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An Examination of COVID-19 on Performance and Engagement Scores of Professional and Frontline Employees

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AN EXAMINATION OF COVID-19 ON PERFORMANCE AND ENGAGEMENT SCORES OF PROFESSIONAL AND FRONTLINE EMPLOYEES

by

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ABSTRACT

The year 2020 has been a year of change and adaptation largely due to the presence of the COVID-19 pandemic. Changes in the way we live and work have impacted us all to varying degrees. This paper explores the changes in the workplace of a food-and-beverage company to determine the impact on employees due to the pandemic. Specifically, this paper explores the impact of workplace changes on professional and frontline populations (as defined in the Method section) by examining their levels of engagement and performance. The role of age and gender is also examined in relation to engagement and performance. Results are mixed and are in the opposite direction of the hypotheses examining the role of population, gender, and time on engagement and performance scores. There is partial support for the research questions that explore the role of generation on engagement and performance scores. A discussion and implications of findings follows.

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And to sweet Winston, for being the world's most joyful and patient four-legged companion.

CHAPTER 1

INTRODUCTION

The COVID-19 pandemic has interrupted normal processes across the globe: travel, the stock market, healthcare, business operations, even day-to-day activities (McKibbin & Fernando, 2020). These interruptions have also required adaptation in personal and professional ventures. While social distancing and mask requirements have had an impact on the majority of people, changes in the workplace are often dependent on specific needs of an industry (Baker et al., 2020; Bartik et al., 2020; Topcu & Gulal, 2020). Some companies have been able to continue fairly normal operations by leveraging parts of their workforce in a new way. Popular companies like Facebook or Twitter have allowed their entire workforce to work from home during the pandemic and will continue to for the foreseeable future if not permanently (Dwoskin, 2020; Kelly, 2020). Other companies have allowed professional populations to work from home but have continued with normal operations from their frontline workers while implementing updated health-and-safety standards. For this study, I will be looking at changes, if any, that have occurred for those allowed to work from home, specifically professional workers, compared to those who continued to work on site in updated conditions, specifically frontline employees. This potential impact on employees will be important to understand as companies look to update their workplace policies around remote working.

Problem Statement

A global snack-and-beverage company headquartered in the northeastern United States (hereinafter "Company Z") was interested in investigating the impact of corporate responses that targeted the diminishment of the effects of COVID-19 on the workforce. Specifically, Company Z was interested to determine whether their professional and their frontline populations differed from one another in terms of their levels of engagement and performance due to sudden changes in the workplace (i.e., whether working remotely or continuing to be physically present at the work site made a difference). If there are differences between populations, Company Z could use this information to evaluate future workplace policies, though not directly addressed in this study. All members of the professional population were working from home as of March 2020, while the frontline population continued to work from plants. In order to evaluate the impact of a changing workplace, Company Z evaluated survey data from September 2019 and September 2020 to gauge how their employees rated their engagement among other factors. These data contain information from over 30,000 employees from both professional and frontline populations. Performance data from February 2020 are available for professional workers and performance data from February 2021 were used for the same population for comparison.

Theoretical Grounding

The work-engagement literature will be used to explore the work demands faced by in-person workers versus teleworkers due to workplace interruption and the potential impact on engagement and work performance. Research on work engagement has linked higher work engagement to increased performance on the job (Shimazu et al., 2015), while specific models, such as the Job Demands-Resources model (JD-R), further link demands and resources employees face to levels of engagement, whether negatively and positively, respectively (Schaufeli et al., 2009). Furthermore, how employees perceive these demands impacts their engagement (Crawford et al., 2010).

Demographic variables such as age and gender have reliable associations with, for various reasons, engagement and adaptability. For instance, many reports (Allen & Finkelstein, 2014; Alon et al., 2020; Del Boca et al., 2020; Power, 2020) indicate that, before and during the COVID-19 pandemic, women shouldered a greater proportion of home responsibilities, even when both partners (in a cross-sex couple) are working full time. Such burdens — additional home responsibilities, greater difficulty in adapting to sudden changes — pertain to work engagement and performance and will be explored through the lens of the JD-R model and engagement literature (Campbell, 2012; Crawford et al., 2010; Pulakos et al., 2000; Schaufeli et al., 2009; Shimazu et al., 2015; Viswesvaran et al., 2005), and in the current study I am examining differences across these demographic groups. Additionally, theoretical and empirical literature supports the notion that younger individuals adapt more slowly to changes in the workplace (Ackerman & Heggestad, 1997; Ng & Law, 2014; Salthouse, 2010), and I will explore if age-related differences exist between professional and frontline populations.

Engagement

Understanding the impact of work engagement is important not only for employee well-being (Crawford et al., 2010; Schaufeli et al., 2009) but can also help organizations have a deeper understanding of employee performance (Shimazu et al., 2015). In 1990, work engagement appeared in the literature with an article discussing work conditions

(Kahn). Kahn's interests were around momentary changes that employees may experience that could make them feel more or less invested in their work. Kahn (1990) went on to term these moments where employees might put more or less of themselves into their work as personal engagement and disengagement, respectively. Employees tend to identify with their work when they are engaged, meaning that an engaged employee is likely to incorporate their cognitive, physical, and emotional resources into their work. Individuals may alter their investment of their resources of safety, availability, and meaningfulness into their work depending on the situation (Kahn, 1990). Schaufeli et al. (2002) defined engagement in a new way calling it "a positive, fulfilling, work-related state of mind characterized by vigor, dedication, and absorption" (pg. 74). In 2008, Macey and Schneider entered a new definition of engagement into the literature as "an individual's sense of purpose and focused energy, evident to others in the display of personal initiative, adaptability, effort, and persistence directed toward organizational goals" (pg. 7).

When engagement was first introduced there was some contention around the uniqueness of the construct or if it was too similar to constructs like commitment or satisfaction to warrant further exploration. While overlap exists with other job attitudes, work engagement was found to be a separate construct, although overlap with other job attitudes exists (Albrecht, 2010). Work engagement may also be complex to parse out with some measurements (Albrecht, 2010). Furthermore, researchers also found that engagement is separate from the other constructs of job involvement, citizenship behaviors, intrinsic motivation, task performance, and job satisfaction (Rich et al., 2010). Following findings such as these, the existence of work engagement was less debated and instead the focus moved to the application of work engagement, and its incorporation with other relevant areas.

In 2001, Demerouti et al. introduced the JD-R model, which organizes attributes of the workplace into demands and resources. When working on her dissertation with Nachreiner in 1996, Demerouti focused on the demands and resources that people face at their jobs that could contribute to burnout (Bakker & Demerouti, 2017). The negative aspects of a person’s job that are generally associated with some cost to the individual are known as job demands (Demerouti et al., 2001). Specific examples of demands could include role ambiguity, high workload, or difficult coworkers. A further distinction of job demands can be made through hindrance versus challenge job demands (Bakker & Demerouti, 2017). While hindrance demands are generally defined as undesirable job constraints that prevent employees from reaching their goals (Cavanaugh et al., 2000), challenge demands can aid employees in reaching their intended goal, although more effort may be required (Podsakoff et al., 2007). The positive aspects of a person's job are termed job resources. Resources may help employees do their job by creating learning or development opportunities, reducing the effect job demands, and even contribute to employees reaching their goals. While an individual level of engagement may be impacted by both individual and situational factors at any time, specific examples of job resources may include social support, role clarity, and autonomy (Schaufeli et al., 2002). Furthermore, resources and demands can be either psychological or physical and can occur at individual or organizational levels (Demerouti et al., 2001).

