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Research Notes

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Celia Rose Lofink, University of Hartford

ORGANIZATIONAL AWARENESS AND IMPLEMENTATION OF SUSTAINABILITY ACTIVITIES IN BUSINESSES - MOVING TOWARD THE CIRCULAR ECONOMY
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Journal of Business, Economics and Technology

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JBET Research Notes include, but are not limited to updates to previous work, additions to established methods, relatively short articles, research where the thesis is narrow in scope, null results, case series, research proposals, and data management plans: Articles of good quality which cannot be considered as full research or methodology articles. Further, each article in the Research Notes category has undergone the same double-blind peer review process as all articles that are published in JBET. For the papers in the Research Notes section of the 2020 Issue, we encourage further development of those articles. At JBET, we support the research community across all of the disciplines of Business, Economics, and Information Technology by providing this forum for sharing information and data regarding the works-in-process of our constituents. Also, for this issue of JBET, the Research Notes category is subdivided into regular Research Notes, and Research Notes that focus on research related to the COVID Pandemic.

We thank the officers of the National Association of Business, Economics and Technology, the NABET Executive Board, as well as the referees for their support and hard work in the production of this 24th Volume of JBET.

Jerry D. Belloit, co-Editor
Clarion University of Pennsylvania - Retired

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STOCK PRICE REACTIONS TO ANNOUNCEMENTS OF MERGERS AND ACQUISITIONS

Tibebe Assefa, Bowie State University
Sunando Sengupta, Bowie State University
Satina Williams, Bowie State University

ABSTRACT

This paper investigates whether abnormal returns exist around the announcements for Mergers and Acquisitions (M&A) that occurred from 2000 to 2019. We analyze the impact of the M&A announcements on the stock price of acquiring and acquired firms. Earlier research has shown that M&A events related to stock-generated investor reactions tend to affect the stock price of the companies involved in the M&A transactions, usually on a very short basis. When a company acquires another company, the stock price of the target company typically will rise, and the stock price of the acquiring company declines, in the short term. It is predicted, in prior research, that the target company's stock will rise because the acquiring company pays a premium for the acquisition. Amazon, Facebook, General Electric, Google and Cisco are examples of well-known companies that have participated in M&As. Our sample consists of 200 pairs of firms that announced M&As over twenty-years period from 2000-2019. We first identify the announcement or event dates and then utilize Event-Study methodology Eventus, from the Wharton Research Database (WRDS), to test for the presence of abnormal returns around the event dates. Our results show significant positive 11. 10 percent Cumulative Abnormal Returns (CAR) for the acquired firms one day before the announcement date up to the announcement date for acquired firms. On the contrary, the results show significant negative CAR of 1.63 percent for the acquiring firms from 1 days before the announcement date, which could be due to the premium paid to acquire.

INTRODUCTION

Mergers and acquisitions are the "acts of consolidating companies or assets, with an eye toward stimulating growth, gaining competitive advantages, increasing market share, or influencing supply chains" (Palmer, 2019). Every year mergers and acquisitions are announced between an acquiring company and a targeted company. On the date of the announcement, stock prices have proven to be impacted by it. Statista shows that in 2019, the value of the global M&A deals amounted to $3.7 trillion U.S. dollars (Szmigier, 2020). This makes up 4.3% of the $86 trillion in the world economy (Desjardins, 2019) and it is an important corporate strategic plan for business growth and global competition. This study is important because it can give investors, business owners, and traders beneficial information to make wise business decisions, while also providing evidence of the announcement date boosting the economy.

This paper investigates the presence of abnormal returns in the stock market on the announcement date of mergers and acquisitions for publicly traded companies from 2000 to 2019, and if there are any effects post-announcement date. Prior studies have shown positive abnormal returns for the targeted company but have shown mixed returns for the acquirer. In order to conduct our study, we have researched multiple articles covering mergers and acquisitions, along with our own empirical investigations for better understanding. The stock market has always been volatile, so we can expect to find interesting results.

LITERATURE REVIEW

The literature suggest that the targeted company will experience positive abnormal returns in stock market. In contrast, the acquiring company may see no significant impact at all. Manuel and Rhoades (2014) found in their study that "the impact of the merger announcement on the target airlines is positive except for Northwest due to the weakening demand for air transport as the U.S. economy faltered at the time of its merger with Delta." These results align with our own hypothesis because we expect to see positive abnormal returns on the targeted company's stock during the announcement date. Additionally, the researchers found that "The share prices of acquiring and target airlines increased around the merger completion date, suggesting that new information is available as the merge nears completion." This particular study found that both the acquiring and targeted firm showed significant positive abnormal returns in their results. One of the M&A formed were between America West and US Airways, in which the shareholders of America West saw a return of more than 55% on the share price.

In a study on the short-and-long run share performance mergers and acquisitions on the Saudi Arabia Stock Exchange, researchers found that "(1) investors could earn positive market adjusted abnormal returns during the few days surrounding the announcement date and (2) investors could earn positive and significant market-adjusted Buy and Hold Abnormal Return (BHAR) for shares that are held up to 36 months following the completion months of M&A events" (Zakaria and Kamaludin, 2018). This article gives another perspective on the relationship between the announcement of M&As and the stock market due to the sample of the study using a foreign stock market. Also, the researchers are expecting to see the acquiring company attain positive abnormal returns in contrast to what we expect to see in our study. Their study showed "The short-run abnormal return reflects the expected synergy between the acquirer companies and target companies, consistent with the notion of value creation in the event of M&A" (Zakaria and Kamaludin, 2018). This gives evidence to the notion that the share price of the acquiring company is certainly capable of seeing a positive return during an M&A. This article was an interesting study because it adds to the ongoing debate of whether the targeted company's or the acquiring company's share price results in a positive return during the announcement date of M&A.

Varmaz and Laibner (2016) discuss announced vs. canceled bank mergers and acquisitions from the European banking industry. The article states "The paper finds that European bank M&As have not been successful in terms of shareholder value creation for acquiring banks, whereas targets experienced significant value gains" (Varmaz and Laibner, 2016). This study provides insight to how different sectors of the stock market react to M&As because the sample of it uses banks instead of public trading companies or airlines. Furthermore, it pushes the notion that acquiring companies do not see positive abnormal returns during M&As, while the targeted companies do see positive abnormal returns. However, Mall and Gupta (2019) conducted a study on the National Stock Exchange in India and their results were contrary. The sample used in the study consisted of 383 mergers and acquisitions between 2000-2018 and "findings suggest that consolidation in Indian banking sector leads to positive average abnormal returns and wealth creation for acquirer bank's shareholders" (Mall and Gupta, 2019). The remainder of this paper will contain our sample and methodology in section 2, data and analysis in section 3, our model in section 4, and finally our conclusion.

Event Study: An event study is a statistical method of an empirical investigation of the relationship between security prices and economic events (Dyckman et al., 1984). Most event studies have focused on the behavior of share prices in order to test whether their stochastic behavior is affected by the disclosure of firm-specific events. Furthermore, "in a corporate context, the usefulness of event studies arises from the fact that the magnitude of abnormal performance at the time of an event provides a measure of the unanticipated impact of this type of event on the wealth of the firms' claimholders" (Kothari and Warner 2006).

EMPIRICAL MODEL

Methodology

This study employs a standard event study methodology, using Eventus from WRDS and we fit a standard market model to measure normal performance:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it}, \qquad \text{where } E(\varepsilon_{it}) = 0 \text{ and } \operatorname{var}(\varepsilon_{it}) = \sigma^2_{\varepsilon t} \tag{1}$$

Each sample calendar date is converted to event time by defining the date of the merger announcement date as event date 0. So, for a merger announcement date, event date 0 is the same trading day. The regression coefficients α_i and β_i are estimated in an ordinary least squares (OLS) regression during the estimation period one year (255 trading days) prior to the event period (event days -300 through -46). The event period consists of 61 trading days centered on merger announcement date (-30 through +30). We define four event windows based on the event date, [-30,-2], [-1, 0], [+1, +2] and [+3, +30]. As proxy for the return for the market portfolio R_{mt}, both the CRSP value weighted index and the CRSP equal weighted index are used.

Under standard assumptions, OLS is a consistent estimation procedure for the market model parameters. Under the assumption that asset returns are jointly multivariate normal and independently and identically distributed (iid), OLS is also efficient. The prediction errors, $PE_{i\tau}$, which represent abnormal returns, are simply the OLS residuals, $\hat{\varepsilon}_{it}$.

$$PE_{i\tau} \equiv \hat{\varepsilon}_{i\tau} = R_{i\tau} - (\hat{\alpha}_i + \hat{\beta}_i R_{mt}) \tag{2}$$

with

$$\hat{\sigma}^2_{\varepsilon t} = \frac{1}{255-2} \sum_{\tau=t-299}^{t-46} (R_{i\tau} - \hat{\alpha}_i - \hat{\beta}_i R_{m\tau})^2 \tag{3}$$

The prediction error, PE_{it} is used as an estimator of the abnormal return. In other words, the abnormal return is the residual term of the market model calculated on an out of sample basis. Let $AR_{i\tau}, \tau = t-30, t-29, \ldots t+29, t+30$ be the sample of 61 abnormal returns for firm i in the event window. Under the null hypothesis, conditional on the event window market returns, the abnormal returns will be jointly normally distributed with a zero conditional mean and conditional variance:

$$AR_{i\tau} \sim N(0, \sigma^2(AR_{i\tau}))$$

The conditional variance $\sigma^2(AR_{i\tau})$ has two components. The first component is the disturbance $\hat{\sigma}^2_{\varepsilon t}$ from (3), and the second component is additional variance due to sampling error in estimating the market model parameters α_i and β_i :

$$\sigma^2(AR_{it}) = \sigma^2_{\varepsilon\tau} + \frac{1}{255}\left[1 + \frac{(R_{m\tau} - \bar{R}_m)^2}{\hat{\sigma}^2_m}\right] \text{ where } \bar{R}_m = \frac{1}{255} \sum_{\tau=t-299}^{t-46} R_{m\tau} \tag{4}$$

Since the estimation window is large (255 trading days), I assume that the contribution of the second component to $\sigma^2(AR_{i\tau})$ is zero.

To draw inferences about the average price impact of an event, abnormal return observations have to be aggregated across securities and through time. Average abnormal returns AAR_τ are formed by aggregating abnormal returns $AR_{i\tau}$ for each event period $\tau = t-30, t-29, \ldots t+29, t+30$. Given N events (for our sample, $N = 147$),

$$AAR_\tau = \frac{1}{N} \sum_{i=1}^{N} AR_{i\tau} \tag{5}$$

Under the assumption that average abnormal returns are independent across securities, the asymptotic variance equals to

$$Var(AAR_\tau) = \frac{1}{N^2} \sum_{i=1}^{N} \sigma^2_{\varepsilon\tau} \tag{6}$$

The average abnormal returns are aggregated through time to give the cumulative average abnormal return,

$$CAAR_i(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} AAR_{i\tau} \tag{7}$$

Setting the covariance terms to be zero,

$$\operatorname{var}(CAAR_i(\tau_1,\tau_2)) = \sum_{i=1}^{N} \operatorname{var}(AAR_{i\tau}) \tag{8}$$

Hence $CAAR_i(\tau_1,\tau_2) \sim N(0, \operatorname{var}(CAAR_i(\tau_1,\tau_2))$

This can be used to test the null hypothesis that the abnormal returns are zero.

The estimated variance of AAR_τ is

$$\hat{\sigma}^2_{AAR} = \frac{\sum_{\tau=t-299}^{t-46} (AAR_\tau - \overline{AAR})^2}{255-2} \text{ where } \overline{AAR} = \frac{\sum_{\tau=t-299}^{t-46} AAR_\tau}{255} \tag{9}$$

The portfolio test statistic for day τ in event time is

$$t = \frac{AAR_\tau}{\hat{\sigma}^2_{AAR}} \tag{10}$$

Assuming time series independence, the test statistic for $CAAR_i(\tau_1,\tau_2)$ is

$$t = \frac{CAAR_i(\tau_1,\tau_2)}{\sqrt{(\tau_2-\tau_1+1)}\hat{\sigma}_{AAR}} \tag{11}$$

The abnormal return estimators often have different variances across firms. A common way of addressing this problem is the standardized residual method (Patell, 1976). Define the *standardized abnormal return*, $SAR_{i\tau}$ as

$$SAR_{i\tau} = \frac{AR_{i\tau}}{\hat{\sigma}_{MLE_{i\tau}}} \tag{12}$$

Where

$$\hat{\sigma}_{MLE_{i\tau}} = \hat{\sigma}^2_{\varepsilon\tau}\left(1 + \frac{1}{T} + \frac{(R_{m\tau} - \bar{R}_m)^2}{\sum_{\tau=t-299}^{t-46} (R_{m\tau} - \bar{R}_m)^2}\right) \tag{13}$$

Is the maximum likelihood estimate of the variance. Under the null hypothesis each $SAR_{i\tau}$ follows a Student's t distribution with T-2 degrees of freedom. Summing the $SAR_{i\tau}$ across the sample yields

$$ASAR_{i\tau} = \sum_{i=1}^{N} SAR_{i\tau} \text{ where } ASAR_{i\tau} \sim N(0, Q_\tau) \tag{14}$$

The Z-test statistic for the null hypothesis that $CAAR_i(\tau_1,\tau_2) = 0$ is

$$Z(\tau_1,\tau_2) = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} Z_i(\tau_1,\tau_2) \text{ where } Z_i(\tau_1,\tau_2) = \frac{1}{\sqrt{(\tau_2-\tau_1+1)\frac{T-2}{T-4}}} \sum_{\tau=\tau_1}^{\tau_2} SAR_{i\tau} \tag{15}$$

The two test statistics so far discussed use the variance estimate from the market model during the estimation period to estimate the variance of the abnormal return estimator. But frequently, events increase the variance of returns, so that the event period variance is greater than the estimation period variance. The portfolio test statistic for day t in event time is

$$t = \frac{AAR_{\tau}}{\hat{\sigma}_{AAR_{\tau}} / \sqrt{N}} \text{ where } \hat{\sigma}_{AAR_{\tau}} = \frac{1}{N-1}\sum_{i=1}^{N}(AR_{i\tau} - \frac{1}{N}\sum_{i=1}^{N} AR_{i\tau})^2 \tag{16}$$

We use the above equation to calculate *Adjusted-t*

RESULTS

We ran three different Eventus regression using for sample periods around the announcement date. The first one is the acquirer firms, second one is for the acquired firms and the third one for the combination of acquired and acquirer firms. The results for different days before and after announcement of merger and acquisitions date are shown on Tables 1, 2 and 3.

Table 1 shows the results of acquirer firms. For 30 days, up to 2 days before announcement the Cumulative Abnormal Returns (CAR) is 1.02 percent, one day before the announcement up to the announcement date the cumulative abnormal returns is decline of 1.63 percent, one day up to two days after announcement the cumulative abnormal returns 0.25 percent and finally three days up to thirty days of announcement the cumulative abnormal returns is negative 0.94 percent for the acquirer firms. The gain of 1.02 percent and the decline of 1.63 percent are statistically significant with less than 10 percent and less than 5 percent respectively. Specifically, the loss of CAR 1.63 percent one day before the announcement indicates that the acquirer firm is paying premium to acquire the target firm. Which is not surprise since the acquirers pays premium of acquire the smaller firms investors are not willing to pay higher stock price for the acquirer firm. That is in line with the literature in the area of merger and acquisition.

Table 2 show the results of acquired firms. For thirty days up to two days before the announcement the CAR is 2.14 percent, one day before announcement up to the day of announcement the CAR is 11.10%, one days to two days after the announcement day the CAR is 1.95 percent, and from three days up to thirty days after the announcement the CAR is negative 0.94 percent. One day before the announcement up to announcement the CAR of 11.10 percent is strongly statistically significant (at less than one percent level of significant) and thirty day before the announcement date until two days CRR of 2.14 is also statistically significant at less than 10 percent level of significant. These findings are as expected as the literature before the announcement there is significant increase of stock prices in the acquired firms; that is to adjust for the premium the acquirer pay for the merger with the smaller firms.

The increase in the stock prices over reaction increases as high as 11.10 percent immediately before and up to the announcement date indicating that investors are not able to make abnormal returns after the announcement date proving strong form of efficient market hypothesis. The analysis indicate that the market adjusts to the higher stock prices before and up to the announcement date. There will not be abnormal returns after the announcement date.

Table 3 shows the results of acquiring and acquirer firms together. Thirty days before the announcement days up to two days before the announcement date the CAR is 1.51 percent, one day before the announcement up to the day of announcement the CAR is 3.94 percent, one day after announcement up to two days the CAR is 0.98%, and three days up to thirty days after announcement the CAR is negative 0.13 percent. One day before the announcement date until announcement date the CAR of 3.94% is statistical significant at less than one percent of level of significance. The CAR of 1.51 percent for thirty days before announcement until two days before announcement is also statistically significant at less than 5 percent level of significance. Table 3 show that it is better to run separately the acquired and acquirer firms to get the best impact of merger and acquisition on the acquiring and acquired firms since the impact of M&A is different in the two groups.

CONCLUSION

In this paper we revisited Merger and Acquisition (M&A) of companies that are traded in the US stock exchanges. The original samples were 215 pair of firms that M&A were from 2000 until 2019. The methodology used is event study using Eventus and data accessed from Wharton Research Data System (WRDS). The final sample that we were able to get the data are 154 pair of firms. Our aim is to if either the acquirer or acquired firms earned Cumulative Excess Returns (CAR) around the announcement date of the M&A. We observed 30 days before and 30 days after the announcement days. Our results of acquired firms show positive and significant CAR before the announcement date. For thirty days up to two days before the announcement the CAR is 2.14 percent, one day before announcement up to the day of announcement the CAR is 11.10%. These findings are as expected as the literature before the announcement there is significant increase of stock prices in the acquired firms that is to adjust for the premium the acquirer pay for the merger with the smaller firms. The increase in the stock prices over reaction increases as high as 11.10 percent immediately before and up to the announcement date but there is no abnormal returns after the announcement date indicating strong form of market efficiency hypothesis. Investors in the acquired firms earn large Cumulative Abnormal Returns one day before the annulment date.

Acquiring firms did not earn any significant negative or positive cumulative abnormal returns around the announcement date. Acquiring firms usually pay premium to take over the target company which explains why investors are not willing to pay higher prices at least in the short term. But the long-term effect on acquiring firms could be outside of the scope of this paper would be of interest for future research. However, acquiring firms are paying premium either to increase market share or diversification advantages which will have positive impact in the long run. Furthermore, the impact of COVID-19 on M&A would be of an interest for future researcher.

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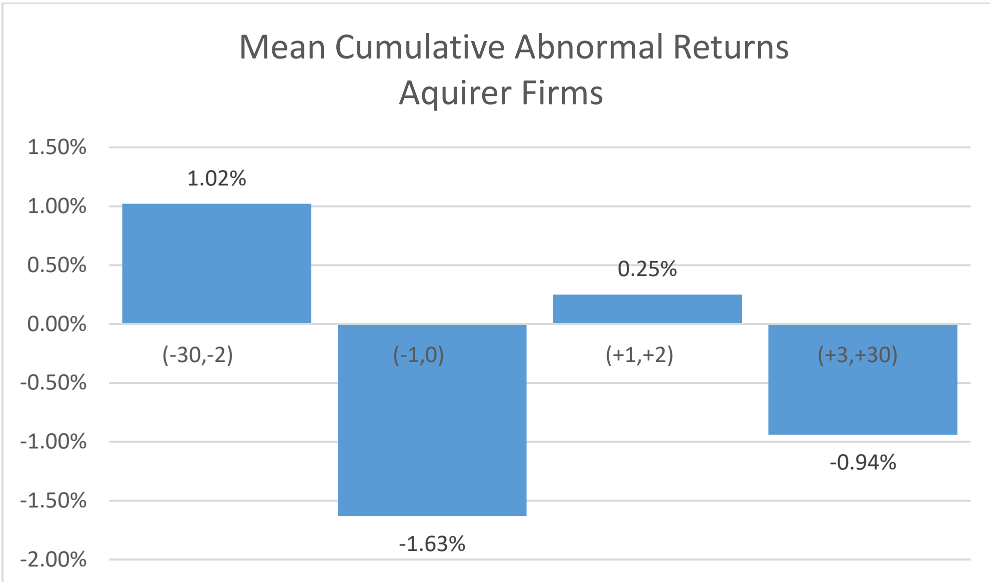
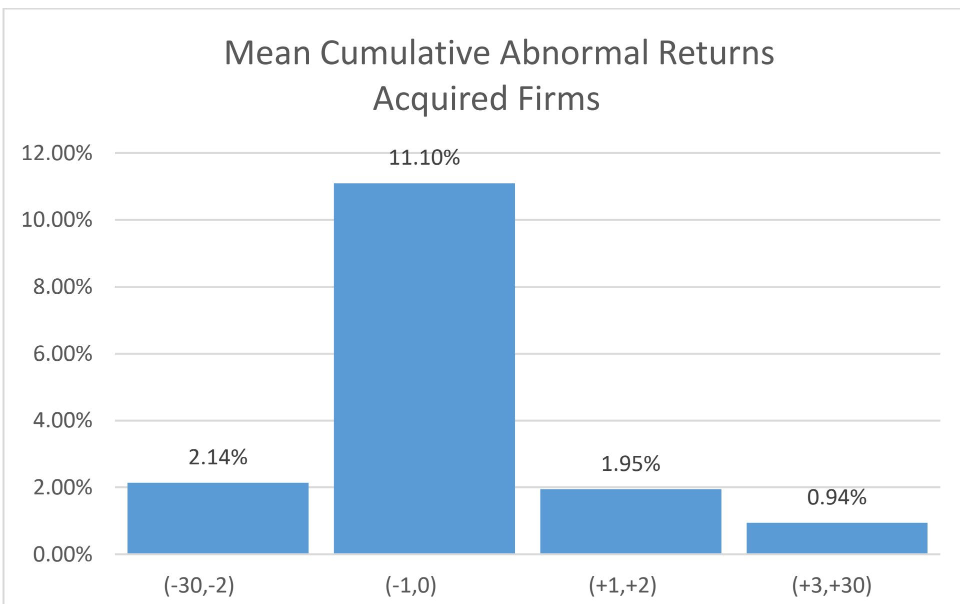
APPENDIX

Figure 1



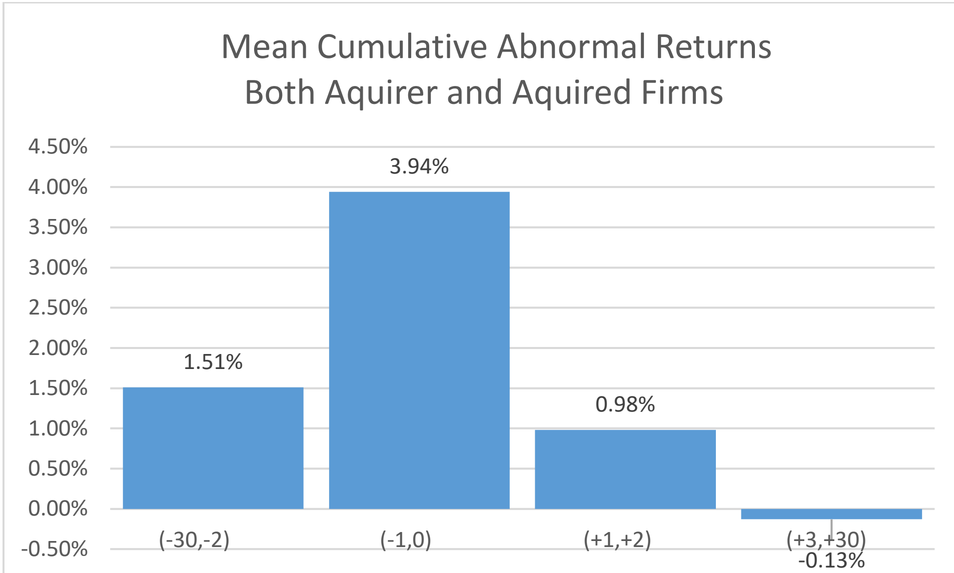
Compared to Equally Weighted Market Returns

Figure 2



Compared to Equally Weighted Market Returns

Figure 3.



Compared to Equally Weighted Market Returns

Table 1. Company A – Acquirer Firms

Market Model Abnormal Returns, Equally Weighted Index

Days	N	Mean Cumulative Abnormal Return	Precision Weighted CAAR	Positive: Negative	Uncorrected Patell Z	p-value	Portfolio Time-Series (CDA) t	p-value	Generalized Sign Z	p-value
(-30,-2)	154	1.02%	0.97%	87:67)	1.559	0.1190	1.382	0.1670	1.822	0.0685
(-1,0)	154	-1.63%	-1.54%	63:91<	-9.451	<.0001	-8.430	<.0001	-2.047	0.0407
(+1,+2)	154	0.25%	0.11%	78:76	0.688	0.4916	1.315	0.1886	0.371	0.7105
(+3,+30)	154	-0.94%	-0.86%	70:84	-1.412	0.1581	-1.301	0.1934	-0.918	0.3585

The symbols (,<,<<,<<< or),>,>>,>>> show the direction and significance of a generic one-tail generalized sign test at the 0.10, 0.05, 0.01 and 0.001 levels, respectively.

Table 2. Company B- Acquired Firms

Market Model Abnormal Returns, Equally Weighted Index

Days	N	Mean Cumulative Abnormal Return	Precision Weighted CAAR	Positive: Negative	Uncorrected Patell Z	p-value	Portfolio Time-Series (CDA) t	p-value	Generalized Sign Z	p-value
(-30,-2)	120	2.14%	2.42%	68:52)	2.920	0.0035	1.686	0.0917	1.731	0.0835
(-1,0)	120	11.10%	9.61%	94:26>>>	44.176	<.0001	33.384	<.0001	6.479	<.0001
(+1,+2)	116	1.95%	1.47%	63:53	6.733	<.0001	5.855	<.0001	1.194	0.2325
(+3,+30)	116	0.94%	0.79%	52:64	0.937	0.3485	0.756	0.4496	-0.849	0.3957

The symbols (,<,<<,<<< or),>,>>,>>> show the direction and significance of a generic one-tail generalized sign test at the 0.10, 0.05, 0.01 and 0.001 levels, respectively.

Table 3. Both Acquirer and Acquired Firms

Market Model Abnormal Returns, Equally Weighted Index

Days	N	Mean Cumulative Abnormal Return	Precision Weighted CAAR	Positive: Negative	Uncorrected Patell Z	p-value	Portfolio Time-Series (CDA) t	p-value	Generalized Sign Z	p-value
(-30,-2)	274	1.51%	1.55%	155:119>	3.101	0.0019	1.906	0.0567	2.511	0.0120
(-1,0)	274	3.94%	2.90%	157:117>>	22.149	<.0001	18.969	<.0001	2.753	0.0059
(+1,+2)	270	0.98%	0.65%	141:129	4.932	<.0001	4.723	<.0001	1.064	0.2873
(+3,+30)	270	-0.13%	-0.21%	122:148	-0.452	0.6516	-0.172	0.8633	-1.249	0.2116

The symbols (,<,<<,<<< or),>,>>,>>> show the direction and significance of a generic one-tail generalized sign test at the 0.10, 0.05, 0.01 and 0.001 levels, respectively.

MODELING SHORT TIME PERIOD CAR REDISTRIBUTION POLICY IN THE CAR SHARING INDUSTRY

Wei Chen, York College of Pennsylvania

ABSTRACT

Economic, environmental and social impacts have increased popularity of car sharing program. More firms consider entering this market to satisfy rising demands from public. In general, a car sharing company faces two very practical problems: 1). Station Size/Capacity; 2). Strategies for imbalance of vehicles distribution for each station. Although literature presents that such questions have been studied in the past, almost all of them use optimization models to address these questions; and the problem of those optimization models is these optimization models are specifically question-oriented, therefore it is difficult to be implemented in practice and cannot be easily generalized in common situations. In this study, we develop a novel model to address these questions. Our models require few inputs and offer quick analytic results. An application of the models on Zipcar illustrates how our models work and shows that our models perform well, achieving expectations.

INTRODUCTION

Background Introduction

In the United States, Car-sharing programs start from 1994. Compared with traditional car rental industry, car-sharing programs rent vehicles in usual shorter rental time period by hours or actual driven miles. The design of these programs makes themselves very attractive to consumers who make occasional use or short time period use of vehicles. The car-sharing companies select some locations as their stations and deploy vehicles in specified stations for consumers' use. Consumers can make reservations online and pick up vehicles at the scheduled time and return the vehicle either the original station or other companies' permitted stations. Since programs are perfectly designed for short time period users, a reserved parking space, prepaid fuel and vehicles regular insurance are all included in the hourly rental fee. It helps consumers financially not to pay unused time and any other additional fees.

In recent years, along with recognizing positive contributions on environment and society, car-sharing has emerged as an important alternative as public transportation choices, the market of car-sharing expands extremely fast. Barth et al. (2002) depict all kinds of situations that could favor using car-sharing programs to save expenses, time etc. In 2002, Shaheen et al. (2013) reported there were about 16,000 members in North America; in terms of the recent report from Shaheen et al.(2020), Membership of car-sharing has grown exponentially to more than 2 million in the 2018. They reported the vehicles used in car-sharing programs in United States have grown from 696 in 2002 to 15,224 in 2018. And according to Navigant Consulting, the total global revenue for car-sharing industry reached $1 billion in 2013 and is expected to continue growing to $6.2 billion by 2020.

Besides financial help on consumers, car-sharing can also bring significant social benefits, such as reducing air pollution, emissions and traffic jams on the road. According to San Antonio government report (2011), each car-sharing vehicle can take 4.6~20 cars off the road on average a day. This brings a variety of benefits not only for users but also for all other stakeholders. For users, car-sharing reduces traffic on the road, it saves money and time to park shared vehicles in preserved spots instead of finding spaces for self-owned car. For other stakeholders, car-sharing reduces Carbon emission, and thus it is more friendly and sustainable to our environment. Due to the programs providing tremendous environmental and social benefits, Enoch et al. (2006) advocate governments should offer more incentives for car-sharing companies. In recent years, car-sharing has been encouraged by many governments' agencies. Several cities' government in Texas have collaborated with car sharing companies, such as Car2go, to encourage their employees to use car-sharing services as many as possible, they offer free street park on any city-owned street parking spots.

Research Motivation

Zipcar is a US based car-sharing company, and it is the largest car sharing and car club service in the world. It provides an alternative relative to car rental and personal car ownership. The members of Zipcar just need to pay a fixed amount monthly member fee and rental fee based on actual driving hours to Zipcar, everything else like gas, insurance would be included in the hourly rate. The most convenience for Zipcar members is that cars from Zipcar are usually just parked minutes away from some popular public facilities and high-density population area, like universities, hospitals, downtown, airports etc. So, Zipcar members can easily pick up cars in these popular spots and return them with guaranteed parking spots. This new business style has attracted over millions of members all over the world with more than 15,000 vehicles served in North America and some parts of Europe.

This study is motivated by regular operations from Zipcar. Besides vehicles purchasing and maintenance, in its regular business operations, Zip car primarily faces one major question - Capacity/Size decision: given a selected location, the company needs to make a strategy to decide how many vehicles are needed to be deployed in the station; and what would be the strategies for Zipcar to react imbalance situations of vehicles distribution if that is the case? Sending more vehicles or simply declining surplus demands are decisions that managers need to make. Although these two questions look similar to a traditional operations management issue: capacity issue, due to the uniqueness of car-sharing business, commonly used methodologies that address capacity issue cannot be directly employed in car-sharing business. Since locations of ZipCar stations were selected carefully, the company's regional managers need to deal station size/capacity and how to balance the number of vehicles at different locations when having skewed usage.

Research has been active in studying these problems. However, almost all of these studies fall into using optimization models to solve the problems. In general, optimization models can perfectly answer problems; however these models are difficult to be generalized and very question oriented. At the same time, validating models requires collecting significant amount data. In practice, not all car-sharing companies can have sufficient data that they could analyze, therefore a relatively simple and easy to be implemented model is needed, which may serve a better role to provide managerial suggestions and while keeping fewer inputs. Our research takes a few steps in proposing a brand new integral mathematical framework to address resource allocation and redistribution problems in car-sharing industry. We study these tradition problems from a new perspective and our models' settings are different with traditional optimization models. And through our computational study, we showed our models require less information.

Our contributions from this study are primarily as follows: 1). Compared with past models, since most of those models-built integer optimization models, simulations were often used to find optimal solutions for specific questions. Our model provides analytic results that can offer swift decisions on general car-sharing management issues; 2). Our model requires fewer data inputs; and through practical examples, our model predictions achieve expectations; 3). From methodology perspective, we employ differential equations from control theory to set up our models. To best our knowledge, this is the first paper using control theory solve car-sharing management issues. We hope the implications of control theory on car-sharing industry can help managers make better and quick decisions.

The paper organizes the remaining structure as follows. In next section, we will review the literature on all car-sharing business decisions from methodology perspective. Model section introduces the models on vehicle allocations and redistribution; after introducing each model, we solve the models and give solutions of each model. The next section uses Zipcar as an example to illustrate how our models work and what they mean to general car-sharing companies; then, last section summarizes results and business implications and gives future research directions.

LITERATURE REVIEW

Car-sharing business models include the round-trip, one-way and free-float(mobility) three types of rental contracts. Round-trip rental requires users return vehicles to original pick-up places; One-way allows users to return vehicles to any other permitted places; Free floats rental type just emerge recently, which doesn't have any fixed spots for users to pick up vehicles, vehicles could be parked in a certain range area within acceptable walkable distance; users are not required to return the vehicles to a specific station, it could return the vehicles any place in a legal parking area. The research on round-trip type rental is primarily focusing on exploring strategies of offering spatial and temporal customer flexibility to achieve better supply-demand alignment, like Strohle et al.(2019). The research on free-float is just emerging and presenting a promising research direction. The free float system has been studied recently. Weikl et al.(2012) developed two decision support systems(simulation) for user-based relocation strategy and operator-based relocation strategy separately. The most recent study on free float system is to use data analytics. Wagner et al. (2015) present a decision support system that derives indicators for the attractiveness of certain areas based on points of interest in their vicinity. Authors employ data mining techniques to develop the whole system and use real city of Berlin data to validate proposed model. Weikl et al.(2015) proposed a low computational optimization model to provide insights for free-float scenario. Currently most of work concentrates on one-way rental, and our research is also falling into this category.

