SOBIE 2022 Proceedings

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Sandestin Golf and Beach ResortApril 13-15, 2022
Destin, Florida

SOBIE 2022

Registration – Bayview Foyer		
April 13	**April 14**	**April 15**
7:00 – 11:00 AM	7:00 – 11:00 AM	7:00 – 11:00 AM

Wednesday, April 13

	Terrace 1	Terrace 2	Terrace 3
7:30 – 8:45	1-Marketing	2-Pedagogy	3-Accounting
9:00 – 10:15	4-COVID Higher Ed	5-Student Research	6-General Bus
10:30 – 11:45	7- Round Table	8- Labor	9- General Bus
12:00 -1:15	10- Open	11- Open	12- Open

Thursday, April 14

	Terrace 1	Terrace 2	Terrace 3
7:30 – 8:45	Breakfast (Bayview Room and Terrace)		
9:00 – 10:15	13-Round Table	14- Economics	15- Finance
10:30 – 11:45	16-Round Table	17- Management	18- Accounting
12:00 – 1:15	19- Pedagogy	20-Student Research	21- COVID
1:30 – 2:45	22- Pedagogy	23- Marketing	24- Management
3:00 – 4:15	25- Pedagogy	26- Business Analytics	27- Sports
4:30 – 5:45	28- General Bus	29- Finance	30- Productivity

Friday, April 15

	Terrace 1	Terrace 2	Terrace 3
7:30 – 8:45	31-Pedagogy	32-Student Research	33-Management
9:00 – 10:15	34-Finance	35-Student Research	36- Economics
10:30 – 11:45	37- Finance	38- International	39- Marketing/ General Business
12:00 – 1:15	40- Open	41- Open	42- Public Choice

SOBIE 2022 Proceedings

Abstracts Only

Full Papers

OMNI-CHANNEL DISTRIBUTION: LOGISTICS IMPLICATIONS AND A SPECIALIZED OPTIMIZATION TECHNIQUE

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ABSTRACT

In our work, we hypothesize a specialized optimization technique which adapts the general linear programming transshipment model to the ever-growing needs of Omni-Channel distribution in Supply Chain Management. With the rapid adoption of "smart" mobile technologies, customers now acquire merchandise across multiple channels and devices. As a result, retailers are challenged with down-stream operational complexities.

Fulfillment of customer orders now changes the amount of independent demand inventory organizations may hold. Our research integrates the use of Hub or Fulfillment Centers, locations where sellers fill customer orders placed through e-commerce, as a segment of demand. This adaptation to the optimization of transshipment can result in significant benefits to customer retention and profit.

RELATIONSHIPS BETWEEN THE TECHNOLOGY LEVEL OF LOCAL INDUSTRIES AND THE R&D ACTIVITIES OF FOREIGN MNC'S SUBSIDIARIES IN SOUTH KOREA

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Soon-Gwon Choi, Pukyong National University
Young Hee Yun Kim, Tuskegee University
Jong Wook Ha, Columbus State University

ABSTRACT

One of the most critical factors in determining the competitiveness of MNC's subsidiaries is the level of R&D related activities that the subsidiaries conduct in local market. Due to various difficulties associated with collecting real data regarding the R&D activities of foreign MNCs' subsidiaries, studies on these activities have been limited. This paper analyzes the relationships that the technology levels of local related industries and the local R&D activities of foreign MNCs' subsidiaries, along with the effects of other related factors. Empirical analysis is designed for sampling, data collection, and data analysis methodology.
The values of the research are explored while the limitations are expected. The importance of this paper lies in its use of empirical data analysis in finding specific factors that have substantial effect on the level of R&D activities of foreign subsidiaries.

The Utility of Count Inflated Models in Business

Michael Floren, University of North Alabama

Abstract: Count inflated models are an important class of statistical models used to address a variety of non-standard count situations. This presentation provides a non-technical discussion of several count inflated model options, as well as potential situations where each model may be appropriate. Advantages and disadvantages of options, as well as emerging possibilities, will be discussed.