Work Engagement, JD-R, and Performance

Job performance has been conceptualized as those actions and behaviors that are under the control of the individual and that contribute to the goals of the organization (Rotundo & Sackett, 2002, p. 66). Ronan and Prien (1971) define job performance as a latent construct, meaning that it is intangible and therefore not directly measurable. Criteria, they say, are quantitatively measured manifestations or indications of latent job performance and will always contain some degree of error. Furthermore, what is being measured as performance can be influenced by environmental factors (Murphy, 2008). More recently research has discussed that measuring outcomes such as business results opposed to behaviors or processes may be an inadequate method of evaluating performance where there are additional factors outside of an employee's control (Aguinis et al., 2013; Beck et al., 2014). However, criteria are still used as they currently represent the best available approach to measuring job performance (Pulakos et al., 2015). Currently, managerial ratings of performance are the most common method of assessing job performance (Aguinis et al., 2013*;* Murphy, 2008; O'Boyle & Aguinis, 2012; Viswesvaran et al., 2005) and these ratings are generally categorized into comparative and absolute ratings (Wagner & Goffin, 1997). Comparative methods require managers to rate an employee's performance relative to others' performance, while absolute ratings require managers to evaluate an employee's performance against objective criteria. Company Z uses a combined rating scale with both comparative and absolute components to arrive at an overall performance score. With this basic overview of performance and performance ratings, we can now turn its connection to work engagement.

As discussed above, the JD-R model has often been used to predict work engagement by examining the job demands and the job resources that an employee may encounter. Specifically, the availability of job resources is more likely to lead to a more engaged employee and, therefore, to a higher performing one (Hakanen & Roodt, 2010). Professional employees worked from home as offices began closing in early 2020. While their normal work schedules were interrupted and likely contributed to their challenge demands, professional employees were given additional resources (e.g., flextime, remote work) to combat the changes and stressors that arose from the COVID-19 pandemic. Frontline employees continued with their current jobs and tasks by working at offices and/or plants. Their challenge demands would have been that of more stringent safety protocols, including wearing masks and social distancing. Their job resources would have also changed through improved employee benefits and increased communication from the organization adding to their social and psychological wells. Because of this, I propose that:

H1: Population type will moderate the change in engagement scores from 2019 to 2020 such that professional employees will have a greater decrease in engagement scores.

H2: Population type will moderate the change in performance scores from 2019 to 2020 such that professional employees will have a greater decrease in performance scores.

Demographics

While an investigation around engagement and performance during COVID-19 will provide valuable information for Company Z, an examination of demographic variables such as generational cohort and gender will provide a more nuanced view of these areas that may, in the least, be informational when examining future workplace policies.

Age and Generation

Stereotypes for older workers include poor health, resistance to change, and inflexibility that leads to stigmatization in the workplace (Burke & Ng, 2006; Maurer et al., 2008). While it is no secret that physical, cognitive, and mental changes occur as individuals age (Peeters & van Emmerik, 2008), these changes do not always equate to decline in work performance or other work-related factors. In fact, there is little evidence to suggest that increased age leads to worsening work performance (Charness et al., 2007). Furthermore, researchers found that older workers are aware of their age-related declines and that these declines can be counteracted with continued education or even increased physical activity, suggesting adaptability in this population (Ng & Law, 2014). Research also suggests that older workers are also able to offset certain age-related declines by leveraging other resources such as mentoring younger employers or sharing institutional knowledge (Ng & Law, 2014).

As a proxy for age, Company Z often examines generational cohorts to categorize and analyze group differences. Generations are categorized as Baby Boomers: 1946-1964, Gen X: 1965-1980, Millennial: 1981-1994, and Gen Z: 1995-2010. For these reasons, I will explore the following questions:

Research Question 1: Will generation moderate the change in engagement scores from 2019 to 2020 between frontline and professional populations?

Research Question 2: Will generation moderate the change in performance scores from 2019 to 2020 between frontline and professional populations?

Gender

Work-home conflict, particularly in dual-earner households, has been researched pre-COVID and found that women with families, especially with younger children, are more likely to experience competing demands (Allen & Finkelstein, 2014). It is estimated that women are responsible for 75% of unpaid care and domestic work across the globe (Moreira da Silva, 2019) and with the emergence of the COVID-19 pandemic, these demands have seemingly done nothing but increase burdens faced by the female working population, in part due to the closure of schools and daycares and ever-present social norms (Alon et al., 2020). In fact, women are facing increased amounts of time spent on household chores and childcare duties, whether or not they are telecommuting, compared to their male partners (Del Boca et al., 2020). Due to these increased stressors and difficulty in balancing work-life demands (Del Boca et al., 2020), I propose that:

H3: Gender will moderate the change in engagement scores from 2019 to 2020, such that females in both frontline and professional populations will have a greater decrease in engagement scores.

H4: Gender will moderate the change in performance scores from 2019 to 2020, such that females in both frontline and professional populations will have a greater decrease in performance scores.

CHAPTER 2

METHOD

Approach

For this study, I evaluated engagement data from a survey and performance ratings. The timing of the collection of both performance and engagement scores will be explained below. Furthermore, I evaluated if there were age or gender differences between these populations with regard to engagement and performance scores.

Measures

Engagement

A critical component of a larger annual survey at Company Z is an assessment of employee engagement. This survey is conducted in September every year thus engagement scores were collected in September 2019 (pre-COVID-19) and September 2020 (during COVID-19). An overall engagement score is calculated through favorable responses (a rating of 4 or 5) averaged over three survey items, which include:

1. I feel energized by my work.
2. I am very confident in the future success of Company Z.
3. I am proud to work for Company Z.

The rating scale for these items is a five-point Likert scale. For the purposes of this study, I conducted analyses only on aggregated data. See Table 1 for more information.

Table 1

Means, Standard Deviation, and Pearson Correlation Matrix for Continuous Variables (n = 31,497)

	M	SD	1	2	3
1. 2019 Performance	3.2790	0.4402			
2. 2020 Performance	3.3900	0.6130	.317*		
3. 2019 Engagement	81.8568	30.0500	.077*	.017*	
4. 2020 Engagement	87.1000	25.2600	.079*	.057*	.461*

* Correlation is significant at the 0.01 level (2-tailed).

Performance

The collection of performance data starts at the end of the year at Company Z, and ratings are based on performance since the previous year's rating. While managers rate employees at year end, employees do not receive their rating until February of the following year. Thus, the data used in this study were released in February 2020 (during COVID-19) for an employee's performance during 2019 and released in February 2021 (during COVID-19) for an employee's performance for the 2020 year.

In 2019, the performance rating scale definition was as follows: 1 "Did not meet most objectives," 2 "Met some objectives; missed a critical one", 3 "Met all critical objectives," 4 "Exceeded most objectives," 5 "Significantly exceeded most expectations". Managers were asked to consider the employee's short- and long-term performance, evaluating how the employee performed against key objectives and how this impacted the business. Employees received two ratings using the same scale, a rating for short-term performance and long-term performance.

In 2020, the performance rating scale definition was as follows: 1 “Did not meet expectations”, 2 “Partially met expectations”, 3 “Overall met expectations”, 4 “Exceeded expectations”, 5 “Far exceeded expectations”. Managers were asked to evaluate the employee’s performance based on key objectives, how the business was impacted, and a more explicit focus on interactions with team members and others in the organization. Employees received one rating.

In summary, the performance metrics from 2019 to 2020 changed from two scales to one scale; instead of receiving two performance scores, employees now only receive one. However, the type of factors that managers must consider when rating their employees remain the same from 2019 to 2020, so these ratings are adequately comparable. See Table 1 for more information.

Population

Those who are defined as members of frontline and professional populations can differ across the globe. However, inclusion in a population is based on factors such as level and job position. For this study, the populations were defined by the rules provided by each sector that were used in the annual engagement survey as defined in the engagement section above.

Generation

Company Z groups generational cohorts based on date of birth as reported to the organization in the initial application to the organization and is defined as: Baby Boomers: 1946-1964, Gen X: 1965-1980, Millennial: 1981-1994, and Gen Z: 1995-2010.

Gender

Company Z defines gender as male or female as the employee reports to the company in the initial application to the organization.

Sample

Data were gathered from an engagement survey in September 2019 and September 2020, as well as performance data from February 2020 and February 2021. While these data were collected in concord with numerous other data points, the other data points will not be recognized as relevant to this study. The data analyzed were gathered from ~270,000 employees of professional and frontline employees across a variety of job functions in the organization. The employees included in the overall data set have multiple years of both performance and engagement data; however, only employees with data from consecutive years were included in the analyses of this study (e.g., a subject must have engagement data from both 2019 and 2020, and performance data from both 2020 and 2021). I removed employees that had missing data in either performance or engagement scores, or those who had switched populations from 2019 to 2020 from the sample. Finally, I removed employees included in the senior leader population as performance scores are not based solely on individual performance; rather, these individuals receive ratings based on other factors such as market unit and team performance. Therefore, the total sample for this study includes 31,497 employees. The composition of the employees is as follows:

- 300 frontline employees and 31,197 professional employees;
- 12,643 females and 18,854 males;
- 2,871 Baby Boomers, 13,707 Gen X, 13,580 Millennials, and 1,339 Gen Z.