As we state in the previous section, literature on one-way car-sharing mainly tackle one or multiple following problems: 1). What would be the size for one station? 2). How many vehicles should be transferred if vehicle imbalance exists among stations. Barth et al.(1999) use simulations to evaluate vehicles availability, vehicles distribution etc.. They suggest the most effective number of vehicles is about 3-6 vehicles per 100 trips in 24 hours and in order to minimize the number of vehicles relocation, they suggest having 18-24 vehicles per 100 trips. However in practice, having 18-24 vehicles in a few stations creates not only financial difficulty for car-sharing companies to purchase more vehicles, but also parking spots difficulty to find sufficient spaces accommodate all vehicles in high-density population regions.

The optimization models play a center role to address those managerial problems in recent years. Rickenburg et al. (2013) proposes a model to minimize the total costs including station set-up costs, vehicles purchasing costs and parking space costs. They use this optimization model to determine location and size problems for each location. The model was validated by actual data from a city in German. Correia and Antunes (2012) address the issues of number of vehicles of each station. They claim each station readjust the number of vehicles availability each day. The adjustment is on daily basis. The model was built from company's side to maximize profits for the company. However the model cannot handle imbalance situation if it occurs during the day. Similar to Correia and Antunes' work, Jorge et al. (2014) allow the company management dynamically rebalances vehicles at any time of a day. The model is mixed integer linear programming. Authors use simulation to search solutions.

Cepolina and Farina (2012) specifically study relocation problem and build an optimization model that minimize costs of the combination of consumers and companies, subject to the maximal consumers' waiting time. Authors use simulation to solve the model. Kek et al.(2006) build a simulation model together with real commercial data to provide a strategy to relocate imbalance vehicles. The model basically adopts shortest travel time strategy to transfer vehicles from vehicles over-accumulated stations to shortage stations. The shortest travel time is the time of company's staff travel from current places to over-accumulated station plus travel time from over-accumulated station to desired station. Kek et al. (2009) then build an optimization simulation model to revisit problems that they had addressed in 2006. In that study, they minimize shortage time of vehicles, parking space and as well as the number of relocations.

Fan et al. (2008) further construct an optimization model, which allows managers could adjust the number of vehicles on each station on daily basis. A stochastic programming model with simulation method is used to maximize profits for the whole car-sharing system. However, the model requires fleet size, the number of locations and the demand are known beforehand. Cheung et al.(1996) use dynamic program to determine how many vehicles should be assigned at each time periods. Fan et al. (2013) borrow the philosophy from Cheugn's paper and study car-sharing allocation strategy more dynamically, they divide the whole operating time horizon into several periods, operators need to check the status of each station at the end of each period to make decision if vehicles relocation is needed. They use stochastic program in multistage periods to find the strategy of allocating vehicles.

The more recent study on relocation includes Nair et al. (2011) and Shu et al.(2013). In Nair et al. (2011) study, the objective function is to minimize the total redistribution costs given other costs and demands are known. The novel of the proposed model is that authors use chance constraints to model possibilities of vehicles transitions between stations. Shu et al.(2013) develop a decision support system of bicycle in Singapore. They first use available data to estimate demands on daily basis; and then build a linear program to find the optimal number of bicycles should allocated to one particular station. They also build another model to find the highest utilization for all bicycles in order to decide how to redistribute imbalanced bicycles to fulfill the future expected demands. However, it needs to be mentioned that relocating bicycles is much easier than relocating vehicles. From all costs perspective, a bicycle-sharing system is much inexpensive than car-sharing system. Transferring bicycles wouldn't cost company too much; while transferring multiple vehicles at one time, costs are significant higher. The facts force the car-sharing company to make effective strategies even more important.

Smith et al. (2013) consider relocating costs consist of vehicles transfer costs and driver travels costs. They build a model that includes two linear programs to minimize the total costs.

Since vehicles relocation costs are very high if all relocation needs staff and operators supports. In order to reduce such costs for the car-sharing company, instead of traditional operator-based vehicle relocation, Barth et al. (2004) propose user-based vehicles relocation strategy: trip-sharing and trip-splitting. Authors claim that using these two strategies can reduce 40% costs for the car-sharing costs. Ait-Ouahmed et al.(2018) used linear programming model to provide insights by considering costs and quality of services. Wang et al. (2019) used an integer programing model to provide a vehicle relocation and staff rebalancing plans based probabilities.

The literature review revealed that almost all researchers tackle traditional car-sharing questions by using optimization models. Optimization models perform extremely well when questions are very specific, especially input data can be observed. The solutions of optimization models can be very specific and present exact suggestions on those operational issues. However, with such exact comments provided, the limitations are also very clear. A strict model usually lack of flexibility. The most of current research is very question oriented. The model might be extremely fit in one provided data/environments, but on the other hand it could be very difficult to be generalized to other cases; therefore for another situation, researchers need to build another models to find out managerial comments. Another limitation is optimization models used in this area have gradually become more sophisticated and complicated, it leads to simulation become the only tool that can offer meaningful results. While running simulation could be very time-consuming.

In our view, our model proposes a new way to estimate the station's capacity and reveals a new strategy how to decide if a car-sharing company should perform rebalance in a one-way rental. The model provides general policies that could be applied more car-sharing situations rather than constrained by only one or a few situations.

THE MODEL

Deployment and redistribution modeling

Estimating car station size and making vehicle redistribution policy are challenge questions for a management team, a mismatched policy/estimation would create significant loss to the company. Given regardless one-way rental or round-trip rental, redistribution or relocating vehicles would only occur if rental/demand rate is greater than return rate. On the reverse situation, that would be no issues, we consider composite demands, which equal to [Actual Demand – Returned Inflow Vehicles]. In the following discussion, the demand means composite demands rather than actual demand.

We observed that car-sharing companies provide 24*7 services; therefore, our intention is to employ continuous-time differential equations with stochastic replenishment interval to model the problems. For a given location (also called a car station), we can draw the expected demand of the vehicles and timely vehicles redistribution to satisfy the customers' needs. Particularly, we build a continuous-time deployment and redistribution model on a stochastic dynamic process to address the issues.

Model Description

We use the following notations and assumptions.

Notations:

t_s: The time from the highest vehicles inventory level to zero, it is between two vehicles relocations.

z: The time length determined by the car-sharing company to replenish one station. z is a random variable and has a property of independent identically distributed at any given two vehicles' relocations, its value range is in $[z_1, z_2]$. $[z_1, z_2]$ is determined by the car-sharing company, that gives minimal and maximal time breaks of one car relocation, respectively.

r: Basic demand in unit time, $r ³ 0$. We assume the basic demand for a station is greater than zero. We assume basic demand as regular average demand for a station.

$D(t)$: Composite demand at a station at time t ,which is the actual demand minus returned inflow. $D(t)$ has the following form:

$$D(t) = \begin{cases} r + \alpha I(t), & I(t) \geq 0 \\ r, & I(t) < 0 \end{cases}$$

$I(t)$: Vehicles inventory level in a certain business station at time t .

α: Inventory level coefficient, average percentage of customers who are willing to wait for next available cars when customers saw the inventory of the station. $0 \leq \alpha \leq 1$

$DS(t)$: Deferred supply rate. When demand is greater than inventory, the car-sharing company can redistribute according vehicles to satisfy consumer's needs. This late supply is depicted by this parameter.

β: Coefficient of supply shortage influences deferred supply rate, $0 \le \beta \le 1$.

$S(t)$: Vehicle demand when shortage occurs at time t.

T: The length of the relocation cycle.

Assumptions:

$DS(t)$: Shortages could occur. When the number of vehicles in one station is in short supply, deferred supply rate associated with the actual supply shortage. The larger the actual shortage of vehicles, the lower deferred supply rate, because consumers would not make reservations if they saw a long queue. Hence, suppose that the deferred supply rate associated with the supply shortage, then

$$DS(t) = r - \beta S(t), \qquad t_s \le t \le T$$

where T is the time of next vehicles redistributed to the station.

$\bar{Q}$: when shortage occurs, the replenishment (Redistribution) policy of every cycle is to replenish to the initial inventory for the station.

Model Establishment

The relationship between company determining replenishment time z and station vehicle inventory depleting time t_s is: When Z is less than t_s, there will be no shortage in the station; when Z is greater than t_s, shortage will occur in the station in some degree of probability.

Based on the notations made in section 3.2.1, the change of vehicle inventory is affected by the demand that is defined in section 3.2.1, that is:

$$\Delta I(t) = \begin{cases} -r - \alpha I(t), & 0 \le t \le t_s \\ -r, & t_s \le t \le T \end{cases}$$

We rewrite the above notation as differential format: that is inventory level $I(t)$ with respect to time t can be described by the following differential equation:

$$\frac{dI(t)}{dt} = \begin{cases} -r - \alpha I(t), & 0 \le t \le t_s \\ -r, & t_s \le t \le T \end{cases} \tag{15}$$

From $I(t_s) = 0$, we have

$$I(t) = \begin{cases} \frac{r}{\alpha}(e^{\alpha(t_s - t)} - 1), & 0 \le t \le t_s \\ r(t_s - t), & t_s \le t \le T \end{cases} \tag{16}$$

$$I(0) = \frac{r}{\alpha}(e^{\alpha t_s} - 1) \tag{17}$$

(i). Expected inventory in per cycle:

$$\begin{aligned} \bar{I} &= \int_{z_1}^{t_s}\int_0^{z} \frac{r}{\alpha}(e^{\alpha(t_s-t)} - 1) f(z)dtdz + \int_{t_s}^{z_2}\int_0^{t_s} \frac{r}{\alpha}(e^{\alpha(t_s-t)} - 1) f(z)dtdz \\ &= \int_{z_1}^{t_s}\left[\frac{r(e^{\alpha t_s} - e^{\alpha(t_s - z)})}{\alpha^2} - \frac{rz}{\alpha}\right] f(z)dz + \int_{t_s}^{z_2}\left[\frac{r(e^{\alpha t_s} - 1)}{\alpha^2} - \frac{rt_s}{\alpha}\right] f(z)dz \end{aligned} \tag{18}$$

Eq. (18) represents the expected vehicles' inventory in per cycle, where the first term represents the expected inventory when shortage does not occur; the second term represents the expected inventory when shortage occurs.

(ii). Expected deferred supply and lease loss in per cycle

When shortage occurs, there is a linear relationship between deferred supply rate and shortage, thus, $S(t)$ satisfies the following equation:

$$\begin{cases} \frac{dS(t)}{dt} = r - \beta S(t), \quad t_s \le t \le T \\ S(t_s) = 0. \end{cases} \tag{19}$$

The solution of Eq. (19) is

$$S(t) = \frac{r}{\beta}(1 - e^{\beta(t_s - t)}), \quad t_s \le t \le T \tag{20}$$

Since the total expected shortage in one cycle is the sum of expected deferred supply and expected lease capacity, while the expected deferred supply of each cycle is

$$\bar{B} = \int_{t_s}^{z_2} S(z) f(z) dz = \int_{t_s}^{z_2} \frac{r}{\beta}(1 - e^{\beta(t_s - z)}) f(z) dz \tag{21}$$

Thus, the expected lease loss of each cycle is

$$\bar{L} = \int_{t_s}^{z_2} r(z - t_s) f(z) dz - \int_{t_s}^{z_2} S(z) f(z) dz = \int_{t_s}^{z_2} [r(z - t_s) - \frac{r}{\beta}(1 - e^{\beta(t_s - z)})] f(z) dz \tag{22}$$

In Eq. (22), the first term represents the total expected shortage when vehicles are out of stock; the second term represents the expected deferred supply when vehicles are out of stock.
(iii). Expected replenishment in per cycle
Since the replenishment policy of every cycle is to relocate vehicles to initial numbers of the station, thus, the expected relocation in one cycle is the sum of expected lease capacity and expected deferred supply, that is

$$\begin{aligned} \bar{Q} &= \int_{z_1}^{t_s} [I(0) - I(z)] f(z) dz + \int_{t_s}^{z_2} [I(0) + S(z)] f(z) dz \\ &= \int_{z_1}^{t_s} \frac{r(e^{\alpha t_s} - e^{\alpha(t_s - z)})}{\alpha} f(z) dz + \int_{t_s}^{z_2} [\frac{r(e^{\alpha t_s} - 1)}{\alpha} + \frac{r}{\beta}(1 - e^{\beta(t_s - z)})] f(z) dz \end{aligned} \tag{23}$$

Model Solving

By using above analysis, more specifically, using Eq. (15) to Eq. (23) can answer the questions of station size and policies of vehicles' relocation. We use following statement to show how to address these questions:
Since t_s is the total time from the highest inventory level drop to zero, use our assumptions can lead to the following equation:

$$D(t) = \bar{Q} \tag{24}$$

That is

$$r + \alpha I(t) = \bar{Q} \tag{25}$$

Using the substitution of $I(t)$ and $\bar{Q}$, Eq. (25) becomes

$$re^{\alpha t_s} = \frac{r}{\alpha}\int_{z_1}^{t_s} (e^{\alpha t_s} - e^{\alpha(t_s - z)}) f(z) dz + \frac{r}{\alpha}\int_{t_s}^{z_2} (e^{\alpha t_s} - 1) f(z) dz + \frac{r}{\beta}\int_{t_s}^{z_2} (1 - e^{\beta(t_s - z)}) f(z) dz \tag{26}$$

Then, we have

$$e^{\alpha t_s} = \int_{z_1}^{t_s} \frac{e^{\alpha t_s} - e^{\alpha(t_s - z)}}{\alpha} f(z) dz + \int_{t_s}^{z_2} [\frac{e^{\alpha t_s} - 1}{\alpha} + \frac{1}{\beta}(1 - e^{\beta(t_s - z)})] f(z) dz \tag{27}$$

Let $\Phi = \int_{z_1}^{t_s} \frac{e^{\alpha t_s} - e^{\alpha(t_s - z)}}{\alpha} f(z) dz$, $\Psi = \int_{t_s}^{z_2} [\frac{e^{\alpha t_s} - 1}{\alpha} + \frac{1}{\beta}(1 - e^{\beta(t_s - z)})] f(z) dz$ then, we can obtain

$$t_s = \ln(\Phi + \Psi)^{\alpha} \tag{28}$$

Theorem (Existence and Uniqueness). Suppose $Z = [z_1, z_2]$ is the time break between two continuous replenishments, $\forall t \in [z_1, z_2]$ is a random variable and satisfies independent identically distributed. Then, there must exist a unique time point $t_s \in [z_1, z_2]$ such that $I(t_s) = 0$.

Proof: We first prove the existence of t_s.
If t_s is the total time from the highest inventory level to zero, then $I(t_s) = 0, \ (z_1 \le t_s \le z_2)$, we prove the problem according to the following different circumstance:
(i) When $t_s = z_1$, $I(z_1) = D$, represents the expected inventory in per cycle of a certain business station.

(ii) When $t_s = z_2$, $I(z_2) = \bar{Q}$, represents the upper limit of replenishment in per cycle of a certain business station. From the assumptions, we know the replenishment policy is

$$D(t) = \bar{Q} \tag{29}$$

That is,

$$I(z_1) = I(z_2) \tag{30}$$

From Eq. (15) and Eq. (18), we have that the vehicle inventory function $I(t),\ t \in [z_1, z_2]$ is continuous on interval $[z_1, z_2]$ and differentiable on interval (z_1, z_2), from Eq. (30), we have $I(z_1) = I(z_2)$. According to Rolle's Mean Value Theorem (Stewart, 2009), there is at least one point ξ in (z_1, z_2) where $I'(\xi) = 0$. Let $t_s = \xi$, then, the existence of t_s is proved.

Next, we prove the uniqueness of t_s.

Since the running process of each lease and replenishment cycle almost identical. Thus, only one lease and replenishment cycle were discussed in this paper. From the assumptions, we know that as time point of replenishment, t_s will appear only once in one lease and replenishment cycle, in the rest time of this cycle, the replenishment will be gradually increased to the expected inventory, at this moment, a new lease and replenishment cycle was beginning. The uniqueness of t_s is proved.

This completes the proof.

Substitute t_s into Eq. (17) and Eq. (20), the problem of product deployment and redistribution proposed in section 3.2 can be effectively solved.

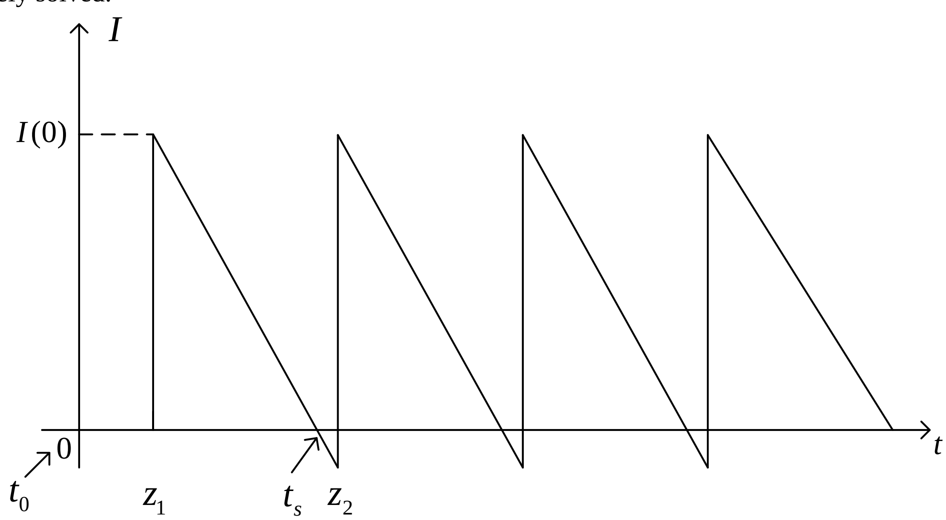


Fig. 2 Variation of inventory over time

APPLICATIONS AND CONCLUSIONS

An application with numerical example:

As we know, a Car-sharing company can only allocate limited number of vehicles to a station; thus, it is impossible to meet all the demands from consumers for every moment. Therefore, it is a challenge for a car-sharing company to face how a station can provide better user experiences with limited vehicle recourses. In this section, we conduct a numerical study to illustrate how to use our previous developed model handle this question.

By following the model, we first need to obtain an estimation of parameter α (Parameter α expresses the continued ramifications of Inventory level/shortage statement on customer car rental behavior). Because customers' car rental behavior is constantly changing, so to better understand the customers' need, a survey was suggested. We conducted a randomized trial to address this question. Details of randomized trial are as follows:

C1: Survey time. Choose a random 10 days as experiments time window (9:00am-3:00pm); Choosing 10-days is to make sure weekend is covered.

C2: Survey place. Zipcar station in the York College of Pennsylvania (YCP);

C3: Survey environment. After the first occurrence of vehicle shortage in the station;

C4: Survey respondent. The first five customers when the first shortage occurred every survey time;

C5. Survey method. Within vehicle replenishment period or rented vehicle return period, no people leaves the station means the influence ratio of shortage on rental behavior is 0 ($\alpha = 1$); one out of five customer leaves The station means the influence ratio of shortage on rental behavior is 20% ($\alpha = 0.8$); two out of five customer leaves The station means the influence ratio of shortage on rental behavior is 40% ($\alpha = 0.6$); three out of five customer leaves The station means the influence ratio of shortage on rental behavior is 60% ($\alpha = 0.4$); four out of five customer leaves The station means the influence ratio of shortage on rental behavior is 80% ($\alpha = 0.2$); all five customers leave The station means the influence ratio of shortage on rental behavior is 100% ($\alpha = 0$).

C6: Survey conclusion. At the end of ten days survey, we obtained the survey data of vehicle shortage on customer rental behavior. And then we calculate results of influence ratio α , detailed results are shown in following table.

Alpha α	0	.2	.4	.6	.8	1
# of Days	4	4	1	1	0	0

Remark1: We may have observed that Zipcar company does not place more than 5 vehicles in one business station, so, this paper limits the number of survey respondent within 5 people.

Remark2: The average vehicle replenishment period should be less than or equal to the time walk to the nearest Zipcar station.

From above Table, we found that different situation (how many customers leave for how many days within the survey period in YCP college station, in the Table, we have 6 different values of α shown in the last column) leads different result of parameter α , each result represents an attitude of customer in using Zipcar service in the station and could not be ignored. Therefore, we use weighted average value of the 6 different α as the final result. The calculate process is

$$\alpha = \frac{4}{10}\times 0 + \frac{4}{10}\times\frac{1}{5} + \frac{1}{10}\times\frac{2}{5} + \frac{1}{10}\times\frac{3}{5} + 0\times\frac{4}{5} + 0\times\frac{5}{5} = 0.18 .$$

For parameter β and time interval $[z_1, z_2]$, as these two parameters can be controlled and counted by the company itself, so, let's assume we set the parameter: $\beta = 0.65, \quad Z = [1, 3.5]$.

Plug $\alpha = 0.18, \beta = 0.65$ and time interval $Z = [1, 3.5]$ (hour) into Eq. (27), we have

$$e^{0.18t_s} = \int_1^{t_s} \frac{e^{0.18t_s} - e^{0.18(t_s - z)}}{0.18} f(z)dz + \int_{t_s}^{3.5} [\frac{e^{0.18t_s} - 1}{0.18} + \frac{1}{0.65}(1 - e^{0.65(t_s - z)})] f(z)dz \tag{34}$$

By solving Eq. (34), we can obtain $t_s = 2.39$.

Plug t_s into Eq. (17), we can obtain initial inventory, which is also the expected replenishment inventory in each cycle.

$$I(0) = \frac{1}{0.18}(e^{0.18\times 2.39} - 1) = [2.98] = 3 \tag{35}$$

From Eq. (35), we can address the deployment and redistribution problem for such a station, the final calculate results show the car-sharing company should deploy no less than 3 vehicles in the surveyed station and every 2.39 hours the Company should make a replenishment to make the number of rental vehicles run up to the initial inventory with offering one-way rental business.

CONCLUSION AND FUTURE WORK

The Car-Sharing industry has grown rapidly in past decades. The popularity of car-sharing programs not only help consumers financially, but also create tremendous social benefits for the public and environment. As a fast-growing business, companies constantly seek business to expand strategies and react to growing demands from public. In this paper, the author developed a novel model to help car-sharing companies make decisions on station capacity/size and vehicles relocation. Inventory philosophy was used to build a model to estimate a station's capacity and the number of vehicles that need to relocate if a sudden demand were to occur. Our new models can be generalized and easily implemented; our models offer suggestions to managers and while require much less inputs, which could reduce companies' significant costs.

The limitation in our paper is that we do not consider availability of parking spots. We assumed transferred vehicles would have guaranteed parking spots which is not a general case in practice. Future research in car-sharing studies could be extended in two directions: Study vehicle relocation problems between regions under the complete free-float scenario, which is more expensive and costly; and new strategies may need to be addressed in this situation – perhaps without free-float. In addition, the car-sharing industry is very promising. But there are over 90 programs running in the US, and competition cannot be avoided in some big cities. However, it would be interesting to see how decisions would be changed if competition would be considered.

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A HOLISTIC SYSTEM-BASED VIEW ON THE EVOLUTION OF RESOURCES

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ABSTRACT

In areas of management and marketing, the resource-based theory has been becoming increasingly important in recent years due to its ability to explain various situations and developments. To make this work theoretically reliable, this paper advances this resource-based theory based on a few starting assumptions by employing the thinking logic of systems science while all other conclusions are derived from these assumptions. Because of such the approach applied here, all conclusions established in this paper represent definite results on various evolutional aspects of resources. In particular, this work looks at the exploitation and exploration of resources; technological opportunism, innovativeness, and performance of firms; improvement, association, and deterioration of resources; and when a firm will not be able to mobilize consistently its available resources. Because conclusions established herein are derived through using logical reasoning based on a few generally true assumptions, their reliability for practical use is not disturbed by the constraints and uncertainties of data analysis, leading to the expectation of universal applicability in practice unless one of the starting assumptions is violated.

INTRODUCTION

In the business world, decisions are made routinely, while some decisions tend to determine the future of firms. Because decisions that determine the fortune of firms tend to involve the prediction of the future, there is a parallelism between such decision-making and prediction of the future. For the latter case, however, scholars have practically tried throughout the history different theories of mathematics and science without much luck in terms of prediction accuracy and reliability (Lin & OuYang, 2010). That explains why in the past nearly twenty years business scholars have been looking at the concept of resources with increasing interest and intensity. They hope that by employing resources decision makers are able to improve their firms' performance and to develop their firms' competitive advantages (Kozlenkova, et al., 2014; Crook, et al., 2008). By summarizing and generalizing anecdotes, scholars have collected some thought-provoking discoveries, although scientifically speaking the general usability of the conclusions drawn on these anecdote-based discoveries is constrained by uncertainties inherently existing in data collection and analysis. That is why business decisions that involve any amount of prediction of the future seem to be unreliable (Lin & OuYang, 2010).

Since the time when Penrose (1959) initially identifies the importance of organizational resources to a firm's success, the literature has been expecting that the resource-based theory might be practically useful in making managerial decisions. By continuing this expectation, this work develops a scientifically sound, cohesive theory of resources for firms based on what has been empirically established in the past decades while avoiding all uncertainties and constraints inherently existing in the collection and analysis of anecdotes and data. We develop such a general theory by using a holistic system-based logic and methodology. Because of the particular approach employed, all conclusions established herein are expected to be generally true and can be practically employed to make generally useful recommendations.

Other than using systems (Lin, 1999) as the thinking logic, this paper employs the yoyo model (Lin, 2009) as the intuition to visualize how organizations evolve and how they interact with each other. On top of such methodology, this work establishes the following general conclusions, among others, on when a firm is likely to possess sustainable competitive advantages, how a firm can avoid paradoxical situations as that of capability-rigidity, what essential factors can improve performance, how relational resources affect a firm's innovativeness, how interactive resources can produce undesirable effects, when and how a capability will evolve and/or cease to endure, how a firm will fail to exploit consistently its available resources, among others.

The rest of this paper is organized as follows: Section 2 reviews literature and explains this work's contributions. Section 3 introduces the relevant basics of systems science in order to make this presentation self-contained. After outlining the fundamental properties of resources in Section 4, Section 5 looks at the exploitation and exploration of competitive advantages. Some issues of technological opportunism and innovativeness of firms are addressed in Section 6; and interactions of resources are looked at in Section 7. Then the development/decay of resources and conditions under which a firm will fail to exploit its resources are investigated respectively in Sections 8 and 9. This presentation concludes in Section 10.

THE RELEVANT LITERATURE

More than half a century ago, Penrose (1959) shows the importance of organizational resources in the success of firms. Then the presently well-known resource-based view of the firm emerges in the 1980s (Porter, 1979; Wernerfelt, 1984). Many scholars since then demonstrate the importance and usefulness of the concept of resources and the resultant resource-based theory (e.g., Barney, et al., 2011; Crook, et al., 2008; Kozlenkova, et al., 2014; Slotegraaf, et al., 2003; Vorhies & Morgan, 2005). The concept offers a framework for explaining resources' synergistic, differential effects on firms' performance and the associated contingencies through combining multiple, dissimilar resources (Fang, et al., 2011). That happens to be parallel to the experience of systems science and methodology, laying the background for us to think about using systems science and methodology to develop the desired general theory of resources for the purpose of making generally reliable recommendations.

Regarding the literature of competitive advantages, by considering associations between 'organizational learning and relational capabilities' and 'organizational product innovation and quality', Lages et al (2009) reveal that capability of learning advances the innovation of products, that relational capability expands products' quality and innovation, and that relationship capabilities expand firms' performance. By looking at how advantages and resources intermingle with one and another, Kaleka (2011) maintains that service advantage helps increase export ventures' performance, capabilities of product development and customer relationship augment service advantage, customer relationship and capabilities of learning enrich experiential resources, while product development and capabilities of learning are improved by financial resources. Empirically, Vorhies and Morgan (2005) provide evidence for benchmarking marketing capabilities to boost capabilities of development and implementation of sustainable competitive advantages. In terms of creating competitive advantages, Jap (2001) suggests that bilateral idiosyncratic investments help, and that ex-post opportunism erodes existing competitive advantages, although idiosyncratic investments, goal congruence, and interpersonal trust can lessen this negative effect. Regarding the evaluation and (re-)development of strategic initiatives that provide operational capabilities for new sources of competitive advantage at the firm-level, Liu and Liang (2015) employ the resource-based view in their study of practical intersections of operations management and strategy. They advance an approach for integrating factors that resolve the performance of operational competitiveness, supported by a case analysis.

For the relevant literature of firm performance, Lonial and Carter (2015) maintain that market, entrepreneurial, and learning orientations, seen as capabilities of small and medium-sized enterprises, can respectively improve a firm's performance, although their individual potentials need to be viewed in concert. Considering the development and improvement of unique products, Ramaswami et al (2009) suggest that the strongest impact on firm performance comes from customer management. For Ruiz-Ortega and García-Villaverde (2008), they discover empirically that although all capabilities improve a pioneering firm's performance, marketing capabilities do so the most; management and technical capabilities help improve early following firm's performance; and technical and marketing capabilities do so for late following firms. By examining firms' processes, comprised of market knowledge competence, Li and Calantone (1998) believe that such processes help increase advantages of new products, which in turn expand the products' market performance. It is recognized (Slotegraaf & Dickson, 2004) that the capability of marketing planning exerts a curvilinear effect on firm performance, and (Zou, et al., 2003) that export-marketing capabilities influence an export venture's performance through low-cost and positional advantages of brands, new products' development, distribution and communication advance an export venture's positional advantage and consequently its financial performance.

For the literature on resources and market deployment, it is empirically found (Slotegraaf et al, 2003) that marketing and technological resources, although they might be intangible, are positively correlated to the effectiveness of market deployment (e.g., distribution and coupon activity), and that financial resources are negatively correlated to the deployment. Investing strategies of marketing differentiation is found (Hughes et al, 2010) to produce indispensable strategic incentives to form innovation ambidexterity, leading to both marketing differentiation and cost leadership advantages and consequent improvement in the performance of export venture. Regarding the alteration between advantages and disadvantages, pioneering firms are found (Boulding & Christen, 2003) to enjoy a profit advantage for about 12 – 14 years; after that time frame early entry becomes a profit disadvantage compared to later entrants. Atuahene-Gima (2005) validates empirically the intuition that market orientation endows the exploitation of established innovation competencies and the exploration of new competencies. Luo et al. (2004) maintain that interactions with customers and the social capital of business partners improve sales growth and return on investment with customer relationship being an important driver behind performance. On the other hand, although governing-agency social capital helps sales growth, it does not improve return on investment. Tomer (2003) finds that social capital increases with economic income, while Wright at el (2009) and Baron and Markman (2003) realize that when possessing stronger human capital and broader social networks, entrepreneurs are effective networkers. Additionally, it is found (Aldrich & Zimmer, 1986) that entrepreneurs could broaden their scope of opportunities through social ties and social network diversity, where connectedness helps increase information exchange and availability of resources.

Through analyzing factors that affect B2B partnerships, Richey et al (2010) realize that there are resource complementarities for data storage resources (but not for communication or customization resources). By studying how capabilities affect and complement revenue and margin growth, Morgan et al (2009) show that the capability of customer management improves margin growth while reduces the rate of revenue growth. Because dynamic capabilities are not always adequate for handling organizational and strategic problems, Ritalam et al (2016) provide theory-driven propositions to illustrate their study on when dynamic capabilities might fail while presenting their ad hoc problem-finding and problem-solving perspective. To understand how company size is associated with the effectiveness on firm performance of investments in the capabilities of marketing and innovation, Jeng and Pak (2016) empirically find that for small firms, such investments diminish their effects on performance; for medium-size firms, the effects are mixed; and for large firms, they prosper.

Chadwick et al (2015) look at the consequences of CEO's resource orchestration by using commitment-based human resource systems, a type of strategic resource. These scholars empirically find that CEO's stress on strategic human-resource management represents a significant factor on firm performance. Zona et al (2016) suggest that interlocking directorates may exert either a positive or a negative effect on firm performance, depending on the firm's available resources, imbalance of power, ownership concentration, and CEO ownership. It is proposed by (Arifin & Frmanzah, 2015) that technology adoption is a functional capability that mediates the relationship between dynamic capabilities and firm's performance. Covin et al (2016) look at 1671 firms from four countries in order to find out what drivers of innovativeness could be common to family and non-family firms. They propose six configurations of behavioral proclivities and resources that precede the appearance of radical innovativeness. In terms of the relationship between business contacts and innovativeness in women-owned firms, Fuentes-Fuentes et al (2017) use a sample of women entrepreneurs in Spain to show that close contacts with managers/entrepreneurs in different industries and customers play an important role in the innovativeness in women-owned firms. Dynamic capabilities are found (Bernardo et al, 2017) to contribute to the knowledge of business process management, to promote adaptation to the environment through assisting organizational change and to boost the performance of business process management.

Compared to the relevant literatures, as reviewed above, this work establishes a series of theoretical conclusions, from which general recommendations can be derived for managers and entrepreneurs with reliability and certainty. In other words, because of the use of the thinking logic and methodology of systems science, all conclusions established in this paper are not constrained by data and relevant uncertainties. More specifically, among others this work establishes the following main results:

- Assume that a resource is simultaneously valuable and rare. If a firm is able to exploit the resource, then the firm will be able to develop a sustainable competitive advantage by making use of the resource;
- Under the same assumption as above, if the managers and shareholders share the same interests, then the particular resource will result in a sustainable competitive advantage for the firm that controls the resource;
- The so-called capability-rigidity paradox does not exist for any firm that is market oriented and is able to act accordingly. In other words, market orientation and capability to take respective actions help a firm sustain its competitive advantage, which in turn improves the firm's performance; and
- Interactions between resources that respectively lead to the realization of two opposing business goals A and B tend to produce undesirable consequences.

In summary, other than developing widely applicable conclusions in real life, the main contribution of this paper to the literature is the introduction of systems logic and methodology into the study of various management and marketing issues.

RELEVANT BASICS OF SYSTEMS SCIENCE

To help the reader follow the threads of reasoning in the rest of this paper, this section summarizes the relevant key concepts of systems science and the yoyo model of the general system.

