibit a negative relationship between Internet Anxiety and Internet Self – Efficacy albeit exhibiting low Internet anxiety does not significantly impact on an individual's Internet self – efficacy in general. It can be seen also from these equations that respondents who are students or are aged 18 – 25 years old and who exhibit low Internet anxiety scores tend to increase their Internet self – efficacy levels more compared to the other subgroup categories. This is in consonance with the conclusion from the analysis of Hypothesis 1 where the reason behind 18 – 25 year olds identifying more with the Internet when they exhibit low anxiety levels is because they were born during the time when the Internet was introduced in the Philippines and therefore, did not use any other technology or process when it came to information searches or doing research (e.g., Google, Google Scholar, etc.), communication (e.g., Facebook, Twitter, etc.), or even, to a certain extent, looking for entertainment (e.g., YouTube, Netflix, etc.). The fact that they grew up in a digital world lends to their exhibiting more confidence in their Internet use and experience.

For Hypothesis 3, regression analysis on the different subgroups (Occupation, Gender and Age) was performed with Internet self – efficacy as the dependent variable and Internet identification as the independent variable. The following table summarizes the different regression equations of the subgroup categories (Occupation (Student, Employee, Entrepreneur); Gender (Male, Female); Age Groups (18 – 25, 26 – 30, 31 – 35, 36 – 40, 41 – 45, 46 – 50, 51 – 55).

As can be seen from the table, all subgroup categories exhibit a positive relationship between Internet Identification and Internet Self – Efficacy albeit exhibiting high Internet identification does not significantly impact on an individual's Internet self – efficacy in general. It is interesting to note that the higher Identification coefficients are those of Entrepreneurs and those in the older age group brackets (i.e., 41 – 50, 46 – 50 and 51 – 55).

Table 2
Hypothesis 3
Summary of Regression Equations of Subgroup Categories under Occupation, Gender and Age

SUBGROUP CATEGORY	REGRESSION EQUATION
Student	Efficacy = 0.396Identification - 0.08
Employee	Efficacy = 0.47Identification
Entrepreneur	Efficacy = 0.624Identification + 0.065
Male	Efficacy = 0.516Identification + 0.015
Female	Efficacy = 0.537Identification - 0.015
18 – 25	Efficacy = 0.412Identification - 0.033
26 – 30	Efficacy = 0.359Identification - 0.08
31 – 35	Efficacy = 0.36Identification - 0.082
36 – 40	Efficacy = 0.501Identification + 0.025
41 – 45	Efficacy = 0.518Identification - 0.065
46 – 50	Efficacy = 0.548Identification + 0.03
51 – 55	Efficacy = 0.604Identification + 0.156

This is most likely because these are people who grew up in the pre – Internet period and, therefore, were exposed to many other ways of information searches or doing research (e.g., reading books in the library, going through encyclopedias or dictionaries, etc.), communication (e.g., snail mail/post office, telegrams, etc.) or looking for entertainment (e.g., radio, non – plasma TVs, cinema houses with the film reels, etc.). Therefore, it is more deliberate on their part to be able to identify with the Internet and all that can be done on it which leads to a higher self – efficacy or confidence in navigating the ins and outs of the Internet once they realize how beneficial it can be to them especially in their business dealings or corporate work environments.

Thus, it can be seen from the analysis and discussion that Hypotheses 2 and 3 are supported while Hypothesis 1 is not supported.

SUMMARY AND CONCLUSIONS

The objective of this research study was to determine and understand the relationships, if any, among three significant factors related to Internet usage and experience (Internet anxiety, Internet identification and Internet self-efficacy) in the Philippines. The research findings determined that Internet anxiety is negatively related to Internet self-efficacy, which, in turn, is positively related to Internet identification. However, it was also determined that, in general, Internet anxiety does not possess a significant negative relationship with Internet identification, except for 18 – 25 year olds who are mostly students. This is similar to what Joiner et al. (2007)

discovered, which is a negative significant relationship between Internet identification and Internet anxiety of students.

This means that there is a possibility that Internet anxiety and Internet identification could be positively related wherein younger people nowadays are expected to be confident about using the Internet and these expectations are carried out in the classroom, workplace or even at home. Yet, especially in the Philippines, it is known that not every young person has had the opportunity to harness the power of the Internet simply because there is a lack of infrastructure in a number of barangays even in the metropolis and even more so, in the far flung villages in the Philippine archipelago. It can also be seen that even older people, as long as they are exposed to the internet, like working people or even entrepreneurs especially in the metropolis, can actually have more confidence in using the Internet compared to younger people. Given that Internet self – efficacy is a strong predictor of Internet identification, it is imperative that opportunities to build Internet self – efficacy in schools, workplaces and in the business environment here in the Philippines such as trainings in using Internet technologies for coursework, workplace productivity and streamlining business transactions and interactions should be provided to help Filipinos level the playing field especially in reaping the benefits of the Internet. To help ensure this, internet infrastructure must be enhanced whether it be in the metropolis or in the countryside. This can be done through the prioritization of such projects by the leadership of the Department of Information and Communications Technology in cooperation with Internet technology providers in the private sector. Then it is the turn of educators, business and government leaders to leverage on these infrastructure projects to help expose more and more people, male or female, young or old, student or employee or entrepreneur to the Internet and the benefits they can experience through fully utilizing it. As we have come to understand through this research study, as long as people are given the opportunities to harness the power of the Internet, they can better identify with it, overcome their anxiety in using it and therefore increase their Internet self – efficacy which in turn can encourage them to help their fellow students, workers or entrepreneurs leverage the Internet and contribute to improving the Internet penetration and infrastructure here in the Philippines. This would allow the Philippines to become more connected to the global digital world and not be left behind.

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ARTIFICIAL INTELLIGENCE IN HEALTHCARE: A POTENTIAL GAME CHANGER

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ABSTRACT

Artificial Intelligence (AI) is advancing rapidly and is playing an increasing role in our lives. The rapidly aging population and the rapidly rising costs of healthcare is currently placing a massive strain on the system, in terms of costs, speed and quality. One of the best uses of AI is in the field of healthcare as it could address all those concerns. In this paper, we explore the evolutionary role of AI in the healthcare space, specifically, how it can rapidly use the large volumes of data to make efficient and effective medical decisions both during a normal situation and a Pandemic such as COVID-19.

INTRODUCTION

Artificial Intelligence (AI) is the science and engineering of making machines, such as computers and robots, act and make decisions like intelligent human beings. AI is now beginning to be utilized in almost all aspects of our lives; from self-driving cars, media, finance, gaming industries, restaurants, factory automation, and healthcare (Barrat, 2015). Since the invention of the digital computers, human beings have been developing various machines smarter, with the aim of making businesses more efficient and profitable, along with making our lives safer and easier than before.

Healthcare is a very fertile area for applying AI. Our present COVID-19 pandemic also highlights how AI might be used to detect diseases and watch for contagion. An AI system called HealthMap in Boston's Children Hospital (Cho, 2020) was actually the first to warn of the COVID situation after analyzing data from social media, news reports, internet searches, and many other information streams related to diseases. For AI algorithms to work, several data points about a disease needs to be available, so that the algorithms "learn" the various nuances about the disease, and learn to recognize patterns of the disease. This is the training phase. In the next phase, the "trained" AI system is used in real world situations, to diagnose live data. With a stream of live data from the real world, the smart machine also "learns" new patterns, and is continuously updated with new facts. Artificial Intelligence technology is hence being rapidly applied in healthcare, and experts believe that AI will revolutionize it by allowing early diagnosis, and prediction of potential illnesses. Imagery Informatics, in particular, will be a leading topic because of the transformation that AI will be contributing to the process of diagnostic imagery (Das, 2017).

The purpose of this paper is to study the vast potential of artificial intelligence in making healthcare industry more efficient, less expensive and result in better healthcare outcomes. We start with a general description of AI and explain the nature of machine learning. Next, we discuss the major uses and applications, advantages, and disadvantages of AI in the healthcare context. Then we discuss how AI could be so much beneficial specially for detecting COVID-19. The last section summarizes and concludes the paper.

METHODOLOGY OF THE STUDY

To understand the overall role of AI in Healthcare, we adopt a Systematic Literature Review (SLR) approach for collecting freely available online contents and articles. Schwarz et al. (2006) indicated that literature review studies in IS research has been a quite healthy type of efforts, especially for achieving objectives such as for developing annotated summary of existing works and explaining summarized results of existing studies. Rowe (2014) also supported similar arguments. In a case of SLR study, Brocke et al. (2015) suggested that IS researchers should make clear decisions on selecting database and journals, defining search terms, selecting criteria for including and excluding papers as well as for developing strategies for citation analysis. In particular for an analysis, it is important for conducting review widely in capturing qualitative attributes for cumulative knowledge-creation and by going beyond systematic review notion to a certain extent (Okoli & Schabram, 2010). Considering the innovative nature of AI and longer time frames for reviews, we focus on collecting sample articles through open-sourced Google Scholar database. We also reviewed technical report or prominent blogs to ensure the rapidly changing nature of AI is validly reflected for our study.

Further analysis of the identified papers was performed adopting content analysis technique which is an established research method for exploring content from human interaction process, verbal and written document with a purpose of analyzing data (Creswell & Poth, 2018). It is an influential method that allows analyzing documents as important sources of information to identify patterns of content quantitatively as well as qualitatively analyze meanings of content to identify or outline new phenomena. We employed a qualitative content analysis for analyzing selected articles. This approach has been widely used in prior research (such as Chan & Ngai, 2011) and is based on analyzing inputs and outputs and understanding the underlying processes, i.e., overview of AI and the nature of machine learning, major uses and applications of AI, advantages and disadvantages of AI in healthcare, and how AI could be beneficial specially for detecting COVID-19.

AI IN HEALTHCARE

The application of Artificial intelligence in various aspects of healthcare has resulted in improved service delivery (Bench-Capon, 2014; Cohen, & Feigenbaum, 2014). Use of artificial intelligence not only reduces costs for treating patients, but, more importantly, it also improves patients' outcomes. Currently, most health care centers are using machine learning (a subset of AI), which has resulted in improved diagnosis in comparison to humans.

AI based chatbots, like the IBM "cognitive computer" Watson, has the ability to use natural language to ask patients relevant questions, and make appropriate responses, initiate business processes, or diagnose the illness (Barrat, 2015). These smart chatbots assist patients to make payments, provide virtual health assistance, follow up on appointments, and as well as to give medical feedback. Artificial intelligence systems have true potential to revolutionize the health care sector. Recently, Xavier University has launched the Xavier Center for Artificial Intelligence to accelerate the use of artificial intelligence to improve healthcare (Heyne, 2017 – they also host the AI Summit event to help participants in the healthcare sector learn about and share the advancements of AI in Healthcare. Doctors too are excited and eager to have new systems in place because AI can assist them in performing at a much higher level (Fornell, 2017).

With the immense increase in medical data collection, AI also boosts workflow, improves efficiency and helps with cost effective, timely and accurate data analysis. For example, Arterys' cardiac MRI automates many routine steps in cardiac analysis, drawing on knowledge gleaned from several MRI images and applying its deep learning algorithms. Such automated analysis "frees up a lot of physician time and brings a huge amount of consistency to imaging and tracking changes over time in a patient," (Arndt, 2017) according to Arterys' head of strategy and marketing. The Arterys browser-based software is being used at 40 sites around the world.

Similarly, Zebra Medical Vision allows radiologists to deliver better care at lower costs, and improve patient diagnoses (Arndt, 2017). These AI systems, however, are still early in the testing stages, and are facing some roadblocks – such as the training of medical staff to use and maintain the system and process, along with meeting the tedious regulatory requirements to obtain FDA certification (Arndt, 2017). FDA approval is important as a first step of gaining trust in the medical community.

Machines with AI are put to use in sorting vegetables, identifying known criminals in a public gathering via CC cameras, driving vehicles on their own, or detecting cancer from MRI images. It is now useful to take a brief look at how machine learning is achieved. For example, if we want to determine whether an MRI image of a lung has cancer cells, we have to create an "AI Model" (based on neural networks) to answer the question. The first step is to "train" the model – which will need a large set of real-world data from past cases. The data is split into two sets – a larger portion for "training" the AI Model, and the remaining smaller portion for "validating" the Model. Clearly, it would not be prudent to test the model on the same data on which it was trained (much like it is not wise to use the same questions in a school homework in the Final exam to test students).