I de-identified data from both the engagement surveys and performance data, but retained unique identifiers allowing me to directly match individuals from 2019 to 2020 for engagement and performance data.

CHAPTER 3

RESULTS

Although my study includes two dependent variables (performance and engagement), a MANOVA was not appropriate (as data collection came from different time periods). Therefore, I chose a mixed designs ANOVA. First, I ran a power analysis was in the computer software G*Power to determine the necessary sample size for a mixed design ANOVA for a medium effect size of 0.50, alpha = 0.05, and power of 0.95; a minimum of 24 individuals was recommended.

I conducted an initial exploratory analysis in SPSS to determine if the data met the criteria for univariate normality following the assumptions of a mixed designs ANOVA in order to inform the accuracy of my predictions. I assessed assumptions of normality through the evaluation of histograms, boxplots, and skewness and kurtosis values. For engagement, the highest value of skewness was -2.043, and highest kurtosis value was 3.449. For performance, the highest value of skewness was -.156, and highest kurtosis value was 1.538.

While these numbers suggested that the distribution was not normally distributed, this is less of a concern with large sample sizes (Field, 2016). I proceeded to test the assumption of homogeneity of variance. Levene's test of Equality of Error Variances was significant at $p < .01$ across performance for 2020 and 2021, and for engagement scores for both 2019 and 2020 based on mean, median, and trimmed means. Following the recommendations of violated assumptions outlined in Field et al., (2012), I calculated Hartley's F_{max} or the variance ratio (Pearson & Hartley, 1954), which compares the group with the biggest variance to the group with the smallest variance. After comparing these ratios to the table of critical values outlined on the website accompanying Field et al., (2012), the ratio for all factors (generational cohort, population, and gender) were larger than the critical values, indicating that the assumption of homogeneity of variance was still violated. Continuing with the suggestions outlined in Field et al. (2012), the next step was to transform the data to see if this would help to correct the problems with homogeneity of variance. As some scores in the data included zeros, I conducted a square root transformation. The resulting Levene's value was still significant at $p < .01$. The next approach was to try a non-parametric equivalent of a mixed-designs ANOVA.

While several nonparametric statistical tests exist for various forms of ANOVA like the Kruskall-Wallis test, Mann-Whitney *U* test, or the Friedman test, none are appropriate for an ANOVA with multiple factors. Conover and Iman (1981) created the simple rank transform procedure which can be used for main effects but results in inflated Type I error if interactions are present (Higgins & Tashtoush, 1994; Salter & Fawcett, 1993). Therefore, the Aligned Rank Transform (ART) procedure was developed (Fawcett & Salter, 1984; Higgins et al., 1990; Higgins & Tashtoush, 1994; Salter & Fawcett 1985, 1993). This procedure aligns responses on "Y" by stripping them of each of the possible main effects, then assigns midranks to each "Y" value. Once the data are aligned and ranked, the ANOVA can be conducted to look at main effects and potential interactions. The results can then be interpreted assuming appropriate Type I error and power

(Wobbrock et al., 2011). The ARTool was extended through the use of an additional procedure, ART-C (Elkin et al., 2021) which facilitates the use of *post hoc* pairwise comparisons. Again, appropriate Type I error and power can be assumed through the use of a correction (Holm's sequential Bonferroni procedure; Holm, 1979; Wobbrock et al., 2011).

Thus, I ran two nonparametric factorial repeated-measures ANOVAs to determine if the time period from 2019 to 2020 predicted changes in gender and age across populations in engagement scores, and if the time period from 2019 to 2020 predicted changes in gender and age across populations in performance scores.

Hypothesis 1: Population and Engagement Scores

In order to find support for H1, there would need to be a significant 2-way interaction between population and time related to engagement scores. However, I first had to test whether there were any higher-order interactions that involved these variables. This would allow me to determine if there was a main effect of a variable and, if an interaction was present, the nature of the relationship and thus the impact on performance and engagement scores. Based on the non-parametric ANOVA for engagement, including the variables of population, gender, generation, and time, there was a significant 4-way interaction, $F(3, 62{,}962) = 9.0473$, $p < .001$.

To further understand this interaction, I separated the dataset by gender. For males, there was a significant three-way interaction between population, generation, and time, $F(3, 37{,}692) = 16.1310$, $p < .001$, which will be further discussed in RQ1. I then separated males into each of their four generational groups and ran analyses on those subsets. For males in the Baby Boomer cohort, the two-way interaction between population and time was significant, $F(1, 3{,}390) = 16.268$, $p < .001$. The increase in frontline employees' engagement scores from 2019 to 2020 is greater than the increase of professional employees during the same time (see Figure 1). This finding does not support H1.

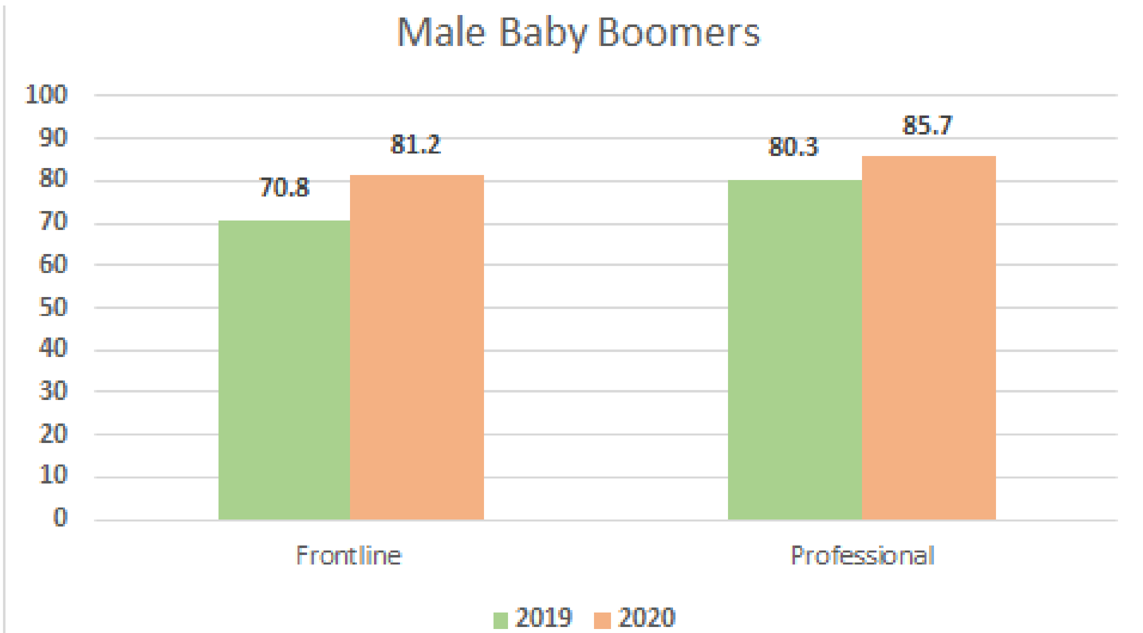

Figure 1: *Engagement Scores by Year and Population: Male Baby Boomers*

For males in the Generation X cohort, the two-way interaction was not significant. Although not significant, the below graph is included because it may be of interest when examining the contrasts used in RQ1 (see Figure 2).