By a system, it means a set of things and such information as to how the things are associated with each so that the totality can be seen as a whole. Here, the set of things becomes a system only because of the specified association(s) or relation(s). When no association or relation between the things exists, the collection of isolated things is known as a trivial system (Lin, 1999). From this definition, we see systems everywhere, especially in investigations of economic issues and business decision-making. For instance, each person is a (biological) system with clear inputs and outputs, known as an input-output system. At the same time, the person is a member of many large-scale systems, such as a family, neighborhoods, a business firm, etc. Other than being a member of different systems, the person also interacts with various systems, e.g., a bank, an electronic device, a retail store, etc. The existence of such individuals makes us feel that systems actually interact with each other constantly.

This concept of systems, or that of implied wholeness, implies that when we study business and economic issues, where organizations are more or less involved, the system-based concepts and methodology are more appropriate than number-based ones, although the literature is mostly developed by employing the latter. Additionally, because system-based approaches are fundamentally different of number-based ones, one can expect that resultant conclusions produced out of such holistic way of thinking would be more reliable when applied to make general recommendations for the purpose of business decision-making.

Historically, theories of systems, either specific or general, can be traced back to the very beginning of human history with the concept of systems introduced in different disciplines in time-specific terms. Even so, the presently known systems science, as an organized systematic investigation of various kinds of systems, has only been widely studied and applied in the past ninety some years. Disproportional to its age, the importance of systems science has been recognized. For example, in economics Rostow (1960) marks that:

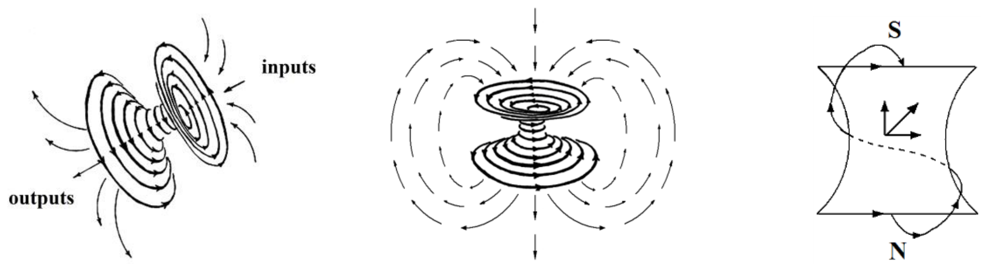
> The classical theory of production is formulated under essentially static assumptions … to merge classical production theory with Keynesian income analysis … introduced the dynamic variables: population, technology, entrepreneurship, etc. But … do so in forms so rigid and general that their models cannot grip the essential phenomena of growth … We require a dynamic theory … which isolates not only the distribution of income between consumption, savings, and investment (and the balance of production between consumers and capital goods) but which focuses directly and in some detail on the composition of investment and on developments within particular sectors of the economy.

In biology von Bertalanffy (1924) points out that "because the fundamental character of living things is their organization, the customary investigation of individual parts and processes cannot provide a complete explanation of the phenomenon of life." Other than these two scholars, many others (e.g., Porter, 1985; Klir, 1985; Lin, 2009) also demonstrate the power of holistic thinking and relevant methodology from different angles when organization is the center of focus. In particular, business entities, economies, and markets, be they whatever kinds and scales, are not only systems but also interacting ones. Hence, these economic beings and their interactions need to be investigated by using the concepts and methodology of systems beyond those of numbers in order to produce practically usable conclusions.

To understand the main difference between numbers and systems, let us look at the origin of these two concepts. Although both numbers and systems come from the physical world, they are intellectualized differently. Specifically, when an organization is seen as a collection of unrelated parts, numbers appear, such as n employees, m dollars invested, etc. When an economic entity is investigated in this way or by using number-based approaches, the entity is in reality divided into unrelated parts, naively hoping that these isolated parts will eventually become whole automatically. So, to understand appropriately how an economic entity evolves and how it grows along with others, we have to look at the entity as a whole, consisting of component parts and their relevant associations. In other words, when an economic being is seen as an organization, systems appear with such elements as employees, capitals, properties, etc., making up the organic totality through relationships (or associations). In fact, when relationships are absent, no economic entity exists. That is, business studies are mainly about organizations and relationships (or systems), be they individual firms of varying scales, markets of whatever kinds, industries of diverse magnitudes, or economies from disparate geographical areas.

The main differences between numbers and systems can be summarized as follows: the former is a local concept, while latter an organizational, structural concept (Lin, 1988; 1999); and the former emerges only post event, while the latter at the same time when the underlying physical or intellectual existence comes into being (Lin, 2009). That illustrates why systems theory is more appropriate than any theory developed on numbers and numerical variables for the investigation of economic entities and events when the underlying internal structures cannot be ignored. That is also the reason why the Wall Street still cannot make advanced predictions for the imminent arrival of economic disasters (Lin & OuYang, 2010).

By systems science, it means the totality of all studies of systems of the past 90 some years (Klir 2001). In this science, dynamic intuitions of systems can be well imagined by using the systemic yoyo model (Lin, 2007), Figure 1. The situation is similar to how the Cartesian coordinate system, consisting of several number lines crossing each other, has been playing its role in the development of the traditional science (Kline, 1972).



(a) (b) (c)

Figure 1. (a) Eddy motion model of the general system; (b) The meridian field of the yoyo model; (c) The typical trajectory of how matters return

The blown-up theory (Wu & Lin, 2002) – a theory of general development and evolution – and discussions on whether or not the natural world can be seen as an ocean of systems (Lin, 1988; Lin, et al., 1990) jointly imply the multi-dimensional model in Figure 1. In this model, such concepts as inputs, outputs, and converging and diverging spinning (or eddy) motions are joined together to describe figuratively the underlying systemic structure of each object and every system imaginable. In other words, each system can be intuitively fathomed as a multi-dimensional entity that 'spins' about its 'axis'. When imagining such a spinning entity in our 3-dimensional living space, we have such a structure as artistically shown in Figure 1(a). All inputs go into one side. After funneling through the 'neck', outputs are given off from the other side. Some of outputs never return to the input side and some will (Figure 1(b)). Because of its shape in our 3-dimensional space, this structure is known as a (systemic) yoyo or yoyo model of the general system.

To be able to apply this model in our analysis of organizations, let us pay a close attention to what this model says: each physical or intellectual entity (seen as a system) in the universe, be it a tangible or intangible thing, a living being, an organization, a market, an economy, etc., can be intuitively seen as a realization of a multi-dimensional spinning yoyo. It spins as depicted in Figure 1(a). Only with spinning motion, it represents an identifiable system. Figure 1(c) shows how the eddy field, which spins perpendicularly to the axis of spin, of the model, and the meridian field, which rotates parallel to axis of spin, interact with each other. That is, all things that are either new to the yoyo body or returning to the input side travel along a spiral trajectory.

As a matter of fact, scholars have already recognized such multiple-inputs and multiple-outputs structure of systems. For example, Swift (2013, p. 114) describes the consequence of human endeavor as follows: "The successful outcome of entrepreneurship or of any human endeavor is a complex activity with multiple inputs potentially relevant to the outcomes."

ESSENTIAL PROPERTIES OF RESOURCES

By resource, it means an asset, either tangible or not (Harmancioglu, et al., 2009), the controlling firm can exploit in order to gain competitive advantages over competing rivals by implementing its strategies (Barney & Arikan, 2001). Speaking differently, a resource, be it physical, financial, intellectual, or organizational, is such a thing that can be utilized by its controlling firm to accomplish its business goals. Hence, in terms of firms, resources, and the ownerships of resources we have the following three assumptions.

Assumption 1 (Resource Heterogeneity): No matter which industry a firm belongs to, it occupies its unique system of resources.

This assumption implies that when 2 arbitrarily chosen firms are compared, they possess their respectively different systems of resources, even if they operate within the same industry. The truthfulness of this assumption is quite intuitively straightforward. In fact, each existing business firm is naturally an input-output system with its unique supplies and offers. So, we can imagine the firm as a spinning yoyo field (Lin, 2009). This system consists of people, equipment, capital assets, etc., as its hard component parts, organized organically into an operational whole in a specific way. It is because of the organizational relationships between these component parts that the firm comes into being and is recognized as a business entity. This systemic modeling explains why any two firms can easily separate from each other by their individually different systems of resources. For example, most definitely, the firms have different sets of employees or different sets of missions. In particular, different employees naturally lead to different levels of capabilities – a form of resources. And aiming at materializing different sets of missions, the employees will behave differently.

We formulate this assumption of resource heterogeneity based on (Peteraf & Barney 2003). The assumption emphasizes on the system-ness of the resources a firm controls, because in reality firms are able to offer their products only by jointly mobilizing various resources. More specifically, two firms' systems of their respectively available resources can be different in two ways: available resources are different or although available resources are the same, the ways they work together are different. Hence, this assumption implicitly means that firms are different in their abilities of carrying out activities and accomplishing goals due to their unique systemic setups of available resources. In this regard, other than the fact that respective sets of resources could be different, what really separates firms one from another is how the available resources are particularly joined to accomplish business goals. In other words, firms naturally possess their individually different strengths and weaknesses.

Assumption 2 (Resource Immobility): As a consequence of the practical difficulty of trading resources and their associations across firms, differences in the system-ness of firms' available resources endure over time.

In fact, from the systemic logic of reasoning of Assumption 1, it follows that for any two firms, their structural aggregates, including available resources, will be different. This assumption of resource immobility represents a further development of the work by Barney and Hesterly (2012). It explains the reason why firms are different even along the dimension of time. For instance, firms generally possess obstinately different systems of resources, where the difference can be that in the sets of available resources or in how different firms are able to associate their resources in their respectively different ways.

Assumption 3 (Different Levels of Efficiency): Firms' performances are different from one firm to another because firms possess different sets of resources that are related to each other in firm-specific ways, and because firms have different efficiencies of utilizing their resources.

To see the truthfulness of this assumption, let us model the performance of each firm of concern as a spinning motion with the overall being of the firm as an abstract yoyo body. Then, for any chosen set of firms, the characteristics of the spinning motion, such as spinning direction, strength, density, etc., of the yoyo fields of these firms are naturally different from each other. This end illustrates why firms have their intrinsically different levels of efficiency in terms of how to mobilize their available resources.

This assumption of different levels of efficiency is theoretically formulated based on the work of Peteraf and Barney (2003). It reflects the real-life fact that firms deploy their individually available resources in strategically different ways. The strategic differences lead naturally to different levels of efficiency.

The statement that a firm has a competitive advantage means that the firm implements a specific strategy or follows a particular routine of operation, production, and/or management so that the firm is able to generate more economic value than other firms that do not employ the strategy and/or routine (Peteraf & Barney, 2003). When a firm possesses a competitive advantage, the firm generally has innovatively introduced a way to organize its resources. If other firms in the marketplace cannot replicate the remunerations of this strategy, then we say that this particular competitive advantage is sustained (Barney & Clark 2007). And if the advantages of the strategy are maintained into the future, then we say that the advantage is sustainable (McGrath, 2013). Now, from the previous three assumptions, the following two propositions follow naturally.

Proposition 1: Assume that a firm possesses a system of rare resources, where the rarity is a consequence of the firm's particular history, relational networks, cost structure, intellectual and/or physical difficulty to replicate, etc. Then this firm has a great chance to develop a sustainable competitive advantage.

To see why this conclusion is true, let us model the firm of concern as a spinning yoyo. Then the proposition's assumption suggests that due to whatever reasons the yoyo fields of most other competing firms do not share the underlying force that has the potential of making the particular firm's yoyo field spin strongly. Therefore, this specific firm's yoyo field has a better chance to spin strongly than the yoyo fields of most other competing firms. However, whether or not the system of this particular firm can eventually develop a sustainable competitive advantage really depends internally on the organizational structure of the firm. For example, does the firm have the discipline to take advantage of its special underlying force? At this junction, please note that Barney and Hesterly (2012) formulated a slightly different version of this proposition,

The assumed rarity of resources indicates explicitly that if the firm could take advantage of its rare resources, then few rival firms, if any, could successfully compete with it in terms of the particular resources. On the other hand, any possible development of sustainable competitive advantages based on the assumed rare resources, of course, depends on the firm's ability of finding an innovative way to mobilize its resources. For example, in the rivalry between Eastman Kodak and Fuji Films, the former had very specific set of available resources, such as market share, available manpower, etc., which the latter did not have. However, Kodak's culture and capability of learning barred itself against developing any sustainable competitive advantage through innovatively taking advantage of its resources against Fuji Films (McGrath, 2013).

A set of resources is valuable to a firm, if the resources strategically help the firm grow its profit through reducing expenditure and/or increasing revenue when compared to the case without the resources. In other words, a resource(s) is valuable to a firm, if it enables the firm to make use of an external opportunity for profits and/or to counterbalance an external danger. A resource is rare, if only a few competing firms have control of it. A resource is exploitable by a firm, if the firm is able to materialize the potential benefits of the resource due to its appropriate organizational culture, existing processes, implemented polices, and procedures.

Proposition 2: Assume that a firm controls a unique resource (or a set of resources). If the resource is simultaneously valuable and rare and the firm is able to exploit it, then the firm is capable of developing a sustainable competitive advantage based on the unique resource.

Barney and Hesterly (2012) formulate a slightly different version of this conclusion; and this result follows readily from Proposition 1. In fact, the truthfulness of this proposition is quite systemically clear. To this end, let us continue the systemic modelling given in the reasoning of Proposition 1. The current assumption that a firm is able to exploit the said resource indicates that the systemic composition of the firm allows it to make good use of the resource.

Additionally, being valuable alone is not enough for a resource to generate a competitive advantage for its controlling firm. In particular, being valuable means that either

- Other competing firms may very possibly have the resource too, or
- Although the controlling firm acknowledges the value of the resource, it is not ready, either culturally or organizationally, to make use of the resource.

For example, in 1979, as the head of Eastman Kodak's Research Division, Tom Whiteley personally witnessed the emergence of personal computers. However, limited by his mindset and the then-culture of Kodak, Whiteley did not see the need and urgency to take advantage of the new technology although the appropriate human talents were at his disposal. Speaking differently, Eastman Kodak's underlying systemic structure of the time was not fit to monetize the new information and talents of relevant technician of the firm through cashing in a time-changing resource. Instead, Kodak unrelentingly exploited and fortified its established advantages in films, leading to its defeat by Fuji Photo that moved along a successful business path without film (McGrath, 2013).

Exploiting a widely available resource generally intensifies the competition in the product market. Confirming this statement is the fact of how the competition in the product market drove personal computers' price down to the present level that almost no profit is made. When a valuable resource is rare, it implies directly that the resource is not perfectly imitable or impossible for competing firms to duplicate or find substitute for the resource. Such imperfect imitability and impossibility are generally consequences of various constraints, including, but not limited to, history, prohibitive cost, intellectual limitations, physical inabilities, organizational complexity, etc. In the contrary, when a valuable resource is imitable, the resource will not be rare, since the recognized value motivates rival firms to duplicate or to find substitute(s) for the resource. That will make the earlier rarity vanish rapidly.

For a resource to lead to a competitive advantage, the controlling firm of the resource has to possess a necessary organizational culture with appropriate philosophical and value system in order for the firm to exploit the resource beneficially. That is, only when the firm possesses an adequate systemic structure and organizational orientation, it will be able to first identify a resource's potential value, second design a unique method, as afforded by the market, to utilize the resource, and third realize practically the embodied benefits of the resource (Barney & Clark, 2007; McGrath, 2013).

Proposition 3: Assume that a firm possesses a simultaneously valuable and rare resource. If the interests of the managers and shareholders are harmonically in line with each other, then the firm will produce a sustainable competitive advantage out of the particular resource.

The truthfulness of this conclusion is verified as follows: the assumption that the interests of the managers and shareholders are harmonically in line with each other implies that the said resource is effectively exploitable by the firm. Hence, Proposition 2 implies that a sustainable competitive advantage will be developed.

To make this presentation self-contained, let us quote the following two results (Forrest, et al., 2017) here without proofs.

Theorem 1. For a coordinately monopolized market that is occupied by m incumbent firms, see details below, at least one enterprise enters the market profitably as a competitor of the incumbents, if and only if the consumer surplus $\beta = 1 - m\alpha \geq \alpha$.

Theorem 2. Assume that the consumer surplus β satisfies $\beta = 1 - m\alpha \geq \alpha$. Then there is a $\alpha^* \in (0, 1/(m+1))$ such that when $\alpha \geq \alpha^*$, the expected selling price of the products offered by the incumbent firms is higher than that of the entering firm and the expected profits of any incumbent firm are lower than those of the entering firm.

Here is how the coordinately monopolized market, as mentioned in the previous two theorems, is defined: It is occupied by m incumbent firms, m = 1, 2, 3, ... Each of these firms has its respective share α of loyal consumers who make purchases only from their respective firms as long as the price is not more than their reservation price, which is set to be 1. Assume without loss of generality that each of the incumbents has an equal percentage market share α of loyal consumers. And there is a market segment β (in percentage) of consumers who switch from the product of one incumbent firm to another depending on whose price is more competitive. These incumbent firms compete over the switchers with adjustable prices charged to their consumers. The managements of these m firms are well aware of the pricing strategies of the other firms and have established their best responses by playing the Nash equilibrium through pure self-analyses.

In particular, Theorem 1 spells out the reason why incumbent firms either in theory or in practice have to compete over the market switchers instead of just holding on to their respective bases of loyal consumers by charging them the reservation price. In fact, if the incumbent firms do not compete over the switchers, as implied by Theorem 2, when the segment of switchers grows larger than the size of the loyal consumers' base of any incumbent firm, new competition will not only enter into the market, but also potentially make as much profit as any of the incumbent firms.

EXPLOITATION AND EXPLORATION OF COMPETITIVE ADVANTAGES

Market-based resources (Lee & Grewal, 2004; Li & Calantone, 1998; Moorman & Slotegraaf, 1999) include marketing capabilities, technology and R&D capabilities, innovation ambidexterity, and market competencies. It is these market competencies that help a firm sense and respond to developments, either about customers or competitors or both, in the market environment. The following tough managerial challenge is the so-called capability-rigidity paradox (Dougherty 1992; O'Reilly & Tushman, 2004; Leonard-Barton, 1992): Many firms are adept at exploiting existing capabilities, but faltering in simultaneously exploring and developing new capabilities. A resolution of this paradox will help firms sustain their competitive advantages.

Proposition 4: If a firm is market orientated and able to take appropriate actions accordingly, then the firm is able to resolve the capability-rigidity paradox, which leads to better sustainability of its competitive advantages and consequent superb performance.

The description of the paradox implies that to resolve this challenging situation, one needs to find at least one organizational factor that assists a firm to simultaneously exploit existing innovation capabilities and explore new ones. The former sustains the firm financially for the present, while the latter, although risky, is a more active process of discovering new resources and technologies (Noble, et al., 2002). It directs the firm's attention to the future. Such split of attention between the present and the future requires the firm to have sufficient knowledge and learning capability about the current and future customers and competitors. This end implies that a firm's market orientation helps the firm resolve or lessen the severity of the capability-rigidity paradox (Day 1994; Hurley & Hult, 1998; Atuahene-Gima, 2005).

By using the systemic yoyo modeling, the firm of concern can be seen a spinning yoyo field that is fighting against all other spinning pools in the ocean of competing yoyo fields in the marketplace. So, for the firm to succeed in its fight against others, it needs to foretell how rival firm spins currently and expectedly into the future. On the backdrop of such knowledge, if the firm can act accordingly with insightful strategic actions, then it will surely be able to resolve the capability-rigidity paradox, leading consequently to better performance.

Now, firms with similar customer and competitor knowledge display varied levels of capacities of competence exploitation and exploration (Grant, 1996). Such differences in capability are rooted in the firms' varied abilities in interpreting the knowledge and in coordinating and integrating the interpretations within the operations and productions of a firm' functional units. That is why a firm's capability to act correspondingly empowers the firm to resolve completely or lessen the severity of the capability-rigidity paradox. Different interpretations of the knowledge and relevant actions taken naturally lead to different degrees of business success or failure.

Proposition 5: Organically interacting marketing, R&D and operational capabilities represents a very important aspect of a firm's operation, underlying the firm's good performance.

First, a firm's marketing capability demonstrates what the firm is and what it can do; and it reveals what consumers want and what the current and expected focus of firms' competition is (Kotler & Keller, 2016; Jaworski & Kohli, 1993). That is, such capability affects a firm's innovative output and presents the firm to consumers. Second, a firm's R&D capability translates learned market information into conceptual products to satisfy market's evolving demands while creating difficulties for competitors to imitate (Irwin & Klenow, 1994). If a firm has a strong track record of successful innovations with associated externality benefits, then the record will boost the firm's image and market's favorable expectations. Third, the complexity of operational capability generally makes it imperfectly mobile and imperfectly imitable. So, practically, when an appropriate operational capability can implement the knowledge learned from the marketing capability and realize ideas and designs of original products of the R&D capability into market offers, then the firm will enjoy an improving good performance (McGrath, 2013; Hayes, et al., 1988). Therefore, Proposition 2 implies that interacting marketing, R&D, and operational capabilities represents a very important aspect of a firm's operation, underlying the firm's good performance.

TECHNOLOGICAL OPPORTUNISM, INNOVATIVENESS AND PERFORMANCE

A firm's capability stands for a process through which the firm is able to deploy its available resources (inputs) to reach its business goals (outputs) (Dutta, et al., 1999). That is, by each capability it represents a firm's input-output mechanism. The collection of a firm's all capabilities can be well modeled as a systemic yoyo such that the higher the functional capability, such as the interaction of the firm's marketing, R&D, and operational capabilities, the firm is of, the more efficiently the firm can deploy its productive inputs to achieve its business objectives. Speaking differently, the more able the yoyo field of a firm is to predict how rival fields would behave, to react proactively, and to implement what is necessary, the fiercer (or the better performance) the yoyo field of the firm will spin (or achieve).

Proposition 6: A firm's competence of comprehending market information boosts new product advantage, and raises the firm's performance in the product market.

This conclusion follows readily from Proposition 5. It is because the competence of comprehending market information means such capability that captures and integrates market information and knowledge (Li & Calantone, 1998).

Proposition 7: A firm's technological opportunism affects the firm's magnitude of radical technology adoption; and top management's future focus and advocacy for new technologies encourage the firm's technological opportunism.

By technological opportunism, it means (Srinivasan, et al., 2002) a firm's capability for it to sense and to respond to the challenge of what radical technologies it should adopt. This definition implies that the more technologically opportunistic a firm is, the greater possible the firm would adopt radical technologies. Since for a firm, its top management represents the systemic center within the organization of the firm, a slight vibration in the top management's vision sends large waves of changes across the entire organizational system (Lin, 1999; Hall & Fagen, 1956). Hence, top management's future outlook and promotion of new technologies upsurge the firm's technological opportunism.

Theorems 1 and 2 indicate jointly that the market invites competition and stimulates innovation. Because in reality firms possess their individually varied capabilities of learning, different firms generally comprehend the same market signal differently. It explains why a firm's networking relationships with actors within its environment are critical for information gathering, testing, and the adoption of innovations (Arnold, et al., 2011; Romijn & Albaladejo, 2002). To this end, the following conclusion shows how a firm's relational resources influence its innovativeness.

Proposition 8: Assume that a firm of concern exists to satisfy a specific market niche through creating a positive cash flow by profit making in the marketplace, or by receiving investments from investors, or by using both of these means. Then the firm's relational resource carries an extremely important weight on the firm's innovativeness.

The truthfulness of this conclusion can be seen through the following systemic reasoning. The assumption about the firm's existence implies that the underlying systemic yoyo field of the firm absorbs whatever inputs necessary from its environment for the firm to survive by making indispensable adjustments and by repositioning itself in the marketplace. It means that the firm has to interact constantly with the outside world. These interactions provide the firm with such inputs as new and crucial information, knowledge and additional resources. These inputs strengthen the competitiveness and innovativeness of the firm (or speaking systemically, the intensity of spin of the yoyo structure of the firm).

Related to this conclusion, empirical studies, such as Freel (2003), Ritter and Gemunden (2003), Beugelsdijk and Cornet (2002), Landry et al (2002), Romijn and Albaladejo (2002), Souitaris (2002), and Kaufmann and Todtling (2001), have shown either positive or non-significant correlation between relational resource and innovativeness. By clearing these empirical uncertainties, this systemic conclusion carries the previous studies to a theoretical height with a definite claim. By continuing our systemic modeling, the spiral trajectory in Figure 1(c) means that each innovation generally represents a nonlinear evolution of ideas and processes that convert ideas into marketable offers, just as what is empirically confirmed by various authors (Dosi et al, 1988; Kaufmann & Todtling, 2001; Kline & Rosenberg, 1986); Malecki, 1997).

HOW RESOURCES INTERACT WITH EACH OTHER

Intangible resources, such as brand, relational assets, capabilities of knowledge generation, etc., are valuable, rare, and imperfectly imitable. Therefore, any firm that possesses such intangible resources is likely to develop sustainable competitive advantages (Proposition 1). In such situations, several resources generally work together to produce a desirable advantage. In other words, because of systemic effects, such as the whole is greater than the sum of parts (Lin, 1999), we can expect to produce better outcomes by placing different resources in service jointly than those produced out of a single resource (Kozlenkova, et al., 2014). However, the reality is that when some particular resources are jointly placed in service, undesirable effects can be produced. To this end, Ramaswami et al (2009) find that trade-offs may appear among different resources when these scholars investigate interacting capabilities regarding new product development, customer management, and supply chain management. For example, customer management capabilities interact positively with those of product development, but negatively with those of supply chain management.

Regarding the interaction of resources, the following general conclusion holds true. **Proposition 9**: Assume that X and Y are mutually exclusive sets of resources such that resources in X lead to the realization of goal A and those in Y help with that of goal B, where A and B are two opposite business goals. Then any interaction between resources in X and those in Y tends to produce undesirable effects or outcomes.

To see why this conclusion holds true, let us look at the following example. Let business goal A be "exploit the proven successful competitive advantages" and B "constantly discover new competitive advantages." Then resources purposefully developed only for realizing A and those for B generally do not work right (McGrath, 2013). Of course, there are resources, such as relationships that lead to information sharing, risk taking, and adoption of innovations (Dutta, et al., 1999), which can be deployed easily in realizing different business goals.

The general truthfulness of Proposition 9 is shown in Figure 2, where the sets of resources exclusively developed for business goal A and for B, respectively, do not overlap. And the general-purpose resources can be deployed and redeployed readily to serve different, even opposing goals.

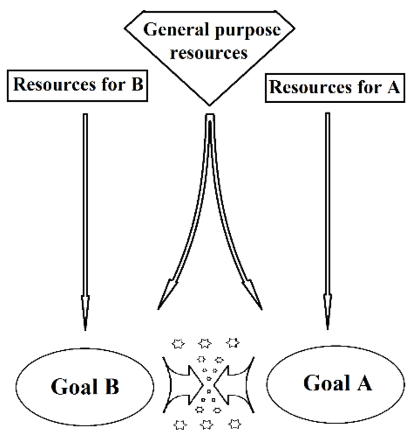


Figure 2. Division of available resources

Proposition 10: Let a firm's resources be divided into two categories: market-based and non-market-based. Then market-based resources affect the firm's performance more than the other resources do.

Market-based resources of a firm are those assets of the firm that directly relate to market conditions and expectations (Lee & Grewal, 2004; Li & Calantone, 1998; Moorman & Slotegraaf, 1999) and can be employed to implement strategies (Harmancioglu et al. 2009). Examples of market-based resources include marketing capabilities, technology and R&D capabilities, innovation ambidexterity, and competencies of sensing and responding to changes in the market environment, be they about customers or competitors or both.

This definition of market-based resources implies directly that these resources exhibit stronger effects on a firm's performance than other resources. In particular, the former helps bring the firm's offers directly to where the consumer demand is, and the latter complements the former by playing a supporting-role. Empirically, Hooley et al (2005) suggest a slightly weaker version of Proposition 10.

EVOLUTION OF RESOURCES

Collis and Montgomery (2008) document the following two historical events: Since the time when Walt Disney passed away, the equity of Disney's brand suffered from two decades of neglect, while within a few years the innovativeness of Xerox in the production of photocopiers disappeared. These anecdotes suggest the fact that resources and capabilities evolve differently. Helfat and Peteraf (2003) employ the concept of capability life cycle to articulate how organizational capabilities evolve over time through stages and how heterogeneity in these capabilities appears. Here, the phrase "organizational capability" means such ability with that an organization performs a coordinated set of tasks through utilizing resources to achieve a particular end result, known as objective. In practice, an objective may cease to exist due to the reason of having been either accomplished or be altered within the changing market environment. Now, the following conclusion clearly tells what factors would help lengthen or shorten the effective life of an organizational capability.

Proposition 11: Assume that a firm's leadership develops an organizational capability A to achieve a particular objective B through coordinating joint efforts. Then capability A will evolve from birth to development to maturity until the time when objective B no longer exists; and

- When objective B ceases to exist, capability A will retire;
- When objective B is altered, then capability A will evolve into one of the following six branches:
    - Retirement (death),
    - Retrenchment,
    - Renovation,
    - Replication,
    - Redeployment, and
    - Recombination (or pooled together with other capabilities).

Now, let us see why this conclusion holds true. First, when the market segment of switchers is large enough, the market sends out a call and invitation for additional competition (Theorems 1 and 2). By answering the call, a capable person (or a team of people) with special talent will identify an opportunity and then organize a group of individuals, endowed with human capital, social capital, and cognition, to achieve a specific objective by coordinating joint efforts (Helfat & Lieberman, 2002; Levinthal & Myatt, 1994). Although these individuals could be total strangers, a leadership naturally appears within the newly formed group of talents, as guaranteed by the following theorem of systems science:

Theorem 3 (Lin, 1999): *Assume that:*

(1) *κ is an infinite cardinality and $\theta > \kappa$ a regular cardinality satisfying that, for any $\alpha < \theta$, $|\alpha^{<\kappa}| < \theta$;*
(2) *$S = (M, R)$ is a system satisfying $|M| \geq \theta$; and*
(3) *Each object $m \in M$ is a system with $m = (M_m, R_m)$ and $|M_m| < \kappa$.*

If there exists an object that is contained in at least θ objects in M, then there exists a partial system $S' = (M', R')$ of S such that S' forms a centralized system and $|M'| \geq \theta$. Because the proof of this result is very technical, it is left to the appendix of this paper.

In non-symbolic, non-technical terms, Theorem 3 says that if a group of people is pulled together to undertake an intricate task, although each person has only a limited role in the work, then a leader or a group leadership will emerge, no matter whether or not the people know each other initially. See (Lin, 1988) for more details on how such an interpretation of a result similar to Theorem 3 is established.

As a goal-oriented system aiming at realizing the identified central objective, the group (or team) of people with individually endowed talents starts to devise a particular organizational capability. The team's search for viable ways to accomplish the end result leads to the appearance of an appropriately working capability (Winter, 2000). The selection of a particular way to pursue is determined by learning-by-doing both individually and collectively as a team and dictated by the boundary conditions at the beginning stage (Helfat & Peteraf, 2003). This initial stage of development finishes when the team perceives the working capability as sufficient (Winter, 2000). Then, the capability enters into its mature stage for maintenance and repeated applications.

At this moment of development, if the central objective no longer exists or is materialized successfully, then the organization, resulted from the initial group of individuals, will either dissolve or start to aim at a different objective. For the former situation, the established organizational capability will cease to exist, because its use value diminishes. For the latter situation, the capability evolves in several possible directions, Figure 3, depending on practical needs and environmental constraints.

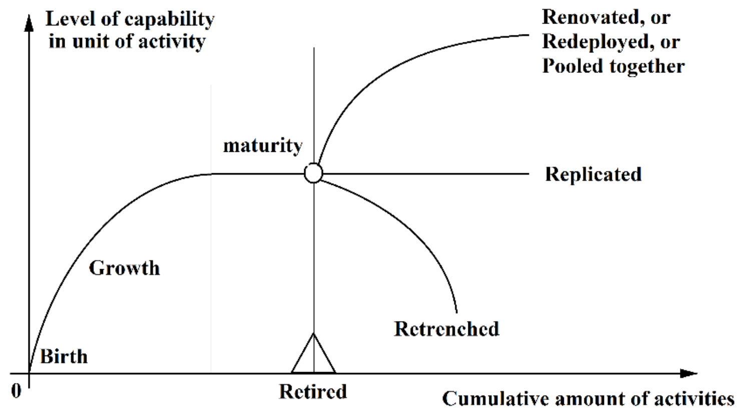


Figure 3. How a capability evolves

These practical needs and environmental constraints can be either internal or external to the hosting organization of the capability. Figure 3 shows the general evolution of a capability starting from its birth to the eventual branching. Although there are only two clearly labeled moments in Figure 3, one at the beginning of maturity and the other at that of branching, in real life, capabilities do not always have clearly marked moments of separation between development stages. In fact, branching can take place at any stage from that of growth onward, depending on the initial endowments available at the birth stage and the central objective the organization aims at materializing. Additionally, the specific branch the capability will take on is determined by the particular capability and selection effects, external to the capability, and what internal reactions the firm is taking (Helfat & Peteraf, 2003). All determinants of selection are ingrained in the varying description of the central objective at which the capability was initially developed to aim. When the central objective advances with the fluctuating market call and invitation, some selection effects become threats, making the capability obsolete, while others provide opportunities for the capability to further cultivate and evolve.

Proposition 12: Only when a firm is able to recognize market calls and invitations adequately, the firm's resources will help improve its performance.

The truthfulness of this conclusion follows from the fact that the firm's products and/or services, offered on top of the firm's resources, satisfy the market demand better than those of other competing firms. For this end to occur, the design and/or production of the firm's products or services must have done a better job in the market competition than other firms do. That, of course, means that the firm is able either consciously or unconsciously to use

- Relevant information of the market, such as what the market is inviting for (Theorems 1 and 2);
- How competitors are positioned in the marketplace;
- What the selling points of the competing products and services are,
- What the competitors' pricing strategies are, etc.,

on its product development, as confirmed by Stigler (1961). In other words, information, such as market invitation, can facilitate consumer search and increase competitive activities. Empirically, Moorman and Slotegraaf (1999) suggested a special case of Proposition 12 regarding only technology and marketing resources.