In the next step, one will have to determine the important factors/dimensions that differentiate the lung cancer cells from normal lung cells. It could be dimensions like shape, location, color, and contrast. A weight is then assigned to each of these four dimensions, and is represented in a Weights matrix (denoted by W). Another matrix called the "bias" matrix (denoted by w) has "bias" values, which can be also be adjusted, so that the predicted results of the model can account for input "bias, and better reflect reality. Google's DeepMind Health is now, for instance, using mammograms from Japanese patients to get rid of any bias (Wiggers, 2018b) when trying to diagnose breast cancer in different ethnic populations (breast tissue density differs considerably for different ethnic groups).

The weights matrix and the bias matrix are used along with the values for each dimension (input) to predict an outcome. The prediction is then compared to known results in the "training" data set, and the difference is known as the "loss function." Clearly, the initial results of the Model will not be an accurate prediction, but the *weights* and *bias* values (w and b values) are adjusted after each iteration, until the output of the model matches reasonably well with the actual known results of the test data. Essentially, we are trying to minimize the loss function in the training process. It is akin to a medical resident learning how to do a surgery. Initially he/she will not know how to use the tools safely and effectively, but after extensive training, will be able to get adept at the procedure. Figure 1 is a very simplified diagram of the AI training process assuming a single Layer. As we will see later, modern machine learning often uses a technique called deep learning, in which the system learns in hierarchical layers.

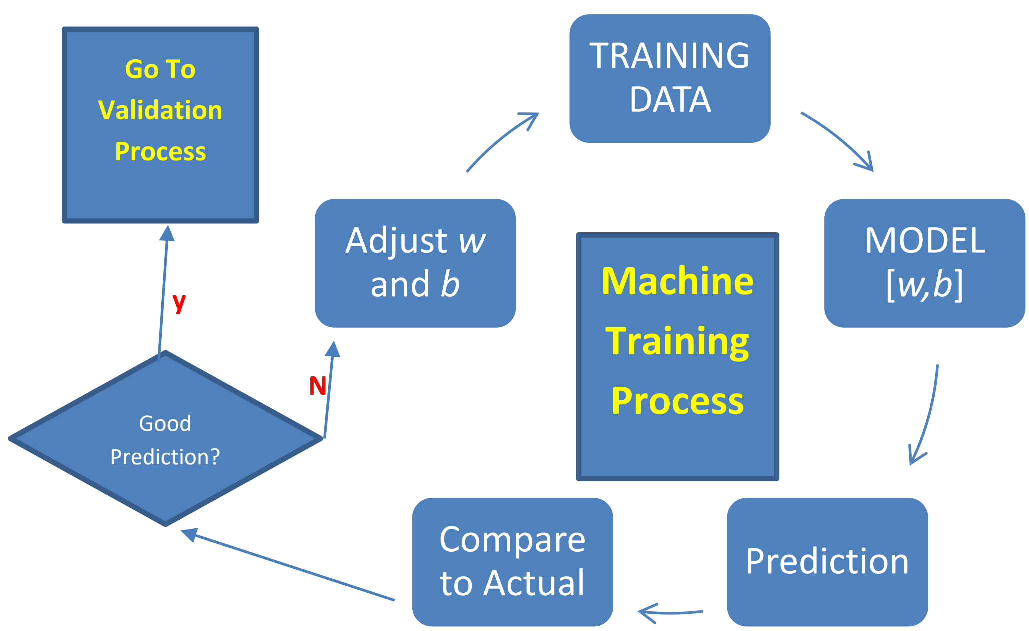

FIGURE 1: Machine Training

Once the training process is completed the adjustment of the w and b values so that the predicted answers are acceptably close to the actual answers in the testing data set, we run the AI Model against the "validation" data set that we had kept aside. This validation process allows us to see how well the "trained" AI Model can predict cases it has never encountered, thus simulating a real-life future situation. If the AI performs adequately in the validation process, doctors can start to use it with real patients in the production mode. The AI, however, will always be learning from new results, so it is a process of continuous improvement while it is on the job – much like humans. If the AI-Model is performing poorly in the validation or production mode, the training process has to be studied, modified, and repeated until it performs well.

A more detailed discussion of the neural network AI modeling techniques and training is beyond the scope of this paper. For instance, the assignment of the initial values of *w* and *b* can make a significant difference in the "learning rate" of AI system. The learning rate is the degree to which the predicted results of the AI move towards the actual results after each training step. Most of the current systems use "deep learning," in which the machines learns in a hierarchical fashion from "understanding" at a higher level first, and then in each layer drilling down and learning more details – for example identify a living thing, then an animal, then a mammal, and finally a cat.

The type of machine learning described above is called *supervised learning*, because the objective is to train the system to come up with a function that takes the input and generates results that approximate known results in the real world as depicted in the test data. The common types of supervised learning are done for classification or regression, as shown in Figure 2 [Soni, 2018] below. In our lung cancer example above, we can ask the system to say whether the patient had cancer or not.

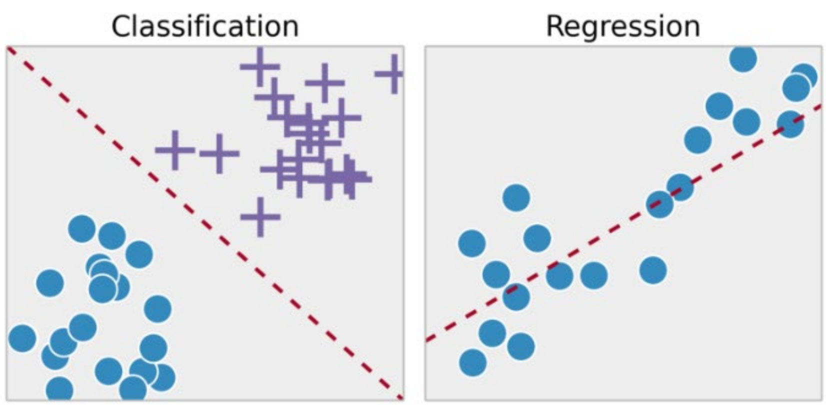

FIGURE 2: Supervised Learning

Another type of learning is called *unsupervised learning*, in which we do not have knowledge of what the correct results are. The AI needs to look for patterns by itself by studying the data set, and is often used in the context of clustering, representation learning and density estimation [Soni, 2018]. In our lung cancer example, the system employing unsupervised learning can group a given set of MRI images into subgroups for further analysis. In Figure 3 [Soni, 2018], for example, the AI groups the images into different types of animals. It will be up to us with coming up with labels for each group (for example, "ducks"). Hence, this type of machine learning is great for exploratory analysis because it can automatically find hidden patterns in data. We can then use the groups to test other features in each group (say, analyze segments of customers)

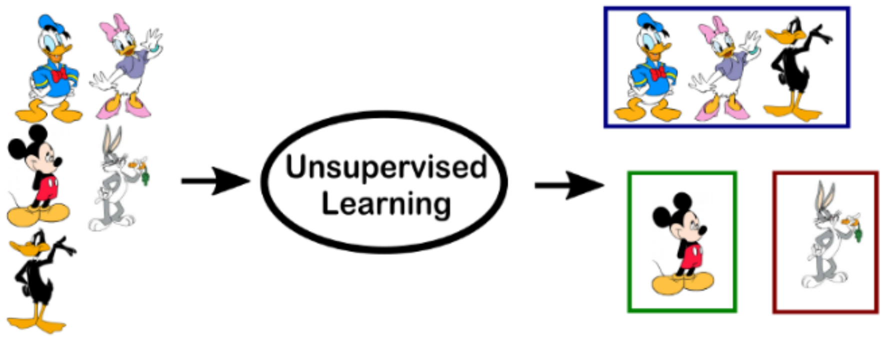

FIGURE 3: UNSUPERVISED MACHINE LEARNING

It is clear from above that the quality and quantity of data is critical for achieving machine learning and the use of artificial intelligence. We next discuss some specific advantages and shortcomings of AI in healthcare.

Healthcare Advantages And Disadvantages of AI

The use of AI in healthcare has now become a potentially powerful tool to diagnose and offer suggestions for treatments, as AI based systems now have the capacity to store and analyze large volumes of data efficiently and accurately. However, despite the vast advancement of AI, healthcare is still far behind than other industries such as auto manufacturers, financial institutions, communications, and aeronautics. In this section, we will explore the advantages and disadvantages of AI in the healthcare industry, specifically as it relates to Medical Imaging Informatics, along with the impact on patient care.

AI Advantages To Healthcare

Healthcare providers and patients will both benefit immensely from the prudent use of AI, as it can potentially make the healthcare system more efficient, effective, and result in superior patient outcomes. AI-based systems are the next generation of clinical decision support – technology designed to enhance the ability to identify and correctly diagnose problems, especially using diagnostic images or data from medical sensors. The American Recovery and Reinvestment Act of 2009 ushered in the first use of electronic medical records (EMR). This was the beginning of centralizing patient information. AI researchers say the expansion of this data will serve as the foundation for programming systems for clinical analytics. This includes mining imaging data to improve medical treatment. (Jackson, 2016). We next discuss the major expected advantages of these AI systems in healthcare.

Speed and Accuracy

AI has the immense potential to make accurate medical diagnosis using medical imaging data. Healthcare decisions and diagnosis are made after considering a vast number of factors, and this is where AI excels over humans – finding that proverbial needle in the haystack. AI imaging systems utilize enormous amount of data that we collect these days, such as CT scans, magnetic resonance imaging (MRI), ultrasound and nuclear imaging to both train the system in the initial phase, and then to make diagnosis (McKendrick, 2018). The systems also use abnormal cases as a part of the training to help with identifying rare anomalies. In the testing phase of the system, if the AI does make an erroneous diagnosis, software programmers and medical experts can refine the algorithm until the system gets it right. In addition, unlike with human diagnosis, where misdiagnosis could go undetected for long periods, artificial intelligence helps us catch errors/misdiagnosis in a shorter amount of time.

For some tasks, like medical image analysis, AI with their advanced deep learning capabilities seem to perform just as well, or even better than medical professionals do (Fornell, 2017). What is amazing is that, AI seems to outperform humans in the diagnosis of rare diseases. The reason for that is the ability of machines to rapidly refer to much greater amounts of data pertaining to illnesses than humans could ever hope to do, In addition, the humans might never come across these rare diseases during the span of their careers.

Google's DeepMind researchers plan to review 30,000 mammogram images from Japanese patients, along with 3,500 images from MRI scans and 80,000 historical mammograms (Wiggers, 2018b) from U.K.'s National Breast Screening System, to refine its AI system and investigate whether the system can accurately spot signs of cancerous tissue of people from all over the world. Every year, nearly five hundred thousand deaths are caused by cancer, and of those 90% are due to metastasis. Researchers at the Naval Medical Center at San Diego and Google AI have now developed promising AI based algorithms called Lymph-Node Assistant (LNA) that are an astounding 99% accurate. Surprisingly, LNA is far better than human pathologists who miss small metastases 62% of the time, especially when under time constraints (Wiggers, 2018c)

AI can help immensely in other healthcare settings as well. For example, Corti is a AI-powered device that looks like a Google Home Speaker, that listens to Medical Emergency calls in Copenhagen, and tells the human call operator if a cardiac arrest is likely. It does this by listening to the caller, the background noises. Corti was able to accurately diagnose 93% of calls compared to only 73% accuracy achieved by human operators – and it did so about 30 seconds faster (Marr, 2018). Speed is an important factor in such emergencies. Corti will be rolled out in other European countries as well, and the designers are also planning to expand its capabilities to diagnose stroke and drug overdosing.

In addition, AI based surgery simulators can assist surgeons perform even better, resulting in better patient outcomes. AI is also being used to help advance neurological medicine.