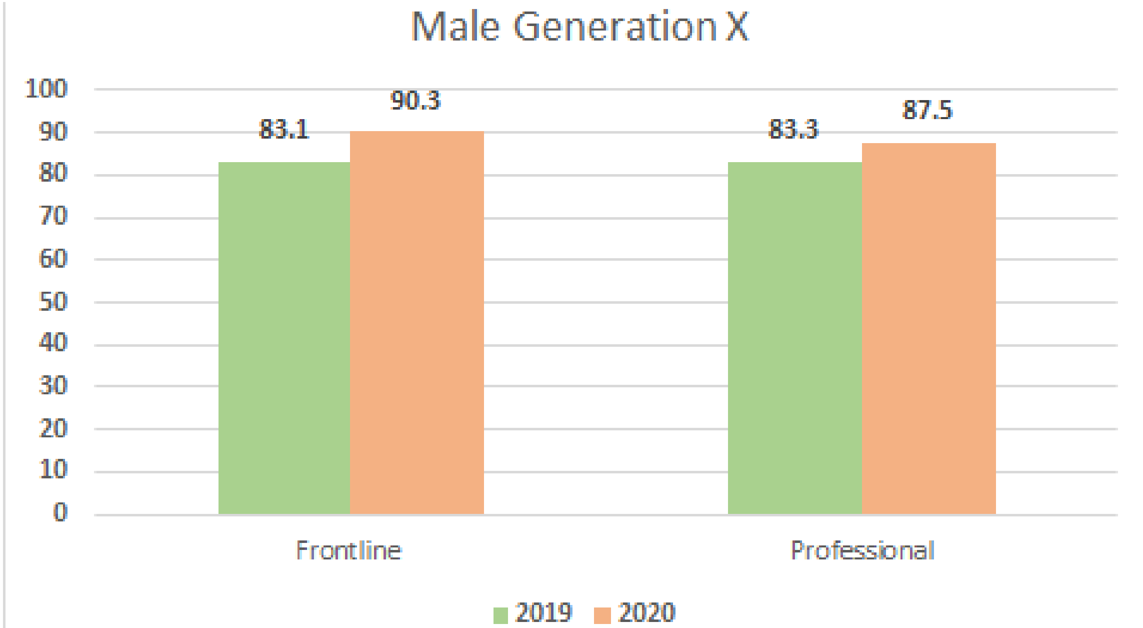

Figure 2: *Engagement Scores by Year and Population: Males from Generation X*

For males in the Millennial cohort, the two-way interaction was not significant. Although not significant, the below graph is included because it may be of interest when examining the contrasts used in RQ1 (see Figure 3).

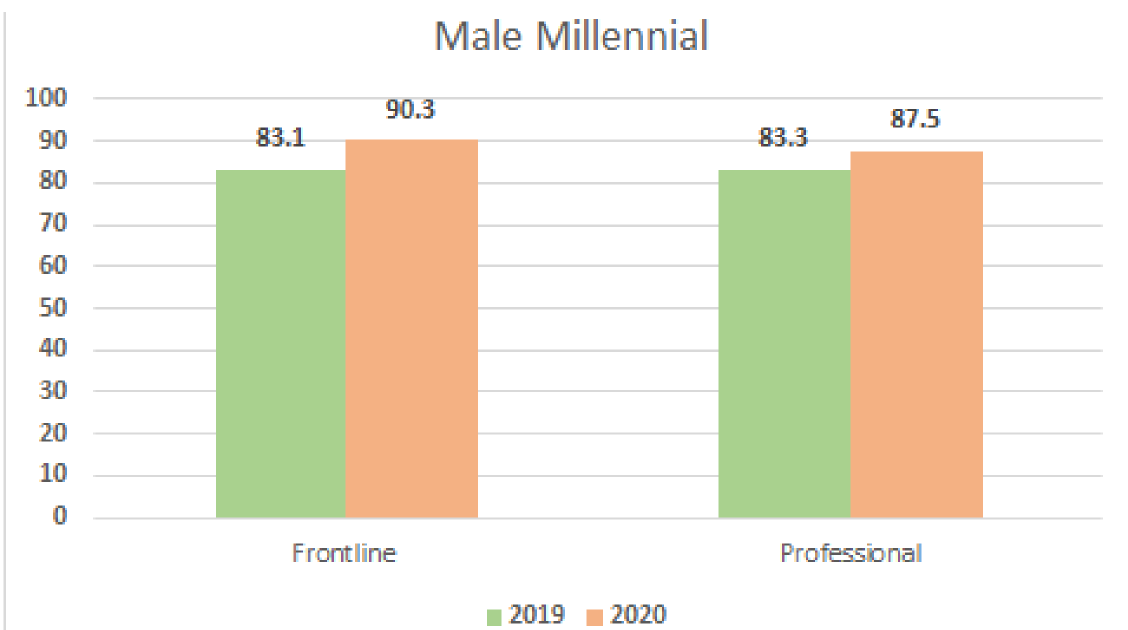

Figure 3: *Engagement Scores by Year and Population: Male Millennial*

For males in the Generation Z cohort, the two-way interaction was significant, $F(1, 1008) = 5.5739$, $p < .05$. The decrease in frontline employees' engagement scores from 2019 to 2020 is greater than the increase of professional employees during the same time (see Figure 4). This finding does not support H1.

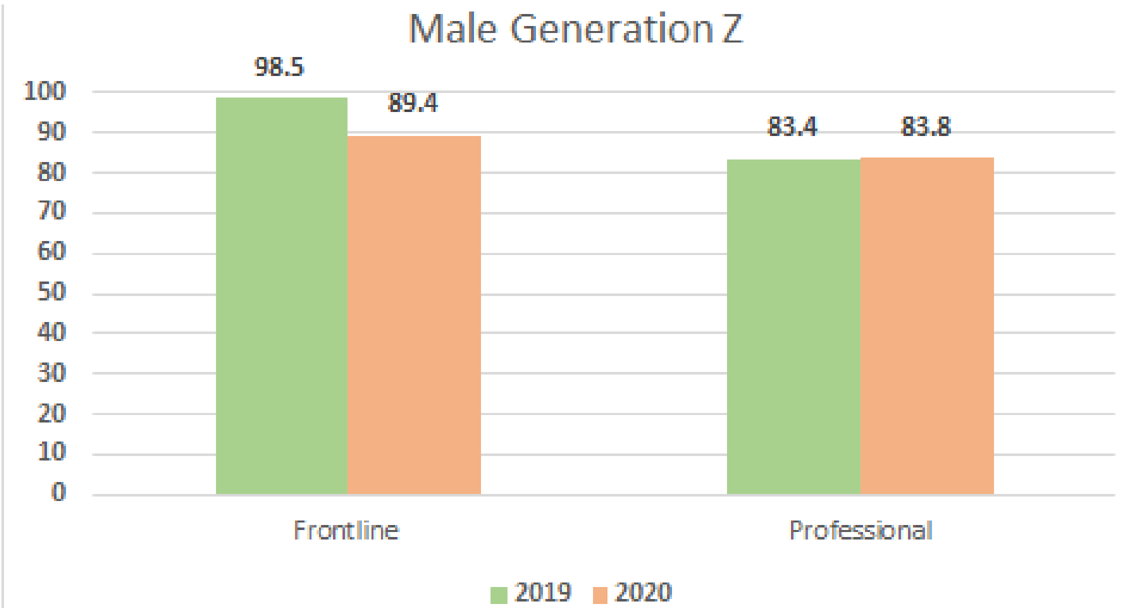

Figure 4: *Engagement Scores by Year and Population: Males from Generation Z*

For females, there was not a significant 3-way interaction. I then tested if there was a two-way interaction for females by population type and year (see Figure 5). This was not significant; however, a graph is included for those interested.