The conclusion in Proposition 12 can be seen systemically. In particular, the firm's improving performance implies that the yoyo field of the firm moves in advantageous ways when compared to the movement patterns of the yoyo fields of other competing firms (Figure 4).

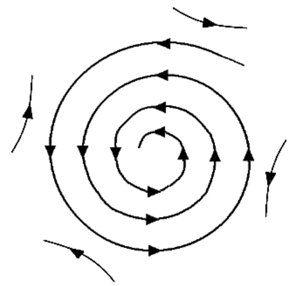


Figure 4. An advantageous situation of a product

CONDITIONS UNDER WHICH FIRMS CAN NO LONGER CONSISTENTLY EXPLOIT ITS RESOURCES

The following proposition spells out clearly when a firm could potentially fail to exploit beneficially its available resources.

Proposition 13: If a firm meets one or more of the following conditions, then the firm will fail to consistently and beneficially exploit its available resources in its effort to achieve superior performance:

1. There is no constantly reinforced policy or procedure in place to exploit available resources;
2. There is no orientation toward the market;
3. There is no capability to react to market invitations;
4. There is no capability to combine marketing and R&D capabilities with appropriate supporting operations; and
5. There is no timely sense about what the market is signaling when compared to rival firms.

Let us see the logical reasoning behind this conclusion. To achieve superior performance by *consistently* exploiting its available resources, the firm must possess a developed mechanism that unremittingly pushes itself towards superb performance. Therefore, the firm needs to have constantly reinforced policies and procedures to support the exploitation of its resources (Proposition 1). Hence, condition 1 holds true.

If a firm is not market oriented and/or unable to answer to market calls (Theorems 1 and 2) accordingly, the firm will not be able to dependably tweak its strategies to stay in sync with market evolution (McGrath, 2013). In this case, the firm will not be able to exploit consistently its available resources for the purpose of achieving superior performance (Proposition 4), other than by chance once in a while, like the situation of a broken clock that tells the correct time twice a day. Therefore, conditions 2 and 3 holds true.

Condition 4 holds true for a similar reason as above for conditions 2 and 3 and follows from Proposition 5. If condition 5 holds true, it means that the firm is mostly behind its competitors in terms of appropriately understanding market cues. So, compared to its competitors, the firm will not be able to exploit consistently its available resources to achieve superior performance (Proposition 6).

For the purpose of managerial decision-making, we can rewrite the previous proposition as follows. **Proposition 14**: If any of the following conditions hold true for a firm, then the firm will fail to exploit its available resources consistently for the purpose of developing a competitive advantage:

1. The leadership is unable to maximize the potential of the available resources;
2. The interests of the managers and owners diverge;
3. The philosophical and value systems of the top management hinder financial performance.

The reason why this conclusion is true is that if condition 1 is true, then various versions of the four conditions in Proposition 12 follow. Therefore, the conclusion that the firm will fail to exploit its available resources consistently for the purpose of developing a competitive advantage follows.

When either condition 2 or condition 3 is true, conditions 2 and 4 in Proposition 13 become true. Therefore, the conclusion of this proposition follows. Hunt (1997) also establishes a similar result by using resource advantage theory (Hunt & Morgan, 1995).

Proposition 15: If poor financial performance stimulates a firm to innovate, then the stimulation is both endogenous and exogenous to the firm.

When poor financial performance stimulates a firm to innovate, the firm has implicitly employed the feedback mechanism (Lin, 1999), Figure 5, of the market information as follows: Relative to its competitors the firm occupies an inferior position in the marketplace. In other words, the firm realizes that it is in a comparatively disadvantageous position when compared to its rivals. Hence, the stimulation for the firm to innovate stems from its internal recognition of and external analysis of its performance. In particular, when the firm introduces its desired innovation after recognizing where its disadvantage is, the earlier poor performance will improve and be soon replaced by better performance. Here, this feedback loop makes the firm become more competitive than before.

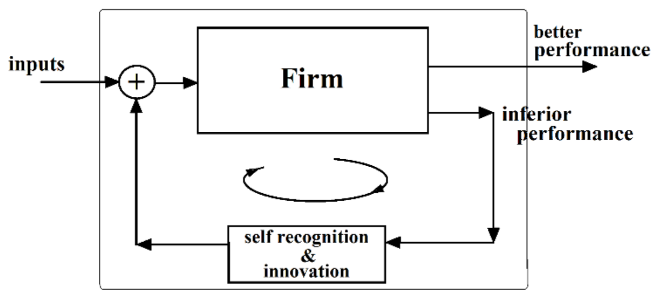


Figure 5. A diagram of the feedback mechanism

In the contrary, if the firm receives the market cue (Theorems 1 and 2) about consumer demand, then the subsequent innovation the firm embarks on is exogenous to the firm.

SOME FINAL WORDS

By utilizing systemic thinking logic and the yoyo model, this paper studies several research topics in the areas of management and marketing based on the resource-based theory. Through addressing issues regarding characteristics and operations of organizations, this work establishes general and practically useful conclusions from the angle of resources without being constrained by uncertainties of empirical analysis. More specifically, after formulating three basic assumptions as the starting point of reasoning, this paper develops:

1. Conditions under which a firm develops either likely or certainly sustainable competitive advantages;
2. A way of how to resolve the capability-rigidity paradox;
3. Conditions that potentially lead to improved firm performance;
4. Factors that impact the magnitude of radical technology adoption;
5. An explanation on how relational resource impacts a firm’s innovativeness;
6. When interactions of resources can produce undesirable outcomes;
7. How a capability evolves from birth to maturity and when it ceases to exist; and
8. When a firm fails to consistently exploit its resources.

Other than establishing these generally applicable conclusions, an impossible task if only empirical analysis is used, another contribution this work makes is the introduction of systems science into the study of management science and marketing in a logical fashion. Comparing to empirical analysis, employing systems science avoids all limitations and uncertainties of data collection, analysis and inference. That explains why this paper can establish general conclusions that are practically applicable to produce tangible economic benefits.

Speaking differently, established results in the literature, be they conceptual or empirical, are generally affected adversely by limitations and uncertainties of data analysis. When deciding on what to do in their business operations by employing such results of limited validity, managers and entrepreneurs face a great deal of uncertainty in terms of what to expect as the consequence of their chosen actions. Different from such uncertainties that widely exist in the literature, this work derives conclusions that are generally applicable in real life by using logical reasoning starting on three very straightforward assumptions.

As for the limitation of this work, there is no doubt that all conclusions derived above are based on the definitions of resources of various kinds and that of competitive advantages. The key words and phrases are *asset* and that the firm makes "*more economic value than other firms*". In other words, this work did not consider firms that only strive to "stay alive" instead of creating more economic value than other firms. In real life, many firms actually fall into this category unwillingly. If each firm is seen abstractly as a system, then two natural questions arise out of the key word *asset*: Which part(s) or process(s) of the organizational system of a firm need to be treated as assets is not clear. The importance of this question is reflected in the fact that the definition of assets changes from one person to another. Assume that one can identify all the assets that have contributed to the success of a particular business operation. Then which of the assets have played fundamental roles than others? These and other relevant issues need to be studied in future works, maybe first empirically and then theoretically.

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APPENDIX: PROOF OF THEOREM 3

This technical argument is provided here to make this presentation self-contained. For related definitions of concepts, see (Lin, 1999). And for those readers who are only interested in the role this result plays, skipping this proof will not interrupt the flow of comprehending this presentation.

Without loss of generality, assume that $|M| = \theta$ and that there is a common element in each and every object system m in M. Then the following holds true, where each system is defined as an ordered pair of sets $x = (M_x, R_x)$ with M_x stands for the collection of all elements of the system and R_x the set of all relations between the elements:

$$|\cup \{M_x : x = (M_x, R_x) \in M\}| \leq \theta.$$

Because the specific objects in each M_x, for each object $x = (M_x, R_x) \in M$, are irrelevant, assume that

$$\cup\{M_x : x = (M_x, R_x) \in M\} \subseteq \theta.$$

Then, for each $x = (M_x, R_x) \in M$, the object set M_x has some order type $< \kappa$ as a subset of θ. Because θ is regular and $\theta > \kappa$, there exists a $\rho < \kappa$ satisfying that $M_1 = \{x \in M : M_x$ has order type $\rho\}$ has cardinality θ. Let us fix such a ρ and deal only with the partial system $S_1 = (M_1, R_1)$ of S, where R_1 is the restriction of the relation set R on M_1.

For each $\alpha < \theta$, $|\alpha^{<\kappa}| < \theta$ implies that less than θ objects of the partial system S_1 have object sets as subsets of α. Thus, $\cup\{M_x : x = (M_x, R_x) \in M_1\}$ is cofinal in θ. If $x \in M_1$ and $\xi < \rho$, let $M_x(\xi)$ be the ξth element of M_x . Since θ is regular, there is some ξ such that $\{M_x(\xi): x \in M_1\}$ is cofinal in θ. Now fix ξ_0 to be the least such ξ. Then the condition that there exists a common element in each system in M_1 implies that $\xi_0 > 0$ is guaranteed. Let

$$\alpha_0 = \cup\{M_x(\eta) + 1 : x \in M_1 \text{ and } \eta < \xi_0\}.$$

Then $\alpha_0 < \theta$ and $M_x(\eta) < \alpha_0$ for all $x \in M_1$ and all $\eta < \xi_0$.

By transfinite induction on $\mu < \theta$, pick $x_\mu \in M_1$ so that $M_{x_\mu}(\xi_0) > \alpha_0$ and $M_{x_\mu}(\xi_0)$ is above all elements of earlier x_v; i.e.,

$$M_{x_\mu}(\xi_0) > \max\left\{\alpha_0, \bigcup\left\{M_{x_v}(\eta) : \eta < \rho \text{ and } \nu < \mu\right\}\right\}.$$

Let $M_2 = \{x_\mu : \mu < \theta\}$. Then $|M_2| = \theta$ and $M_x \cap M_y \subseteq \alpha_0$ whenever $x = (M_x, R_x)$ and $y = (M_y, R_y)$ are distinct objects in M_2. Since for each $\alpha < \theta$,

$$|\alpha^{<\kappa}| < \theta,$$

there exists an $r \subset \alpha_0$ and a $B \subset M_2$ with $|B| = \theta$ and for each $x \in B$, $M_x \cap \alpha_0 = r$, $S_2 = (B, R_B)$ forms a centralized system, where R_B is the restriction of the relation set R on B. QED

INFORMATION DIAGNOSTICITY INFLUENCES ON ONLINE CONSUMER PURCHASE INTENTIONS

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ABSTRACT

Utilization of online sales is increasingly prevalent, creating a direct interest in understanding online purchase intention formation. Understanding the diagnostic aspects impacting consumer behavior allows for more accurate prediction of customer purchases. In this study, we look at Information Diagnosticity and its role in explaining criterion differentiation during the purchase intention formation process. Self-reported consumer purchase intentions were solicited in a cross-sectional study of English-speaking Amazon.com customers presented with five survey stimuli. The 218 participants were recruited using Amazon's MTurk platform. This research focused on the impact of information diagnosticity on purchase intentions. Study findings indicate trust and valence-based constructs offer increased insights into purchase intention behavior formation within ecommerce.

INTRODUCTION

Online sales are growing with estimated e-commerce sales of $599 million by 2024 (Statista, 2020). Ease of online shopping from home at e-retailers like Amazon.com allows for direct home delivery. While the online buyer is unable to assess the physical product while selecting items for purchase, the selection of items maybe greater than those of local brick and mortar stores, as with Amazon.com, including Amazon Marketplace, offers over an estimated 350 million items (Dayton, 2020). While the attraction of online hours of operation (24/7), delivery directly to customers, and selection are all aspects of online shopping, the plethora of items can be overwhelming.

How can a customer determine items to purchase without physically evaluating them? Many consumers substitute traditional word-of-mouth between friends with electronic word-of-mouth (eWOM) from online customer reviews to base selection criteria for purchase (Kim & Park, 2013; Wu, 2013; Guo, Wang, & Wu, 2020). The one-to-many communication reach of eWOM, specifically consumer-generated, consumption-related communications, increases the influential power of a single consumer's review from the traditional face-to-face word-of-mouth sharing to a wider, internet-based audience.

Selecting an online retailer is similar to adopting new technology. Prior research into online commerce evaluated customer acceptance of retailers using ecommerce technology acceptance model (eTAM) (Klopping & McKinney, 2004), this parsimonious model focuses on three constructs of online retail purchase intention predictors. Constructs representing behavioral intentions, which equate with purchase intentions (PI), perceived ease-of-use (PEOU), and perceived usefulness (PU) were determined to be predictive of e-commerce adoptions (Klopping & McKinney, 2004).

eTAM was found to be useful in predicting e-commerce platform selection, but does not account for diagnostic criterion consumers utilize in determining purchase intentions. Once a platform is selected, the influence of eWOM and additional factors influencing purchase intentions are not represented in eTAM, leaving room for an improvement on the model. This study builds on research by Gurney, Eveland, and Guzman (2019) to assess additional aspects influencing consumer purchase intention formation in online sales.

Social media style communication is significant in determining opinions and gaining insight into online elements. Ecommerce sites facilitating electronic sharing of opinions allow customers to substitute face-to-face evaluations and recommendations of products with social media posting style opinions. eTAM lacks assessing criteria for the influences of socially shared electronic opinions prevalent on product pages online. Contributing factors from eWOM customer reviews include written sentiment (tone) regarding the item, opinions, and experiences expressed (Filieri, 2015). Additionally, valence, representing the positive and negative opinions within written reviews, conveys emotion, impacting reader trust in the review and its diagnostic content (Guo, Wang, & Wu, 2020). Previous research has shown support for emotional diagnosticity influences, positive and negative valence of content, within eWOM reviews sway purchase intentions (Ghasemaghaei, 2020; Guo, Wang, & Wu, 2020; Gurney, 2018; Gurney, Eveland, & Guzman, 2019).

Decision criteria gleaned from online reviews directly impacts diagnostic aspects of consumer's decision processes. Determining if a product demonstrated positive characteristic that fit the potential buyer's need criteria can be gained from a diagnostic reading of online reviews from previous customer experiences. These experiences, opinions, and expressed written tone (valence) all form part of the purchase intention formation diagnostic criteria and were found to have influences on the categorization of trust within eWOM reviews (Ghasemaghaei, 2020; Filieri, 2015; Mortazavi, Esfidani, & Barzoki, 2014;).

Additionally, trust in the eWOM customer review is impacted by overall trusting tendencies. According to Lee and Hong (2019), consumer trust in the review host site is transferred indirectly to the eWOM review. Increased trust levels a customer has in the vendor indirectly impact trust in the content. Thus, trust in the e-vendor's site allows consumers to determine purchase intentions based on the eWOM feedback.

This research focuses on extending the eTAM through the applications of Information Diagnosticity to account for additional influences impacting purchase intention formation within ecommerce at Amazon.com. Utilizing different valence conditions, the model presented to Amazon customers via an online survey with 218 online participants.

To further provide theoretical foundational information literature on information diagnosticity and purchase intentions is discussed. Furthermore, we present the research model and study description and results, followed by a discussion and conclusion.

THEORETICAL BACKGROUND

Tversky's seminal study (1977) on diagnostic effect, analyzed how diagnosticity was utilized to assess criteria into classification of subgroup clustered items (Evers & Lakens, 2014; Pothos, Barque-Duran, Yearsley, Trueblood, Busemeyer, Hampton, 2015; Menon,1995). This clustered criterion comparison are used to demine differentiation of dissimilar concepts, creating information criteria groups for preference judgements (Andrews & Allen, 2016; Pothos, et al., 2015) as denoted in Information Diagnosticity (ID).

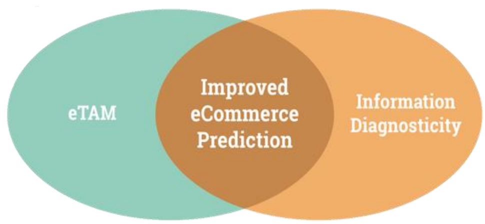
Using the grouping criteria found in eWOM customer product reviews, published on electronic vendor product pages, buyers are able to form differentiating categorization regarding products based on the shared experiences of prior purchasers and create a purchase intention grouping categorizations (Andrews & Allen, 2016; Chau & Banerjee, 2014; Menon, 1995). The diagnostic elements derived from the valence, ratings, documented customer experiences, and engendered trust form informational influences on purchase intention formation, thus the basis for informational differentiation regarding purchase consideration (Andrews & Allen, 2016; Chau & Banerjee, 2014; Evers & Lakens, 2014; Filieri, 2015; Mortazavi, Esfidani, & Barzoki, 2014; Wen, 2020). These categorizations can be thought of as 'low, neutral, or high' potential purchase candidates (Filieri, 2015; Mortazavi, Esfidani, & Barzoki, 2014).

While the trust engendered and experiences evaluated from customer reviews assist in assessing purchase potential, those are not the only information diagnostic elements influencing purchase decision formation; trust in the electronic vendor and in online sales ecommerce platforms (Klopping & McKinney, 2004; Wen, 2020). Attitudes concerning perceive ease-of-use (PEU) and perceived usefulness (PU) have been determined assessable via application of TAM (Beldad & Hegner, 2017; Gefen, Karahanna, & Straub, 2003; Phuong & Vinh, 2017; Yang, Sarathy, & Walsh, 2016). The affective impact of PEU and PU on purchase (behavioral) intentions is illustrated in electronic commerce TAM (eTAM) (Klopping & McKinney, 2004).

Extending eTAM via Information Diagnosticity theory to include the constructs of trust and valence strengthens the predictive aspects of the model and assist in ecommerce purchase intention influence assessment. The perception of positive valence and credibility within eWOM customer reviews impacts purchase decisions (Andrews & Allen, 2016; Filieri, 2015; Chau & Banerjee, 2014; Ghasemaghaei, 2020; Guo, Wang, & Wu, 2020). The influence of diagnosticity on purchase decisions is moderated by the emotional content, valence, of positive or negative reviews. The perception of relevant product information, diagnostic criterion, impacts consumer decision formation, based on the content of eWOM reviews. Recent studies conducted into the impact of positive and negative valenced information and information diagnosticity's supported an effect on decision formation (Dessel, Cone, Gast, & De Houwer, 2020; Guo, Wang, & Wu, 2020).

Trust aspects directly impact the behavioral aspects of purchase intentions (TAM's behavioral construct): without trust in the vendor, the item would not be assessed for purchase. Trust in the customer review is based in the theory of reasoned action (TRA), the antecedent or TAM) and assesses the subjective norms as measured by valence (written tone) within eWOM customer reviews (Gefen, Karahanna, & Straub, 2003; Phuong & Vinh, 2017; Guo, Wang, & Wu, 2020). The proposed model combines elements of the technology acceptance model, theory of reasoned action, and information diagnosticity to enhance the predictive strength of assessing customer purchase intentioned, as based on customer reviews, in ecommerce. Increase the Explanatory Power of TAM through ID extension for e-commerce with eWOM customer reviews on Amazon.com, see Figure 1.

Figure 1: *Intersection of eTAM and Information Diagnosticity*



The inherent trust trait within a person is a contributing factor to online purchasing. Without an inclination to trust online vendors, customers will not seek online purchase options nor trust unfamiliar vending platforms. Commitment to online purchasing is proposed to be higher in those who have greater inclinations to trust (IT) (Chang & Chen, 2008; Gefen, Karahanna, & Straub, 2003; Lee & Hong, 2019).

H1: Greater inclination to trust increases purchase intentions.

Belief that an online transaction will be honored, the financial obligations met, and elements of the transaction will proceed as expected are all part of the buyer's evaluation of trust in an electronic vendor (Chang & Chen, 2008; Hassanein & Head, 2007; Lee & Hong, 2019). Purchase intentions, even item selection, is lowered when a lack of trust is present with regards to an online sales site. Reduction of perceived risk and increase in trust in the vendor (TV) represents a diagnostic aspect that contributes to purchase intention criteria. Increased TV contributes to greater purchase intentions.

H2: Greater trust in the vendor increases purchase intentions.

Trust is an influencing factor in the perception of security in online transaction and interactions. Perceived trust within customer reviews, as assessed from the writing style and content, impacts the diagnostic value of the review in categorization of items for purchase. Potential customer review another's written post about experiences, opinions, and ratings given for a particular product and determine the reliability based on an emotional connection formed by the writing, representing the emotional trust in the review (Lee, Sun, Chen, & Jhu, 2015).

Within the tone, or valence, and verbiage used, a reader is able to evaluate the perceived trustworthiness and honesty of the review in regards to the product. This allows for an assessment of the weight a potential buyer will place in the diagnostic clues identified from the written review forming the emotional trust in eWOM available.

Additional trust aspects influencing buyer consumption of written review cues is cognitive trust. A logical assessment of the written review based on information presented and the manner presented. The cognitive aspects of trust formation in relation to the customer written review are based on the presumed reviewer's motivation as assessed from the valence and wording (Lee, Sun, Chen, & Jhu, 2015; Guo, Wang, & Wu, 2020). The combined trust, cognitive and emotional, are close in nature and allow users to form a mental credibility ranking of reviews read. Trust in the review, based on the content and valence impacts the value placed on decision criteria gleaned from eWOM reviews (Mortazavi, Esfidani, & Barzoki, 2014; Yang, Sarathy, & Walsh, 2016). Lee, Sun, Chen, and Jhu (2015) found that cognitive and emotional trust directly impact purchase intentions as a result of a decision making process.

H3: Greater emotional-cognitive trust in the customer review increases purchase intentions.

Written tone cues (positive, neutral, or negative) represented perceived valence within a customer review impact and emotional trust connections are formed. The trust in the review is impacted by the 'tone of voice' presented, influencing the level of trust in the diagnostic aspects available within the written review. The emotional trust connections derived from the tone present in the eWOM will have an impact on the reader's purchase intentions (Fogel & Zachariah, 2017; Kim & Park, 2013; Guo, Wang, & Wu, 2020; Lee & Hong, 2019). Stronger valence influenced trust are expected to increase purchase intentions.

Additionally, the cognitive trust inspired by the assessment of the language and intents presented by the written aspects of the customer review impact belief in the statements made. Cognitive trust is partially based on the perceived valence of the written review. The greater the trust in the reviewer's message, the greater the impact on purchase intentions (Filieri, 2015; Fogel & Zachariah, 2017;).

H4: Greater emotional-cognitive trust mediates the relationship between perceived valence and purchase intentions.

Pulling from the ecommerce technology acceptance model (eTAM) (Klopping & McKinney, 2004), online platform adoption is related to user's perceptions of ease-of-use and perceived usefulness (Lim, Osman, Salahuddin, Romle, & Abdullah, 2016). Specifically, the ease in which a consumer can access and complete transactions attracts customers to a specific platform. The ease of using online shopping sites allows for greater acceptance rates of sites with easy to use interfaces.

H5: Greater perceived ease-of-use increases purchases intentions.

Positive shopping experiences, based on usefulness, increase user adoption of online sales sites, according to eTAM. Reducing travel time, the ability to compare multiple items with the click of a mouse button, increased select as with Amazon.com, all contribute to perceived usefulness. Increased adoption rates of online vendors is increased with greater perceived usefulness (PU) (Cho & Sagynov, 2015; Lim, Osman, Salahuddin, Romle, & Abdullah, 2016). Greater PU is expected to increase consumer purchase intentions.

H6: Greater perceived usefulness increases purchase intentions.

These two constructs are interdepended, perceived usefulness and perceived ease-of-use (PEU), as Klopping and McKinney (2004) demonstrated with their eTAM model. The greater the ease-of-use and usefulness the more likely customers will be to utilize the site and report higher purchase intentions.

H7: Greater perceived ease-of-use increases perceived usefulness; and
H8: Valence condition moderates the relationship between inclination to trust and purchase intentions.

The agreement within a written customer review online is not always consistent. The perceived valence (PV) within the written review may differ from the valence condition presented, normally represented by star ratings. Emotional tone and auditory cues presenting emotional nuances are lacking in the written post of a person's eWOM review. A conflict between a low star rating (1 star being negative) and a high star rating (5 stars being positive) as indicated on Amazon.com, may not relate directly with the perceived valence (Filieri, 2015; Liang, Li, Yang, & Wang, 2016). Positive, neutral, or negative tone, valence, may not match with the star rating listed, causing a dissonance in affective information perceived in the diagnostic process for purchase decision making (Ghasemaghaei, 2020; Koo, 2015; Lee, Kim, & Peng, 2013).

RESEARCH METHODOLOGY

Utilizing a one-time cross-sectional survey exposing participants to multiple emulated online product conditions similar to Amazon.com product pages, five surveys were administered to randomly selected participants, Figure 2. Employing Amazon's MTurk survey service, 218 English-speaking, U.S. Amazon customers self-selected to partake in the study. Previous research indicated the participants on MTurk more accurately represent the U.S. population than university students (Wu, 2013).

As per standard operating procedure on MTurk, each participant was compensated with a small monetary payment. Demographics indicate the participants were 'not listed' (N=1, .4%), female (N=122, 46.9%), and male (N=137, 52.7%), a predominately equal distribution between male and female – note that other gender options were available for indication, but not selected.

Administration of surveys on Amazon's MTurk service automatically randomizes and obscures participant ids. Responses were therefore anonymous. Repeat MTurk ids were not identified in the data review between surveys. Five separate valence-based surveys were administered to random participants, to limit expected participant fatigue if all five stimuli were presented in one survey.

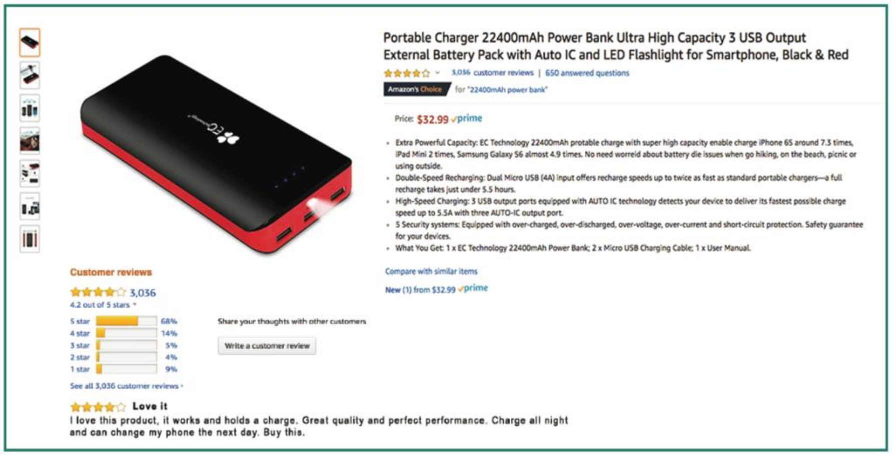
Figure 1: *Research Flow*

Price point was a consideration in example product selection, choosing to keep the price point low to reduce 'sticker shock' purchase intention influencers. An image of the product, product description, valence conditions, and eWOM customer reviews were mocked up to resemble as closely as possible an Amazon product page, see Figure 3.

To accommodate the different valence combinations, five separate but similar surveys were created. The surveys were identical in all aspects except the adjustment of valence conditions and written review. Customer reviews and the connected star ratings represented the sentiment score (SC) conditions (valence) and the aggregate star ratings (AR) changed per stimuli to create five different valence conditions. Aggregate star ratings specifically represent the overall average of rankings all customers have given a product based on stars. Valence conditions were created using combinations of star ratings, aggregate star ratings (Fagerstrom, Pawar, Sigursson, & Foxall, 2017), and sentiment score valence benchmarked written reviews (Mauri & Minazzi, 2011; Guo, Wang, & Wu, 2020).

Using the IBM Watson Developer Cloud Tone Analyzer tool (Watson: Tone Analyzer, 2017), each written customer review was quantified as 'positive, negative, or neutral' (Liang, Li, Yang, & Wang, 2016; Wu, 2013). IBM Watson generated a numeric score representing strength of valence, or sentiment score.

Figure 3: *Valence Condition Example Stimuli*



Implementing a natural language lexicon analysis for assessment of sentiment score, IBM Watson determine numeric levels of written emotions from 'join, anger, fear, disgust, sadness, and others verbal tendencies. The score is based on combinations of words, structure of the sentences, and the algorithm implemented in the Watson engine (Watson: Tone Analyzer, 2017; IBM, 2018). Written tone, valence, received quantified scores ranging from -1.00 (negative emotions) to +1.00 (positive emotions). Stimulus examples presented to participants were a combination of sentiment score benchmarked written customer review samples, star ratings, and aggregate star ratings, see Table 1.

Table 1: *Sentiment Score Comparisons*

	Sentiment Score Analyzer and Scores		
Verbal Stimuli	**IBM's Watson Tone Analyzer**	**TwinWord Ratio/Score**	**Text2Data**
I hate this product, it doesn't work and won't hold a charge. Poor quality and bad performance. Charged all night and can't charge my phone the next day. Don't buy this.	-0.84 Joy 0.0, Anger 0.22, Disgust 0.12, Sadness 0.73, Fear 0.07	-0.809/-0.414	-0.674
I love this product, it works and holds a charge. Great quality and perfect performance. Charge all night and can charge my phone the next day. I recommend this.	0.90 Joy 0.86, Anger 0.01 Disgust 0.00 Sadness 0.73 Fear 0.07	0.993/0.439	0.889
Standard product, it works and holds a charge. Average quality and performance. Charge all night and can charge my phone the next day. I'd buy again.	-0.03 Joy 0.13, Anger 0.09, Disgust 0.05, Sadness 0.21, Fear 0.02	0.605/0.116	0.193
Sentiment scores +1.00 positive, -1.00 negative, 0.00 neutral.			

Using a Likert scale, participants selected their response ratings from strongly disagree (1) to strongly agree (5). Each of the five stimuli based surveys were administered to randomly selected groups of participants. Each survey asked participants to review the product page presented, valence based stimuli being the only difference between surveys. All questions presented were the same between surveys, see Figure 3 (Gurney, 2018; Gurney, Eveland, & Guzman, 2019). Additional questions assessing length of online shopping and frequency of shopping were included.

Table 2: *Constructs and Reliability*

Construct	Cronbach's Alpha	CR	AVE
Inclination to Trust (IT) Adapted from (Chang & Chen, 2008) IT1: It is easy for me to trust a person/thing. IT2: I tend to trust a person/thing, even though I have little knowledge of them/it. IT3: Trusting someone or something is not difficult. IT4: I feel uncomfortable putting my trust in another person/thing.	.90	.93	.76
Trust in Vendor (TV)	.76	.77	.46
Adapted from (Chang & Chen, 2008; Kim & Park, 2013; Park & Kim, 2008) TV1: Promises made by Amazon's web site are likely to be reliable. TV2: I expect that Amazon's web site's intentions are honest. TV3: I feel comfortable using Amazon's interface to purchase items. TV4: I am likely to purchase products on Amazon. TV5: I find reviews presented on the Amazon's website helpful to my purchase decision making.			
Emotional and Cognitive Trust (ECT)	.93	.94	.67
Adapted from (Lee, Sun, Chen, & Jhu, 2015; Hassanein & Head, 2007) ET1: I feel secure about relying on this customer review for my purchase decision. ET2: I feel comfortable relying on this customer review for my purchase decision. CT1: I trust this customer reviewer had good knowledge about this product. CT2: I feel this product review is honest. CT3: I feel this product review is trustworthy. CT4: I feel that this product reviewer cares about other customers. CT5: I feel that this product review provides relevant information for purchase decision making. CT6: I have reservations about relying on this customer review for my purchase decision.			
Perceived Ease-of-Use (PEU)	.88	.92	.73
Adapted from (Hassanein & Head, 2007) PEU1: Amazon is easy to use to purchase an item. PEU2: Amazon is a user-friendly website. PEU3: Interaction with Amazon's website is clear and understandable. PEU4: I can quickly find the information I need on Amazon's website.			
Perceived Usefulness (PU)	.78	.85	.54
Adapted from (Kucukusta, Law, Besbes, & Legoherel, 2015) PU1: I can complete online purchasing quickly at Amazon. PU2: Purchasing online allows me to use my time efficiently. PU3: Using Amazon to purchase items is easier than traveling to a store. PU4: Using Amazon gives me a larger selection to choose from. PU5: I find it difficult to purchase items on Amazon's website.			
Purchase Intention (PI)	.84	.92	.86
Adapted from (Yang, Sarathy, & Walsh, 2016; Animesh, Pinsonneault, Yang, & Oh, 2011) PI2: Based on the image above, my willingness to purchase this product is high. PI3: Based on the customer review, I would consider purchasing this item.			

MEASUREMENT MODEL ASSESSEMENT

Evaluation of relationships between latent constructs in the model were assessed using SmartPLS 3.0, see Figure 4. A dummy reference variable, for the latent variable with neutral condition, represented the moderating conditional valence category as demonstrated accurate by Henseler, Hubona, and Ray (2016) in their discussion on PLS path modeling. Multiple level categorical variables, in PLS, can be represented through the formation of representative dummy variables. A composite is then utilized representing all levels, minus one, which acts as the reference level, therefore dichotomizing the data. Categorical variables of this type should 'play the role of exogenous variable in a structural model' (Henseler, Hubona, Ray, 2016; Schuberth, Henseler, Dijkstra, 2018).

A weak effect size was indicated for the endogenous constructs of ECT (R^2=.14) by PV, meeting the Garson (2016) suggested cutoff. Moderation was found between the dependent construct PEU and PU with R^2=.54 (moderate effect), while the variance explained by exogenous constructs on PI was R^2=.39 (Streukens & Leroi-Werelds, 2016) see Table 3 and Figure 4.