The systems are able to simulate brain functioning all in an effort to provide a diagnosis and recommend. Essentially, machine-learning AI algorithms, are trained to find patterns in images, and identify specific anatomical markers that are not easy or fast for humans (Channin, 2016).

Early Detection and Proactive Targeted Prevention

We may only be a few years away from using artificial intelligence, at scale, to detect and even prevent life-threatening diseases. AI could potentially be used to rapidly and routinely screen for diseases such as lung or breast cancer in a cost-efficient manner. Steve Tolle, the chief strategy officer and president of iConnect Network Services says that human radiologists miss about 15% of breast cancer diagnoses (Jackson, 2016), and predicts that AI can significantly reduce that rate due to its ability to incessantly and thoroughly look at each image, using all the knowledge that has been used to train it.

Earlier this year, medical imaging giant Arterys got the first cloud-based AI or deep learning algorithm for cardiac imaging approved by the FDA (Arndt, 2017). Many see this as a revolutionary benchmark for the industry, but most importantly for patients and improved health outcomes. Arterys specializes in medical image analysis, data visualization and software and has offices in the United States, Canada and France. The Arterys system is being developed to identify stroke victims even before they experience an episode, and its algorithm was trained on images of brains suffering an attack. By teaching the machine the characteristics of a stroke, it can be used in real life situations – and the system becomes even more accurate with time, as it constantly updates its algorithms with the new real-world data.

In another interesting study, scientists at the University of Adelaide in Australia programmed an AI machine to predict death, and it had an astonishing 69% accuracy rate. The test pool included 48 patients who had their CT scans feed into the deep learning system to tell if they would die within 5 years. The AI system was trained to analyze over 16,000 image features that could indicate signs of disease in all organs (Mesko, 2017).

Finally, AI can potentially use patient data to help doctors assess patients' health risks and even suggest prescriptions and treatment options along with possible side effects and drug interactions of medications – thus opening the door to personalized medicine.

Early Detection of Pandemics and Control

Sensors can report incidences by feeding data to AI powered servers via a network, and trained AI algorithms can rapidly detect any patterns that are developing and recommend a course of action. Centene (2018) for example is using advanced machine learning to assess health trends in communities and identifies the strengths and vulnerabilities. Centene's complex algorithms through machine learning displays the segments of populations that are at high risk for important health concerns, and provides targeted, personalized programs and interventions.

Unlike humans, AI can rapidly identify biomarkers (O'day, 2018) that allow healthcare professionals to zoom in on "at risk" humans, and perhaps prevent or start early treatments to avert expensive and dangerous human conditions. Another great advantage of analyzing massive amounts of appropriate data in real time using AI is to detect pandemics (McKendrick, 2018) before they spread too much, and limit the harmful effects to society.

Round-the-clock Availability and Remote Access

This advantage is rather intuitive, as unlike human medical personnel, machines are available round the clock, and always at peak, consistent performance. They also do not complain, demand extra or overtime pay, or want more benefits. Patients can also access these systems from their network-connected devices from anywhere; so routine and non-emergency diagnosis and issues can be handled remotely, conveniently, and cost-effectively. The best aspect is that patients, even in remote isolated parts of the country, can have access to expert health care at all times.

Faster Discovery of New Pharmaceutical Drugs

Pharmaceutical companies spend enormous amounts of money, time, and personnel to discover new treatments and drugs. A start up called Researchably is now employing AI to "read" and "analyze" research papers in scientific journals, and past studies to rapidly and filter out relevant results to achieve their goals faster and cheaper. Researchably has built a specialized database of about 30 million papers, 340,000 clinical trial records, 750,000 patents, and tens of millions of company and researcher profiles. The AI system cuts the amount of time spent scanning a paper from 13 minutes to less than 1 second (Wiggers, 2018a). In addition, 3 out of 10 papers are currently categorized incorrectly, and so does not reach the right people who need it, but Researchably eliminates those kinds of mistakes that were made before. Pharmaceutical giant Sanofi is extremely happy with Researchability, as it totally disrupts the traditional slow, erroneous processes, and claims that it makes drug discovery much faster, simpler, cheaper and more accurate.

AI also has the potential to make new drug discovery much more time and cost efficient. Traditionally, the drug discovery process involved many trial-and-error procedures using large quantities of many chemicals, employing several scientists, buying and maintaining lab equipment, taking a lot of time, and expending a lot of money. Enormous number of failed attempts and serendipity was the norm. The newer approach using AI is far more efficient in identifying the right chemical structure, and hence increase the efficiency of both drug design and synthesis, making pharma companies more efficient, more profitable, and reduce chemical waste (Carbeck, 2018). AI algorithms analyze all known past experiments and then suggest new molecular formulas for drugs and possible ways to synthesize (manufacture) them. These automated systems using AI have dramatically accelerated the identification of new drug leads. BenevolentAI is among the many startups that are exploring AI for drug discovery. BenevolentAI is attempting to apply AI to the entire drug development process, from the discovery of new molecular structures, synthesis and finally the design and analysis of human clinical trials to establish effectiveness and safety for human use (Carbeck, 2018).

Help Humans with Emotional Decisions

In China, the PLA General Hospital in Beijing has developed an algorithm using machine learning to determine the probability of coma patients waking up in the future – so that doctors and family members can make a more informed decision on how to proceed in trying to revive or just say goodbye. They used functional MRI (fMRI) data from 1000s of coma patients to train the machine. Surprisingly, the machine also successfully predicted that a number of patients would regain consciousness, even when many of the human experts predicted that there was almost no hope. The system was about 90% accurate for the 300 initial patients (Tangermann, 2018) on which it was tested, and now China is hoping to roll it out for about 50,000 coma patients in China.

It must be noted that life-and-death suggestions from AI based systems, such as keeping coma patients alive or not, should not be seen as a final decision. The AI algorithms are only using past data to determine a probability (an "AI score") of regaining consciousness for a specific coma patient. The AI researchers at PLA General in Beijing recognize this, and tell the doctors and family members that the AI Score should only be weighted from 20% to 50% in the final decision. The final decision to keep the coma patient alive or not, is ultimately left to humans, such as doctors and family members, as it would be horrible to let a machine make that final decision to kill a human patient. The AI system designers at PLA General Hospital recommend that the AI score be considered only in cases in which the human doctors deem the patient as a lost cause, but the AI score indicates that there is hope of revival (Tangermann, 2018).

Lower Costs and Higher Profits

Many of the previously mentioned advantages invariably leads to cost reduction and higher profits to organizations. The ability to rapidly diagnose a patient correctly results in increased productivity of healthcare systems. An AI-infused system can likely use less human personnel for handling more patients in a given amount of time. Alternatively, the number of patients that can be handled in a day can be increased using the same number of healthcare personnel. In either case, there is potential for higher profits and/or lower costs for healthcare organizations. Lower costs, in combination with better patient outcomes is a winning proposition. Igor Barani, MD, chief medical officer of deep learning healthcare company Enlitic (Jackson, 2016), believes that the Deep Learning is particularly useful in radiology because there are a lot of data variables accessible in electronic formats, and that there is a clear to need to speed up radiology given the growth of medical imaging while keeping costs low.

In the modern world, it is important for healthcare organizations to deliver their services quickly, at lower cost, and with higher quality. Healthcare is very expensive in US, and we spent $3.3 trillion (17.8% of US GDP) – which is the highest among developing countries (Markman, 2018). The budget for physician and clinical services grew remains the fastest-growing portion of overall annual budget, and the use of AI to reduce escalating costs will serve well. Use of smart systems can take the screening and other routine activities off the Physicians workload and free them for more value-added services. Proponents also believe that deep learning machines can best serve the healthcare industry by becoming the workhorse when it comes to performing repetitive or time-consuming tasks.

We have discussed many of the amazing benefits of using Artificial Intelligence in the healthcare area. Table 1 summarizes the important advantages of artificial intelligence to the healthcare area. In the next section, we discuss some of the major disadvantages of using AI in this area.

Table 1: Advantages to AI-based Healthcare

ADVANTAGE	**REASON**
Speed and Higher Accuracy	Able to Learn from vast amounts of past knowledge and Apply it consistently and quickly using superfast machines using Deep Learning
Early Detection and Proactive Targeted Prevention	AI can discover new biomarkers
Early Detection of Pandemics and Control	Sensors can report incidences and AI can see the pattern rapidly
Round-the-clock Availability and Remote Access	Advantage of Network -based services
Faster Discovery of New Pharmaceutical Drugs	Simulate several combinations of relevant chemicals and make predictions of the results
Help Humans with Emotional Decisions	Should treatment be continued – make decision less emotionally taxing
Increased Profit	Cheaper than human experts, works 24/7, Less errors

Ai Disadvantages To Healtcare

Like most technology, while AI does offer many benefits to healthcare; it also comes with its own unique set of potential problems. It is clear that AI deployment in healthcare will adversely affect many of its current stakeholders, and so naturally, there is pushback from opponents like healthcare providers, ethicists and government agencies. These disadvantages are primarily based on product limitations and the consequences of using these efficient, but increasingly non-human healthcare systems. We next explore some of these adverse consequences of deploying AI.

Loss of Human Jobs

Healthcare professionals are naturally apprehensive of AI, as it has the very real prospect of infringing on their employment. Radiologists see accurate and fast image-diagnosing AI systems as a real threat, as do many physicians and nurses. This threat is more than just a perceived threat, as these systems are already part of the plan for certain hospitals. One of United Kingdom's biggest Hospitals, the University College London Hospitals (UCLH) and the Alan Turing Institute are collaborating to bring the efficiencies of AI to the National Healthcare

System (NHS). UCLH plans to use AI to diagnose cancers using CT scans and speed up patient waiting times in Emergency Rooms (Devlin, 2018). They later plan to expand the system to also identify at-risk patients and proactively direct resources to prevent expensive treatments at a later stage, if they were left untreated.

Medical personnel can easily see the great advantages of artificial intelligence, but are also aware that they can eventually become a major threat to their livelihood. Proponents of deploying AI often counter this fear by stating that the systems will be a welcome relief to medical personnel as it eliminates the routine, boring and mundane tasks, and thus freeing up time for doctors and nurses. The extra time can then be devoted to more meaningful and higher-value patient care.

When employing “smart” technology, there is the danger of “learned helplessness,” when humans become too reliant on machines. This could adversely affect human problem solving abilities, lateral thinking and multitasking abilities. With so much assistance from machines, if humans do not need to use their thinking abilities, these abilities will gradually decline, and they will just start accepting the machines’ results as always correct. Even if machines are accurate 99.9% of the time, it would be prudent for a human to ultimately apply “common sense” and “approve” the machine’s recommendations.

Inability to Explain AI Healthcare Decisions

One big hurdle for widespread AI adoption maybe the lack of any explanation of the healthcare decisions made by AI to existing human experts. When IBM tried to promote its AI Watson system to cancer doctors, it was met with extreme resistance for this reason, and the human doctors often just dismissed the systems diagnosis (Bloomberg, 2018). Perhaps as the next generation of medical professionals get more familiar and comfortable with AI and Machine Learning, AI in Healthcare might be embraced much more readily (ScienMag, 2018). There are new developments in the AI field, such as the IBM AI OpenScale Program that aims to encourage AI systems to be more transparent, increase the explainability of AI decisions and build trust. The inability to fully explain healthcare decisions by complex, but accurate AI-based healthcare systems also makes it hard to regulate them by the governmental agencies like the FDA.

Some AI experts, such as Harvard’s senior researcher David Weinberger, however, caution that making a AI-system simple enough to explain to humans, will undermine the very reason of using an AI – as their main advantage is complexity and nuance (Gershgorn, 2018). Human models are necessarily constrained to a few variables due to our cognitive limitations, but machine models optimized for healthcare decisions cannot be reduced for human understanding – and still be effective. Instead, it is suggested that we should simply focus on what the AI-system is optimized to do, and then constantly improve the results with more data, when necessary, so that it yields the result we seek.