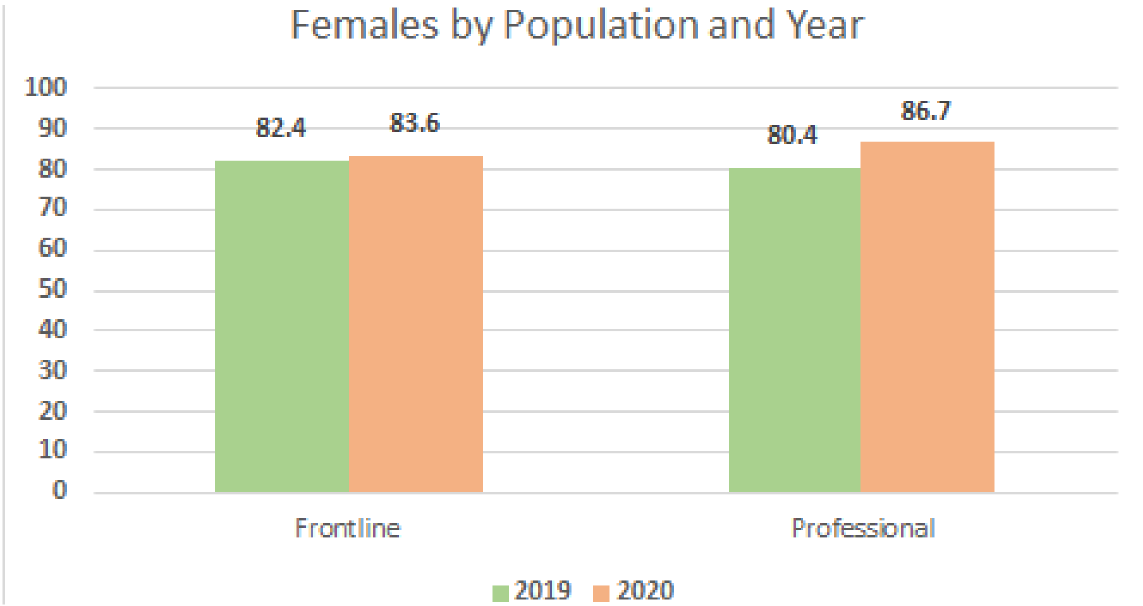

Figure 5: *Engagement Scores by Year and Population: Females (all generations)*

In sum, H1 was not supported. The groups that evidenced significant results were male Baby Boomers and male Generation Z, and the direction of these results were in opposition to the hypothesis.

Hypothesis 2: Population and Performance Scores

In order to find support for H2, there would need to be a significant 2-way interaction between population and time related to performance scores. However, I first had to test whether there were any higher-order interactions that involved these variables. Based on the non-parametric ANOVA for performance, including the independent variables of population, gender, generation, and time, there was a significant 4-way interaction, $F(3, 62{,}962) = 5.02977$, $p < .01$.

To further understand this interaction, I separated the dataset by gender. For males, there was a significant three-way interaction between population, generation, and time, $F(3, 37{,}692) = 4.8196$, $p < .01$, which will be further discussed in RQ2. I then separated males into each of their four generational groups and ran analyses on those subsets.

For males in the Baby Boomer cohort, the two-way interaction was not significant. Although not significant, the below graph is included because it may be of interest when examining the contrasts used in RQ2 (see Figure 6).

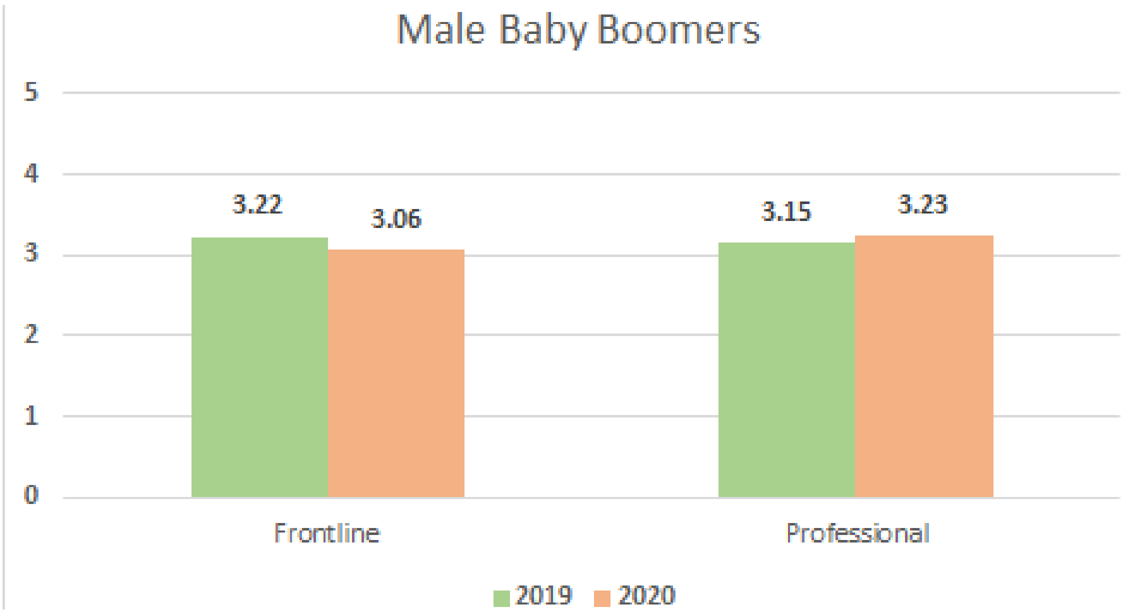

Figure 6: *Performance Scores by Population and Year: Male Baby Boomers*

For males in the Generation X cohort, the two-way interaction was not significant. Although not significant, the below graph is included because it may be of interest when examining the contrasts used in RQ2 (see Figure 7).

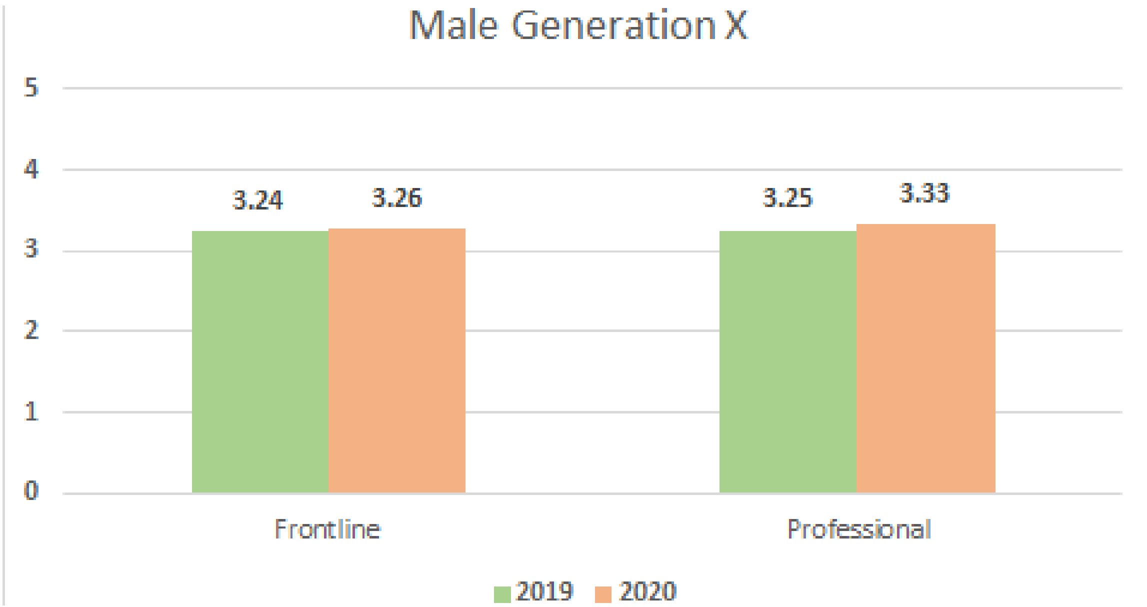

Figure 7: *Performance Scores by Population and Year: Males from Generation X*

For males in the Generation Z cohort, the two-way interaction was significant, $F(1, 1008) = 9.210$, $p < .01$. The increase in frontline employees' performance scores from 2019 to 2020 is greater than the increase of professional employees during the same time. In other words, while the hypothesis proposed a decrease in scores from 2019 to 2020, there was actually an increase in performance scores for both populations (see Figure 8). This finding does not support H2.