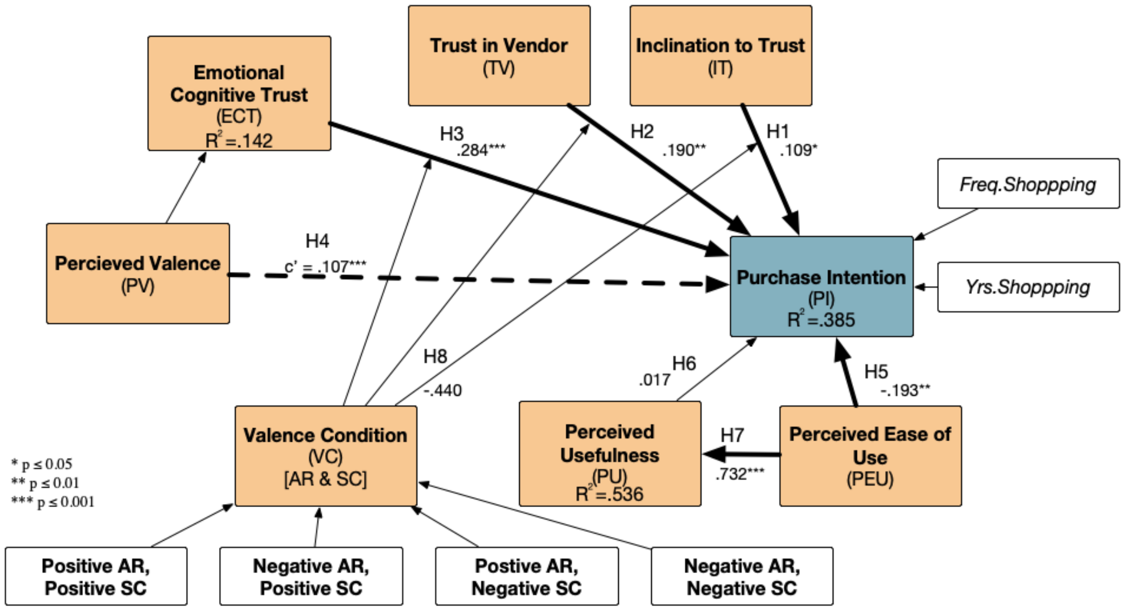
Table 3: *Effect Size*

	R Square	R Square Adjusted
ECT	.14	.14
PI	.39	.36
PU	.54	.53

Cronbach's alpha measures, as noted in Table 2, show ECT variable α>.93. All values resulted as α>.76 level, greater than the suggested cutoff of α>.70. Composite Reliability greater than CR>.77 for all values, exceeding the suggested level of CR>.60. Additionally, the AVE exceeded .50 values reporting AVE>.54 except TV (AVE=.47).
SmartPLS 3.0's bootstrapping with J=5000 reported significant with t-values at t>1.96, p<.05 (Streukens & Leroi-Werelds, 2016).

H1: (t=2.05, p=.041) was supported, indicating a positive relationship between inclination to trust and increased purchase intentions.
H2: (t=2.83, p=.000) was supported, demonstrating the relationship between trust in vendor and purchase intentions to be positive. Increased trust in vendor results in increased buyer purchase intentions.
H3: (t=4.80, p=.000) was supported. A significant positive indication of relationship between greater emotional-cognitive trust and consumer purchase intentions was shown.
H4: (c'=.107, p=.000) was supported. Emotional-cognitive trust shows a mediating relationship between perceived valence and purchase intentions.
H5: (t=2.66, p=.008) was supported. Concurring with results from previous eTAM's research, a positive relationship was seen between perceived ease-of-use and purchase intentions.
H6: (t=.239, p=.811) demonstrated no support for the relationship between perceived usefulness and purchase intentions.
H7: (t=22.90, p=.000) shows support for a positive relationship between perceived ease-of-use and perceived usefulness, confirming past eTAM models.
H8: (t=.990, p=.322) was unsupported. No moderation between the trust relationship and purchase intentions was demonstrated.

Figure 4: *Structural Model Results*



Buyer experience in online shopping was assessed using frequency of shopping (Freq.shopping) per year and years shopping (Yrs.Shopping). Significant according to Spearman's rho (Rs=.149, p<.05), they demonstrate a strong relationship. Interestingly, the two buyer controls (see Appendix) did not show a direct influence on purchase intentions, yet strengthened the relationship between inclination trust and purchase intentions. Inclusion of the two buyer controls increased insights into shopper's behaviors and strengthened the overall predictive ability of the model. This supports others' findings regarding trust and purchase intentions, those with low trust levels would be expected to limit online purchase activities and demonstrate lower frequency of shopping and years shopping (Kim & Park, 2013; Cho & Sagynov, 2015; Guo, Wang, & Wu, 2020). The greater the inclination to trust, the more one would be expected to trust in online purchasing and actively shop online and to do so for a greater length of time (Yrs.Shopping) and more frequently (Freq.Shopping) (Kulviwat, Bruner, & Neelankavil, 2014). The two controls were only significant when used in combination. Those who have been shopping 8 years or more and purchase 15 or more times per year online are more likely to have inclination to trust influence their purchase intentions. A latent variable with neutral condition as the dummy reference level represented the moderating conditional valence category (Henseler, Hubona, & Ray, 2016; Schuberth, Henseler, Dijkstra, 2018).

DISCUSSION AND CONCLUSIONS

In an era where online purchasing continues to show growth, understanding diagnostic aspects of purchase intention formation is of greater importance to online vendors (Guo, Wang, & Wu, 2020). Information Diagnosticity offers greater insights into how consumers determine product purchase categorization. Electronic social sharing of product experiences impacts decision making within online sales. Extending Klopping and McKinney's (2016) eTAM to account for diagnostic criteria derived from eWOM customer reviews strengthens the predictive ability of the model.

The extended model confirms six of eight hypotheses, giving a clearer understanding of purchase intention formation. Greater trusts, represented by cognitive-emotional trust, inclination to trust, and trust in vendor, all were supported with positive relationships on purchase intentions.

As theoretically supported, a person's increased inclination to trust has a positive impact on purchase intentions, those with depressed intrinsic trust behaviors are not expected to risk online financial exchanges. Without the initial inclination to trust ecommerce, limited expectations of online shopping would be expected. Trust in the electronic vending platform and in the shared consumer reviews would be hard for anyone with unlikely inclination to trust (Cho & Sagynov, 2015; Kulviwat, Bruner, & Neelankavil, 2014; Guo, Wang, & Wu, 2020; Lee & Hong, 2019).

Trusting the ecommerce platform increases the likelihood for a consumer to purchase items. This research demonstrated that increased trust in vendors, specifically Amazon.com, increases the purchase intention formation. The trusting diagnostic criteria contributing to purchasing is dependent on believing the vendor is trustworthy, and is consistent with Information Diagnosticity. Trust in vendors can be generated by eWOM, previous experiences, and reputation. Increased trust increases the comfort of the consumer in taking a financial risk with a specific evendor (Cho & Sagynov, 2015). Increasing trust in online vendor transactions can include 'no risk' trail periods, ease returns, free shipping, and other risk mitigating options. Promoting a positive and trustworthy image online and in response to consumer reviews may also assist in trust generation.

Consistent with previous research on eTAM, the relationship between perceived ease-of-use and purchase intentions was supported (Klopping & McKinney, 2004). It is logical that the harder the platform is to use the less customers will complete transactions. With the wide selection of online vendors available, e-vendors with hard to use interfaces would attract fewer customers (Davis, Bagozzi, & Warshaw, 1989; Davis & Venkatesh, 1996; Klopping & McKinney, 2004; Guo, Wang, & Wu, 2020). Increase consumer traffic may be generated through the implementation of intuitive user interface, specifically product selection and purchasing. Additionally, online assistance in purchasing using friendly and trustworthy support interactions may increase consumer use comfort.

Perceived ease-of-use compliments the construct of perceived usefulness, as indicated in past eTAM research. The easier a technology is to use, the more useful the technology appears. Harder to use interfaces may cause frustration, decreasing the worth of the site to the user, a hard to use evendor will be less useful than an ease to use brick-and-mortar store. It is assumed that the effort expended to use an online shopping site should be less than traveling and shopping in person. Effort expended should be limited, increasing ease-of-use and perceived usefulness. Implementing simple use tutorials, offering overviews, and online assistance may increase ease-of-use perceptions and increasing perceived usefulness, thus giving a better experience for the effort expend (Davis & Venkatesh, 1996; Klopping & McKinney, 2004; Guo, Wang, & Wu, 2020). Useful websites are more likely to attract repeat customers.

Hypotheses 6 and 8, while unsupported, may show important findings. While inconsistent with previous findings, perceived usefulness was not supported as influencing purchase intentions. This could be a lack of variance in the participant base. The selection criteria of participants assumed Amazon patronage and users of Amazon's MTurk service. This population already assumes the website is useful, therefore skewing the results and limiting variance (Gurney, 2019). Perceived usefulness becomes a less influencing intention formation factor is the group already assumes usefulness. The homogeneity of the sample may be affecting this construct. Further research with a more diverse sample is suggested.

Strengthening the ecommerce technology acceptance model through the implementation of Information Diagnosticity allows for greater accuracy in assessing impacting criteria within eWOM customer reviews. Increasing the measurability of valence and trust elements present in online product pages, hosted on websites such as Amazon.com, allows for increase insights into purchase intention behaviors. Improved understanding of how diagnostic information available in online product pages and trusting elements influence ecommerce can facilitate improved vendor-customer interfaces. Information Diagnosticity extends eTAM to account for additional elements impacting purchase behaviors, improving the model's predictive abilities.

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ANALYSIS OF MACHINE LEARNING TECHNIQUES FOR DETECTING MALICIOUS PDF FILES USING WEKA

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ABSTRACT

The expansion of cloud and connected software and hardware has increased the attack surface of the modern enterprise. The growth in quantity and quality have led to greater possibilities of system vulnerabilities leading to exploits. One of the threat vectors attackers use is embedding malware to Portable Document Format (PDF) files. The popularity and flexibility of these file formats have made PDFs an ideal target for unaware users. Malicious PDFs contain executable code used by attackers to steal company information or disrupt normal business operations. Adobe Acrobat and Reader users can view, create, manipulate, print, and manage files in PDFs shared hence increased risk. The National Technology Security Coalition report (2020) shows that 68% of data breaches occurred through email and 5% successful attacks through PDF files. In 2019, CVE recorded 17,306 software vulnerabilities on the Adobe Acrobat PDF reader. These software vulnerabilities on Adobe Acrobat PDF may lead to unauthorized users controlling the system, resulting in malicious programs, unauthorized access, and confidential data modification. The attacker may also delete data or create user accounts undetected. This study seeks to; identify threats, detect, classify, and create awareness of PDF malware on emails. This paper will present and compare different WEKA machine learning algorithms in malicious PDF detection and propose the best classifier from the analyzed algorithms.

INTRODUCTION

Digital commerce relies on sharing information and documents. In 2019, users opened over 250 billion PDF files, according to Adobe Fast Facts (2020). Around 8 files of billion Fortune 100 companies depend on the Adobe electronic signature to validate transactions over the internet from the statistics. Historically, attackers would use executable files to attack computer systems. However, with the growth of email use in businesses, attackers have shifted their focus to using email to spread malware (Singh, 2016). For instance, most people interact with non-executable files such as Microsoft Word files, PDFs, excel sheets, and photos mostly shared via email for communication purposes. According to Singh (2016), computer users presume that non-executable file formats such as PDFs are secure and prevalent, thus assuming virus scanners and Advanced Threat Protection (ATP) are adequate to ascertain safety. However, attackers are now using PDF files and embedding them with malware that is difficult to detect and result in data breaches and computer harm.

Portable Document Format (PDF), a standard of ISO, is now the most popular file format in most offices today (Torres and Santos, 2018). PDF is a product of Adobe Systems launched in 1992 to enhance digital file-sharing and comfortable viewing and printing of the shared documents ("What is a PDF? Portable Document Format | Adobe Acrobat DC", 2020). PDFs are convenient and run on different platforms allowing the free exchange of files regardless of device or operating system. These files are easy to use, provide a method to exchange files and images, and offer various content management tools to facilitate information sharing. According to Kuo, Hsu, & Yang (2015), the files have application programming interfaces (APIs) that enhance user experience. For instance, the PDF has APIs that remind the user of the time or provide options to fill in a PDF. Although APIs are convenient for users, they have vulnerabilities that can make hackers modify the features of a PDF (Bhuiyan, 2018). The attacker can embed malware in attractive PDF files and target unaware PDF users to open the files.

CVE-2020-6398 exhibits a vulnerability in the Google Chrome PDFium, which allows an attacker to use uninitialized PDF resources to execute malware. CVE -2020-6112 exposes a vulnerability in the JPEG2000 Nitro Pro software, where an attacker can embed malicious code in an image inside a PDF file targeting an unaware user. When the user opens the data on the initializing tiles, the Nitro Pro application miscalculates the pointer on the tile resulting in memory errors ("CVE -Common Vulnerabilities and Exposures (CVE)," 2020).

In 2020, another software vulnerability was found in the Okular before 1.10.0 that required no user manipulation of a PDF for malicious code to execute. Attackers have also utilized the vulnerability in the PDF code of Nitro Pro 13.9.1.155 to execute malicious code remotely. According to CVE-2020-6074, attackers send malicious PDF files to victims, which triggers malware execution in the PDF parser of Nitro Pro 13.9.1.155. The severity of the attack is high and can cause systems to crash after establishing a use after free errors. CVE-2020-10904 shows exploitation of the

Foxit PhantomPDF 9.7.1.29511 in procuring a remote attack to a system when a user opens a corrupted PDF file ("CVE -Common Vulnerabilities and Exposures (CVE)," 2020). The attackers embed an executable code on the PDF's U3D object then send the file to an unaware user (NVD - Statistics, 2020). If the user fails to validate the source of the file and opens the PDF file, the attacker executes the code, which results in the crash of a program due to writing past the end of the PDF object.

This paper involves analyzing different machine learning classification techniques to determine whether a PDF file is malicious or clean. Machine learning classification consists of the analysis of PDF files based on its features. The main objective is to determine if the PDFs have an embedded object or not. The dataset used in this study contains multiple PDF files with different features classified using WEKA, a data mining software. Waikato Environment for Knowledge Analysis (WEKA) is an open-source software developed for data mining in various fields like education, research, etc.(bin Othman & Yau, 2007). The report consists of the analysis and comparison of NaiveBayes, BayesNet, J48, RandomForest, and Logistic Regression algorithms.

NaiveBayes is a classifier that uses Bayesian methods to form simplified networks depending on past probabilities (Van der Heide et al., 2019). The technique relies on the independence between the input variables and the output variables to produce results. Therefore, the input variables and the output variables contribute equally but independently to the computation's final product (Ting & Tsang, 2018).

The BayesNet classifier also uses Bayesian Network to predict the outcome of an analysis. The technique works well in datasets with complexity and where a change in one variable changes another variable. The classification involves the computation of probability distributions and the development of a directed acyclic graph where a variable is regarded as a node (Özdemir, Yavuz & Dael, 2019.) Random Forest is a classifier that uses decision trees to predict the outcome. Each tree forms a subset of the training sample (Van der Heide et al., 2019), and the classification only runs once all the trees have been constructed. The results produced by this classifier are a summation of the predictions made by all the trees. The classifier has an advantage in completing data computation on a dataset with missing attributes (Huljanah et al. 2019). J48 is also a tree-based algorithm. This algorithm uses decision tree methods that have leaves and branches. The result is based on the many outcomes from the leaves and branches computation (Özdemir, Yavuz & Dael, 2019).

The Logistic Regression is a linear classifier that shows the relationship between a dependent and an independent variable. The technique uses a logistic function to estimate the probability between the variables. The classifier is based on probability, and the results are represented in a linear form (Khairunnahar et al., 2019). The Zero R algorithm is a simple classification method that uses algebraic expressions to categorize groups of data. This algorithm ignores all predictors to nominal and numeric data (Kaur & Singh, 2019). The Xero algorithm was the base algorithm for this study. The algorithms were evaluated, and the results were presented in a table. The outcome of the analysis will help identify a potential classifier that will predict malicious PDF files from the email that may harm computer systems.

Classification involves machine learning by using existing features. The dataset studied was extracted from GitHub, a platform for software developers to share programming codes and information. The dataset extracted on May, 5th 2020, has a total of 19,986 PDF files. From the dataset, 10,981 malicious PDF files, and 9,007 clean files. The data was selected because the variables are PDF attributes that attackers use to embed malicious codes. The sample data was collected by Rajeshwaran (2019) for machine learning and data analysis projects. This study aimed to understand the PDF structure, explore different algorithms used for classification, and propose the best classifier for detecting malicious PDF Files. The experiment was limited to five algorithms present in WEKA; therefore, additional comparisons may have been better suited for detecting malicious PDFs.

This paper is organized as follows: Section 2 presents the background of the study. Section 3 describes the methodology used in the research, and section 4 outlines the results/findings/discussion from the experiment. Section 5 describes the conclusions made from the experiment. The PDF basic structure includes the PDF header, the PDF body, the cross-reference table, and the trailer. The sections are static. The PDF header contains the PDF version, and the PDF body has the objects such as the font, length, filter, and in some cases, animations, and security objects (Torress & Santos, 2018). The cross-reference table (Xref) contains the pointers to all the objects in the PDF file, which helps the user locate all the files' contents on different pages. The trailer is the last section of the PDF basic structure that contains the EOF pointer, which refers to the cross-reference table. The trailer helps the user to find and locate the contents of the PDF file.

Figure 1: Sample of the PDF structure Source *http://infosecinstitute.com*.

BACKGROUND

Previous studies have proved that machine learning is a valuable tool in medicine, education, and research (bin Othman & Yau, 2007). Machine learning techniques involve developing models without prior knowledge of the variables (Van der Heide et al., 2019). One way machine learning has been used in cybersecurity is to develop models to detect PDF malware. PDF files are popularly used for communication in digital businesses (Zhang, 2018). PDF files shared over emails include articles, research papers, business reports, and electronic receipts (Zhang, 2018). These file formats are popular because of their flexibility and acceptability.

Recent CVE reports show that PDF files have an API vulnerability that has made them a popular attack vector (CVE -Common Vulnerabilities and Exposures (CVE), 2020). The attackers embed an executable code on PDF files that result in massive data breaches and considerable damages to computer systems ((NVD - Statistics, 2020). According to Torres & Santos (2018), traditional antivirus and sandboxes are not sufficient to detect such malicious PDFs because they have high false positives and negative rates.

Machine learning techniques have the potential to complement traditional methods for detecting malicious PDFs. Various machine learning algorithms can develop an accurate and versatile model to detect malicious PDF files from emails. However, it is difficult to determine the most accurate and most versatile algorithm in WEKA because different classifiers use different techniques to predict the outcome based on the specified variables (Beaugnon & Chifflier, 2018). Furthermore, different classifiers have specific attributes that may make them suitable to study malicious PDF files.

Three WEKA algorithms proposed as competitive classifiers for this study are Random Forest, Naïve Bayes, and BayesNet. RandomForest is a tree-based classifier that uses cross-validation to analyze data (Smutz & Stavrou, 2018). The classifier extracts the PDF file objects that run through the tree before providing an evaluation. Naïve Bayes and BayesNet use the Bayesian theory to classify based on PDF attributes such as the heap spray, JavaScript syntax, and shellcode (Cheng et al., 2012). Logical regression is a traditional technique that uses linear modeling to predict the outcome. Despite the algorithm being superior in providing linear models, logical regression cannot analyze data with missing entries (Van der Heide et al., 2019). We shall study the accuracy and potential of RandomForest, Naïve Bayes, BayesNet, in detecting malicious PDFs and compare the accuracy with traditional classifiers like Logical Regression and Zero R.

METHODOLOGY

For this study, a dataset was extracted from the GitHub software, a platform where software developers interact and share ideas. The dataset has a total of 19,986 PDF files. Ten thousand nine hundred eighty-one are malicious files, while 9,007 files are clean. The attributes used include the PDF components obj, endobj, stream, endstream, Xref, trailer, page, encrypt, JS, and JavaScript code. Other features analyzed include the AA, openaction, startxref,acroform, JBIG2Decode, rich media, launch, embedded file, XFA, and colors. The dataset had no errors and null values.

The data mining process involved using the open-source software WEKA. WEKA is a tool for knowledge analysis that has multiple machine learning algorithms for data analysis. The software is necessary to develop models in different sectors, such as bioinformatics, education, and medicine. This study involves using an algorithm efficient in cybersecurity (bin Othman & Yau, 2007). The classification algorithms utilized in this paper include NaivesBayes and BayesNet, which are probabilistic classifiers. Other classifiers used include tree classifiers such as the J48 and RandomForest, and Logistic Regression, a supervised algorithm based on the variables. The Xero was used as a base algorithm to compare the rest of the models.

The data was sorted and prepared for mining. The dataset contained attributes required for analysis, and no attribute was excluded from the study. The data were tabulated, as shown in Figure 2. The attributes analyzed include the PDF components obj, endobj, stream, Xref, trailer, etc. (Figure 2). All the attributes had numerical data; therefore, no separation was required. The PDF files were then classified as malicious or not malicious based on the components. Malicious files were classified as "yes," and clean files were classified as "no.

endstream	xref	trailer	startxref	Page	Encrypt	ObjStm	JS	Javascript	Malicious
16	2	2	2	3	0	0	0	0	no
2	0	1	1	0	0	0	1	2	yes
3	1	1	1	1	0	0	1	2	yes

Figure 2: Sample of malicious PDF dataset

This study evaluates different machine learning techniques and proposes a model that can detect malicious PDF files accurately. The analysis will give us a perspective on how machine learning techniques can determine malicious files and clean files. The research involved analyzing and comparing five different machine learning models and selecting the best classifier from the outcome. The techniques involve two probabilistic classifiers, two tree classifiers, and one classifier based on x and y variables. The algorithms were selected to explore different types of classifiers according to the aims of the research.

For this paper, the algorithms used include NaiveBayes, BayesNet, J48, RandomForest, and Logistic Regression. The Xero was the base algorithm for the analysis and comparisons.

RESULTS

The evaluation involved different classification methods, i.e., NaiveBayes, BayesNet, J48, RandomForest, Logistic Regression, and Xero. In this study, WEKA was used to classify the malicious PDF dataset. 30% of the data was used for training, and 70% was used for testing. The classifiers analyzed the data using specific PDF features for easy evaluation. As shown in Table 1, the first results tabulated include the correctly classified instances and its percentage, the incorrectly classified instances and its percentage, the Kappa statistic, and the time in seconds that the model took to complete the classification. Table 2 shows the error analysis, which summarizes the mean absolute error, the relative absolute error, the root mean squared error and each algorithm's root-relative error. Table 3 summarizes the accuracy of each algorithm using the true positive and false positive. Figures 5 and 6 show the accuracy of each algorithm based on the correctly classified instances and incorrectly classified instances, and error analysis, respectively.

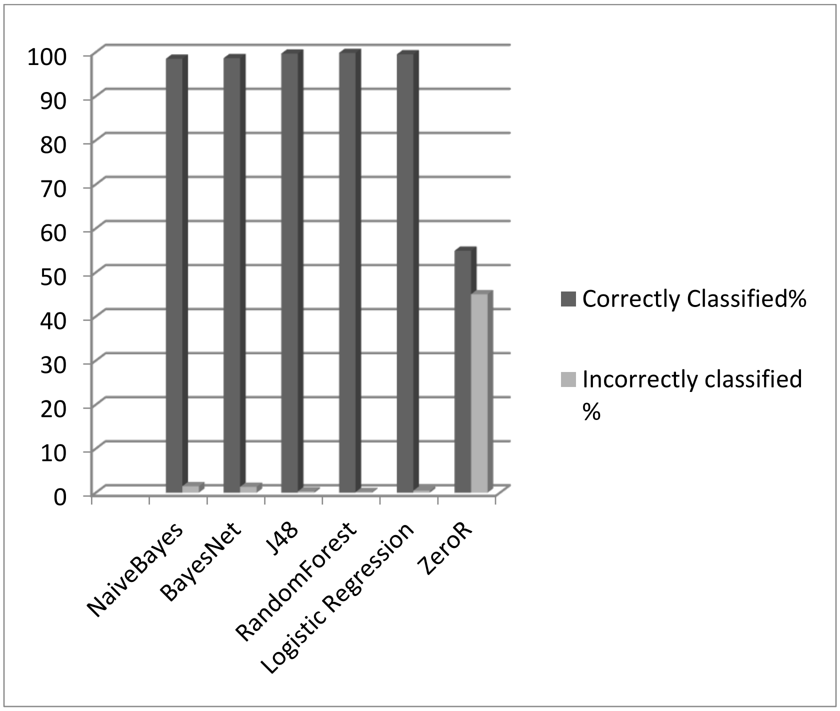

Figure 5: Accuracy visualization

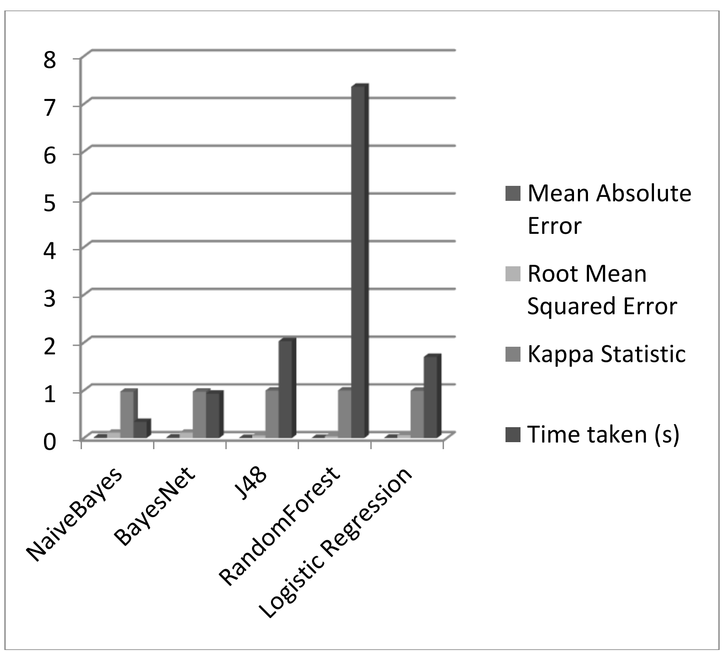

Figure 6: Error analysis visualization

DISCUSSION

Based on the evaluation results from Table 1 and Table 2, the RandomForest algorithm has the highest correctly classified instances of 19,955, which is 99.8449%. The least accurate classifier has several correctly classified cases of 19,690 (98.519%), the naive Bayes algorithm. Other algorithms have an accuracy of more than 98.65%, with the BayesNet correctly classifying 19,718 instances, J48 correctly classified 19,924 instances, and Logistic Regression correctly classified 19,892 instances. Our experimental base algorithm ZeroR correctly classified 10,980 instances, with 54.93% accuracy. The RandomForest takes a longer time of 7.36 seconds to finish the classification, while the Xero takes the shortest time to complete the computation.

The Kappa value defines the relationship between the reliability and the accuracy of the data (Vierra & Garrett, 2005). The Kappa is a metric that shows whether data is reliable and accurate. The results of reliability versus accuracy and comparison to the Kappa criteria define the relationship. For instance, data with a zero Kappa value has both reliability and accuracy. From our results, Xero has a zero Kappa value. The other algorithms have a Kappa value of more than 0.9, which shows that the reliability and accuracy relationship is almost perfect (Vierra & Garrett, 2005).

The error evaluation shows that the NaiveBayes algorithm has the highest mean absolute error compared to other algorithms. The algorithm has a mean absolute error of 0.0147, while the RandomForest has the lowest mean absolute error of 0.0032. This experiment's error analysis involves using the relative absolute error, the root mean squared error, and the root relative squared error.

From the True Positive and False Positive evaluation, the BayesNet has the highest True Positive rate of 1.0. The results show that the algorithm based on the True Positive rate accurately identified the malicious files which indeed had malware. Its false positive rate is 0.024, which is when PDF files were classified as malicious yet had no malware. The algorithm with the highest accuracy and lowest mean absolute error was selected as the best classifier for detecting malicious PDF files.

CONCLUSION

The five techniques used in this experiment were able to detect malicious PDF files and clean files. According to the results, the RandomForest, a tree-based algorithm, had an accuracy of 99.8449%. The algorithm was more accurate than NaiveBayes, BayesNet, Xero, and Logistic Regression because it minimizes the overall error rate, works well with massive data sets, and is highly sensitive. Random Forest, NaiveBayes, and BayesNet had a Kappa value of 0.9, making them excellent classifiers for this experiment. NaiveBayes algorithm had the highest mean absolute error because of the complexity of the data and the simplicity of its hypothesis. It was possible to propose using a RandomForest algorithm to complement other cybersecurity techniques, such as antivirus, to mitigate malware in PDF files.

In practice, this study will enhance future works in cybersecurity to understand and resolve vulnerabilities on PDF files. The results will be a reference for other studies that seek to study the potential of machine learning in detecting malicious PDF files.

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CHAOS IN US INDIVIDUAL INTRADAY SECURITY PRICES

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ABSTRACT

We examined intraday security prices using Bloomberg market prices from October to December 2018. Our sample consists of 12,193,335 data points, covering 495 stocks, 63 trading days and 391 minutes per day. It is well known that news arrival impacts market prices. Casual empiricism suggests that news arrival is random and therefore intraday market prices may also be random. However, following Lo and Mackinlay (1988) and Chow and Denning (1993), we reject the linear process of randomness in intraday security prices. Following Webel (2011), we then examine the non-linear chaotic process using the zero-one test adjusted by wavelet denoising prior to testing. Our results are consistent with chaotic intraday security returns and inferentially with chaotic news arrival.

INTRODUCTION AND LITERATURE REVIEW

Fama (1976) was perhaps the first to define an efficient capital market as one where the joint distribution of security prices, given the set of information the market uses to determine security prices is identical to the joint distribution of prices that would exist if all relevant information were used. Any precise formulation of an empirically refutable efficient markets hypothesis is of necessity model-specific. Historically, many examinations of the efficient market hypotheses have focused on the paradigm of the random walk. A random walk is a stronger hypothesis than the efficient market hypothesis because it indicates that there is no difference between the security return distribution given the information structure and the unconditional distribution of returns. Any test of security returns and the responsiveness of returns to information is a joint hypothesis: one that market pricing is efficient and simultaneously one that the model used to identify price dynamics is the correct one. Therefore, a precise formulation of an empirically refutable efficient markets hypothesis must be model-specific. Initially we employ the random walk modeling process. However, rejecting this linear process, we then examine a chaotic stochastic process using the 0-1 test.

Our initial examination focuses on the random walk. A property of a random walk process is that the variance of the increments is linear in the sampling interval. Specifically, for example, the volatility of monthly returns must be four times as large as that of weekly returns. Fama and French (1988), Lo and MacKinlay (1988), Poterba and Summer (1988), and Chow and Denning (1993) use this property to examine the stochastic process of security market returns. Analogous to the variance ratio property, under a joint hypothesis of efficient markets and a random walk in prices (and therefore inferentially in news arrival), the correlation of two processes must be identical a different time horizons. [1] Daniel and Titman (1997) argue that it is the characteristics rather than the covariance or correlation structure of returns that explain the variation in stock returns.

Consistent with Daniel and Titman, we reject the random walk hypothesis. Rejecting the linear structure of security prices using random walk modeling, we then examine the financial time series using a chaotic time series modeling. Our approach is consistent with that of Webel (2012) which avoids the potential biases in chaotic time series testing by employing the 0-1 test. Modeling returns using a chaotic stochastic process has the benefit of greater accuracy in short term return predictions. [2] 'The benefit of modeling analysis using a chaotic time model is that it potentially leads to greater accuracy in short term predictions and also indicates that haphazard price fluctuations (such as those resulting from news and the information impact of news on prices) actually represent an orderly system in disguise.
Considering the Daniel and Titman (1997) results, we first employ principal components analysis to identify the characteristic factors underlying the distribution of our sample of security returns. Hasbrouck and Seppi (2001) implement principal components analysis for the thirty Dow stocks in 1994 at 15-minute intervals using time-aggregated trade and quote data. They find that common factors exist which and can explain part of the common variation in returns and the quotes.[3]. Aït-Sahalia and Xiu (2018) conduct weekly principal component analysis on intraday returns of S&P 100 stocks which are computed using the latest prices recorded within 1-minute interval over

[1] The unity of the correlation ratio (CR) for different holding periods can also be used as a powerful tool to jointly test the random walk hypothesis. See Chow and Denning (2005).
[2] See Williams (1997).
[3] The first eigenvalue can explain 21% and 11.2% of the total variation in returns and quotes, respectively.

the 2003-2012 period. They find that, consistent with the Fama-French factor model at low frequency, the joint dynamics of the S&P 100 stocks at high frequency can be explained by the first three eigenvalues.[4] Section 2 presents our methodology. Section 3 presents data. Section 4 presents our empirical results, and Section 5 discusses our conclusions.

METHODOLOGY

The multiple variance ratio test for randomness:

Variance-ratio tests have been widely employed in empirical finance studies to assess the rate of information flow over time and across stocks. Our tests of the randomness of intraday trading price are based on the variance ratio statistics developed by Lo and MacKinlay (1988) (LOMAC, thereafter) and a multiple variance ratio extension developed by Chow and Denning (1993). Let X_t denote a stochastic process satisfying the following recursive relation:

$$X_t = \mu + X_{t-1} + \varepsilon_t, \qquad E[\varepsilon_t] = 0, \quad for\ all\ t, \tag{1}$$

where μ is an arbitrary drift parameter and ε_t is an independent stochastic disturbance with zero mean. Consider a sequence of this time series with a q-period holding time, $(X_0, X_1, \ldots, X_{nq})$. Let $\sigma^2(1)$ be the variance of the first difference of the one-period series, $Var(X_t - X_{t-1})$, and $\sigma^2(q)$ be the variance of the first difference of the q-period series, $Var(X_t - X_{t-q})$. Under the LOMAC random walk hypothesis that X increments are uncorrelated, the variance of these increments must be linear in any observation interval, and the variance ratio $\sigma^2(q)/q\sigma^2(1)$ equals one. A variance ratio's deviation from unity can then be considered to be proportional to the amount of inefficiency present in that stock or index.