Loss of Patient Data Privacy

AI training is best when large samples of relevant data is available. If privacy is not a concern at all, the Healthcare systems could store and analyze the entire population's data to make very accurate diagnosis and decisions. But that would mean giving up data privacy. In countries like the USA and in the EU, data privacy is paramount (McKendrick, 2018), but that will likely limit the full potential of AI systems. Whereas in countries like China, where all the data is available for these systems, the AI based system might produce some amazing results.

Some prudent measures to safeguard confidential data is an important aspect of any large medical information system. The UCLH AI Program in UK mentioned before does not want to repeat the privacy mistakes made by predecessors such as the Royal Free Hospital and Google's DeepMind project, in which the hospital inadvertently shared the identifiable health records. All the AI algorithms and training will be done on the hospital's private servers and data will not be shared with any private company (Devlin, 2018).

Built-in Bias from Non-Representative Healthcare Data

Machines are supposed to be unbiased, in theory, and under ideal situations. However, the objectivity of an AI system depends on its algorithms, which in turn depend on the nature of the data used for training the system. So, for example, if a Healthcare AI system is trained on data that represents predominantly Caucasian patients, then it may not be accurate or effective when diagnosing patients of other ethnicities, as there may be significant differences in risk factors and natural propensities. The AI system will then lead to misdiagnosis and suboptimal treatments for the non-Caucasians, because of the inadvertently built-in bias.

One study (Knight, 2020) reported that when they analyzed 94 data sets with more than 500,000 images to spot Eye diseases, it discovered that almost all of the data came from patients in North America, Europe, and China. They concluded that AI based eye-exam algorithms were less reliable to work for racial groups from under-represented countries. It is therefore, very critical to be aware of the possible bias in the data, and include a very wide sample of data from well diversified populations and situations, so that the AI system can account for the differences in the population.

Unethical Use of Healthcare Data

Confidential healthcare Data can be used for questionable purposes, regardless of the use of Artificial Intelligence. For example, an employer might be reluctant to employ a person known to be predisposed to cardio vascular health issues, or a degenerative condition (like Parkinson's Disease, Muscular dystrophy or Alzheimer's), or cancer because of possible absenteeism and higher healthcare costs. What makes the introduction of AI into that mix particularly concerning is the ability to do real time analysis of data of all applicants or all employees – and without even asking for the data. Just observing video feeds from interview rooms or from activities an office building can trigger potentially “unhealthy” employees or applicants.

Certainly, the diagnosis from these “healthcare surveillance” AI systems can also be used for good purposes. For example, that same system from above can also be used to inform the employees of early stage Parkinson’s Disease so that they can seek early intervention treatments and possibly prevent major damage. However, the sheer ease of analysis and the ability to do it at scale, unobtrusively can be easily abused as well. With the installation ubiquitous sensors and cameras, the potential for using AI for unethical purposes is not trivial.

Machines Making Vital Human Healthcare Decisions

It was noted in the advantages section above that AI decision making can assist humans make emotional decisions more objectively, with less pain. The bigger question is whether we should defer our critical healthcare decisions to AI algorithms. It is true that machines would have access to a lot more relevant, current data, and be able to analyze it consistently, thoroughly, far faster, and better than humans can ever hope to do. However, even AI-machines are not truly “intelligent” like human experts, and do not think as creatively. They are not yet able to bring in “unusual” factors that can affect specific cases and situations. So, even though machines will often make decisions based on facts and not be affected by emotions, human society still has to decide whether we should cede control to machines. There is also the potential of machines to be controlled by rogue humans for selfish purposes, which might not be in the best interest of the patients.

Dependence and Vulnerability

As with many technologies, humans and healthcare organizations can eventually get very comfortable with healthcare decisions being made by machines. These would likely come a time when we may not be able to function effectively without these smart systems. That naturally makes the healthcare organizations vulnerable to system malfunctions, bugs or cyber hacks. Many medical personnel in the future may not even know how to deliver healthcare without these systems. Consequently, many redundancies may be necessary to keep the system operational under many adverse conditions.

Ongoing Cost of Maintaining AI System

It is well known that the initial cost of developing a computer system is only 20% to 35% of the total cost. The remaining costs are for maintaining and improving the system, and can be anywhere from 65% to 80% of the total cost (Reynolds, 2020). This regular and significant maintenance cost must be accounted for in the organizational budget. Maintenance of software can be to correct past errors and bugs, make it adapt to new data sources or devices, add new functionality for improvements, and finally to prevent any possible future problems by increasing system reliability. These costs could be for hardware, software, cloud based or other outsourced services, and specialized personnel. It is hoped that AI based healthcare will eventually reduce the cost of healthcare, but recent surveys (Landi, 2020) indicate that AI has increased healthcare costs rather than decreasing. Increased costs, though, is only one factor, the other important factor being the final outcome for the patients.

Table 2 summarizes the various shortcomings and disadvantages of utilizing artificial intelligence based healthcare systems.

Table 2: Disadvantages to AI-based Healthcare

DISADVANTAGE	**REASON**
Loss of Human Jobs	AI taking some of the work done by humans previously. Enable humans do more in the same time.
Inability to Explain AI Healthcare Decisions	AI Decision Making logic is so complex with so many factors that even human experts may not be able to understand. Blackbox Approach.
Loss of Patient Data Privacy	The more data the system has, the better the training the results. Incentive to collect more types of data from more people.
Built-in Bias from Non-Representative Healthcare Data	Data reflects past behavior, which may have human bias baked in.
Unethical Use of Healthcare Data	Use of AI and data for doing harm or for very selfish reasons.
Machines Making Vital Human Healthcare Decisions	Handing over critical life-and-death decisions to machines. This could be good also as it will be more objective and consider more factors, but humans lose control.
Dependence and Vulnerability	Healthcare is compromised if the system malfunctions, stops working or is hacked.
Ongoing Cost of Maintaining AI System	The initial cost of a system is usually on 20% of the Total cost of the system. The remaining 80% is for maintaining and updating these systems.

AI FOR DETECTION OF COVID-19

The world is currently in the grip of a COVID-19 pandemic; hence it is very pertinent to study the current and potential role of AI during this challenging time. The outbreak of the novel Coronavirus SARS-CoV-2 known as COVID-19 started in December 2019, and has turned out to be one of the deadliest viruses in the history. COVID-19 has now spread almost all over the world, and has caused immense global harm in terms of health, safety, and economy.

Researchers around the world are attempting to help build AI-based tools to fight the deadly COVID-19 virus in various ways such as early detection of the virus, combating the virus, patient monitoring, drug development, and support the healthcare professionals. Some of these are discussed below.

AI has been played a very important role in the detection of the COVID-19 infection. Jamshidi et al (2020) illustrated that some Deep Learning AI methods could accelerate the process of diagnosis and treatment of the COVID-19 disease, including Generative Adversarial Networks (GANs), Extreme Learning Machine (ELM), and Long /Short Term Memory (LSTM). Ilyas, Rehman, and Nait-ali (2020) studied some AI based approaches for the detection of COVID-19 that showed promising results such VGG19 with 98% of accuracy, ResNET with 96%, ResNet50 with 95% of accuracy, and InceptionV3 with 96%. They used x-ray images to train the AI Algorithm.

Soltan et al (2020) developed two AI-based early-detection models to identify COVID-19 using routinely collected data typically available within one hour (laboratory tests, blood gas and vital signs) during 115,394 emergency presentations and 72,310 admissions to hospital, and the AI models perform effectively as a screening test for COVID-19 in emergency departments and hospital admission units, offering high impact in settings where rapid testing is unavailable. Allam, Dey, and Jones (2020) documented the power of AI-driven algorithms for the early detection of the novel coronavirus (COVID-19) through the work of two companies, BlueDot and Metabiota, in China. There are several other studies conducted in regards to the detection of COVID-19 using AI and AI-based models and algorithms (Kumar & Rana, 2020; Mohamadou et al., 2020; Arni et al., 2020; Wong, Ho, & AR, et al., 2020; Simsek & Kantarci, 2020; Mei et al., 2020).

AI is also being investigated as a potent tool for patient monitoring and drug development. Online medical chatbots can be helpful for patients to recognize any symptoms and provide people guideline for hygiene (Ting et al., 2020). To fight this deadly virus, the world needs suitable drug for treatment. AI can be a helpful tool for the discovery of drugs for COVID-19 treatment by speeding up drug testing which may not be possible by using human labor (Ting et al., 2020; Vaishya et al., 2020). A recent research utilizing AI methods by Benevolent AI and Imperial College London reported that a drug named Baricitinib used for rheumatoid arthritis can be used against the COVID-19 virus, and another Hong Kong based company Insilico Medicine argued that it was able to design 6 new molecules that could stop viral replication utilizing AI algorithms (McCall, 2020). A deep learning system "Alpha Fold" created by Google DeepMind discovered valuable information about protein structures related with COVID-19 which can be beneficial for vaccine formulation and the process is significantly faster than the traditional experimental approaches (Alimadadi et al., 2020).

Ćosić et al. (2020) also addressed the need for timely detection of high distress situations of frontline healthcare workers during the COVID-19 pandemic, and proposed AI based multimodal neuro-psycho-physiological features to detect mental health disorders early enough to prevent and reduce the emergence of severe mental illnesses. Healthcare workers may develop mental disorders, such as elevated rates of anxiety, depression, posttraumatic stress disorder (PTSD), or even suicidal behaviors. AI-based tools could play an important tool in our healthcare arsenal to prevent or minimize distress for Healthcare workers (or any one).

Additionally, McCall (2020) also discussed how AI could be used for protecting the health-care workers and curbing the spread.

SUMMARY AND CONCLUSIONS

Healthcare is a very important component of society and the global economy. As the human population grows, along with longevity, healthcare also comes at a very large cost. In this paper, we have demonstrated that technology, and specifically the use of artificial intelligence (AI), is a promising way to increase the quality and speed of healthcare in a cost effective manner. AI is also a great tool for detecting health problems at an earlier stage, thus preventing crisis situations and pandemics like the current COVID-19 one that is ravaging us. AI, however, does have some drawbacks such as jobs displacement, loss of human control, and the potential loss of privacy and excessive dependence on the technology.

As promising as AI is for superior healthcare outcomes, speed and cost reduction, it does face some formidable barriers to adoption. A major barrier may be the resistance from humans in the medical industry, who may fear rapid changes and potential threats to their jobs. Another hurdle may be the liability issues and jumping regulatory hurdles. Finally, the initial costs and effort needed for obtaining unbiased, but large quantities of relevant data for training these AI systems, and maintaining data privacy, may be a formidable obstacle as well.

Despite the hurdles, it is very likely that AI will rapidly get adopted by the healthcare industry, as the potential benefits may far outweigh the disadvantages. Major technology companies such as Apple and Google are also pushing hard for a much more tech-centric healthcare industry by providing cost-effective solutions. It will be an understatement to state the AI is about to completely revolutionize healthcare.

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THE BURDEN OF THE TEACHERS RETIREMENT SYSTEM IN GEORGIA

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ABSTRACT

The Teachers Retirement System (TRS) of Georgia was established to provide a reliable retirement income to Georgia educators. The system's unfunded liabilities is $23.7 billion and growing. This research analyzes how changing the formula used to calculate defined benefits would change the unfunded liabilities. We simulate the impact of changes in the assumed rate of return on investments, member contribution, the multiplier, the number of years of income, and cost of living adjustment. We simulate these changes for a hypothetical individual, project it for the entire system, and use a Monte Carlo simulation to account for uncertainty.

INTRODUCTION

The Teachers Retirement System (TRS) of Georgia is responsible for providing its teachers with a fixed, monthly pension determined by the following formula:

$$Monthly\ pension = average\ monthly\ salary\ (highest\ consecutive\ 24\ months) * 2\%\ (multiplier) * years\ in\ service\ (maxed\ out\ at\ 40\ years).$$

(equation 1)

For instance, a member working for 30 years and earning an average monthly salary of

$5,000 (for the highest consecutive 24 months) would start with a monthly $3,000 in retirement income. During retirement, members are also eligible for a Cost of Living Adjustment (COLA). Based on current rules, this means that retired members' monthly income can be increased by 1.5% two times a year. (The COLA is not guaranteed and is applied if inflation is high).