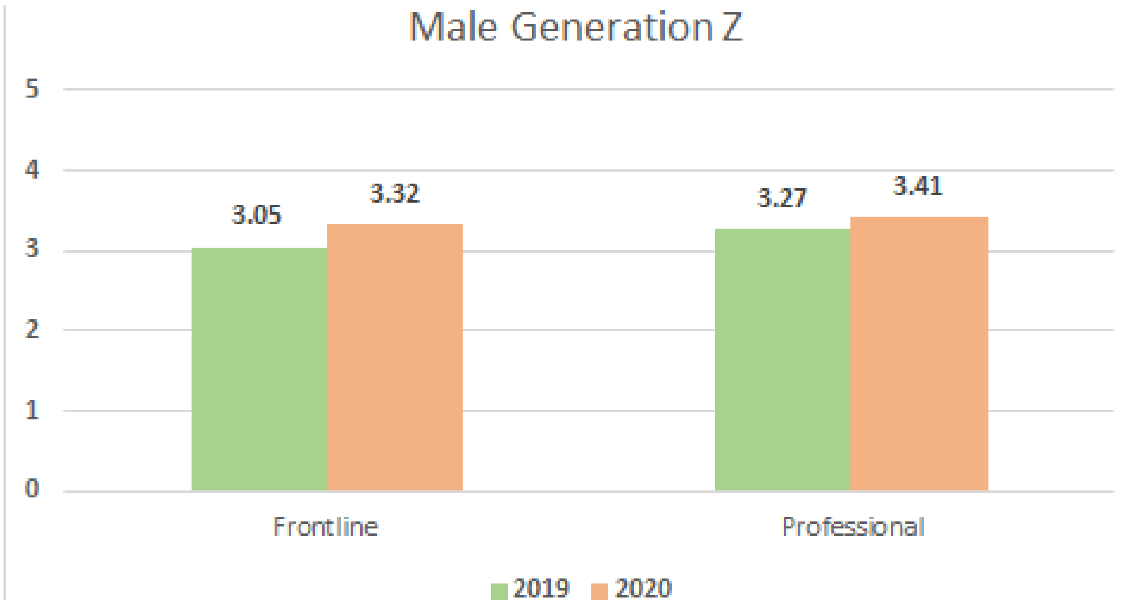

Figure 8: *Performance Scores by Population and Year: Males from Generation Z*

For males in the Millennial cohort, the two-way interaction was significant, $F(1, 15{,}838) = 17.563$, $p < .001$. The increase in frontline employees' performance scores from 2019 to 2020 is greater than the increase of professional employees during the same time. In other words, while the hypothesis proposed a decrease in scores from 2019 to 2020, there was actually an increase in performance scores for both populations (see Figure 9). This finding does not support H2.

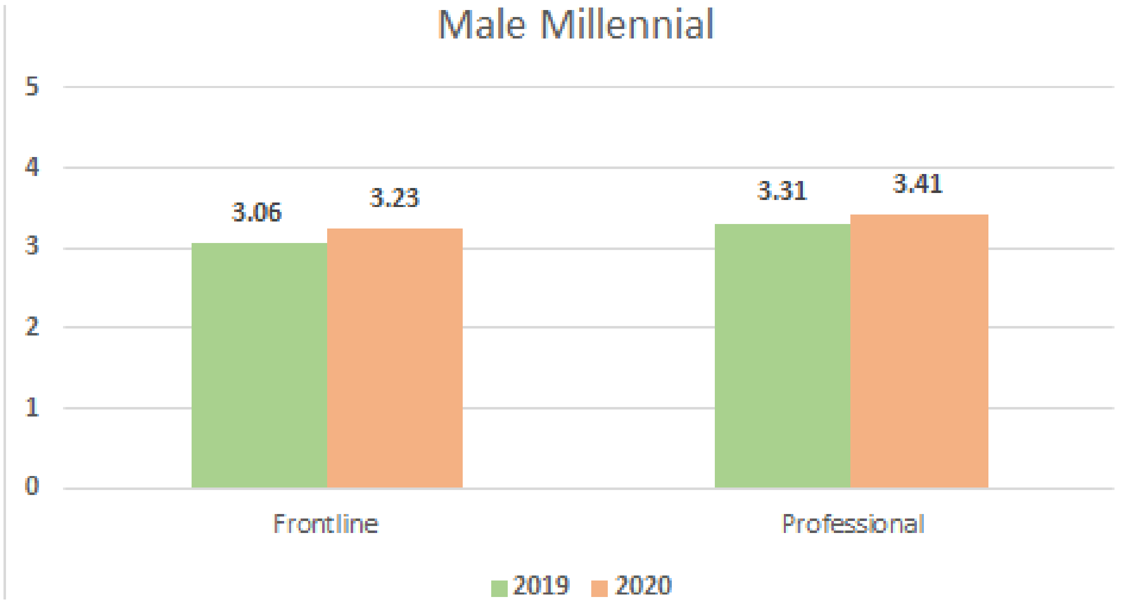

Figure 9: *Performance Scores by Population and Year: Male Millennials*

For females, there was not a significant 3-way interaction. I then tested if there was a two-way interaction for females by population type and year. This two-way interaction was significant, $F(1, 25{,}282) = 21.138$, $p < .001$. The increase in professional employees' performance scores from 2019 to 2020 is greater than the increase of frontline employees during the same time (see Figure 10). This finding does not support H2.

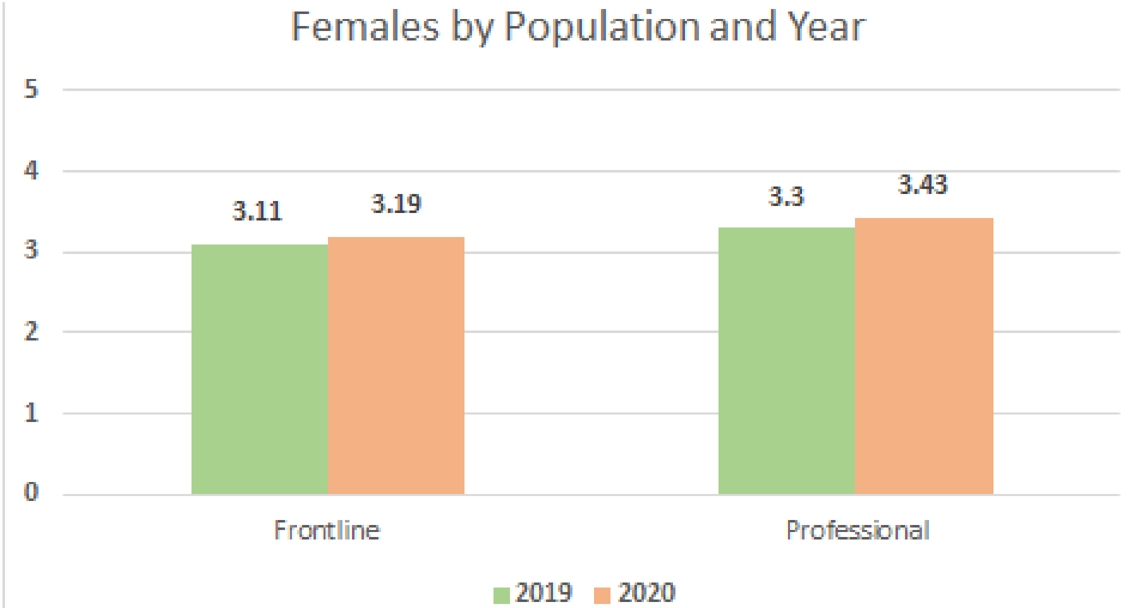

Figure 10: *Performance Scores by Population and Year: Females*

In sum, H2 was not supported. While Millennial and Generation Z males, and females by population type and year were significant two-way interactions, none were in the hypothesized direction.

Research Question 1: Generation and Engagement

This research question explores the potential three-way interaction of generational cohorts on population type and year related to engagement scores. As with H1, I first had to account for the significant four-way interaction present for engagement, $F(3, 62{,}962) = 9.0473$, $p < .001$ (see H1), and then examine the significance and nature of the three-way interaction present for males, $F(3, 37{,}692) = 16.1310$, $p < .001$ (see H1).

A follow-up contrast test indicated that there were significant differences between male populations from 2019 to 2020 for Generation Z and Baby Boomer, Baby Boomer and Millennials, Generation X and Generation Z, and Generation X and Millennial (see Table 2).

Table 2

Pairwise Comparisons of Generational Cohorts for Engagement Scores

Pairwise	*df*	*t* ratio	*p*
Baby Boomers - Generation Z	37692	-3.427	0.0024
Baby Boomers - Millennials	37692	-5.398	<.0001
Generation X - Generation Z	37692	-2.516	0.0357
Generation Z - Millennials	37692	-5.753	<.0001

H1 contains more graphs relevant to this research question (see Figures 1-5). The three-way interaction for females was not significant.