LOMAC also generates the asymptotic distribution of the estimated variance ratios and defines test statistics under two null hypotheses - H_1: homoscedastic increments random walk and H_2: heteroscedastic increments random walk - as follows:

Under H_1: $$Z_1(q) \equiv \sqrt{nq}\left(\frac{\hat{\sigma}^2(q)}{q\hat{\sigma}^2(1)}\right)[2(2q-1)(q-1)/3q]^{-1/2} \sim N(0,1), \tag{2a}$$

Under H_2: $$Z_2(q) \equiv \sqrt{nq}\left(\frac{\hat{\sigma}^2(q)}{q\hat{\sigma}^2(1)}\right)[V(q)]^{-1/2} \sim N(0,1), \tag{2b}$$

Where $V(q)$ is the asymptotic variance of $\frac{\hat{\sigma}^2(q)}{q\hat{\sigma}^2(1)}$ under H_2. The LOMAC approach provides a way to test random walk by comparing the test statistic, $Z_1(q)$ or $Z_2(q)$, with the standard normal critical value.

Chow and Denning (1993) extend the LOMAC approach and provide a more statistically powerful approach to test the random walk by controlling the test size. Compared to LOMAC's individual variance ratio tests for a specific aggregation interval, the Chow-Denning method tests the random walk hypothesis simultaneously over multiple aggregate time intervals.

Consider a set of variance ratio estimates corresponding to a set of pre-specified aggregation intervals, $\{q_i | i = 1, 2, \ldots, m\}$. The Chow-Denning method defines that test statistics $|Z_1^*(q)|$ and $|Z_2^*(q)|$ to be the largest absolute value of the all the LOMAC test statistics from (2a) and (2b) over all the holding periods,

$$Z_1^*(q) = \max_{1 \le i \le m} |Z_1(q_i)| \tag{3a}$$

$$Z_2^*(q) = \max_{1 \le i \le m} |Z_2(q_i)| \tag{3b}$$

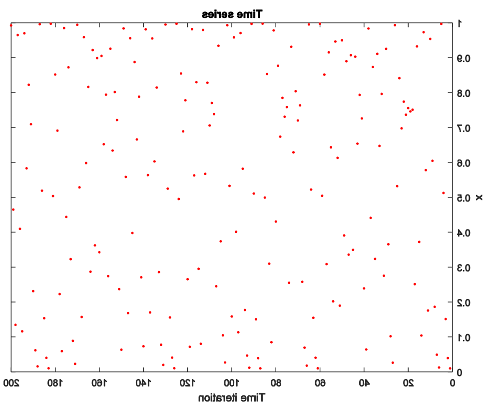
$Z_1^*(q)$ or $Z_2^*(q)$ can then be compared to $SMM(\alpha; m; N)$, which is the upper point of the Studentized Maximum Modulus (SMM) distribution with parameters m and N degrees of freedom, to test the random walk based on Hochberg (1974). If $Z_1^*(q)$ or $Z_2^*(q)$ is greater than the SMM critical value at a predetermined significance level α then the random walk hypothesis is rejected.

[4] In this research, the first eigenvalue accounts for on average 30-40% and the second and third account for 15-20% of stock variations.

The 0-1 test for chaos:

Chaos deals with long term evolution—how something changes over time and it is nonlinear, deterministic and dynamic. A chaotic time series looks irregular or random in time domain, however, chaos has structure seen in a reconstructed phase space. Let us use a logistic map as an example to explain or define chaos. The chaotic data generated by the logistic function are displaced in time domain as shown in Figure 1. It appears random and provides few conclusions. If we transfer the data into a reconstructed phase space where a two dimensional space is built, we can see a parabola in the phase space (as shown in Figure 2). This parabola is hidden in time domain. As such, it is much easier for us to build a model in Figure 1 than in Figure 2 in terms of data interpretation. Analyzing data for chaos can help indicate whether haphazard-looking fluctuations such as in Figure 1 actually represent an orderly system such as in Figure 2 in disguise (see Zhao, Kwiat, Kwiat, Kamhoua, and Njilla (2018)).

Figure1: Chaotic data in time domain



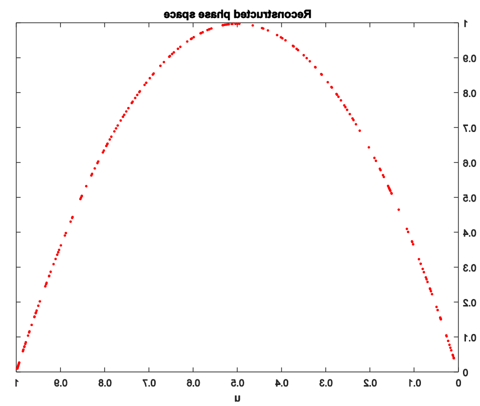


Figure 2: The Chaotic data shown in a reconstructed phase space

Chaos theory has found its applications in many fields such as computer science, engineering, communications, biology and finance based on different aspects of chaotic systems. Chaos theory lets us describe, analyze, and interpret temporal data (whether chaotic or not) in a new, different, and often better way (see Williams (1997)). Being able to differentiate between regular and chaotic dynamics in a financial stock market is important in analyzing a financial time series. Most methods for testing chaos apply largest Lyapunov exponents, and correlation dimensions, which rely on a phase space reconstruction from a finite amount of observations of a noisy time series. This implies accepting certain biases so as to determine the immersion dimension, mean period and time of delay in reconstructing phase space.

The 0-1 test for chaos has recently been developed to solve these inconveniences in order to identify chaos in a financial series. The 0–1 test for chaos is based on a Euclidean extension and does not depend on phase space reconstruction. It works directly with time series. According to Gottwald and Melbourne (2009), the 0-1 test method is described as follows.

Consider a one-dimensional time series $\phi(j)$ for $j = 1,2,\ldots,N$. We use the data $\phi(j)$ to derive the two-dimensional system, in which the translation variables $p_c(n)$ and $q_c(n)$ are calculated as shown in Equation (4).

$$p_c(n) = \sum_{j=1}^{n} \phi(j) \cos jc \;\; ; \;\; q_c(n) = \sum_{j=1}^{n} \phi(j) \sin jc \qquad (4)$$

Where fixed frequency $c \in (1, \pi)$ and $n = 1,2,\ldots,N$. The diffusive (or non-diffusive) behavior $p_c(n)$ and $q_c(n)$ can then be investigated by analyzing the mean square displacement $M_c(n)$ as defined in Equation (5).

$$M_c(n) = \lim_{N\to\infty} \frac{1}{N} \sum_{j=1}^{N} [p_c(j+n) - p_c(j)]^2 + [q_c(j+n) - q_c(j)]^2 \qquad (5)$$

Note that this definition requires $n \ll N$. The 0-1 test for chaos is based on the growth rate of $M_c(n)$ as a function of n. The limit is assured by calculating $M_c(n)$ only for $n \ll n_{cut}$. In practice, $n_{cut} = N/10$ is usually selected for good results, and $D_c(n)$, a smoothed version of mean square displacement $M_c(n)$ as shown in Equation (6), is used in the 0-1 test for chaos.

$$D_c(n) = M_c(n) - \left(\lim_{N\to\infty} \frac{1}{N}\sum_{j=1}^{N} \phi(j)\right)^2 \frac{1-\cos nc}{1-\cos c} \quad (6)$$

Then, based on $D_c(n)$, the asymptotic growth rate K_c can be estimated by deploying a regression method or a correlation method. In this paper, we use the correlation method. That is, for vectors $\alpha = [1,2,\dots,n_{cut}]$ and $\beta = [D_c(1), D_c(2), \dots, D_c(n_{cut})]$, the correlation coefficient K_c is determined in Equation (7) from the mean square displacement $D_c(n)$.

$$K_c = corr(\alpha,\beta) = \frac{cov(\alpha,\beta)}{\sqrt{var(\alpha)\times var(\beta)}} \in [-1,1] \quad (7)$$

Where $cov(\alpha,\beta) = \frac{1}{n_{cut}}\sum_{j=1}^{n_{cut}}(\alpha(j)-\bar{\alpha})(\beta(j)-\bar{\beta})$, $var(\alpha) = cov(\alpha,\alpha)$, and $var(\beta) = cov(\beta,\beta)$. Under general conditions, the limits $D_c(n)$ and K_c can be shown to exist, and we can use K_c to determine the chaotic pattern of a time series. For regular dynamics, K_c is close to 0; for chaotic dynamics, K_c is close to 1.

DATA

To test for random walk and chaos in stock price, we collect intraday stock trading prices for each of the individual companies listed on Standard & Poor (S&P) 500 index from Bloomberg. We eliminate weekends and observed holidays during which the market is closed. We focus on the stocks with the complete 63 trading days over three-month time span from October 1, 2018 to December 31, 2018. We divide each trading day into successive 1-minute intervals when the market is open at 9:30 a.m. through 4:00 p.m., Eastern Standard Time. We calculate the average trading price across each 1-minute interval for each stock. Therefore, our sample consists of 12,193,335 data points, covering 495 stocks, 63 trading days and 391 minutes per day.

Figure 3 presents the average number of intraday trades per minute from 9:30 am to 4:00 pm over three-month period (Oct 1st – Dec 31st, 2018) for the companies in the S&P 500. We observe a U-shaped pattern in the number of trades by minute of the day. Over the average trading day, there are more trades that occur during the morning and afternoon hours and less during midday periods. The flow of trades shows a decrease beginning at 9:30 am, and continues to drop until 1:30 pm, when new information is presumably light. The flow then starts to rise and peaks at 3:59 pm. The average number of trades during the last ten minutes is over three times greater than that for other times of the trading day.

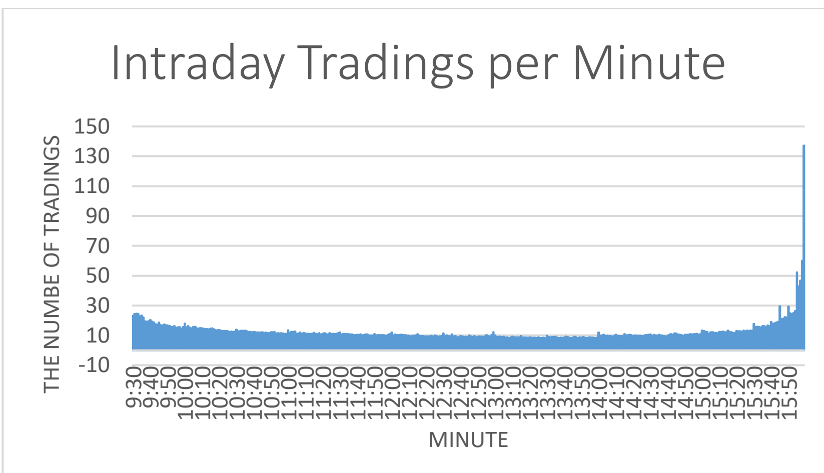


Figure 3 The Frequency of Intraday Tradings

This figure presents the average number of intraday trades per minute from 9:30 am to 4:00 pm over three-month period (Oct 1st – Dec 31st, 2018) for S&P 500 companies.

EMPIRICAL RESULTS

Our first test focuses on multiple variance ratio tests for the randomness of intraday trading price. We start by calculating the variance ratios based on Lo and Mackinlay (1998) for the average trading price per minute of each company in the S&P 500 index at sampling intervals of q=2, 4, 6, 8, 10, 12, 14, and 15 minutes. Table 1 reports the summary statistics of variance ratios for the intraday trading price of S&P 500 companies. For each interval, we report the mean, median, and standard deviation of the variance ratios across S&P 500 companies. We show that the mean and median of the variance ratios are greater than one at all sampling intervals. In addition, as the sampling interval q increases, the mean, median, and standard deviation of the variance ratios increase monotonically.

Table 1: Summary statistics of variance ratios:

This table reports the summary statistics of variance ratios for the intraday trading price of S&P 500 companies. The variance ratios are calculated based on Lo and Mackinlay (1998) for the intraday trading price per minute of each company over three-month period (Oct 1st - Dec 31st, 2018). The mean, median and standard deviation of the variance ratios across S&P 500 companies are reported at q=2, 4, 6, 8, 10, 12, 14, and 15 minutes.

Variance ratio	S&P 500 Sampling interval (q) in minutes							
	2	4	6	8	10	12	14	15
Mean	1.222	1.354	1.403	1.429	1.440	1.451	1.462	1.468
Median	1.180	1.291	1.326	1.351	1.363	1.374	1.386	1.392
Std Dev	0.632	0.956	1.057	1.111	1.143	1.165	1.179	1.182

For each interval, we then estimate the homoscedastic- and heteroscedastic-robust LOMAC test statistics, $Z_1(q)$ and $Z_2(q)$, for the trading price of each company in the S&P 500 index. Using the multiple variance ratio procedure from Chow and Denning (1993), we compare the maximum absolute values of these test statistics to the $SMM(\alpha; m; N)$ critical value, where N is our sample sizes, $m = 4, 5, 6, 7, and\ 8$, and $\alpha = 1, 5, and\ 10$ percent level of significance. For each set of test statistics for a stock, if the maximum absolute value exceeds the SMM critical value, we reject the random walk.

Table 2 reports the rejection rates of the random walk with homoscedastic and heteroscedastic disturbances from intraday trading price of S&P 500 companies. The homoscedastic-robust test results show that the percentage of rejections of the random walk from S&P 500 companies is 83.67%, 85.08% and 85.69% for the significance level α=1, 5, and 10 percent, respectively. In principle, the rejection of random walk could result from heteroscedasticity in the stock price. From our heteroscedastic-robust test results, the rejection rates are relatively lower, but still significant at 68.75%, 72.58%, and 74.60% for α=1, 5, and 10 percent, respectively. Our results provide strong evidence that more than two thirds of our samples listed on S&P 500 reject the random walk of security prices.

Table 2: The multiple variance ratio test for the random walk for intraday trading price:

This table reports the rejection rates of the random walk with homoscedastic and heteroscedastic disturbances from intraday trading price of companies listed on S&P 500 index. The variance ratios and the homoscedastic- and heteroscedastic-robust test statistics, $Z_1(q)$ and $Z_2(q)$, are calculated based on Lo and Mackinlay (1998) for the intraday trading price per minute of each company over three-month period (Oct 1st - Dec 31st, 2018). According to Chow and Denning (1993), we then compare the LOMAC test statistics with the SMM$(\alpha; m; N)$ critical value at the α=1, 5, and 10 percent level of significance to test the random walk hypothesis. We report the rejection rates as the percentage of rejections of the random walk for S&P 500 companies at multiple (m) aggregate time intervals (q).

Multiple (m) aggregate time interval (q) in minutes	Homoskedastic-robust test rejection rate at the significance level α			Heteroskedastic-robust test rejection rate at the significance level α		
	α =1%	α =5%	α =10%	α =1%	α =5%	α =10%
m=4 q=2,4,6,8	88.31%	89.72%	90.12%	76.21%	79.84%	81.65%
m=5 q=2,4,6,8,10	86.90%	88.91%	88.91%	73.59%	76.81%	78.43%
m=6 q=2,4,6,8,10,12	85.28%	87.30%	87.70%	70.56%	74.80%	77.02%
m=7 q=2,4,6,8,10,12,14	84.27%	85.48%	86.69%	69.35%	73.39%	75.20%
m=8 q=2,4,6,8,10,12,14,15	83.67%	85.08%	85.69%	68.75%	72.58%	74.60%

With such a large percentage of rejection rate for the random walk, we next test whether intraday trading price follow a chaotic stochastic process. We start the test by exploring the commonality among the time-series intraday trading price of S&P 500 companies. For this purpose, we use principal components analysis (PCA), a technique in which the time series of a sample of S&P 500 companies are decomposed into orthogonal factors of decreasing explanatory power (see Muirhead (1982) for an exposition of PCA). Specifically, we compute the natural log of stock return as $\mathrm{LN}(P_t/P_{t-15})$ for every 15-minute interval based on the time-series intraday trading price P_t from October 1, 2018 to December 31, 2018. The PCA approach yields a decomposition of the variance-covariance matrix of returns of S&P 500 companies into the eigenvectors of the correlation matrix of returns and the diagonal matrix of eigenvalues. Based on our results of the PCA, the first three eigenvalues explain 52.37% of the variation of the stock returns with the first principal component capturing 41.85%, the second for 7.23% and the third for 3.29%. These three eigenvalues capture a large portion of the total variation when the majority of returns tend to move together at the time of information arrival. Therefore, we focus our attention on only this subset and use the generated three PCA vectors – the principal component factor time series for the following tests.

We then apply the 0-1 test to the three principal component factor time series to characterize the dynamics of intraday trading price. For each PCA vector, we randomly select 100 samples at the sampling frequencies $c \in (\pi/5, 4\pi/5)$ and calculate K_c according to Gottwald and Melbourne (2009). Table 3 reports the median K_c as the chaos factor K for each of the three S&P 500 PCA vectors in 0-1 tests. Our results show that the chaos factor K is 0.9976 for PCA1, 0.9979 for PCA2, and 0.9984 for PCA3, respectively. The close-to-1 chaos factors provide strong evidence that the three principal component factor time series exhibit chaotic dynamic pattern. As the three PCA vectors capture the majority of the variation of the 15-minute stock returns, it is rational to infer that the intraday trading prices of S&P 500 companies follow a chaotic stochastic process.

Table 3: The chaos factors for the three S&P 500 PCA vectors in 0-1 tests:

This table presents the chaos factors of the three S&P 500 PCA vectors in 0-1 tests. We use the PCA approach and 0-1 test to derive the chaos factor, K. Specifically, we compute the natural log of stock returns for every 15-minute interval based on the time-series intraday trading prices of S&P 500 companies from October 1, 2018 to December 31, 2018. We deploy the PCA approach on the log-returns and then apply the 0-1 tests on the generated three PCA vectors. For each PCA vector, we randomly select 100 samples at the sampling frequencies $c \in (\pi/5, 4\pi/5)$ and calculate K_c according to Gottwald and Melbourne (2009). The median K_c are reported as the chaos factor K for each of the three PCA vectors.

PCA vectors	Chaos Factor K
PCA1	0.9976
PCA2	0.9979
PCA3	0.9984

DISCUSSION AND CONCLUSION

An informationally efficient capital market is one where security prices respond quickly and *accurately* to information, However, accurately is a challenging word. It requires a precise specification of the underlying model of the price sequence. Numerous empirical examinations of the efficiency of market pricing have generally failed to support the statistical process of a random walk despite the apparent evidence that unexpected news does impact market prices. Our results which examine the individual securities which comprise the Standard and Poor's 500 index also reject randomness in security pricing. However, following Webel and denoising our data, our results provide support for chaos in security pricing and therefore inferentially in news. It might therefore be argued that chaotic pricing actually represents an orderly system. Future research will have to consider whether these large S&P 500 firm results are robust to differing groups of securities and differing time series,

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Research Notes

RESUME ANALYSIS: A COMPARISON OF TWO METHODS

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ABSTRACT

This study concerns the fact that the landscape of competitive job seeking is changing rapidly with the advancement of technologies to conduct applicant-screening and tracking. Artificial Intelligence (AI) in practical terms referred to as expert systems save time and money for employers swamped by online applicants taking the first pass at screening the large applicant pool to a more manageable number of applicants that would get a human review of their submitted materials. This investigation examined the use of Artificial Intelligence (AI) known as expert system technology in student preparation of resumes on the basis of error frequency, time, cost and tiring/bias compared to a human reader. Implications suggest to augment or even replace the need for a human to do initial reviews of student resumes. Further, if expert system technology is effective in initial resume preparation would this free up a professional's time to actually do more meaningful student career advising and coaching.

INTRODUCTION

This study concerns the fact that the landscape of competitive job seeking is changing rapidly with the advancement of smart technologies to conduct applicant-screening and tracking systems that are increasingly powerful job-market gatekeepers (Schellenberger, 2019). Early studies of machine-learning systems save time and money (Brindley, 1988; Khasiani, 1988) supporting the potential employers swamped by online applicants taking the first pass at screening the large applicant pool to a more manageable number of applicants that would get a "human" review of their submitted materials. Schellenberger further noted that these systems scan résumés and applications for keywords showing hard skills, such as financial analysis or cybersecurity, and sometimes for softer skills such as team leadership. They may ask elimination questions for must-have attributes, such as whether you can work at a particular location. Some use text tools or chat bots to administer skills tests. Most employers disqualify applicants who don't meet basic requirements, then list qualified applicants in a ranked order, based on how well they fit the employer's specs. The concept of Artificial Intelligence (AI) applied as expert system technology is increasing in fields, including hiring, and is predicted to further increase in the future (Campbell, 1989). If the premise that these tools are here to stay in the employers hiring process then "Teaching to the tool" in University career preparation becomes critical to job placement success (Feloni 2017). The implication upheld by the results of this study indicates that as students prepare their resumes it is critical to teach them to build a "robot-proof" resume; one that will improve their odds of successfully getting past these expert system technology gatekeeper tools. Further supported is the need to teach an understanding of howthe new frontier of Applicant Tracking Systems (ATS) work which will help increase the odds that expert system tools don't bounce the resume before a human reader considers the submitted application.

THE RESEARCH QUESTIONS: HYPOTHESES

The focus of this research was established to conclude from the hypotheses under investigation if it is really possible to use expert system technology to augment or even replace the need for a teacher (or career counselor) in a university setting to do initial reviews of student resumes as part of an overall career preparation program. The following research questions were central to this investigation:

Research Question 1 (RQ1): Is there any significance in the comparison of error frequency, time, cost or bias in the comparison of expert system technology to a human reader? (Null Hypothesis: There is no significant difference in the comparison among conditions of error frequency, time, cost or bias in the comparison of expert system technology to a human reader).

Research Question 2 (RQ2): Would expert system technology free up a professional's time to actually do more meaningful advising and coaching (goal setting and career launch activities)? (Null Hypothesis: There is no significant difference in the comparison of expert system technology to a professional's time in review of resumes).

THEORETICAL FRAMEWORK

For the purpose of this investigation, three literature areas were reviewed:

- Career preparation – expert system technology in the job search process
- Early pioneering of expert system technology; information retrieval
- Advancements in expert system technology; machine learning, algorithmic cognitive mapping of mental models

Career Preparation

Taking what is now accepted expert system technology and applying it to career preparation, there was an investigation conducted regarding the use of technology for recruiters to be able to pick out the top candidates in a more organized and efficient way (Feloni 2017). The study noted that recruiters can customize the algorithms within technology to focus the decision support to determine the types of people they are looking for. The study concluded that the technology was effective in an initial screening but that ultimately the program still needs to be reviewed by humans to make the final decision. (Shellenbarger, 2019) reported that machine learning systems save time and money for employers swamped by online applicants possibly reducing bias in hiring. Schellenbarger references a 2016 survey by a Social research group that focuses on trends in HR Technology & Services. They surveyed 1200 job seekers and managers and it was reported from their respondents that expert system technology in the career preparation space is multi-faceted in use ranging from scanning applicant's qualifications, employer postings, tracking user's behavior and employing algorithms similar to marketplaces like Amazon.

Early pioneering of expert system technology

The study of artificial intelligence (AI) in the form of decision support systems (DSS) and expert system technology tools goes back in the literature to the 20th century. Studies compared a computerized research effort to a manual, or non-computerized effort. In the early days of AI, Kollmeier and Staudt (1984) demonstrated that working on-line for the purpose of conducting research most accurately narrows and refines research topics while also allowing for analysis of the subject in relation to broader and more varied contexts. Furthermore, a study was conducted to compare the results of an on-line versus manual search of text and articles on a specific topic (Roboz, 1986). His results suggested that both manual and electronic information retrieval searches should be used in order to capture the highest coverage of relevant information. In addition to Roboz (1986), another study compared the search outcomes of a manual and on-line search and retrieval of specified information. Naber (1985) found that the electronic information retrieval found 87% more relevant match to criteria than the manual search.

Fast forward to the 21st century, we continue to find and refine the study of technology that more closely mimics the human decision-making process to include adaptive machine learning and cognitive modeling (Phillips-Wren, 2008).

ADVANCEMENTS IN EXPERT SYSTEM TECHNOLOGY

The algorithms that result in more modern decision support databases or what we also term machine learning underlying expert system technology tools now support and with each iteration approximate more complex decision making than the early studies of criteria-based search and find strategies (Brindley, 1988; Khasiani, 1988).

Schank (1988) demonstrated in earlier research that it was possible to develop an automated system to successfully categorize, like a human resource making (judgements) decisions, articles into categories. The automated system in the study had three features that although primitive at the time, are now exemplar to the evolving expert system technology (Campbell, 1989) modeling the capability of machine learning to mimic the human thinker/reader and be more effective than the human in these three features.

The first feature is tireless decision making on topic categorizations. Human readers get tired and that affects the accuracy of their decisions whereas the computer tiring is limited to their capacity. An illustration of this kind of decision capabilities made by the automated system is Duke-Moran (1996), where human judges were more likely to say an article was "not specified" where the expert system would use its inference rules and logic to make a correct decision about the topic being covered in the article. The computer tended to use its phrase list and inference engine to make a choice rather than not, where the human resource conceded the decision about the article they were reading.

The second feature is objective patterns of decisions, where the expert system appears to exceed a human reader's ability. Many factors impact decision making in humans and in computers. However, while computers only have objective parameters, humans have objective and subjective factors. Often, humans are guided by a confluence of previous decisions, current preferences, and the familiarity of the question to arrive at a decision. The computer treats each article as a new event and allows itself to make very specific decisions with a very different "memory effect" of its previous decisions than a human. In machine learning, the computer is trained on an objective rule, and it uses each decision it makes to add to their memory. They will be able to use their memory to decide future decisions. The difference with machines is that there is no emotions involved, i.e. they are all objective decisions and not subjective. Illustration of this objective patterning of decisions made by the automated system by the same paper (Duke-Moran, 1996). The expert system in that investigation used phrases, broader logic and logarithmic constraints within its inference engine to vary its decisions more to the atypical editorial type and featured stories about individuals or organizations versus a human resource deciding on the more typical and patterned decision that articles are generally of a certain type.

Finally, Summation versus Expansion is the third defining feature of an expert system. Human readers have a tendency to summate their decisions. They need to bring an article to a conclusion that it is about one or two topics at the most versus an expert system which tolerates broader decision bases allowing that an article to be about several topics that relate to each other. Once again, Duke-Moran (1996) demonstrated this point when the expert system took, for example, an article and categorized it as an article into three areas: budget, employment of the handicapped and welfare benefits. It is primarily a story about budget but, in a subtle way that the automated system picked up on, it was also about providing programs to employ the handicapped and welfare programs to stem abuse problems through budgeting. The human readers in the comparative study under investigation categorized the article into only one area, budgeting.

The literature continues to support and suggest that electronic availability of information and decision support systems will continue and eventually outweigh the alternative manual (or human) efforts because of the balance of costs and benefits. The emergence of more sophisticated modeling of the human brain is best explain by Wren in what is now the technological model of Decision Support Systems (DSS) – see Figure 1. This model starts with three inputs; database, knowledge base, and model base. Database holds information relevant to the problem. Knowledge base holds information on alternatives and gives guidance to selecting those alternatives. The model base holds models and algorithms to help create a decision. The processing factor of this model is there to help find the best solution based on the information inputted into the system and the constraints the process was given. The feedback of this model allows a decision maker to introduce more inputs or constraints to help improve the solution. The last factor is the outputs. Outputs are there to make recommendations, forecast, and give advice. Philips-Wren (2008) concludes that the current use of intelligent interfaces are able to act as virtual humans taking in data, applying computer-human communication as a problem to be solved, and drawing conclusions on that data.

The review of the literature in these three specific areas supports the investigation of advancement of expert system technologies to determine effectiveness of its use in competitive job seeking of applicant-screening and tracking. The investigation, as supported by the literature, will seek answers to the use of Artificial Intelligence (AI) in practical terms referred to as expert systems examined for time and money savings while maintaining accuracy of the decision process. If proven to be effective, there is a great opportunity to provide significant and objective results for employers swamped by online applicants taking the first pass at screening the large applicant pool to a more manageable number of applicants that would get a human review of their submitted materials.

METHOD

The use of expert system technology was examined on the basis of error frequency, time, cost and tiring/bias compared to a human reader of student resumes. Results were further examined to determine if any implication existed in initial resume preparation freeing up a university professional's time to actually do more meaningful student career advising and coaching (career goal setting and career launch activities)?

The expert system technology chosen for use in this study is Quinncia (https://quinncia.io/about). With the system, resumes can be analyzed by the algorithms within the system for immediate feedback. The system is built upon the same technology that corporations use to scan resumes for initial screening purposes referred to as Applicant Tracking Systems (ATS).

Participants

The approach of this study involved collecting one hundred and fifty five (N=155) resumes. The resumes were collected from students in a sophomore level university course. Students are required to develop and submit a resume as an assignment for the class.

Instrumentation

Students in all conditions of the study were given the same sample example resumes (templates) to use as they developed their resumes to submit. The sample example resumes were recognized format and readability by Applicant Tracking Systems (ATS). The same set of resumes were used in the study of all five conditions:

Condition 1: Raw Resumes (first draft of student resumes with NO prior feedback) uploaded to the expert system (Quinncia).

Condition 2: After students reviewed and made changes based on Instructor requirement to get a “resume score of 200+” (re-run through the expert system; Quinncia).

Condition 3: After students reviewed and made changes based on Instructor requirement that “they must reduce all errors and suggestions to <5 and have a resume score of 200+” (re-run through the expert system; Quinncia).

Condition 4: Raw Resumes (first draft of students’ resumes with NO prior feedback) done by a human reader.

Condition 5: Grad Assistant reviewed and made changes only based on Human Reader feedback and re-run through the expert system (Quinncia) AFTER changes were made.

Procedure

Data was collected across the five conditions to compare and determine significance of the average time to review each resume (RQ1 and RQ2), the resume error count for each resume (RQ1) and the cost of human resource review (RQ1) were compared to cost of technology. In addition there was an analysis done of Condition 4 compared to Condition 5 for indications of the concept of human bias and human tiring (RQ2) as discussed in the literature review.

Data Collection

The data collected for each of the five conditions identified in the methodology for this study is depicted as raw data in Table 1.

RESULTS

Data and Analysis

The data was analyzed in a comparative of the conditions to determine if there were any significant differences in error rates, time, cost and human bias or tiring.

In support of RQ1, a one-way analysis of variance (ANOVA) was calculated on time to review resumes across Conditions 1, 2, 3 and 5 (essentially all conditions using the expert system; Quinncia). The Null Hypothesis is NOT rejected meaning there is no significant difference in the time to review resumes across the four conditions that used the expert system (Quinncia), $F(3) = 7.60$, $p = .05$.

In support of RQ1, a second one-way analysis of variance (ANOVA) was calculated on total suggested changes to a resume under review across all 5 conditions. The Null Hypotheses was rejected meaning there are statistically significant differences in total suggested content changes between conditions, $F(4) = .036$, $p=.05$. In contrast tests, best scenario of total suggested changes was found to be attributed to Condition 3 ($M=4.91$, $SD=3.22$) and the most suggested changes was found to be attributed to Condition 1 ($M=16.14$, $SD=9.94$) and Condition 5 ($M=14.42$, $SD=8.65$)

In support of RQ2, independent T-Tests were performed comparing Condition 4 to each of the other four Conditions on the basis of time to review resumes.

Other Key Observations

The expert system technology review appeared to review resume content compared to a human reader that seemed to focus more on format. The total improvements suggested by the expert system technology were also double the improvements than a human could find. The expert system technology also found more grammatical and spelling mistakes in the resume which are very critical for any job application, as one mistake can result in instant rejection. The expert system technology was clearly able to achieve the improvements faster than the time taken by the human.

Visual Modeling of Preliminary Analysis

Looking at the data collected for a visual analysis, the Figure 2 depicts the total error counts across the five conditions. Condition 3 (the condition where students reviewed and made changes based on Instructor requirement that "they must reduce all errors and suggestions to <5 and have a resume score of 200+" (re-run after fixes through the expert system) illustrates clearly that it has the lowest of error counts across all categories of error and total errors.

The next visual, Figure 3, is another way to look at the comparison across conditions. Condition 1 is Raw Resumes (first draft of students' resumes with NO prior feedback uploaded to expert system). Condition 2 is after students reviewed and made changes based on Instructor requirement to get a resume score of 200+ (re-run through expert system) leading ultimately to the best scenario of least error results being Condition 3. After students reviewed and made changes based on Instructor requirement that they must reduce all errors and suggestions to <5 and have a resume score of 200+ (re-run through expert system).

The illustration of human tiring and bias can be seen in the data visual of Figure 4. Condition 1 compared to conditions 4 and 5 – The expert system finds more errors across factors – this supports the theory that humans tire reading from one instance of a document resume to the next. Further the human reader had more format suggestions that are not relevant in developing a resume that will meet the benchmark of an applicant tracking system but creates a bias of a human reader's opinion of what makes a good resume without relevance to the need to meet the standard set by the initial employment review process.

Finally looking at cost factors the Figure 5 illustrates the comparison of the cost of the expert system technology (factor used was cost per individual license x time) compared to human reader (cost of hourly wage of a human resource x time), The cost of the human reader as seen in the illustration is 70x the cost of the expert system technology per instance of resume reviewed.

DISCUSSION AND CONCLUSIONS

Clearly expert system technology for resume review has proven to be effective in twice the amount of overall improvements and suggestions, is more focused on the content of the resume and in 10% of the time resulting in significant cost savings over a human reader. This would give the advisor critical time to work on advising and helping. This study concludes that; YES – it is possible to use artificial intelligence (expert system technology) to augment or even replace the need for a human to do initial reviews of resumes for error correction in spelling/grammar, format and content, and YES - it can reduce a professional's time (and realized costs) to actually do higher order career advising and coaching.

LIMITATIONS AND FUTURE DIRECTIONS

The long-range effect of intelligent technology on several criteria are yet to be determined and should be looked at in further study as it relates to factors such as number of interviews granted comparing expert system technology to human review and ultimately student project placement rate at graduation.