The TRS has a major impact on the Georgia economy: exceeding $78.1 billion in assets, creating 66,000 jobs and contributing $7.42 billion in total economic output (TRS, 2020).

However, the current level of unfunded liabilities, $23.7 billion in 2020, is threatening the sustainability of the system.

This research aims to analyze how to improve the financial sustainability of the TRS by adjusting the different elements of the benefit formula as well as other factors impacting the unfunded liabilities.

THE BURDEN OF THE TEACHERS RETIREMENT SYSTEM IN GEORGIA

The Teachers Retirement System (TRS) is a network of state and city-level organizations that administers retirement funds for public education employees along with other education-related workers (Kagan, 2019). The TRS manages, what we call defined benefit (DB) plans, plans that in exchange of employer contributions during the active years promise a fixed amount of monthly income during retirement until the member's death (and, in some cases, to the spouse after the member's death)[1].

The advantage of DB plans is that they provide a steady and predictable income in retirement since any risk of investment stays with the TRS fund and the member's monthly pension will not be affected by the performance of the investment made by the system. This is in stark contrast to what we call defined contribution (DC) plans, such as 401K accounts, that are popular in the private sector. Employees enrolled in DC plans typically contribute a tax-deferred amount, part of which may be matched by the employer. For DC plans the employee is responsible to make investment decisions, which will impact how much money the employee will have in retirement. So, while DB plans basically promise a fixed benefit in retirement until the member's death, employees enrolled in DC plans have accounts with a balance that fluctuates depending on the performance of the invested amount.

A problem with DB plans occurs when the value of assets held by the retirement system is less than the actuarial value of the promised liabilities, i.e. when the system has unfunded liabilities. Eventually this problem can escalate into a situation where the DB plan contributions from active members and earnings on accumulated assets do not cover the promised benefit payout to retired members and even result in an inability to meet payout obligations. The longer life expectancy coupled with lower interest rates and lower investment returns earned during the first two decades of the 2000s have exposed the risks of DB plans. According to Public Plans Data (2020), public pension plans in the U.S. were 102% funded in 2001 but only 72.2% funded in 2019.

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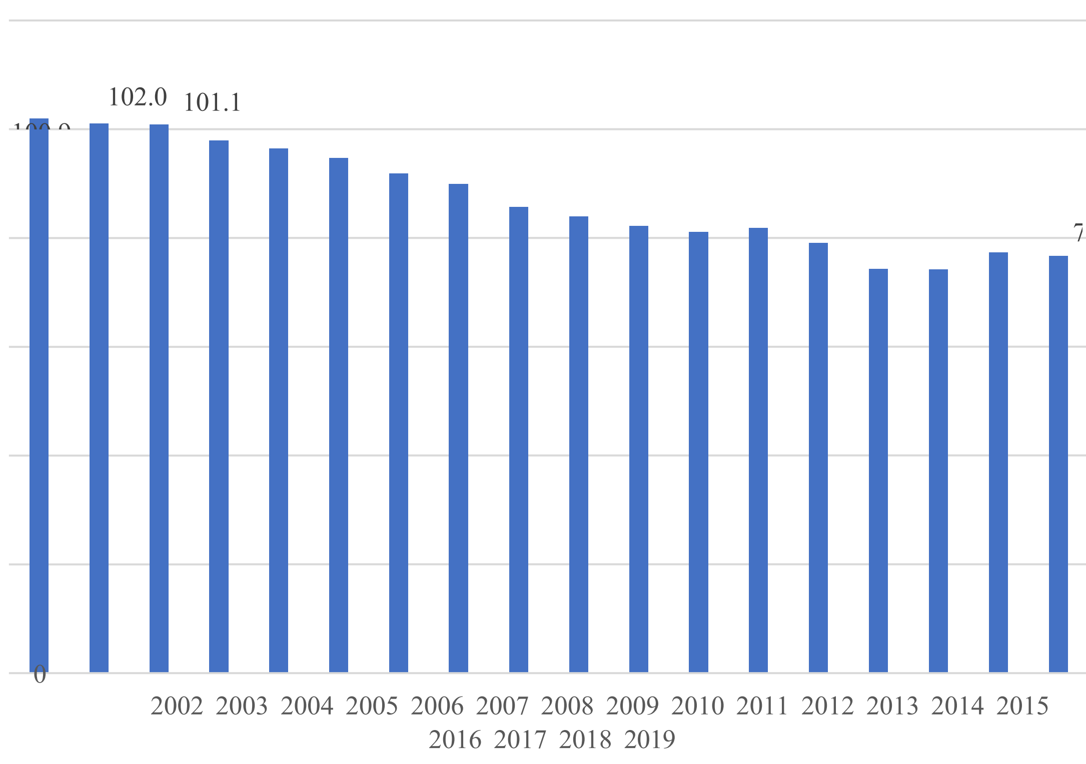
[1] Indeed, there are multiple plans members can choose from. In what is referred to as a survivorship plan, members can select to provide a lump-sum payment or monthly benefit payment to their beneficiary. In such a case the member's benefit would be reduced. Since the most members select the regular plan with the maximum payout to the member, we will use that as the base of our simulation and disregard the other options. For more detail on all the options, see page 12 of Teachers Retirement System of Georgia [TRSG], (2020).

THE TEACHERS RETIREMENT SYSTEM IN GEORGIA

As of the most recent fiscal year report, the Georgia TRS manages over 231,000 active member accounts and pays a pension to over 135,000 retired members and survivors with an average monthly benefit of $3,190. The overall benefits paid to retired members grew to over $5 billion for the first time in 2020 (TRSG, 2020). As a result of demographic trends and recent developments in the financial markets, the TRS of Georgia has not been immune to the overall national trend in unfunded liabilities. The actuarial value of plan assets in TRS in 2019 was

$78.1 billion, while the liabilities grew to $101.8 billion for a funding ratio of 76.7% (TRSG, 2020). In contrast, the actuarial value of plan assets in 2002 was $40.5 billion, while the actuarial value of liabilities amounted to $39.7 billion for a funding ratio of 102% (TRSG, 2008). Figure 1 shows this trend year by year.

Figure 1. Funded ratio in the Teachers Retirement System of Georgia



While the state has the ability to pay monthly income to its current retirees, without significant changes, at some point outside funding is likely to be required to meet the system's obligations. This means either a reallocation of state tax revenues or an overall increase in state taxes, both of which may pose politically unfavorable consequences. As a matter of fact, in only the past three years, the state has poured nearly $600 million dollars of taxpayer money into the system in the hope that it will alleviate the problem (Kagan, 2019). Another recent significant change was in 2012 when the member contribution rate was increased from 5.53% to 6.00% (TRSG, 2020). However, these changes could only temporarily break the overall trend and the funded ratio is likely to decrease further in the absence of a more significant change. Also, the state and school districts currently spend around $2 billion dollars per year on the TRS (Salzer,

2019). An audit performed by the senate budget committee claims that amount will climb to $2.4 billion per year by 2025 and $4 billion per year by 2045 if no changes are made (Salzer, 2019).

As a matter of fact, the state and school district contributions grew by 67% between 2002 and 2017, while Georgia's economy only grew by 23% during the same timeframe (Sidorova and Niraula, 2018).

THE INDIVIDUAL'S BURDEN

In the TRS, active members currently contribute 6% of their salary[2], which is then invested by the TRS with the stated goal of obtaining a 7.25% annual return[3]. Once members begin to collect retirement benefits, the amount paid to the retired member is deducted from the member's balance while leaving the remainder invested. The question is at what point in their retirement will members begin to exhaust their accumulated account balance and start to 'burden' the system.

In this section, we will take a hypothetical individual and analyze how changing different factors impact when this individual's balance turns negative. The factors that we are looking at are the ROI on TRS investments, the active member's contribution rate, the multiplier (in equation 1), the number of years calculated in the average (in equation 1), and the COLA.

The hypothetical individual whose retirement account we will simulate begins working at the age of 43 at a $49,250 starting salary[4]. The member's salary grows at 1% per year until retirement at the age of 65 at which time the member begins collecting his/her benefit. Selecting a different starting salary will change the balance, but will not change the number of years after which the individual exhausts his/her account.

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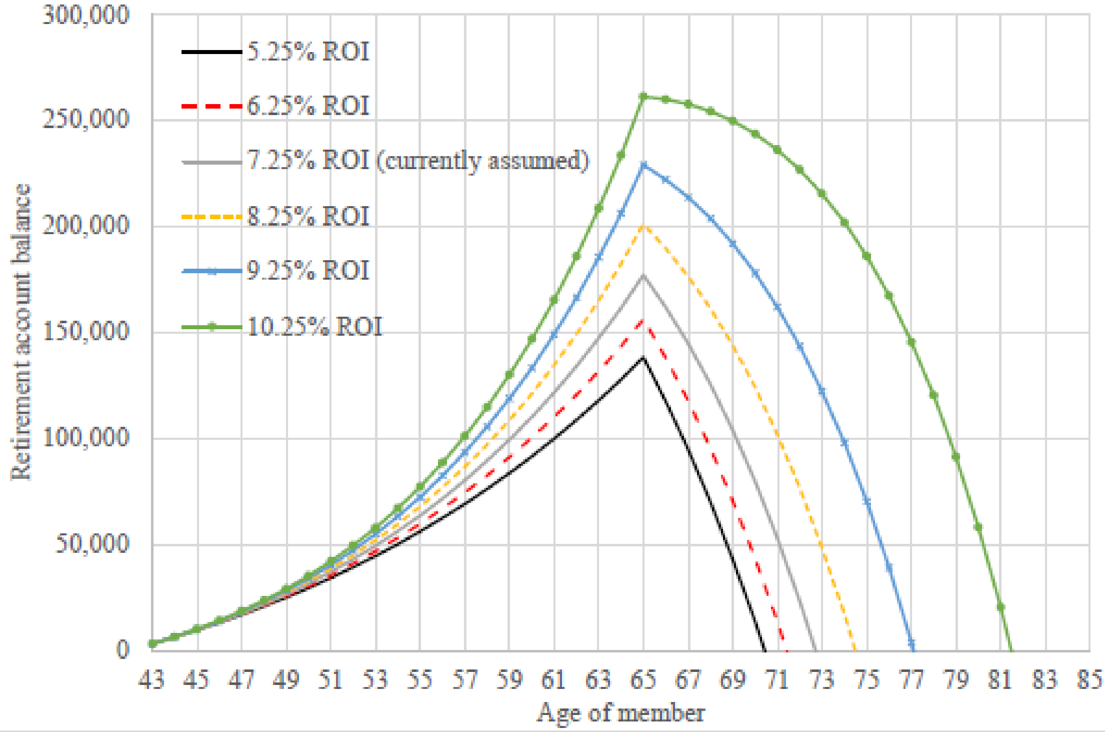
[2] The employee contribution is supplemented by an employer contribution, but since that is equivalent with the government taking money from one pocket and putting it into another one, we will only take the employee contribution into account.

[3] We use this rate of return in our baseline analysis on all balances, unless stated otherwise.

[4] We picked the starting salary amount so that after 23 years of service and about a growth of 1% per year the individual's final salary equals what is reported for the average final year salary for those retiring in FY2020.

Also, we decided that our individual starts at the age of 43 and works until retirement, since based on the most recent financial report, the average number of active years for those retiring in Fiscal Year 2020 (FY2020) is around 23 years (CRFA, 2020)[5]. Figures 2.a-d. show the impact of changing one factor at a time. For instance, when we present the impact of the different rates of return on investment, the other factors determining the balance are assumed constant. This means that the member's contribution rate stays constant at 6%, the multiplier is 2%, the COLA during retirement is 3.02% (which is 2*1.5% compounded), and the average salary used in the calculation are the last two years.

Figure 2.a. Retirement account balance with different return on investment (ROI)



[5] The assumed retirement age of 65 is between the earliest age individuals can claim Social Security (62) and the full retirement age of 67 years of age. While many claim Social Security benefits as early as possible, the more educated tend to retire at later ages (Knoll and Olsen, 2014).