As the Pendulum Swings: Labor Relations Past, Present, and Future

E. Hill Mayfield, Jacksonville State University
Daniel P. Mertens, Jacksonville State University
Brent J. Cunningham, Jacksonville State University

ABSTRACT
Labor unions continue to be a major concern for both management and the employee workforce. Nationally, a union represented less than 11% of American workers in 2020. (www.bls.gov/cps) This research presents a brief history of labor unions, which includes the early struggles of the labor movement efforts of the 1800's; the advent of modern unions and the strategies by key union leaders of the time for success; the key legislative efforts and the significance of the federal government's attempt to balance power between management and unions. This research further addresses recent labor relations' activities including the highly publicized legal cases involving Janus V. American Federation of State, County, and Municipal Employees (AFSCME) and the status of the ongoing battle between Amazon and the Retail, Wholesale and Department Store Union (RWDSU) in Bessemer, Alabama and Staten Island, New York facilties. Finally, the status of the desired balance of power between labor and management is addressed with discussion of the current "Great Resignation" phenomenon and guidance to both parties in labor relations concerning the question: What is the current position of the pendulum regarding the relationship between labor and management today?

Brand Equity Methodology: Exploring a Cross-Cultural Analysis

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ABSTRACT: Branding has been around for centuries as a means to distinguish the goods of one product from those of another. According to the AMA, a brand is a "Name, term, design, symbol, or any other feature that identifies one seller's good or service as distinct from those of other sellers and to differentiate them from those of competition." Brands offer tangible and intangible benefits to the companies who manufacture them, the retailers who sell them, and the consumers who buy them.

Brands are a key source of value to a firm, but there are wide variations in valuation percentages accounted for by brand names. In 2016, Wall Street Journal estimated that $8 trillion of the $18 trillion market capitalization of the S&P 500 index was on the account of intangible assets (Monga 2016). S&P market value soared to $40 trillion in 2022. Like this, brand valuation can provide smooth process of mergers and acquisitions. It can also help decision makings for internal resource allocation.

This paper will explain two major methodologies of brand equity measurement: residual and valuation approaches. Emphasizing the advantages of the latter, the paper will try to connect the cultural difference with the valuation methods. After Hofstede's six dimensions of culture are introduced, Individualism and Collectivism (IDV) index will be used to identify the different measurement for brand valuations.

ONLINE VS. ON-GROUND: A COMPARATIVE ANALYSIS OF DELIVERY MODE EFFECTIVENESS ON STUDENT LEARNING OUTCOMES IN A PRINCIPLES OF ECONOMICS COURSE BOTH PRE AND POST PANDEMIC

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Abstract

This paper considers whether online delivery of principles of economic courses results in improved student learning outcomes as reflected in measures of student performance. We utilize exam grades, class participation rates, midterm, and final course grades and gender to estimate ordinal logit specifications of achievement levels as a function of course delivery varaibles – online and on-ground delivery. Parameter estimates are expected to reveal that while online delivery increases accessiblity for remote and working students, limited interaction with classmates and faculty reduces the positive effect of course accessibility on learning outcomes. Study results may suggest that increasing course accessibility via online delivery could reduce student learning outcomes as reflected in traditional measures of student performance.

Keywords: Principles of Economics, economic education, online delivery, learning outcomes

JEL classification: A20, A22

Evaluation of Inventory Allocation in Dual-Channel Retailing using Simulation: Fulfillment Cost and Cycle Time Considerations

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Abstract

Omni-channel retailing has grown exponentially since the onset of the COVID-19 pandemic and the associated demand for fully online and buy-online-pickup-in-store (BOPIS) shopping options. As part of the evolution of demand fulfillment, retailers must reassess their fulfillment strategies with a focus on maintaining or improving customer service (in the form of product availability, shortened order fulfillment cycle times, and order accuracy) while maintaining or reducing inventory and order fulfillment costs (which incorporate order pick, packaging, and delivery costs). Achieving these objectives may include store fulfillment in addition to direct fulfillment from distribution facilities. The purpose of this research is to evaluate inventory allocation decisions in a retail dual-channel order fulfillment process, incorporating store fulfillment, for the purpose of minimizing order fulfillment costs and order fulfillment cycle time. A case approach, combined with discrete-event simulation modeling, is used to determine optimal inventory levels at both facilities. Strategic decision points are also assessed to maximize customer service within the bounds of cost constraints. Opportunities for further order fulfillment improvements are also discussed.