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Artificial Intelligence Software used in the Treatment of Conditions:

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Figure 1: Technological Model of Decision Support Systems

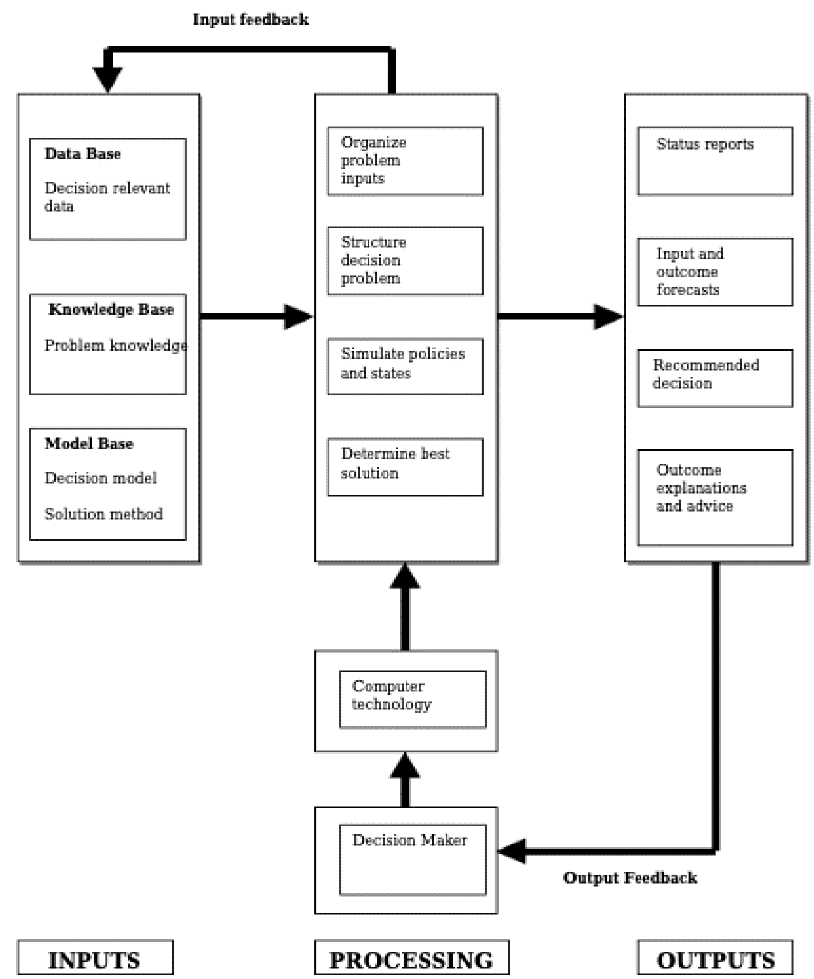

Figure 2: Total Error counts – All Conditions

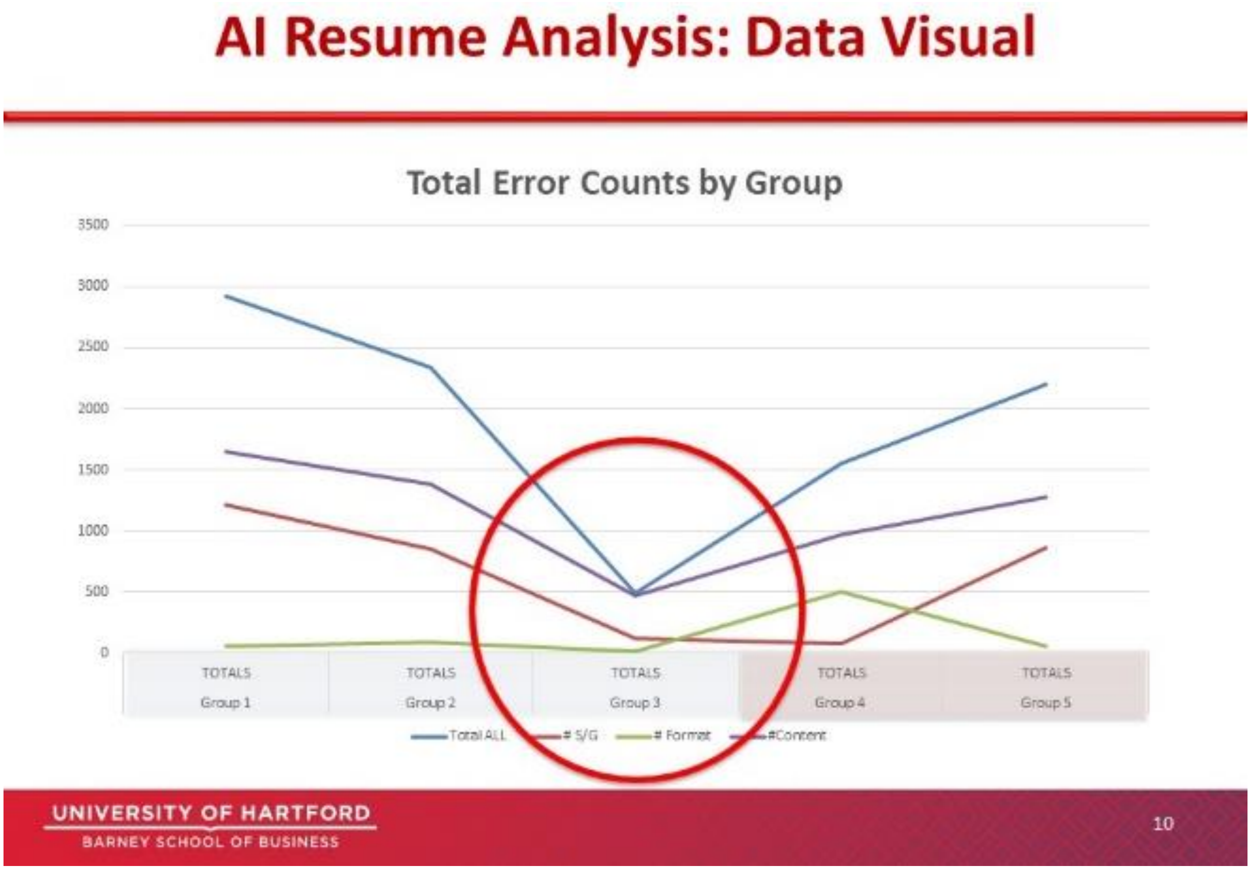

Figure 3: Total Error Counts by Condition; Transitions 1-3

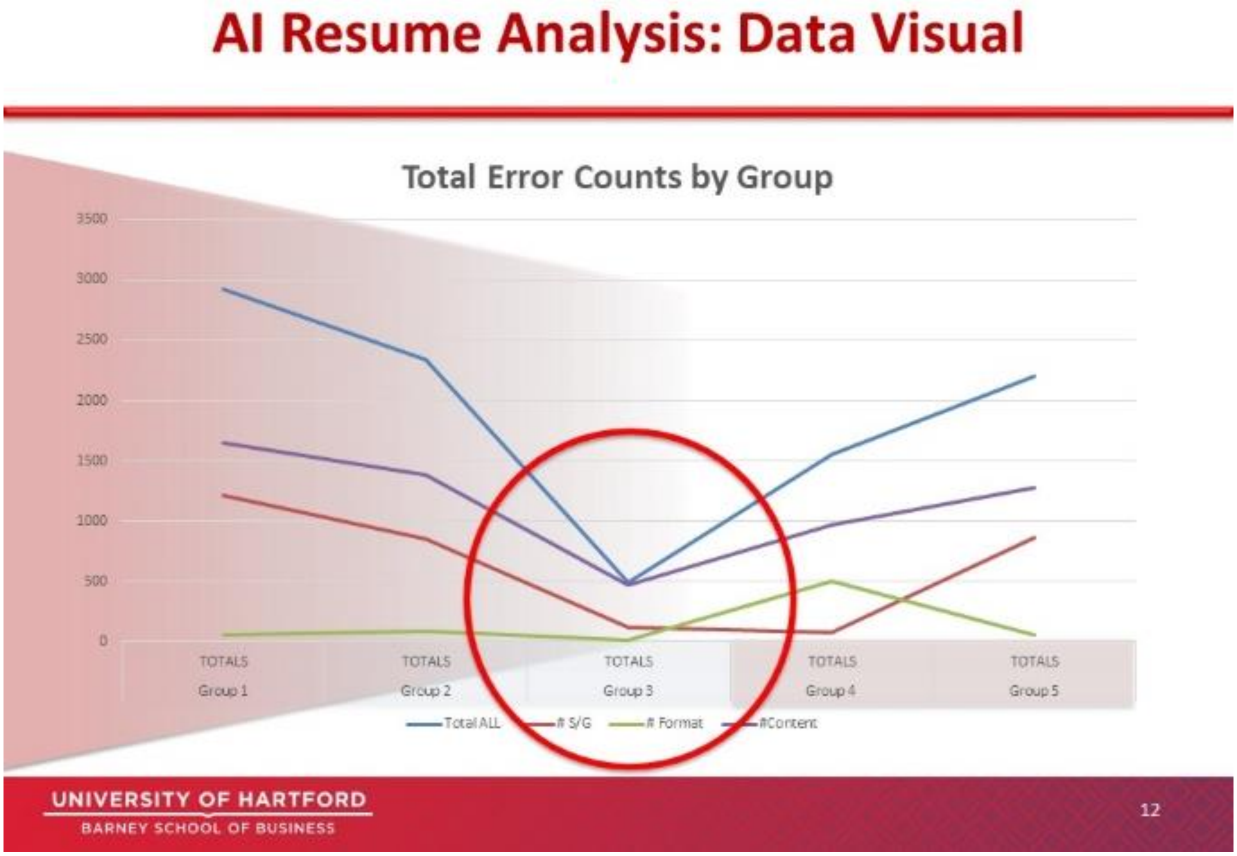

Figure 4: Illustration of Human Tiring – 1 compared to 4-5

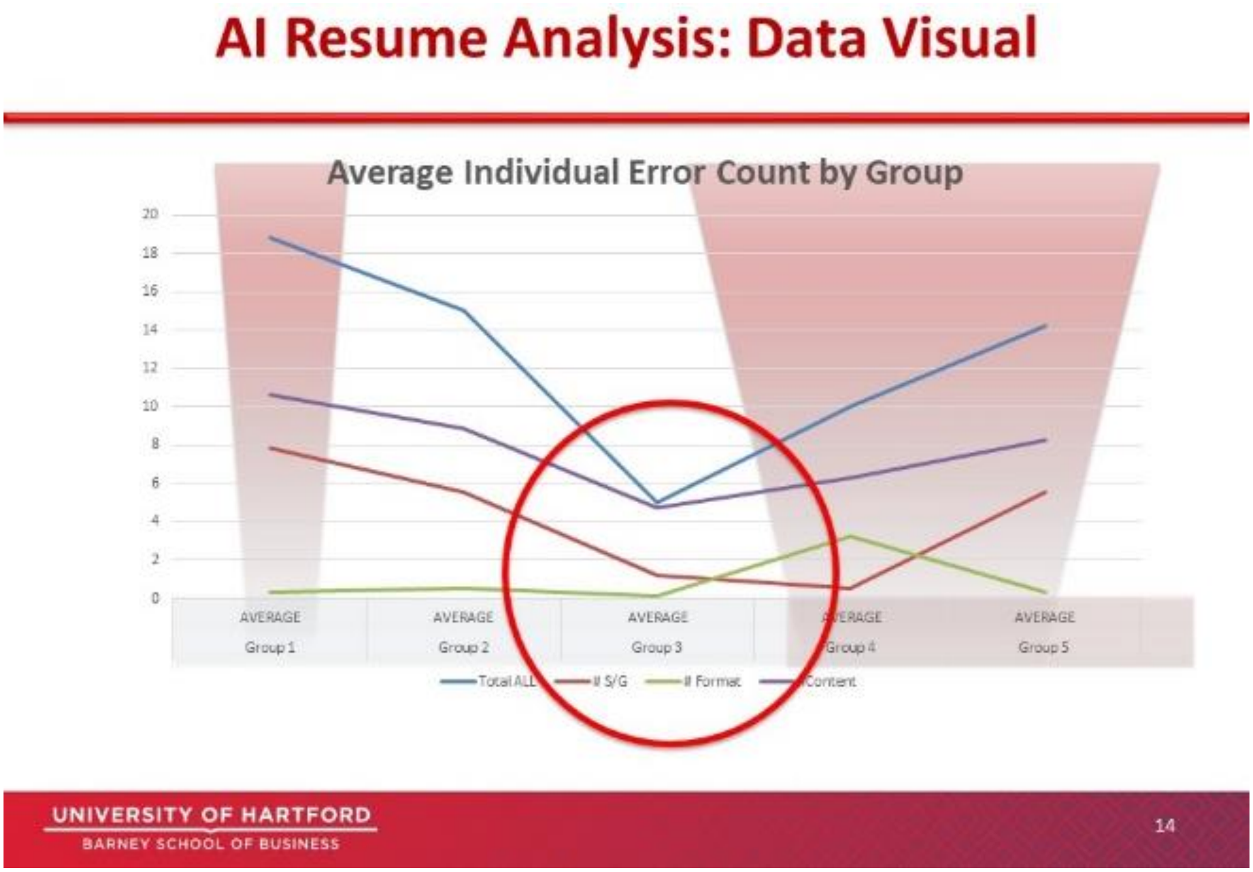

Figure 5: Average Review Time in Seconds – All Conditions

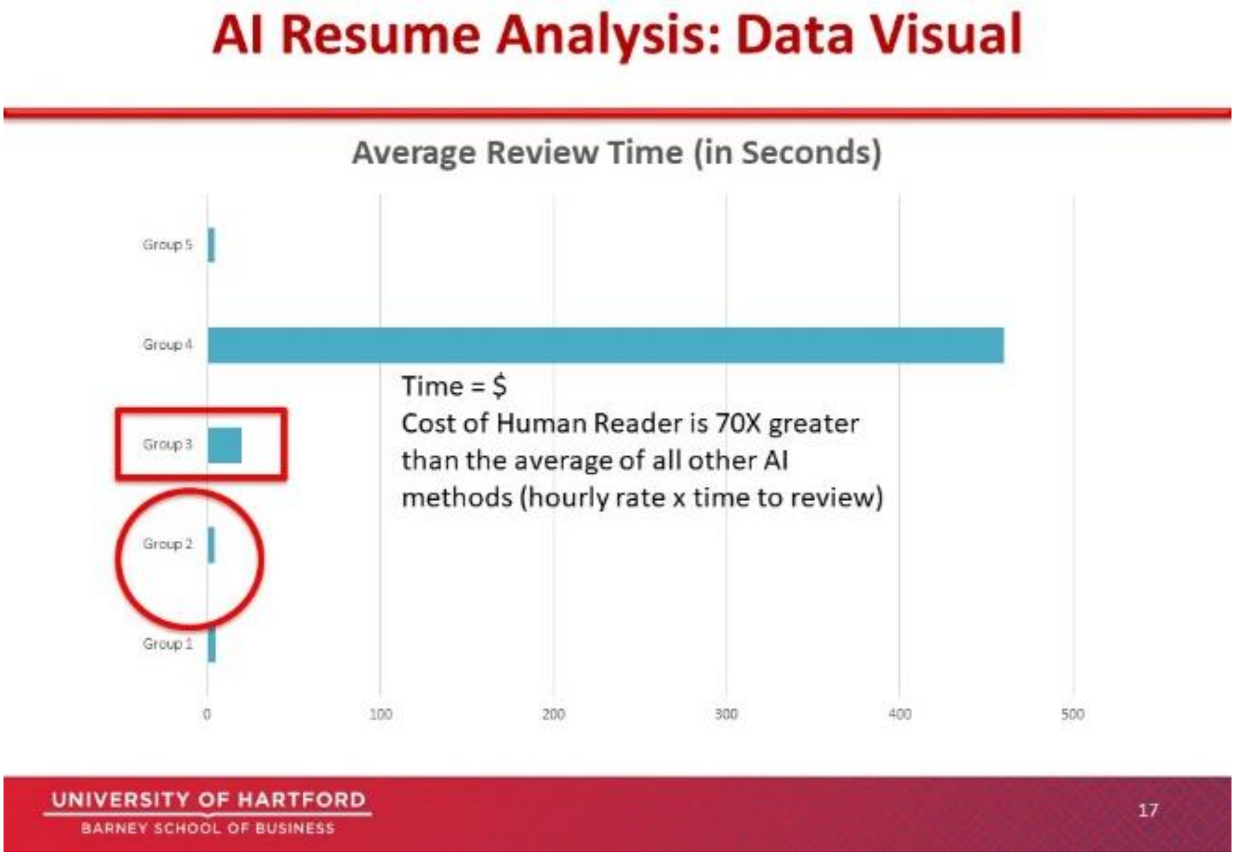

Table 1: Summary Data

155 Resumes reviewed (the SAME resumes were reviewed in every data set)					
Raw Resumes (first draft of student resumes with NO prior feedback) uploaded to the expert system computerized tool.					
CONDITION 1	**Total suggested improvements**	**# of spelling/ grammar errors**	**Format suggestions**	**Content suggestions**	**Total time to review resumes in seconds**
TOTALS	2921	1217	56	1648	797.49
AVERAGE	18.85	7.85	0.36	10.63	5.15
After students reviewed and made changes based on requirement to get a “resume score of 200+” (then re-run through expert system computerized tool)					
CONDITION 2	**Total suggested improvements**	**# of spelling/ grammar errors**	**Format suggestions**	**Content suggestions**	**Total time to review resumes in seconds**
TOTALS	2335	858	87	1380	589.16
AVERAGE	15.06	5.54	0.56	8.90	3.80
After students reviewed and made changes based on requirement that “they must reduce all errors and suggestions to <5 and have a resume score of 200+” (then re-run through expert system computerized tool)					
CONDITION 3	**Total suggested improvements**	**# of spelling/ grammar errors**	**Format suggestions**	**Content suggestions**	**Total time to review resumes in seconds**
TOTALS	494	123	15	467	1935
AVERAGE	4.99	1.24	0.15	4.72	19.55
Raw Resumes (first draft of students resumes with NO prior feedback) done by a human reader					
CONDITION 4	**Total suggested improvements**	**# of spelling/ grammar errors**	**Format suggestions**	**Content suggestions**	**Total time to review resumes in seconds**
TOTALS	1553	79	500	974	71,340
AVERAGE	10.02	0.51	3.23	6.28	460.26
Human Reader reviewed and made suggested changes to student resumes, those changes were made then uploaded to expert system computerized tool.					
CONDITION 5	**Total suggested improvements**	**# of spelling/ grammar errors**	**Format suggestions**	**Content suggestions**	**Total time to review resumes in seconds**
TOTALS	2206	863	58	1283	684.2
AVERAGE	14.23	5.57	0.37	8.28	4.41

Table 2: Descriptives of the Data

		N	Mean	Std Deviation	Standard Error	Lower Bound	Upper Bound	MIN	MAX
Time to Review a Resume	Condition 1	182	4.41	9.94	0.36	4.10	4.72	2.92	7.78
	Condition 2	156	3.8	9.06	0.39	3.52	4.08	2.3	6.95
	Condition 3	94	20.81	3.22	0.50	20.71	20.91	13	43
	Condition 5	154	4.47	8.65	0.39	4.20	4.74	3.23	7.26
Total Suggested Changes	Condition 1	182	16.14	9.94	4.94	15.83	16.45	1	61
	Condition 2	156	15.06	9.06	5.33	14.78	15.34	0	61
	Condition 3	94	4.91	3.22	6.86	4.81	5.01	0	28
	Condition 4	162	6.05	5.09	5.25	5.89	6.21	0	21
	Condition 5	154	14.42	8.65	5.37	14.15	14.69	1	46

Table 3: Results of ANOVA

		SUM OF SQUARES	df	MEAN SQUARE	F	cv of F	Reject Null?
Time to Review a Resume	Between Condition	21501.45	3	7167.15	7.60	2.62	NO
Conditions 1, 2, 3, 5	Within Conditions	2380.76		4.89			
	Total	24332.21					
Total Suggested Changes	Between Condition	17580.61	4	4395.15	0.36	2.38	YES
All Conditions	Within Conditions	49240.90		66.54			
	Total	66821.51					

Table 4: Results of T-Tests

T TEST RESULTS	
Condition 1 to Condition 4	The 180 sample resumes in Condition 1 (M=4.41, SD=9.94) compared to the 162 sample resumes in Condition 4 (M=440.37, SD=5.09)demonstrated significant difference in time to review t(179, 161)=-11.73,p=.05. The result is significant.
Condition 2 to Condition 4	The 155 sample resumes in Condition 2 (M=3.80, SD=9.06) compared to the 162 sample resumes in Condition 4 (M=440.37, SD=5.09)demonstrated significant difference in time to review t(154, 161)=-10.87,p=.05. The result is significant.
Condition 3 to Condition 4	The 93 sample resumes in Condition 3 (M=3.80, SD=9.06) compared to the 162 sample resumes in Condition 4 (M=440.37, SD=5.09)demonstrated significant difference in time to review t(92, 161)=-8.08,p=.05. The result is significant.
Condition 5 to Condition 4	The 154 sample resumes in Condition 5 (M=3.80, SD=9.06) compared to the 162 sample resumes in Condition 4 (M=440.37, SD=5.09)demonstrated significant difference in time to review t(153, 161)=-10.78,p=.05. The result is significant.

ORGANIZATIONAL AWARENESS AND IMPLEMENTATION OF SUSTAINABILITY ACTIVITIES IN BUSINESSES - MOVING TOWARD THE CIRCULAR ECONOMY

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ABSTRACT

In the past decade, sustainability programs have played a larger role in strategic planning. More recently the ideas around the circular economy have gained momentum. The circular economy recognizes the limits to linear consumption and replaces the outdated model with a shift to renewable actions. While many business professionals use the terms associated with the circular economy, their company actions are often limited to waste and recycling. This paper explores sustainability and circular economy awareness and activities used by businesses. A survey was developed to determine awareness of sustainability and circular economy concepts and whether activities around the circular economy are limited to waste and recycling.

INTRODUCTION

Sustainability is the manner in which companies manage their business processes to positively impact society through economic, environmental, and social actions (IBM, 2008). It essentially refers to the balanced integration of social and environmental considerations in business strategy and operations. The term sustainability appears to be gaining favor over Corporate Social Responsibility (CSR) as the term sustainability is more acceptable to managers than the language of CSR, which is more normative. This makes the language of sustainability more CFO friendly than CSR (Strand, Freeman, & Hockerts, 2015).

Within the umbrella of sustainability, the circular economy (CE) concept is trending and gaining popularity (Korhonen, Honkasalo, & Seppälä ,2018). Per Ellen Macarthur Foundation (2017, para 1), "Looking beyond the current take-make-waste extractive industrial model, a circular economy aims to redefine growth, focusing on positive society-wide benefits. It entails gradually decoupling economic activity from the consumption of finite resources and designing waste out of the system. Underpinned by a transition to renewable energy sources, the circular model builds economic, natural, and social capital."

Managers of global companies are beginning to realize the benefits of sustainability. "Debates about sustainability have moved all the way into corporate boardrooms" (Porter & Kramer, 2006, p.78). Corporate leaders recognize that divisional and country managers feel the pressure of community groups, NGOs, suppliers, employees, and other external stakeholders; even employees prefer to work with companies aligned with their values (IBM, 2008). Investors value not only a company's financial performance, but also how corporations meet their social responsibilities (Barnett & Salomon, 2006; Min, Desmoulins-Lebeault, & Esposito, 2017). Corporations exist to serve social needs – profit is a motivation for action, not the reason for existence. Like it or not, sustainability in business can no longer be overlooked.

A linear economy follows a take-make-dispose pattern where materials are harvested and extracted, these are used to manufacture products which are sold to the consumer and eventually discarded (World Economic Forum, 2014). More companies are realizing that the linear economy is no longer desired as costs rise and resources are depleted. The circular economy is a way to better use resources and improve profits. CE is most frequently depicted as a combination of ***Reduce, Reuse*** and ***Recycle*** activities (3R), which is limiting (Cairns, 2005). Hence, we use a broader term and scope of CE. The sustainable manufacturing approach focuses on a broader, innovation-based 6R methodology is used for this research. In addition to the 3Rs listed above this enhanced scope also covers ***Recover***, ***Respond***, and ***Remanufacture*** **(**Jawahir & Bradley, 2016).

Our research questions probe the awareness of business professionals of sustainability and circular economy terms and the activities that indicated movement toward a circular economy. This pilot study will help to further understand sustainability activities practices by organizations.

LITERATURE REVIEW

Sustainability

The United Nations defines sustainability as business practices that "meet present needs without compromising the ability of future generations to meet their needs" (WCED, 1987). Sustainability covers three pillars, namely Environment, Economic, and Social. According to Slovick (2008), environmental sustainability "refers to maintaining the quality and longevity of environmental resources used by the business. This can include energy, water, waste management, emissions, etc." (para 8). Economic sustainability "includes the overall financial model and productivity of a company. The income and expenses must provide for a financially sustainable business" (para 8). Finally, social responsibility "refers to the social impact of a business. It includes ethical principles, giving back to society, health and safety, respect for human rights, equal opportunities, fair compensation, ensuring a high quality of life" and "eliminating unethical and corrupt behavior" (para 8).

The environmental, social, and economic dimensions constitute the terminology Triple Bottom Line (TBL) first coined by John Elkington in 1994. Under Friedman's stockholder theory (1970, p. 126) "there is one and only one social responsibility of business--to use its resources and engage in activities designed to increase its profits so long as it stays within the rules of the game." Managers, according to Friedman, have responsibility only to the stockholder. After all, stockholder's own shares in the firm and they have certain rights and privileges. Managers are employees of the owners, the stockholders. Managers' responsibility is to their owners, and to conduct business to make as much money as possible while abiding by the basic rules of society, both legally and ethically. By including social responsibility, Friedman argues, the manager is not acting in the interest of the owners (i.e., stockholders). He would essentially be spending someone else's money for general social interest, which would reduce stockholders' returns. Investments relating to social activities that do not create shareholder value or that only impose a cost on the company need to be rejected.

Key thinkers have challenged Friedman's position. Porter and Kramer (2002) disagree with Friedman's argument, seeing flaws in his two implicit assumptions: (i) Social and economic objectives are separate and distinct; and (ii) Corporations provide no greater benefit than individual contributors when they address social objectives. We also disagree with Friedman's notion, and accept Freeman's concept that managers bear fiduciary responsibility to "stakeholders," not just to stockholders. According to Freeman, "stakeholders are those groups who have a stake in or claim on the firm" (2008). Freeman includes as stakeholders, "suppliers, customers, employees, stockholders, and the local community, as well as management in its role as agent for these groups" (p. 39). Each of these stakeholder groups has a right not to be treated as a means to an end, and they need to participate in determining the future direction of the firm in which they have a stake. Stakeholders conceived more broadly have a claim on the firm, as all these groups can benefit or be harmed, and their rights can be violated or respected by corporate actions. The concept of TBL is encapsulated well in Stakeholder Theory.

The Circular Economy (CE)

The circular economy (CE) concept is trending both among scholars and practitioners. More than 100 articles were published on the topic in 2016, compared to only about 30 articles in 2014 (Geissdoerfer, Hultink, Bocken, & Savaget, 2017). Practitioner studies have also grown, led by major consulting firms such as Accenture, Deloitte, Ernst & Young and McKinsey & Company in the recent years (Hannon, Kuhlmann, & Thaidigsmann 2016; Ernst & Young, 2015). The CE concept is of great interest to both scholars and practitioners because it is viewed as an operationalization for businesses to implement the much-discussed concept of sustainable development (Ghisellini, Cialani, & Ulgiati 2016; Murray, Skene, & Haynes, 2017).

This concept, with growing interest from various stakeholders, can get blurred since it frequently operates in different worlds of thought (Gladek, 2017). CE can be defined in many ways (Lieder & Rashid, 2016) resulting in a lack of consensus on its definition (Yuan & Moriguichi, 2006). Scholars argue that the traditionally known linear economy, based on the "take – make – dispose" model, continues to fall short of being able to meet the sustainability challenges of a world that concurrently requires sustained economic growth, environmental protection, and societal wellbeing. Many researchers take sustainability into consideration in their expansive definition of CE. Per Kirchherr, Reike and Hekkert (2017, pp. 224-225), "A circular economy describes an economic system that is based on business models which replace the 'end-of-life' concept with reducing, alternatively reusing, recycling and recovering materials in production/distribution and consumption processes, thus operating at the micro level (products, companies, consumers), meso level (eco-industrial parks) and macro level (city, region, nation and beyond), with the aim to accomplish sustainable development, which implies creating environmental quality, economic prosperity and social equity, to the benefit of current and future generations." This broad definition clearly puts the CE concept within the realm of sustainability (WCED, 1987).

Pearce and Turner (1990) proposed the transformation of the "resource-products-pollution" mode to "resource-products-regenerated resources." This concept translated into the principles of 3Rs: Reduce, Reuse and Recycle. The 3Rs are essentially the foundation for green manufacturing derived in the 1990s from lean manufacturing. The current trend shows that achieving sustainable value in manufacturing requires transformation from lean to green to sustainable manufacturing (Jawahir and Dillon, 2007). Jawahir and Bradley (2016) introduce the 6r methodology which takes into consideration products, processes, and systems.

In the 6R methodology, as discussed by Jawahir and Bradley (2016), ***Reduce*** mainly focuses on the first three stages of the product life-cycle, and refers to the reduced use of resources in pre-manufacturing, reduced use of energy, materials and other resources during manufacturing, and the reduction of emissions and waste during the use stage. ***Reuse*** refers to the reuse of the product as a whole, or its components, after its first life cycle, for subsequent life cycles, to reduce the usage of virgin materials to produce newer products and components. ***Recycle*** involves the process of converting material that would otherwise be considered waste, into new materials or products. Ghisellini, Cialani, &Ulgiati (2016) state that most sustainability efforts are focused on recycling efforts in comparison to reuse efforts.

The process of collecting products at the end of the use stage, disassembling, sorting, and cleaning for utilization in subsequent life cycles of the product are referred to as ***Recover***. The ***Redesign*** activity involves the act of redesigning of next generation products, which would use components, materials and resources recovered from the previous life-cycle, or previous generation of products, while ***Remanufacture*** involves the re-processing of already used products for restoration to their original state or a like-new form through the reuse of as many parts as possible without loss of functionality.

For our analysis we also probed ***Rethink*** (Is it even necessary to use the materials, or how to use it so that waste is not created) and ***Respond*** (provide feedback on the need of the material that ends up generating waste) (ellenmacarthurfoundation.org).

Implementing Sustainability Initiatives

Implementation of sustainability initiatives can typically take two forms: top down with formal champions or function (Baumgartner, 2014); bottom up, cross-functional grass roots membership with informal champion (cultivating.capital.com). Hemingway and Maclagan (2004) address managers' personal values as factors explaining the formulation, adoption, and implementation of companies' sustainability programs. They contend that a commercial imperative is not the sole driver of sustainability decision-making, but that the formal adoption and implementation of sustainability by corporations can be associated with the personal values of individual managers. Duarte (2010) finds that to a significant extent the successful development of sustainability cultures in companies was the result of 'championing by a few managers, due to their personal values and beliefs.'

The formal champion is typically nominated by the unit management to execute a specific project, receives training and support to execute the project, and is subordinate to the management for the administration and contents of the initiative (Maier and Brem, 2017). Thus, the formal champion relies on hierarchical power, autonomy, and credibility (Ploeg et al., 2010).

The informal champion, because of his or her lack of formal hierarchical power, relies more on personal resources and interpersonal influence (Warrick, 2009). Furthermore, this lack of formal power means that informal champions enjoy greater flexibility, which allows them to choose practical issues and solutions that need not follow standard procedures (White, 2011).

Our position is the same can be applied for CE sustainability initiatives. A CE initiative could be "bottom-up" project, in which both initiative and action originate from lower organizational levels; or a "top-down" project, in which the initiative originates from upper organizational levels and action originates from upper or lower organization levels. Top-down projects may be more frequently led by formal champions; as managers strive to implement such projects, they probably also assign a formal leader to guide them (Senot et al., 2016). Bottom-up innovation projects, in contrast, grow from the production floor, fostered by individuals who acknowledge the real unit's needs for change without being formally nominated for the task (Kingma, 1998), and are therefore more likely to be led by informal champions (Senot, Chandrasekaran, & Ward 2016).

Sustainability and circular economy activities requires significant management commitment due to the challenges of coordinating supply chain efforts (Ghisellini et al., 2016; Veleva, Bodkin and Todorova, 2017). Employees are important stakeholders and knowledge of sustainability efforts increases support and implementation (Sharma and Tweari, 2017). According to Sharma (2009), employees who are educated and engaged are more likely to support sustainability efforts. It helps when all stakeholders have awareness of an organization's efforts (Yeh, Tseng, Chun-Chang, & Cheng, 2020). According to Markham (1998) "people who (a) adopt the project as their own and show personal commitment to it, (b) contribute to the project by generating support from other people in the organization, and (c) advocate the project beyond job requirement in a distinctive manner" (p. 49).

The questions for this pilot study are as follows:

1. Do business professionals possess an understanding of sustainability concepts?
2. Do business professionals possess an understanding of circular economy concepts?
3. Are companies' implementation of circular economy concepts limited to waste reduction and recycling?
4. How is sustainability managed within companies?

METHODOLOGY

Based on the review of literature, a questionnaire-based survey (see appendix) was developed to collect descriptive data from sustainability and other management level professionals. The survey was delivered between the fall of 2017 and spring 2018 using Qualtrics software. The Qualtrics Research Suite builds the database and records the completed responses as they are submitted. The tool has the functionality to aggregate the responses by questions and create Excel or SPSS-compatible data files. The responses were exported to Microsoft Excel, where we further coded the questions and grouped them by research questions. Statistical analysis was performed using SPSS software.

Survey participants were recruited via a number of means. We first developed a list of sustainability professionals and executives, using our network as well as industry groups (such as Global Sourcing Council, G&A Institute) to send our survey. Responses were mostly blind, though some responders agreed to share their name and firm. Overall, 102 responses were received, after removing unusable surveys, 77 were useable. Once the data was collected, it was ported into statistical analysis software (SPSS) and analyzed to answer the aforementioned research questions.

Demographics

A total of 102 responses were received with 77 survey responses usable, though not all participants responded to all questions. Participants came from a diversity of roles within their organizations. The majority reported themselves as holding "Director" positions (33.80%, n=71), "Manager/Supervisor" positions (21.13%), or "C Suite/Executive" positions (19.72%), while 25.35% reported their position as an "Individual Contributor". In terms of business function, most participants reported a primary function of sustainability (43.28%), followed by procurement (13.42%), supply chain (11.94%), and sourcing/outsourcing (10.45%). Participants' companies were primarily in the services sector (67.14%, n=70), headquartered in the United States (68.57%, n=70), with the participant physically based in the United States (61.97%, n=71). Annual company revenues for the participants ranged from under 100 million USD (37.14%, n=70) to 10 billion USD or more (31.43%). Participants' companies were almost evenly split between being publicly traded (50.70%, n=71) and private (49.30%).