Figure 2.a shows that a retiree under the current rules and with the currently assumed rate of return of 7.25% would exhaust his/her retirement balance at about 73 years of age, 8 years after retirement. If the return on investments is somewhat lower, for instance only 5.25% on average, the balance would be exhausted before the member turns 71, less than 6 years after retirement. This is important, since based on current statistics, a 65-year old is expected to live an extra 20 years on average (Moore, 2018), and is also significant because based on the current rules even a generous 10.25% ROI would not be sufficient for the member's balance to stay positive.

Georgia's House Retirement Committee has proposed (HB 662) to lower the assumed rate of return (ARR) from 7.25% to 6.75%. This alone would result in an additional $17.7 billion in contributions over the next 30 years. "The act of lowering a pension fund's assumed rate of return has the effect of reducing expected contributions resulting from investment gains, which means the system will need higher annual contributions from taxpayers and/or its members to maintain its current funding trajectory". (Sidorova & Gilroy, 2020).

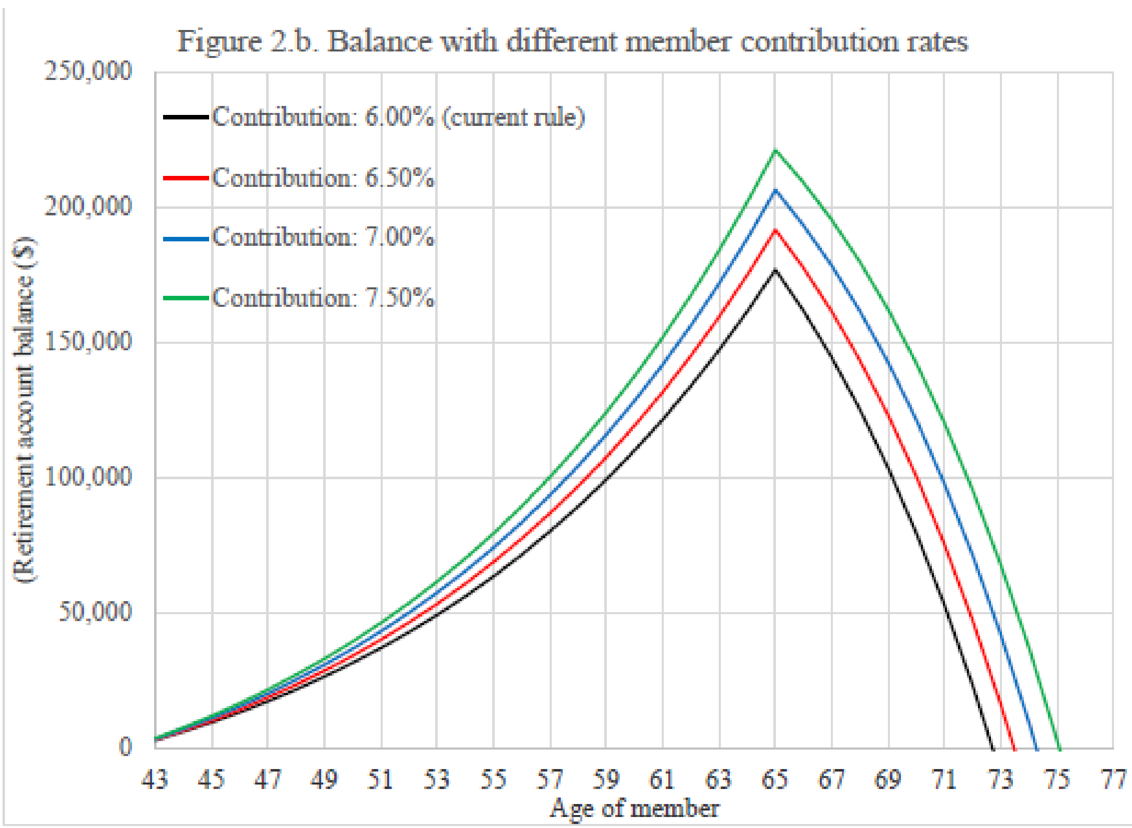


Figure 2.b. shows what happens if the employee's contribution is increased from the current 6% to 6.5%, 7%, and 7.5% (the assumed rate of return of investment is the currently assumed 7.25%). We see that even a drastic increase of 1.5 percentage-points in the member's contribution rate only gains a little over 3 years and the balance would still be exhausted before the member reaches age 75.

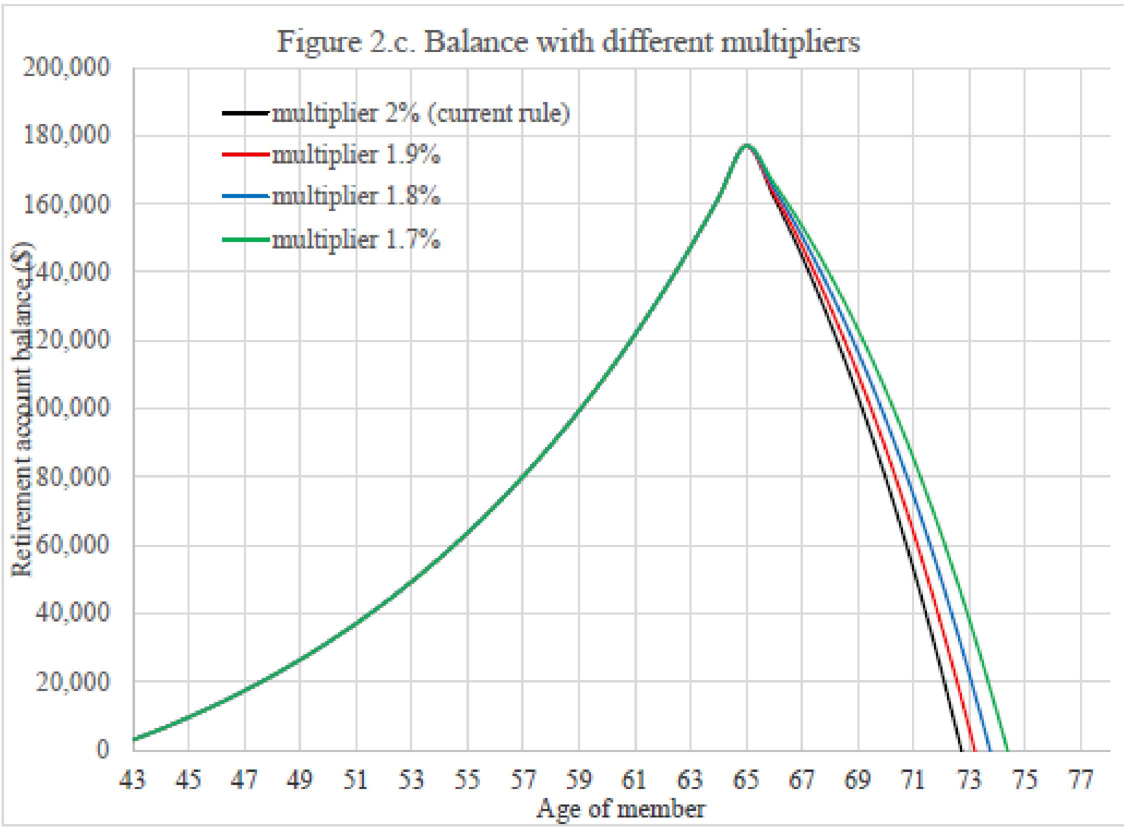
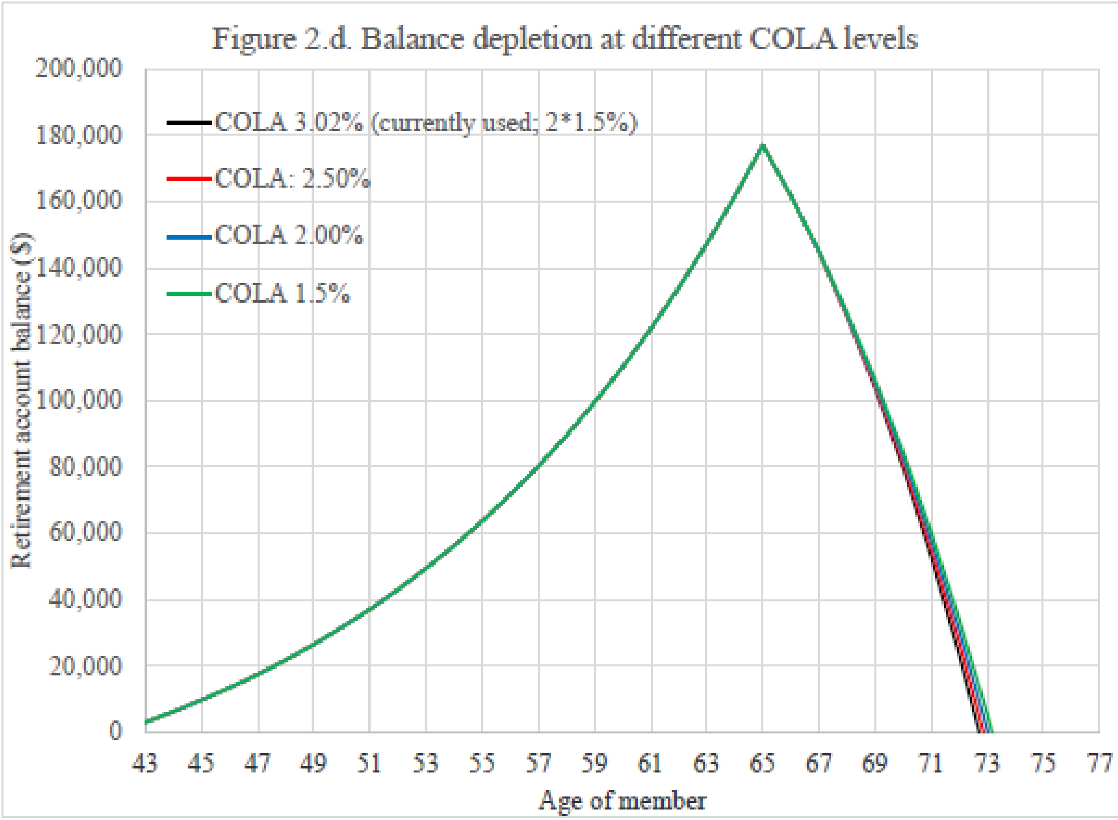


Figure 2.c shows that decreasing the multiplier from 2% to 1.7% only extends the balance life by less than 3 years.



Finally, Figure 2.d. shows the impact of changing the COLA adjustment, which is currently 1.5% twice a year if the value of the Consumer Price Index is greater than the retired member's calculated base index (average monthly CPI over a 6-month period). The figure shows that reducing the COLA from a cumulative 3.02% to a cumulative 1.5% is not too meaningful in helping to extend the retirement account balance.

ACCUMULATED IMPACT

In this section we will look at the magnitude of the potential dollar savings for a cohort retiring at the same time for each factor change: multiplier, number of years used in the calculation of the highest consecutive salary, the COLA, and the contribution rate. The most recent financial report shows that 6890 individuals retired during FY2020 and the average monthly income for those retiring was $5,107.67 in their final year of work (CRFA, 2020). The average of the last year's monthly income was $5,080.38 in FY2019. We make the assumption that these two amounts fairly represent the highest 24 months of income for those retiring in FY2020. Therefore, the average monthly income that was used in the formula (equation 1) for members of a cohort is $5,094.03 ([$5,107.67+$5,080.38]/2). Using this amount with 23 years of service, such a retiree would be eligible for an initial benefit amount of $2,343.25.

$$\$5{,}094.03 * 0.02 * 23 = \$2{,}343.25$$

Such an individual starting with about $28,000 retirement income during the first year in retirement who gets a 3.02% COLA yearly and who lives 20 years after retiring would exhaust his/her account at about 73 years of age and would collect over $500,000 during the rest of his/her life. This amount of over $500,000 is the amount of unfunded liability the system accumulates for one such retiree.