In summary, in order to find evidence that would lead to an affirmative answer to this research question, generational differences would need to exist in engagement scores from 2019 to 2020 in frontline and professional populations. As the three-way interaction was significant for males, there is a partial affirmative answer to this question. Specifically, differences were present between males in Generation Z and Baby Boomers, Baby Boomers and Millennials, Generation X and Generation Z, and Generation X and Millennials.

Research Question 2: Generation and Performance

This research question explores the potential three-way interaction of generational cohorts on population type and year related to performance scores. As with H2, I first had to account for the significant four-way interaction present for performance, $F(3, 62{,}962) = 5.02977$, $p < .01$ (see H2), and then examine the significance and nature of the three-way interaction present for males, $F(3, 37{,}692) = 4.8196$, $p < .01$ (see H2).

A follow-up contrast test indicated that there were significant differences between male populations from 2019 to 2020 between Baby Boomers and Generation Z, and Baby Boomers and Millennials (see Table 3).

Table 3

Pairwise Comparisons of Generational Cohorts for Performance Scores

Pairwise	df	t ratio	p
Baby Boomers - Generation Z	37692	2.868	0.0207
Baby Boomers - Millennials	37692	3.004	0.016

H2 contains more graphs relevant to this research question (see Figures 6-10). The three-way interaction for females was not significant.

In order to find evidence that would lead to an affirmative answer to this research question, generational differences would need to exist in performance scores from 2019 to 2020 in frontline and professional populations. As the three-way interaction was significant for males, there is a partial affirmative answer to this question. Specifically, differences were present between males in Baby Boomers and Generation Z, and Baby Boomer and Millennial cohorts.

Hypothesis 3: Gender and Engagement Scores

In order to find support for H3, there would need to be a significant three-way interaction of gender on population type and year for engagement scores. However, I first had to test whether there were any higher-order interactions that involved these variables. As with H1, I first had to account for the significant four-way interaction present for engagement, $F(3, 62{,}962) = 9.0473$, $p < .001$ (see H1). To further understand this interaction, I separated the dataset into each of the four generational groups and ran analyses on those subsets.

The three-way interaction for population, gender, and year for Generation X was significant. $F(1, 27{,}406) = 4.7965$, $p < .05$. I then tested if there was a two-way interaction for each gender by population type and year. For males, this two-interaction was not significant. If interested, graphs are available under H1 (see Figure 1-4). For females, the two-way interaction was not significant (see Figure 11). As engagement scores did not decrease for Generation X females for both populations, this result does not support H3.

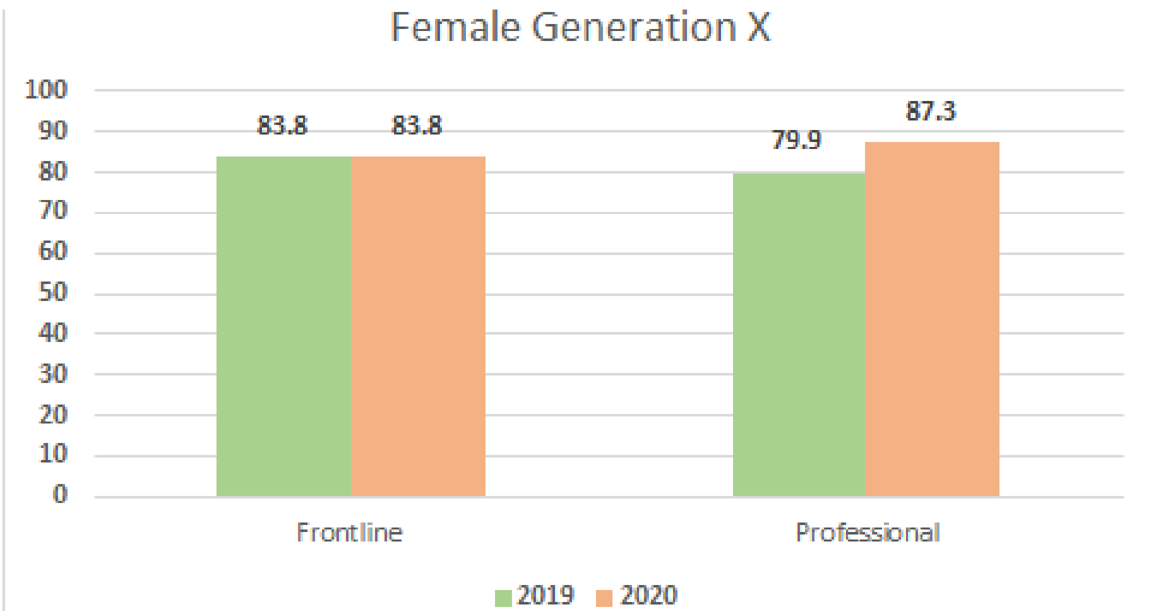

Figure 11: *Engagement Scores by Population and Year: Females Generation X*

The three-way interaction for population, gender, and year for Generation Z was significant, $F(1, 2{,}670) = 7.797$, $p < .01$. I then tested if there was a two-way interaction for each gender by population type and year. For males, this two-interaction was significant, $F(1, 1{,}088) = 5.5739$, $p < .01$. If interested, graphs are available under H1 (see Figures 1-4). For females, the two-way interaction was not significant (see Figure 12). As engagement scores did not decrease for Generation Z females for both populations, this does not support H3.

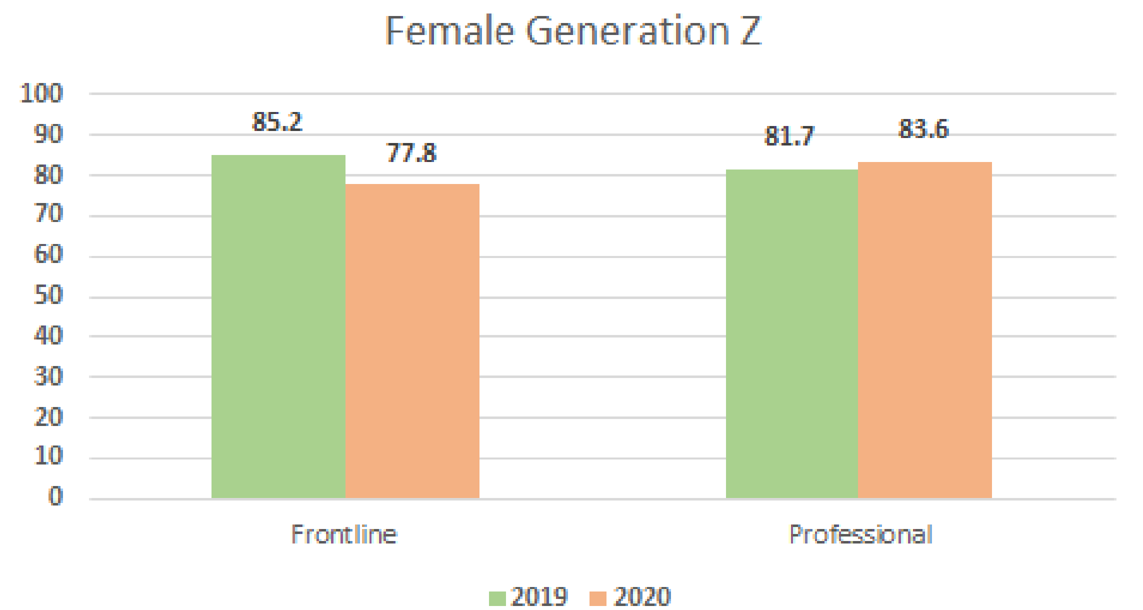

Figure 12: *Engagement Scores by Population and Year: Females Generation Z*

The three-way interaction for population, gender, and year for Baby Boomers was not significant. The three-way interaction for population, gender, and year for Millennials was not significant.

In summary, in order to find support for this hypothesis, scores for females would have needed to both decline from 2019 to 2020 in both frontline and professional populations. Significant interactions were present for Generation X and males in Generation Z, but females' score differences across time (when present) were not in the hypothesized directions, thus not supporting this hypothesis.