A majority of participants reported that their company has a sustainability program or initiative (90.14%, n=71) and that they were either extremely familiar (50.00%, n=70), very familiar (21.43%), or moderately familiar (11.43%) with the program. A majority also reported that their company has a specific sustainability department (59.15%) while 33.80% reported not having such a department and 7.04% were unsure. A vast majority of participants were also personally involved in their company's CS/Sustainability program (66.67%, n=69) though a majority reported they are not personally involved in any such programs outside their company (52.94%, n=68).

RESULTS

Awareness of Concepts

The first and second research question determine whether respondents possess an understanding of sustainability and circular economy concepts. A majority of participants reported that they are familiar with the concept of sustainability in general; 63.38% (n=71) reported being extremely familiar, 19.72% very familiar, and 12.68% moderately familiar. A majority of participants reported that they are at least moderately familiar with the concept of a circular economy; 32.86% (n=70) reported being extremely familiar, 25.71% very familiar, and 18.57% moderately familiar.

A Kruskal-Wallis Test was conducted to examine the differences in means of circular economy familiarity according to the reported industry sector. No significant differences (χ^2 = 1.78, df = 4, p = .78, n=69) were found among the six provided sectors (pharmaceuticals, oil and gas, consumer goods, chemicals, other manufacturing, and services). Similar analyses found no significant differences according to reported job position (χ^2 = 1.85, df = 3, p = .61, n=70) or company revenue (χ^2 = 4.69, df = 3, p = .20, n=69).

Kruskal-Wallis H tests found significant differences in program/initiative familiarity by reported job position (χ^2 = 11.64, df = 3, p = 0.01, n=69). Dunn's pairwise tests with Bonferroni correction showed significant differences between "C Suite/Executive" and "Individual Contributor" positions ($p < 0.01$) and between "Director" and "Individual Contributor" positions ($p < 0.01$). In both cases, participants who identified as "Individual Contributor" were less familiar with CSR/Sustainability programs or initiatives.

Kruskal-Wallis H tests also found significant differences in program/initiative familiarity by company revenue ($\square^2$ = 9.43, df = 3, $p < 0.05$, n=70). Dunn's pairwise tests with Bonferroni correction showed significant differences between reported annual revenues of "Under \$100 million" and both "\$100 million to under \$1 billion" ($p < 0.05$) and "\$1 billion to under \$10 billion" ($p < 0.01$). Significant differences were also found between "\$1 billion to under \$10 billion" and "\$10 billion and over" ($p < 0.05$). In general, participants who reported annual company revenues on either end of the scale ("Under \$100 million", "\$10 billion and over") were more familiar with CSR/Sustainability programs than those in the middle revenue tiers ("\$100 million to under \$1 billion", "\$1 billion to under \$10 billion").

Awareness of Circular Economy Associated Activities

The third research questions is: Are companies' implementation of circular economy concepts limited to waste reduction and recycling? Participants were asked to identify the types of waste/materials management activities their company performs, as well as to assess their company's performance in those activities. Participants were given eight specific activities and asked to assess company performance on each using a five-level scale (0=*I Don't Know*, 1=*Not Performed*, 2=*Slightly Performed*, 3=*Moderately Performed*, 4=*Very Well Performed*, 5=*Extremely Well Performed*). See Table 1 for a summary of the results:

Table 1: Circular Economy Activities

Circular Economy Activity	**N**	**Mean**	**Median**	**SD**
Reduce (waste)	68	3.09	3.00	1.47
Reuse (reuse of the product, or its components)	65	2.68	3.00	1.43
Recycle (materials)	67	3.33	4.00	1.49
Recover (materials from waste)	68	2.34	2.00	1.59
Remanufacture (reprocessing already used materials)	65	1.72	1.00	1.48
Redesign (redesigning of next generation products using components recovered from previous life cycle)	68	1.91	1.00	1.58
Rethink (Is it even necessary to use the materials, or how to use it so that waste is not created)	68	2.34	2.00	1.53
Respond (provide feedback on the need of the material that ends up generating waste)	64	2.20	2.00	1.57

The results of our survey suggest that recycling (materials) and reduction of waste are the circular economy activities with the highest performance assessment – both have a mean and median of *Very Well Performed* or above. There were other activities related to the circular economy. Reuse (reuse of the product, or its components) was close behind recycling and reduction of waste. Reduction of waste and recycling (materials) are the least frequently reported as *Not Performed* (5.88%, n=68 and 4.48%, n=67, respectively). This stands in contrast to four of the remaining activities, each of which has a much higher incidence of not being performed: Remanufacture (33.85%, n=65), Redesign (33.82%, n=68), Recover (23.85%, n=68), and Respond (23.44%, n=64).

Participants were asked whether their company included sustainability questions in four common business products: Requests for proposals, service-level agreements, vendor selection tools, and risk assessment tools. The results, summarized in Table 2, indicate that this integration is not common; in no case did 50% or more of the participants answer "Yes." The results also indicate a lack of awareness on the part of the participants in these areas; "I Don't Know" was a common response and, in one case, the most frequent response (service-level agreements).

Table 2: Inclusion of Sustainability Questions in Business Documents

Sustainability Questions Included In…	**N**	**Yes (%)**	**No (%)**	**I Don't Know (%)**
Request for Proposals (RFP)	70	41.43	24.29	34.29
Service Level Agreements (SLA)	69	28.99	31.88	39.13
Vendor Selection Tools	68	44.12	27.94	27.94
Risk Assessment Tools	68	38.24	38.24	23.53

In terms of reporting and data collection, the survey responses indicate a limited awareness on the part of participants of their company's activities. Participants mostly reported that their companies published sustainability /nonfinancial reports (47.06%, n=68) though 20.59% were not sure. A similar disparity was seen in the reporting of whether their companies responded to voluntary reporting; 43.48% (n=69) reported their company responded and 34.78% were unsure.

Sustainability Management

The fourth research question was: How is sustainability managed within companies? The majority reported that such programs were handled through a cross-functional arrangement (37.14%, n=70), though a dedicated sustainability or CSR department (32.86%, n=23) was also frequently reported (Table 3). Kruskal Walls H tests found no significant differences in the number of waste/materials management activities their company performs based on whether cross-functional management is used (χ^2 = 0.08, df = 1, p = 0.77, n=59) or in the perceived performance level of the eight waste/materials management activities (all p > 0.05).

Table 3: How Sustainability is Managed

Answer	**Percentage**	**N**
Sustainability/CSR Department	30.67	23
Cross-functional	42.67	32
Manufacturing	0.0	0
Communications	9.33%	7
Legal	0.00	0
Supply Chain	1.33%	1
Marketing	0.0	0
Other	16.0%	12
Total	100%	75

DISCUSSION AND CONCLUSION

We have discussed three key issues namely, sustainability, circular economy, and organizational awareness and implementation. The topic of sustainability has been studied extensively. By and large, companies have accepted it, and benefits recognized (Min, et al., 2017). Studies have shown that a firm's participation in sustainability is "positively associated with its performance" (Godfrey, Merrill, & Hansen, 2009).

The survey indicated that more companies are fully embracing sustainability activities. The majority of respondents (95%) had sustainability programs and initiatives in their company and show movement toward circular economy activities. There was also a majority (75%) either extremely familiar or very familiar with their company's sustainability programs. Those respondents at the executive and director level were more familiar with these activities in comparison to the "individual contributor" respondent. This indicates a need to educate more employees on a company's sustainability programs. In addition, 61% of respondents had a CSR or sustainability department in their company. There is still room for improvement as 31% of respondents indicate they are not personally involved with sustainability efforts. These responses appear to support our literature review on implementation occurring formally and informally.

Familiarity with the term, circular economy, was not as high as familiarity with sustainability. Still, 60% of respondents stated they were either extremely or very familiar with the concept. In addition, recycling (materials) and reduction of waste are the circular economy activities with the highest level of activity, indicating that there is still a long way to go.

Per the European Union (European Parliament News, 2018), A circular economy's benefits include reducing pressure on the environment, improving the security of the supply of raw materials, increasing competitiveness, stimulating innovation, boosting economic growth, and job creation. The CE concept is of great interest to both scholars and practitioners because it is viewed as an operationalization for businesses to implement the much-discussed concept of sustainable development (Ghisellini et al., 2016; Murray et al., 2017). Not surprisingly, this topic has garnered interest both for academic scholars and practitioners.

Limitations of this research include the low number of responses. In the future, a larger sample will be used to better assess our research questions. We would also like to delve further into who leads the sustainability efforts within an organization. Nevertheless, this research provides insights into awareness of sustainability and circular economy concepts and activities in business.

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APPENDIX

Note: These questions were part of a larger survey:

Q1.1 Does your company have a CSR/sustainability program or initiatives?

- Yes
- No
- I don't know

Q1.2 If yes – how familiar are you with this program?

- Extremely familiar
- Very familiar
- Moderately familiar
- Slightly familiar
- Not familiar at all

Q1.3 Does your company have a CSR/Sustainability Department?

- Yes
- No
- I don't know

Q1.4 Are you personally involved in any CSR/sustainability program or initiatives in your company?

- Yes (please explain) ____
- No

Q1.5 Are you personally involved in any CSR/sustainability program or initiatives outside your company?

- Yes (please explain) ____
- No

Q1.6 How would you describe your familiarity with the concept of sustainability in general?

- Extremely familiar
- Very familiar
- Moderately familiar
- Slightly familiar
- Not familiar at all

Q1.7 How is sustainability managed in your company?

- I don't know
- Sustainability/CSR Department
- Cross-functional
- Manufacturing
- Communications
- Legal
- Supply Chain
- Marketing
- Other ____

Q1.8 Are you familiar with the concept of circular economy?

- Extremely familiar
- Very familiar
- Moderately familiar
- Slightly familiar
- Not familiar at all

Q1.9 What type of waste/materials management activities does your company perform and how well does it perform (answer all that apply)?

	Don't know	Not performed	Slightly performed	Moderately performed	Very well performed	Extremely well performed
Reduce (waste)	○	○	○	○	○	○
Reuse (reuse of the product, or its components)	○	○	○	○	○	○
Recycle (materials)	○	○	○	○	○	○
Recover (materials from waste)	○	○	○	○	○	○
Remanufacture (reprocessing already used materials)	○	○	○	○	○	○
Redesign (redesigning of next generation products using components recovered from previous life cycle)	○	○	○	○	○	○
Rethink (Is it even necessary to use the materials, or how to use it so that waste is not created)	○	○	○	○	○	○
Respond (provide feedback on the need of the material that ends up generating waste)	○	○	○	○	○	○

Q1.10 Please briefly describe CSR/sustainability programs/initiatives in your company

Q1.4 Are you personally involved in any CSR/sustainability program or initiatives in your company?

- Yes (please explain) ____
- No

Q1.5 Are you personally involved in any CSR/sustainability program or initiatives outside your company?

- Yes (please explain) ____
- No

Q1.6 How would you describe your familiarity with the concept of sustainability in general?

- Extremely familiar
- Very familiar
- Moderately familiar
- Slightly familiar
- Not familiar at all

Q1.7 How is sustainability managed in your company?

- I don't know
- Sustainability/CSR Department
- Cross-functional
- Manufacturing
- Communications
- Legal
- Supply Chain
- Marketing
- Other ____

Q1.8 Are you familiar with the concept of circular economy?

- Extremely familiar
- Very familiar
- Moderately familiar
- Slightly familiar
- Not familiar at all

Q2.1 In your company are CSR/sustainability questions included in the Request For Proposals (RFP)?

- Yes (please provide examples) ____
- No
- I don't know

Q2.2 In your company are CSR/sustainability questions included in the Service Level Agreement (SLA)?

- Yes (please provide example) ____
- No
- I don't know

Q2.3 In your company are CSR/sustainability questions included in the vendor selection tools?

- Yes (please provide examples) ____
- No
- I don't know

Q2.4 In your company are CSR/sustainability questions included in the risk assessment tools?

- Yes (please provide examples) ____
- No
- I don't know

Q2.5 Does your company publish CSR/nonfinancial reports?

- Yes
- No
- I don't know

Q2.6 Does your company respond to any voluntary reporting?

- I don't know
- Don't report
- Yes (please provide examples, such as CDP, DJSI...) ____

Q2.7 Does your company collect any data pertaining to your company in the following areas? (select those that apply)

- Energy
- Water
- Recycling/Packaging
- Labor
- Gender, race, education
- Labor standards
- Volunteerism
- Philanthropy
- None
- I don't know

Q2.8 Does your company collect any data pertaining to your vendors/suppliers in the following areas? (select those that apply)

- Energy
- Water
- Recycling/Packaging
- Labor
- Gender, race, education
- Labor standards
- Volunteerism
- Philanthropy
- None
- I don't know

Q2.9 Are you familiar with any industry/sectors initiatives related to sustainability (certifications? actions? SDG?)

- Extremely familiar
- Very familiar
- Moderately familiar
- Slightly familiar
- Not familiar at all

Q3.1 Is your company

- Publicly Traded
- Private

Q3.2 Where is your company headquartered (country)?

____

Q3.3 Where are you based (country)?

____

Q3.4 Your company revenue (annual)

- Under $100 million
- $100 million to under $1 billion
- $1 billion to under $10 billion
- $10 billion and over

Q3.5 Your company industry sector

- pharma
- oil & gas
- consumer goods
- chemical
- other manufacturing
- services

Q3.6 Your position

- C Suite/Executive
- Director
- Manager/Supervisor
- Individual Contributor

Q3.7 Your function?

- Legal
- Communications
- Marketing
- Manufacturing
- Supply Chain
- Procurement
- Sourcing/Outsourcing
- EHS
- CSR/Sustainability
- Finance
- Student/Intern

Q3.8 How did you hear about us?

Global Sourcing Council

Sourcing Industry Group

Sustainable Purchasing Leadership Council

Governance & Accountability Institute

Council of Supply Chain Management Professionals

World BPO/ITO Forum

Others ____

Special COVID Research Note

TRANSITION TO ONLINE LEARNING: BUSINESS STUDENT PERSPECTIVES DURING THE CORONAVIRUS PANDEMIC

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ABSTRACT

This paper reports the experiences of business students at a public four-year institution through the transition to online instruction during the coronavirus pandemic. Specifically, this paper explores results of transitioning a face-to-face classroom to an online learning modality to finish the spring 2020 semester. Results from this study are important not only to the colleges of business but also to the other colleges, as interest in university communication and instructional delivery has universally changed to better serve students' needs. In this study, 75.8% of the students surveyed agreed or somewhat agreed that the university had communicated well with them about changes to their education due to the coronavirus. However, the levels of stress reported correlated with their degree of preference for instruction modality: Students with a stronger preference for in-person instruction are more likely to agree that they are stressed out. The correlation between a student's confidence in online learning (that they can do well) and the stress of taking online courses is statistically significant. Additionally, male students expressed more confidence in studying online than female students. Senior-level students reported being less stressed out and had more confidence in online learning.

INTRODUCTION

Transitioning to online learning in this unprecedented time in our country and in higher education has had its many challenges. In the spring of 2020, the rapid onset of the pandemic left many educators across the country and world needing to transition a course that had never been taught other than face-to-face to an online modality in a matter of days. Administrators were faced with the challenge of writing effective communications to students to explain the changes the pandemic was going to have on the remainder of their semesters. The author of this paper wanted to determine how well a university transitioned a student body to an online format in a short period. Data was gathered from 165 undergraduate students in a required business course, "Business Workplace Skills and Best Practices." The aim was to assess student attitudes towards the mandated shift from face-to-face instruction to online learning due to the pandemic. The data sheds light on business students' perceptions on the shift from face-to-face class to online learning. This paper reports student preferences about online learning compared to face-to-face instruction, stresses related to the shift to online education, and student beliefs about whether the university had adequately communicated with them.

LITERATURE REVIEW

Distance education is a way for students to maintain their daily schedules, while having the flexibility of completing their required coursework. Several studies document the increasing enrollments of adult students in universities (Chao & Good, 2004; Graham, Donaldson, Kasworm, & Dirkx, 2000; O'Donnell & Tobbell, 2007). Adult students make up more than 40% of the total U.S. undergraduate population (U.S. Bureau of the Census, 2005). In the past 35 years, the college population over the age of 25 has increased. From 1970 to 1991, the number of adult students enrolled in higher education increased by 171.4% (Kasworm et al., 2002). The enrollment of adult students is attributed to our global economy, cultural and ethnic diversity, immigration, competitive job market and its demands for new skills and technology, professional development, more women in the workforce (changing norms and roles), higher professional standards and certifications, and second career retirees (Compton, Cox, & Laanan, 2006; Merriam et al., 2007). Due to the increase of adult students, colleges and universities need to consider redesigning programs and services to meet the needs of these students. An underlying assumption from the literature is that colleges and universities cannot continue with business-as-usual (Apps, 1981, p. 11). Because of these shifting demographics, many universities and colleges over the last decade have been expanding their course offerings to include online modalities in order to better serve the student population. However, some students still prefer the traditional face-to-face instruction and have anxiety associated with online learning. In "Anxiety and Performance in Online Learning," Saadè et al. (2017) found that 30% of students experienced anxiety as it relates to online learning. Numerous studies and articles identify student anxiety as it relates to their performance within the higher education system (Bisson 2017; Bolliger 2011; June 2020; Saadè, Nebebe and Kira 2015; Shibli et.al. 2012; Vitasari and Wahab 2010; Woldeab and Brothen 2019). The stresses from the sudden shift go beyond student learning preferences to worries such as adequate connectivity, access to electronic equipment and the Internet when the university's library is suddenly closed.

In June's article (2020) of The Healthy Minds Network/American College of Health Association, 18,000 college students were asked about their coronavirus stress-related stress; the survey found that administrators and faculty members received high scores for the support they provided: “Sixty-nine percent of students report that their campus administration has been supportive during the pandemic, and 78% perceived their professors as being supportive.”

Much of the stress students felt moving from face-to-face instruction to online learning may have been caused by the abrupt transition to emergency online teaching: students did not know how long the change would be in effect, and the complexity of life issues the student faced included faculty utilizing a videoconferencing platform, Zoom, in order to avoid course content disruption and meet CDC guidelines of social distancing. In an April 2, 2020 interview, Professor Adriano Udani noted that students were feeling “zoomed out;” a reference to being on back-to-back videoconferencing, perhaps for work during the day, and attending at night for graduate school, or having back-to-back classes for undergraduates. Students who thought they were taking a face-to-face course were required to switch to learning virtually along with shifting schedules for work, childcare, pet care, and difficulty with internet bandwidth, health concerns, finances, and stay-at-home recommendations.

The National Research Center for Distance Education and Technological Advances suggests that using only Zoom “may not be the best way to teach online.” (Supiano 2020). While Zoom does provide the visual cues and options for synchronous participation and class discussions, it is limited by student engagement (i.e. if students turn of microphones and video) and ultimately the experience is impacted if there is not adequate internet connectivity. And use of programs like Zoom to meet remotely assumes that faculty are technologically capable of using such programs to replace in-class activities.

Regardless of the pandemic context, students need visual cues, experience with college classes and practice with tools like Blackboard and Canvas under any circumstances to increase their chances of being successful in college. Danesh, Bailey, and Whisenand (2015) found that students respond well to visual cues which furthered the class discussions (synchronous delivery) versus having content simply posted to a course management tool platform (asynchronous delivery). Additionally, they reported that 64% of the students agreed that the professor’s knowledge and use of technology during the synchronous sessions was critical to the overall success of the class. But instructors had little time to transition during the pandemic and little time to learn the technology themselves. This only added to the students’ obvious stressors of internet connectivity (bandwidth issues), sharing computer equipment with family members, and finding a quiet place to focus on their studies.

Also playing an important role in students transitioning to online learning is the learner interface (for example: Blackboard or Canvas). Students that have had proper training and experience with the interface/platform will feel more comfortable enrolling in a hybrid course or online course. Findings by Danesh, Bailey, and Whisenand (2015) match the results found in this 2020 study, indicating that seniors were more comfortable with online learning.

Many students have computer phobias; especially for those students, online classes which award points for attendance and participation could cause concern; taking exams online can be stressful for students without reliable internet access. As Saadè and Kira (2009) note, “A number of studies have provided evidence supporting a direct relationship between computer anxiety and computer use.” Ultimately, means that computer-shy students who are required to use computers to complete tasks in a course, their anxiety increase in direct relationship to the amount they are required to do online putting them at a disadvantage compared to other students.

Gender and age may also play a role in self-efficacy of online learning. Self-efficacy is defined as an individual’s belief that they have the capability of executing behaviors needed to perform. Within the literature, women are often reported to be less comfortable with or confident about online learning and the use of learning management systems; this lack of confidence may be related to a student’s sense of self-efficacy (Saadè and Kira, 2009). Saadè et al. (2017) found that of the total study population, of those expressing anxiety, females outnumbered males 7 to 1 by reporting they felt some sort of anxiety with online courses. Kramarae (2001) writes in *Third Shift: Women Learning Online* that there are a variety of barriers and reasons that female students have a harder time with online learning. She names life-work balance, job responsibilities, community roles, and financial burdens, on top of academic coursework. Nineteen years later, the gender divide on computer literacy is still prevalent in higher education classrooms and often can be related to student efficacy. Where there were differences within the literature, Saadè et al.’s (2017) work found that older students (21-22) reported higher levels of anxiety than a slightly younger age group (17-18).

METHODOLOGY

This study used a survey methodology. Data was gathered from 165 undergraduate students at a preeminent research university in a required business course, "GEB 3033: Business Workplace Skills and Best Practices." Students enrolled in the course were asked to complete the 32-question survey in Qualtrics, an online survey platform after the course transitioned from a face-to-face mode to an online mode because of the coronavirus. One hundred and sixty-five (165) declared business students completed the survey, which included demographic information, confidence and stress levels of online learning, and accounts of students' experiences as they transitioned to online learning to finish the semester.

ANALYSIS AND DISCUSSION OF RESULTS

The survey data of 165 respondents were analyzed using SPSS. A larger majority (60.6%) of the participants were male; 38.8% were female; and one student (0.6%) chose not to gender-identify. First-year students (3.6%), sophomores (19.4%), juniors (54.5%), and seniors (22.4%) made up the class rank. The students' ages ranged from 18 to 44, with 49.1% of the respondents indicating they were 20 years of age or younger. In terms of study behavior, students indicated they studied and used their computer most often at home (97%) followed by school (30.3%), work (13.3%), café (7.3%), and other (6.1%). Students were asked how the Coronavirus had impacted them. Emotional stress was the most mentioned at 69.1% followed by travel plans (65.5%), financially (58.2%), family (50.9%) and other (9.1%).

Students were given a Likert-scale of agree, somewhat agree, neither agree nor disagree, somewhat disagree, and disagree. Figure 1 shows 75.8% of students somewhat agreed or agreed that the school had communicated well with them about changes to their education due to the coronavirus.

Figure 1: University Communication

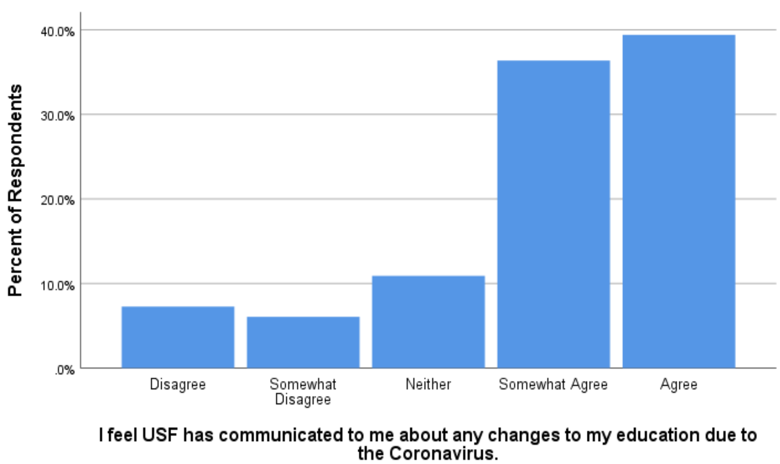
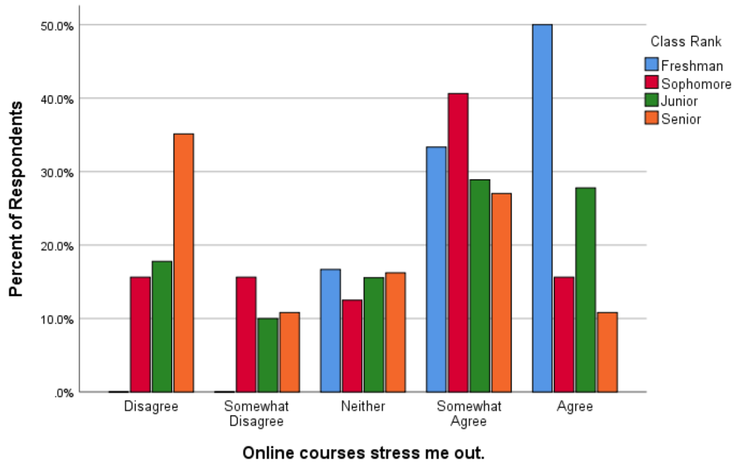


Figure 2 shows student responses based on their class rank. It would be expected that freshmen would most likely have more stress related to online learning since they are new to college and are learning the university's online course management tool. It might be quite different than the one a student was familiar with in high school. By the time students are at a senior level, they have had more experience with the online platform and are likely to be comfortable adjusting to a change in online learning.

To better understand student preference for online versus face-to-face learning, a chi-square test shows that students who express a stronger preference for in-person instruction are more likely to agree they are stressed out (P- value =0.00). The chi-square test shows that students who express stronger preferences for online learning are less likely to agree they are stressed out (P-value =0.00). It is important to note that preferring to do something one way doesn't always indicate the lack of ability or confidence in doing it a difference way. The correlation between confidence in online learning and the stress of taking online courses are -0.60. It is statistically significant at α =0.01. The correlation between preference for online learning and the stress of taking online courses is -0.52. It is statistically significant at α =0.01. The correlation between preference in face-to-face instruction and the stress of taking online courses is 0.54. It is statistically significant at α =0.01. Understanding differences between genders, an Independent

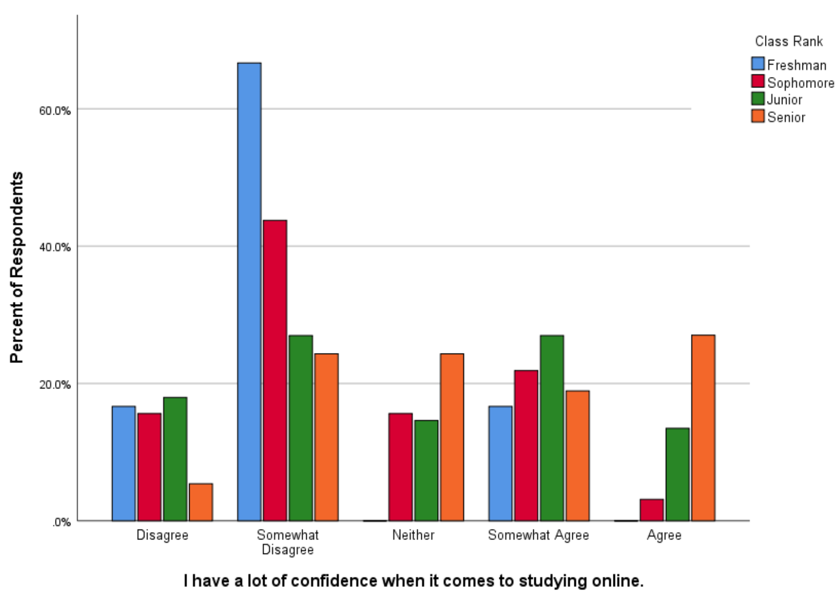
Samples t-Test showed that there is no significant difference between male and female students in their opinions for the statement, "Online courses stress me out" (P value = 0.11).

Figure 2: Online Course Stress by Class Rank



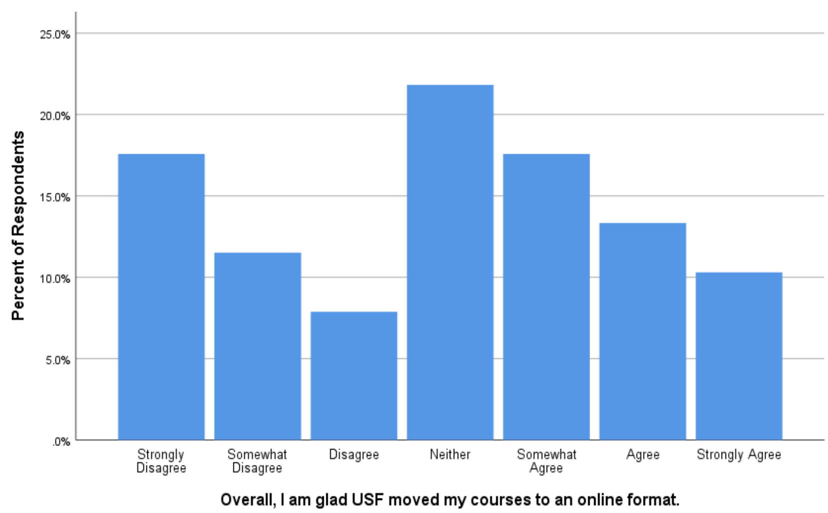
Students in the GEB 3033 Business Workplace Skills and Practices course were developing skills in the areas of communication, negotiations, organizational and time management, teamwork, collaborations, leadership, and critical thinking. Students were graded on written assignments, quizzes, class attendance, discussion boards, and a final exam. When students were asked about their confidence level of learning online,14.5% disagreed that they have confidence in studying online, 30.9% somewhat disagreed, 16.4% neutral, 23.6% somewhat agreed, 13.9% agreed, and 0.6% did not respond. An Independent Samples t-Test shows that male students expressed more confidence in studying for online courses than female students (P value=0.045).

Figure 3: Student Confidence in Online Learning



Despite the educational modality transitions and Internet connectivity uncertainties for students, most students indicated that they were glad that the course moved to an online format from a face-to-face format so that they could complete the semester. Students agreed or somewhat agreed (68.4%) that this would be a good course to offer in future semesters as an online course option. An Independent Samples t-Test showed that female students felt more strongly than male students that this would be a good course to offer in future semesters as an online course option (P value=0.00). A one-way ANOVA test showed that seniors feel more strongly than students of lower-class rank that changing the course to an online format was a good decision by college administration. Additionally, the one-way ANOVA showed that seniors felt more strongly than students of lower-class rank that changing the course to the online format due to COVID-19 lowered their stress level. Finally, the one-way ANOVA showed that seniors are less stressed out and had more confidence about online courses than freshman, sophomores, and juniors.

Figure 4: Glad Course Moved to Online Format



Another interesting finding looked at whether the student's stress level would change for the better when the course rapidly transitioned to online format so the students could finish their coursework. A chi-square test revealed that the answer depended on the student's perceived stress level about online learning (p-value = 0.09). Students who felt stressed about online courses in general felt that changing the learning format to online due to COVID-19 had not lowered their stress level. The chi-square test also showed that giving the students that option to change their letter grade to a pass/fail grade was significantly related to the perceived stress level toward online courses (p-value =0.02). Surprisingly, students who reported being stress about online learning did not think the option to change to a pass/fail grade helped their stress level.

A one-way ANOVA test suggested that students who had taken more online courses prior to COVID-19 tended to disagree or somewhat disagree that online courses stressed them out (p-value = 0.008). An additional one-way ANOVA test also indicated that the total number of online courses taken prior to COVID-19 positively affected the confidence in online learning (p-value = 0.016).

When students were asked "How stressed were you with transitioning this class to an online format midway through the semester?" using 0 as not stressed at all, 100 as extremely stressed, the mean stress level was 52 with a standard deviation of 31.

CONCLUSIONS

Anxiety in online learning is not an issue that will go away anytime soon. There is a likelihood that online learning is here to stay, and more institutions will have to take learning and training to an online format even once the coronavirus passes. Therefore, students' anxieties in online learning clearly needs to be addressed, perhaps through having first year and transfer students complete some sort of training with the online course management tool used by the institution.

Assuming that online classes will frequently be our reality, educators may want to account for these online computer anxieties and there may need to be several steps or approaches to aid in solving the problem. There are many ways to make online learning more attractive to students; course designers and instructors can re-think conventional course contents and design to better address students' needs in shifting to online classes.

Instructors we may need to look at meeting the course learning objectives to determine if synchronous or asynchronous would be better for students when being required to teach online. Synchronous online teaching is not without challenges. The difficulty with an instructor having 40 students on a single synchronous call is student boredom, students not paying attention, and students hesitating to speak up. Perhaps an exam could be more of a project-based deliverable and instead of having 40 or more students on a call there could be small group-based peer learning to offer more chance for each student to contribute but also participate and be engaged. Using innovative teaching strategies such as "flipping the classroom" could be helpful to students. A way to transition students to online learning in a blended, student-centered approach is "flipping the classroom." Wang et al. (2019) found that "flipping the classroom" was successful if there was strong instructor presence and availability.

A broad range of experimental learning opportunities such as guest lectures, virtual tours, virtual study groups are some of the ways to be inclusive of student needs for learning (such as learning styles and honoring their life experience) all while keeping it safe by social distancing.

FUTURE RESEARCH

There are vast opportunities to build on this study. This study could be replicated to other universities and colleges to include a larger group of respondents based on the primary findings of the study in order to validate students' experiences as they transition to online learning during the Coronavirus pandemic. Additionally, there is an opportunity for the study to expand the study beyond business students. More research could look at how computer anxiety impacts the final letter grade of a student that perceives themselves to have computer usage induced stress. Determining the underlying causes of the anxiety will help administrators, faculty, and staff better prepared to help students. Lastly, more research needs to be completed on the gender issues and racial issues related to the digital divide. How can instructions better assist female students that are taking online courses so that they feel more confident? Truly, it may take years to learn of the impacts the coronavirus has had on student retention rates and completion of their educational goals.

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