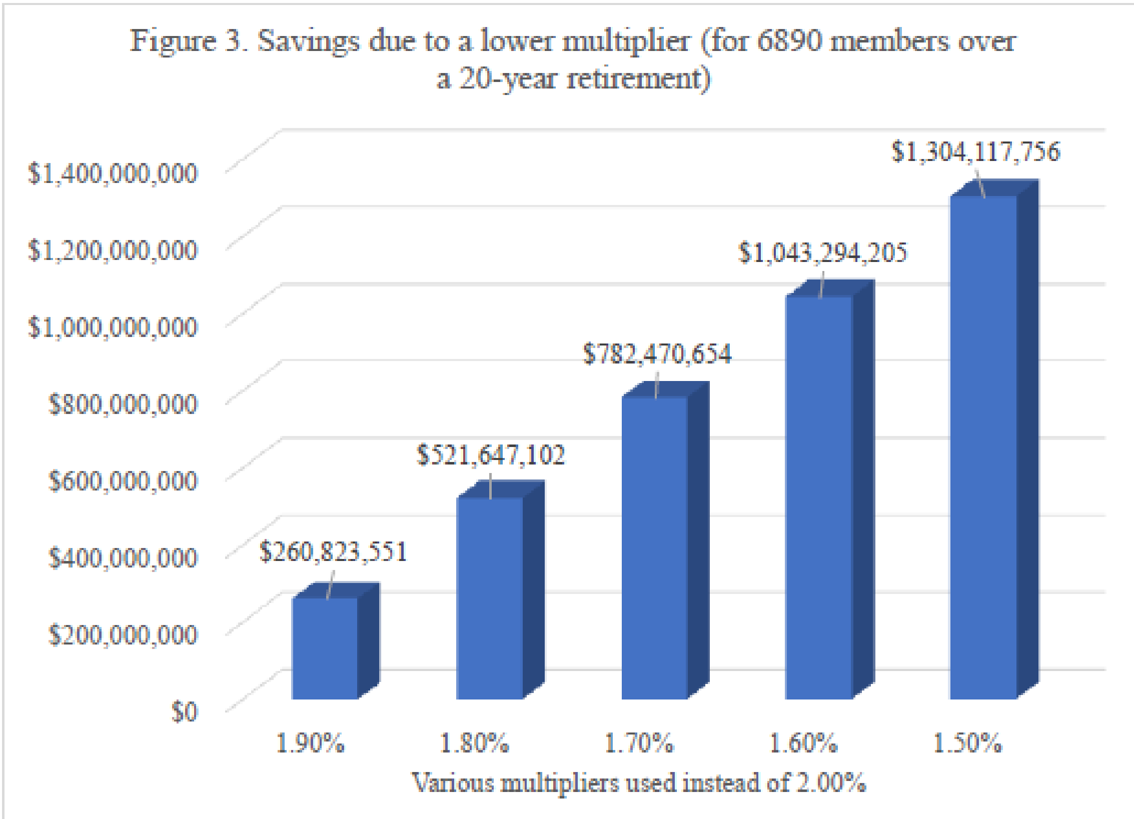
The multiplier (currently 2%)

The multiplier is a fixed number determined by each state to be used in their specific TRS formula. The current Georgia multiplier is 2%.

Table 1. Income in retirement with different multipliers

Multiplier	2.0%	1.9%	1.8%	1.7%	1.6%	1.5%
monthly income in 1st year of retirement	$2,343	$2,226	$2,109	$1,992	$1,875	$1,757
annual income in 1st year of retirement	$28,119	$26,713	$25,307	$23,901	$22,495	$21,089
total ret. income for a 20-year lifespan after retirement	$757,108	$719,252	$681,397	$643,541	$605,686	$567,831
Per person saving over 20-years		$37,855	$75,711	$113,566	$151,422	$189,277
Total savings for 6890 retired individuals	$5,216,471,025	$4,955,647,473	$4,694,823,922	$4,434,000,371	$4,173,176,820	$3,912,353,268
Cohort saving		$260,823,551	$521,647,102	$782,470,654	$1,043,294,205	$1,304,117,756

The potential savings by using 1.90% instead of 2% as the multiplier in equation 1 is about $38,000 for a single individual (the difference between $757,108 and $719,252) and about $260.1 million for a single cohort (6890 people retiring in the same year). The potential savings are shown in Table 1 and Figure 3



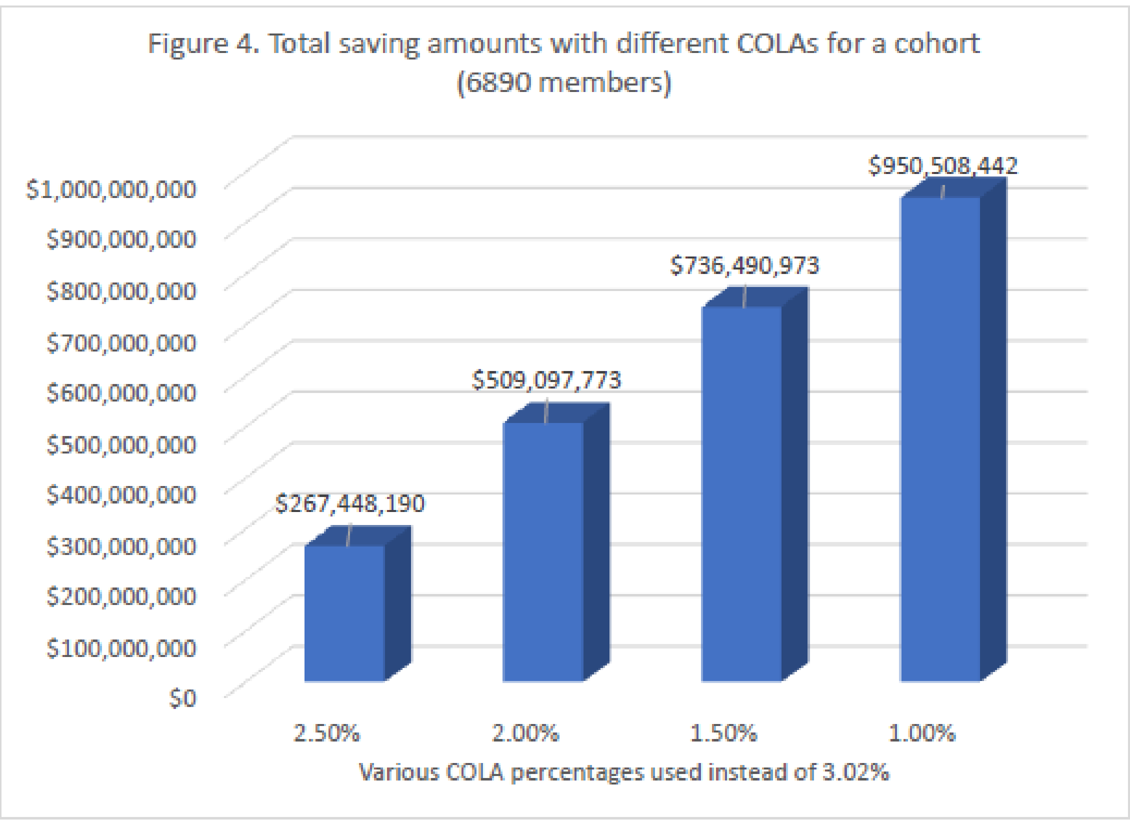
Cost of Living Adjustment (currently 1.5% twice, if applicable)

As stated above, currently benefits can be adjusted twice annually by 1.5%, once in January and once in July. If the adjustment is awarded twice, that is equivalent to a 3.02% annual increase on a compounded basis. Based on our calculations, the Base CPI Index has exceeded the considered CPI number 35 out of 41 times since 2000. That means that TRS applied the COLA adjustment 35 out of 41 times in the past two decades. At the same time the COLA adjustment used by the Social Security Administration averages out to about an annual 2.1% and is only 1.65% considering the average in the last decade.

Table 2 and Figure 4 show the potential savings at various levels of COLA. We see that over a 20-year lifespan after retirement if an annual 2.5% COLA was used, the potential saving for one member would be almost $39,000. Again, this is about 8% of the about $500,000, which is the total amount we estimate an individual with a 20-year lifespan in retirement would draw from the system after depleting his/her balance. The amount of saving from using an annual COLA of 2.5% for an entire cohort would be $267 million. Obviously, reducing the COLA even further would increase the savings even more.

Table 2. Income in retirement with different COLA

COLA	3.02%	2.50%	2.00%	1.50%	1.00%
monthly income in 1st year of retirement	$2,343	$2,343	$2,343	$2,343	$2,343
annual income in 1st year of retirement	$28,119	$28,119	$28,119	$28,119	$28,119
total ret. income for a 20-year retirement lifespan	$757,108	$718,291	$683,218	$650,215	$619,153
Individual saving		$38,817	$73,889	$106,893	$137,955
Total for 6890 retired individuals	$5,216,471,025	$4,949,022,835	$4,707,373,251	$4,479,980,051	$4,265,962,583
Cohort saving		$267,448,190	$509,097,773	$736,490,973	$950,508,442

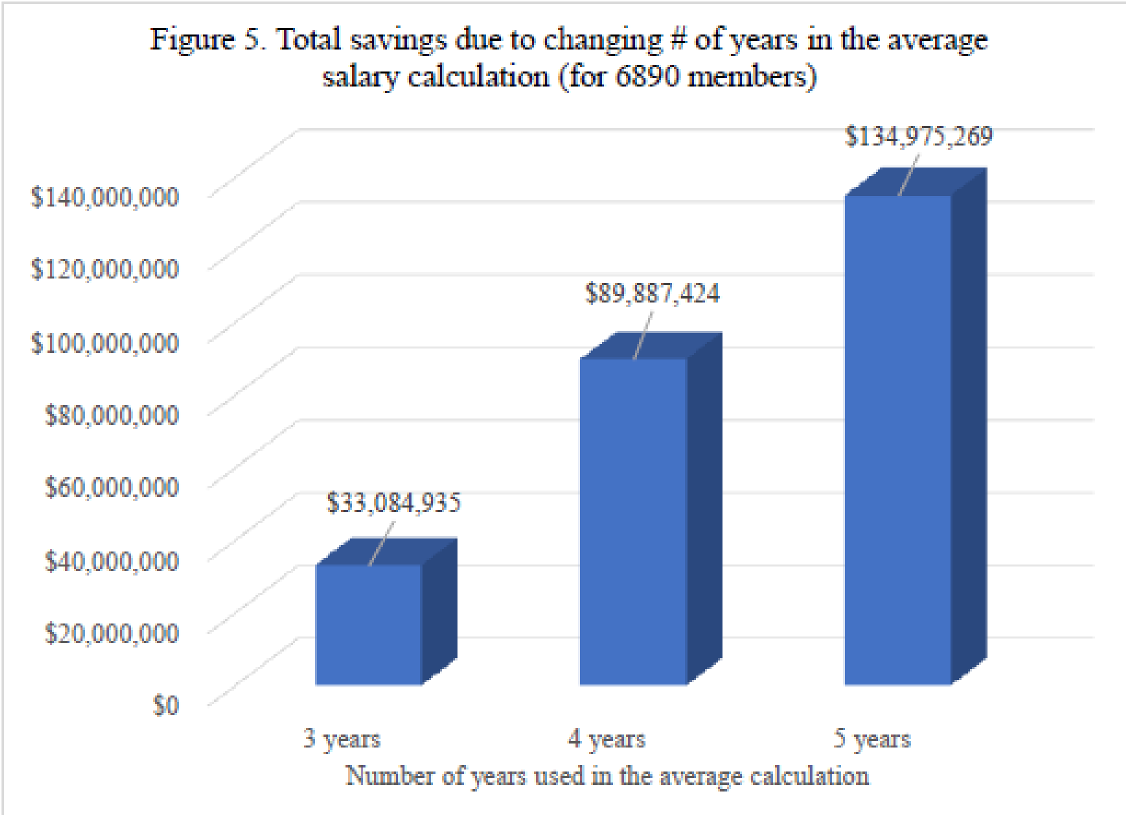


Average salary (currently based on the highest consecutive 24 months)

The formula (equation 1) considers the average salary of the highest consecutive 24 months. There are a number of other states that use 3-5 years of average salary in their formulas. For the sake of simplicity, we assume that the highest 24 consecutive months are the last two years of the members active years. Table 3 and Figure 5 show the potential savings that could be achieved by increasing that to 3-5 years.