Hypothesis 4: Gender and Performance Scores

In order to find support for H4, there would need to be a significant three-way interaction of gender on population type and year for performance scores. However, I first had to test whether there were any higher-order interactions that involved these variables. As with H2, I first had to account for the significant four-way interaction present, $F(3, 62{,}962) = 5.02977$, $p < .01$. To further understand this interaction, I separated the dataset into each of the four generational groups and ran analyses on those subsets (see Figure 13).

The three-way interaction for population, gender, and year for Generation X was significant, $F(3, 27{,}406) = 4.2409$, $p < .05$. I then tested if there was a two-way interaction for each gender by population type and year. For males, this two-interaction was not significant. If interested, graphs are available under H2. For females, the two-way interaction was significant, $F(1, 10{,}030) = 11.165$, $p < .001$ (see Figure 13). As performance scores did not decrease for Generation X females for both populations, this does not support H4.

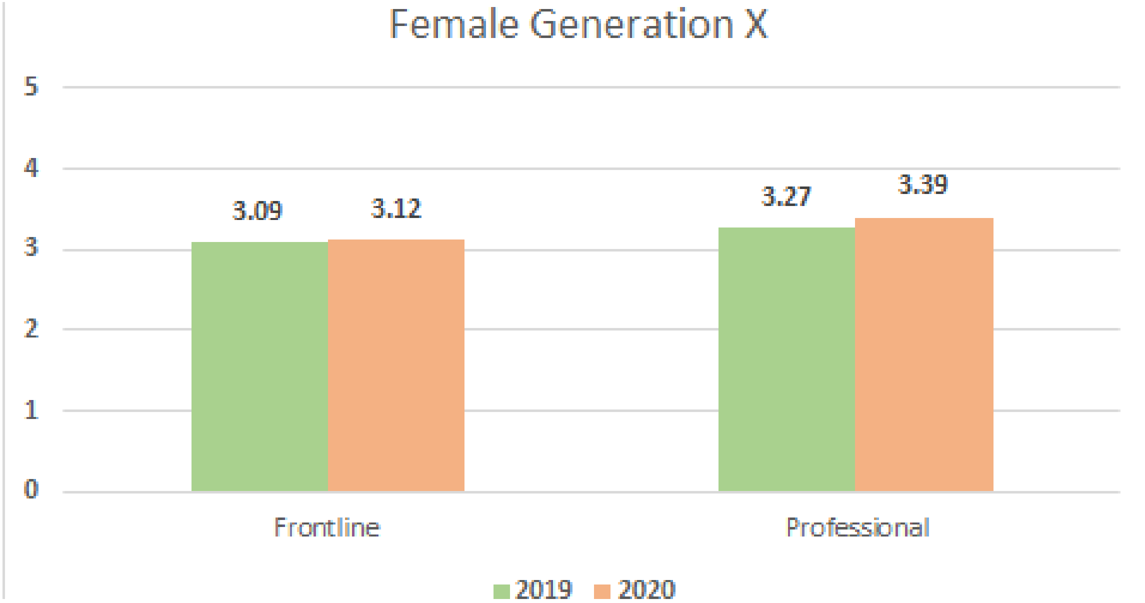

Figure 13:*Performance Scores by Population and Year: Females Generation X*

The three-way interaction for population, gender, and year for Baby Boomers was not significant. The three-way interaction for population, gender, and year for Millennials was not significant. The three-way interaction for population, gender, and year for Generation Z was not significant.

In summary, in order to find support for this hypothesis, performance scores for females would have needed to both decline from 2019 to 2020 in both frontline and professional populations. A significant interaction was present for females in Generation X, but females' score differences across time (when present) were not in the hypothesized direction, thus not supporting this hypothesis.

CHAPTER 4

DISCUSSION

Power and Sample

The goal of this study was to examine the impact of the COVID-19 pandemic on professional and frontline employees from 2019 to 2020, with additional research questions exploring the interaction of age and generation. After an examination of the literature, I was able to identify key areas to be examined with specific, directional hypotheses and research questions. I then obtained a large data set from a global organization to test my hypotheses and research questions.

Specifically, for H1 I expected to see a significant 2-way interaction between population and time related to engagement scores. After accounting for significant four- and three-way interactions, findings indicated that only for male Baby Boomers and male Millennials were there significant interactions between population and time, but, despite expectations, their scores increased rather than decreased. In sum, H1 was not supported.

For H2, I expected to see a significant 2-way interaction between population and time related to performance scores. After accounting for significant four- and three-way interactions, findings indicated that Millennial and Generation Z males, and females by population type and year were significant two-way interactions, but none were in the hypothesized direction. H2 was not supported.

RQ1 explored the potential three-way interaction of generational cohorts on population type and year related to engagement scores. Specifically, in order to find evidence that would lead to an affirmative answer to this research question, generational differences would need to exist in engagement scores from 2019 to 2020 in frontline and professional populations. After accounting for significant four- and three-way interactions, findings indicated that differences were present between males in Generation Z males and Baby Boomer, Baby Boomer and Millennial, Generation X and Generation Z, and Generation X and Millennial, thus providing a partial affirmative answer to this research question.

In order to find evidence that would lead to an affirmative answer to RQ2, generational differences would need to exist in performance scores from 2019 to 2020 in frontline and professional populations. After accounting for significant four- and three-way interactions, findings indicated that differences were present between males in Baby Boomers and Generation Z and Baby Boomer and Millennial cohorts, thus providing a partial affirmative answer to this research question.

In order to find support for H3, there would need to be a significant three-way interaction of gender on population type and year for engagement scores. Specifically, scores for females would have needed to both decline from 2019 to 2020 in both frontline and professional populations. After accounting for significant four- and three-way interactions, findings indicated that significant interactions were present for Generation X and males in Generation Z, but females' score differences across time (when present) were not in the hypothesized directions, thus not supporting this hypothesis.

In order to find support for H4, there would need to be a significant three-way interaction of gender on population type and year for performance scores. Specifically, performance scores for females would have needed to both decline from 2019 to 2020 in both frontline and professional populations. After accounting for significant four- and three-way interactions, findings indicated that a significant interaction was present for females in Generation X, but females' score differences across time (when present) were not in the hypothesized direction, thus not supporting this hypothesis.

Limitations and Future Directions

As briefly mentioned in the method and results sections, there were several limitations in this study. First, operationalization biases may be present for engagement and performance. Specifically, these operationalizations may not be generalizable outside of Company Z. Furthermore, employees' engagement scores are subject to the same biases prevalent in other self-report data (Paulhus, 1991). While managers are provided the same rating scale and factors to consider when rating employees, the ultimate interpretation of that scale by managers and rating given to employees may be impacted by numerous rating biases such as halo effect or primacy/recency effects. Furthermore, as the rating scale changed from 2019 to 2020, this may be associated with a beta change for the managers as the measurement continuum associated with the constant conceptual domain (performance) changed (Golembiewski et al., 1976). Though less likely, it is also possible that managers could have also experienced gamma change, meaning that their conceptualization of the performance domain changed due to the change in the rating scale. Ideally, future studies would have the same rating scale year to year.

In terms of data analysis, there were issues with non-normal data that led to the use of nonparametric statistics. Although nonparametric statistics are robust and can be used when assumptions are violated, they also have less power. However, given the amount of data used in the sample, power is less of an issue. Furthermore, as the majority of hypotheses were in the opposite direction of what was expected, power is largely irrelevant. Nevertheless, a replication of this study with a similar or even larger sample size would prove interesting to determine if similar patterns follow.

Along with a different sample, future examinations could examine the impact of the pandemic based on other organizational variables like country, work function, or tenure in the organization. Cultural and societal impacts could easily alter the findings of this study and may be particularly useful for large organizations that want to better manage employees in a global environment.

Conclusion

While something as pervasive as the COVID-19 pandemic has not been seen since the Spanish Flu pandemic of the 1920s, this particular scenario forced individuals and organizations alike to adapt and re-focus on day-to-day functioning. The findings of this study indicate that generation, time, gender, and population can have an impact on performance and engagement scores during a global pandemic. Understanding the impact of these variables as the effects of the pandemic continue to dwindle may be of interest to organizations.

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