Table 3. Income in retirement with averaging the last 2-5 years of income

# of years in the formula	2 years (current rule)	3 years	4 years	5 years
Monthly income in 1st year of retirement	$2,343	$2,328	$2,303	$2,28
Annual income in 1st year of retirement	$28,119	$27,941	$27,634	$27,39
Total ret. income for a 20- year retirement lifespan	$757,108	$752,306	$744,061	$737,51
Individual saving		$4,802	$13,046	$19,59
Total for 6890 retired individuals	$5,216,471,025	$5,183,386,090	$5,126,583,601	$5,081,495,75
Cohort saving		$33,084,935	$89,887,424	$134,975,26



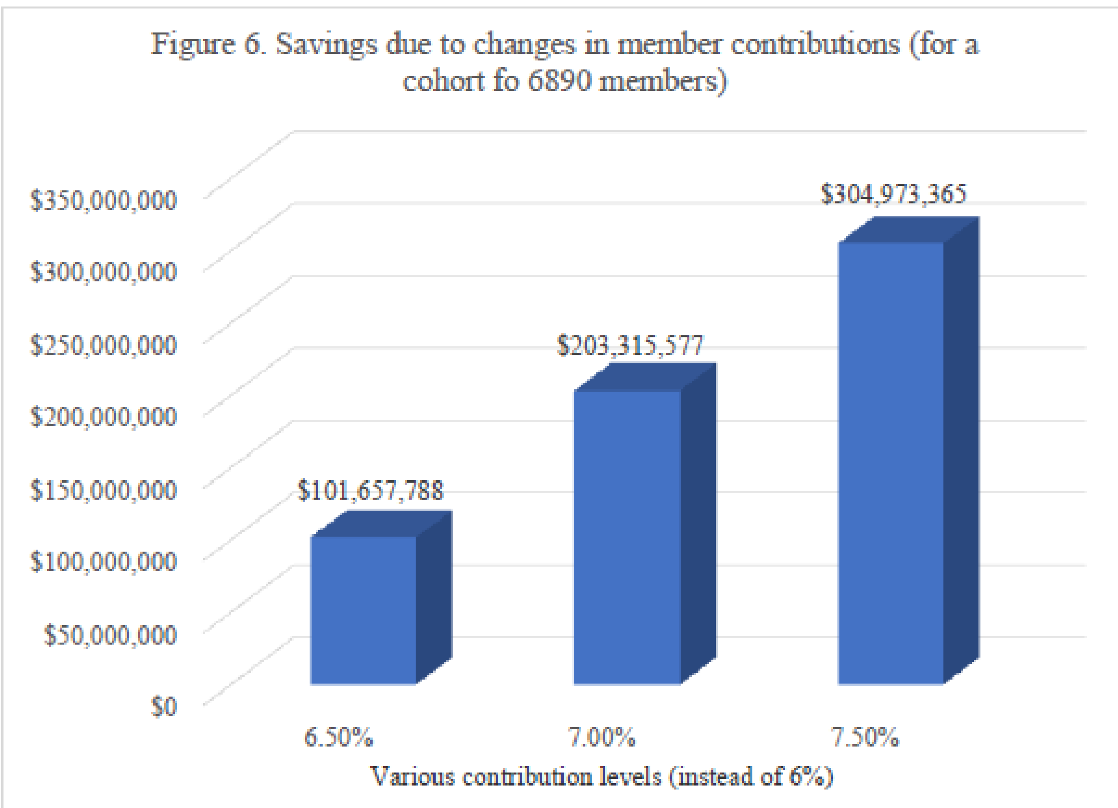
Using the highest 36 consecutive months' salary (3 years) would only save less than $5,000 during an individual's life span. Increasing the average to 5 years would save around $20,000 for the individual. The savings for the cohort in our simulation would be about $33 million if 3 years were used in the average salary calculation and about $135 million if 5 years were used.

Member contribution (currently 6% of salary)

The state of Georgia currently requires a 6.00% contribution of salary for active members. This rate has been unchanged since July 2012 and prior to that it was 5.53%. Below we simulate the total contributions of a hypothetical employee starting with a $49,250 annual income which increases by an average rate of 1% annually. Contributions are assumed to be invested in the TRS at a 7.25% annual return. Such an individual would have about $177,053 in his or her account after 23 years of work. If the member contribution rate is increased to 6.50%, the balance at retirement increases to $191,807, i.e. $14,754 more. Obviously, the saving is even higher if the contribution rate is increased to 7.0% or 7.5%.

Table 4. Total lifetime contribution of someone with a starting salary of $49,250 who works 23 years				
Contribution rate	6.00%	6.50%	7.00%	7.50%
Balance at retirement	$177,053	$191,807	$206,562	$221,316
Individual saving		$14,754	$29,509	$44,263
For 6890 members	$1,219,893,459	$1,321,551,248	$1,423,209,036	$1,524,866,824
Total saving for cohort		$101,657,788	$203,315,577	$304,973,365

Table 4 shows these differences in balance and Figure 6 shows the potential savings for the entire cohort of 6890 retirees.



MONTE CARLO SIMULATION

To complete our analysis, we use Monte Carlo simulation to account for uncertainty in our analysis. Salary growth does not stay constant at 1%, the ROI on investment is not 7.25% in every single year, the COLA is applied only when inflation is high, and some people do not live

20 years after retirement (or do not survive until retirement). The goal of the simulation exercise is to see how many people would collect more money from the TRS system than what they paid in, and how much unfunded liabilities would increase or decrease for an individual. We repeat the simulation 1000 times to minimize the impact of outliers. There are a few common features for these 1000 simulations: starting salary ($35,000), the age at which the individual starts working (30), and the retirement age (62), if he or she survives to that age. The other features determining retirement benefits are random: the lifespan, the rate of return on the balance, salary increases, and COLA adjustment during retirement. To acknowledge that these values may vary from year to year, we generate the following random numbers:

Life span: Each year a randomly generated number is compared against the average of the male-female age-specific survival probabilities from 2017 (Social Security Administration [SSA], 2020). If the randomly generated number is lower than the age specific probability, then the person is assumed not to survive that age, otherwise the individual stays in the system for next year.

Rate of return on investment: The annual rate of return numbers is randomly generated from a normal distribution with a mean of 7.4% and a standard deviation of 8.1% - which is the average annual return of the TRS and its standard deviation since 2004. The average rate of return and its standard deviation were calculated for years 2004-2020 Comprehensive Annual Financial Reports (2008-2020).

Income growth: Salary increases are randomly generated from a normal distribution with a 1.9% mean and 1.4% standard deviation, with the limitation of denying negative outputs and replacing them with zero. The average of the annual salary growth rate and its standard deviation are calculated for years 2003-2019 (CAFR, 2020-2008).

Inflation: Annual inflation values, which directly impact the usage of COLA, are randomly generated from a normal distribution with a mean of 2.1% and 1.1% standard deviation, taken from the average inflation rates from 2001 – 2019 (Federal Reserve Economic Data, 2020). If the inflation output is larger than 1% during a retirement year, then COLA is applied at a 3.02% rate.

If the individual survives until age 62, he or she retires and starts collecting the calculated benefit amount until a random death (at which point in time the simulation stops). Then we look at whether this individual has depleted his/her account or died before the balance turned negative, and how much money the individual cost the system after balance depletion.

The advantage of using a large number of simulations is that we minimize the impact of extremes. For instance, if we were to use only one simulation, the outcome of that could be driven by unlikely events such as a long series of very low returns on investment. Since returns are randomly generated, it could happen for one individual that the random generator creates low (or very high) returns for many years. By increasing the number of simulations and looking at the average of the outcomes, we are minimizing the influence of such outliers. The simulation could be thought of as a way of estimating what to anticipate from an uncertain future.

Table 5 shows the results of our simulations. Each column presents numbers from a different specification. The first column shows the baseline. About three fourths of the simulations ended up with a negative balance, or a net burden. The median net burden is about

$825,000. The table also shows the average, the 75th percentile, the 25th percentile and the largest burden amount. We also show the average life expectancy, which is always between 79-81 years of age (which, reassuringly, is around the average life expectancy).

Columns 2 and 3 show the results when the multiplier is decreased to 1.9% and 1.8% respectively. Columns 4 and 5 show what happens if the member contribution rate is increased to 6.5% and 7.0%, respectively. Columns 6 and 7 show results when the average salary calculation is over 3 and 4 years, respectively, instead of 2 years. Columns 8 and 9 shows what happens when COLA is reduced to 2.5% and 2.0%, respectively. Column 10 shows the results with a combination of changes. The numbers show that even with a pretty ambitious change, where the multiplier is lowered to 1.9%, the active member contribution is increased to 6.5%, the time throughout which the active salary is averaged is increased to four years and the COLA is decreased to 2% (Column 10), over 65% of the total simulations run out of money and contribute to unfunded liability. These results suggest that further tax increases and/or a reallocations of tax revenue are unavoidable if we want to keep the system afloat.

Table 5. Simulations under various scenarios

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Starting salary ($)	35,000	35,000	35,000	35,000	35,000	35,000	35,000	35,000	35,000	35,000
starting age	30	30	30	30	30	30	30	30	30	30
multiplier	2.00%	1.90%	1.80%	2.00%	2.00%	2.00%	2.00%	2.00%	2.00%	1.90%
contribution	6.00%	6.00%	6.00%	6.50%	7.00%	6.00%	6.00%	6.00%	6.00%	6.50%
# of years averaged	2 years	2 years	2 years	2 years	2 years	3 years	4 years	2 years	2 years	4 years
COLA (annual)	3.02%	3.02%	3.02%	3.02%	3.02%	3.02%	3.02%	2.50%	2.00%	2.00%
How many (out of 1000) times do we run out of money?	743	713	663	696	677	704	705	733	677	653
Average net burden ($)	897,873	858,674	779,353	953,227	867,683	867,568	891,396	859,529	769,575	684,727
Median net burden ($)	825,641	770,848	727,377	887,394	800,642	783,562	804,814	824,279	719,440	657,674
75 percentile of net burden ($)	473,644	412,878	394,542	492,677	444,147	413,285	424,386	446,977	396,102	338,558
25 percentile of net burden ($)	1,287,798	1,223,829	1,094,693	1,322,042	1,200,994	1,253,929	1,271,340	1,174,824	1,083,653	937,301
Most net burden ($)	3,596,214	3,095,693	2,748,583	3,045,369	3,011,430	3,401,167	3,215,011	2,565,138	3,327,954	2,404,189
Average age at death	79.33	79.95	78.63	79.79	79.60	78.86	79.07	80.11	78.08	79.27

CONCLUSION

The primary responsibility of TRS is to provide teachers in Georgia with a reliable pension plan that is sustainable for the members' entire retirement period. Members of the TRS contribute a percentage of their salary throughout their years of service to receive a fixed, monthly pension in retirement. This fixed amount is calculated by a state formula that takes into consideration the members' years of service, multiplier, and the final average salary. However, for each of the past few years, the TRS has seen an unprecedented increase in unfunded liabilities. Considering that experts anticipate lower returns than what is assumed by the TRS (Benz, 2020), the Teacher Retirement System is in danger of being unable to meet its obligations without substantial help from the state.

This research focused on calculating approximations of the amount of money that can be saved by the state by readjusting the various factors of the TRS formula. Our research indicates that even small changes like reducing the state multiplier or increasing the number of years used to calculate the final average salary, could save the state a substantial amount. However, the presented changes are still not enough to sustain the long-term viability of the system. For example, by reducing the multiplier to 1.9%, increasing the required contribution to 6.5%, reducing COLA to 2%, and increasing the number of years used to calculate final average salary to four years, the cumulative savings could sum up to around $1 billion for a single cohort over twenty years, which is only a third of what the most recent cohort is anticipated to draw from the system after their balance is depleted.

In order to sustain the long-term viability and continue to provide a safety net in retirement for members in the TRS it is imperative that the state, specifically the legislators, take notice of this dire situation and work on putting measures in place that improve the financial strength of the Teachers Retirement System in Georgia.

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