Key words: Order fulfillment, omni-channel fulfillment, store fulfillment, simulation, order fulfillment costs, order fulfillment cycle time, supply chain management, brick-and-mortar retail

Introduction

Omni-channel retailing has grown exponentially since the onset of the COVID-19 pandemic and the associated demand for fully online and buy-online-pickup-in-store (BOPIS) shopping options. According to Ishfaq and Raja (2018), online sales increased 14.6%, or $341 billion, from 2014 to 2015, while in-store sales increased only 1.4% during that same period. Latest U.S. Census Bureau data shows total e-commerce sales for 2021 of $870.8 billion, continuing the approximate 14% year-over-year increase in online business, with e-commerce accounting for 13.6 % of total sales (U.S. Census Bureau, 2022). Omni-channel fulfillment affords the retailer the opportunity to select the best fulfillment strategy for both buyer and seller, in contrast to traditional brick-and-mortar (B&M) retail, where customer fulfillment expectations are high and no opportunity exists to tap other sources of product (Torabi et al., 2015). In the omni-channel environment, retailers have decision opportunities related to fulfillment source, allocation of inventory to multiple customers when inventory is low, and product substitutionary policies (Torabi et al., 2015).

To provide shorter order fulfillment time, and to make better use of traditional brick-and-mortar retail facilities, retailers have turned to store fulfillment as a means of leveraging store inventory to fulfill online orders, taking fulfillment pressure off currently existing distribution centers and distributing that demand to retail stores, where COVID lockdowns and customer hesitancy about in-store shopping have dramatically reduced sales. As customer shopping preferences continue to evolve due to the availability of omni-channel purchasing options, retail stores are morphing as well, changing from the traditional focus of an indoor shopping experience for customers to a hybrid facility that allows in-store, pickup, and online order fulfillment. Pre-COVID, the Target retail chain fulfilled 50% of its online orders through its brick-and-mortar stores in 2017 (Cain, 2018). Part of this transformation involved re-arranging B&M store square footage to allot more space for digital fulfillment. Target was one of the first major retailers to make this transition (Reddy, 2018). By positioning themselves for omni-channel success ahead of the pandemic, they experienced a 154% one-year increase in online sales at the end of Q3 2020, with 75% of their digital sales filled from existing store inventory (Ali, 2020).

As part of the evolution of retail, companies must reassess their fulfillment strategies with a focus on maintaining or improving customer service (in the form of product availability, shortened order fulfillment cycle times, and order accuracy) while maintaining or reducing inventory and order fulfillment costs (which incorporate order pick, packaging, and delivery costs). Achieving these objectives may include store fulfillment in addition to direct fulfillment from distribution facilities. The purpose of this research is to model a retailer omni-channel order fulfillment process that incorporates store fulfillment using discrete-event simulation. A case approach is used to evaluate strategic decision points within the system, and opportunities for further order fulfillment improvements will be discussed.

Literature Review

Order fulfillment options for omni-channel retailers now include “store-facing distribution centers (DC), dedicated order fulfillment facilities (DTC), retail stores, and direct-fill by vendors” options (Ishfaq and Raja, 2018; Verhoef, Janna, and Inman, 2015). The process of omni-channel fulfillment involves both order picking (from either a distribution center or in-store) and the last-mile home delivery options (excluding store pickup orders). Factors that affect these two decision points include “country specifics (e.g., population density), retailer specifics (e.g., capability for cross-channel process integration) and customer behavior (e.g., possibility of unattended home delivery)” (Hubner et al., 2016). Meeting the expectations of online customers may mean compromises on the retailer’s part involving product variety, availability, and order fulfillment time (Lim and Srai, 2018).

A number of researchers have evaluated the feasibility of store fulfillment as part of an overall omni-channel fulfillment strategy. Known as online-to-offline (OTO) fulfillment, this fulfillment model forwards online customer orders to traditional (offline) brick-and-mortar retail stores. This necessitates collaborative demand management and order fulfillment (Ishfaq and Raja, 2018), since the supply chain is now extended to the consumer’s home or a designed order pickup point (Lang and Bressolles, 2013; Yao and Zhang, 2012). In addition, logistical challenges increase at the retail site due to unpredictable demand, short delivery timeframes, and the small order sizes characteristic of e-commerce (Campbell and Salvesbergh, 2006; Hsiao, 2009). Zhao et al. (2016) modeled this dual-channel supply chain with lateral inventory transshipment allowed to determine the optimal inventory order levels and transshipment price that maximized total profit. Difrancesco *et al.* determined the optimal policy configuration for omni-channel store fulfillment in terms of the number of packers, number of pickers, and pick cut-off time. They found that the trade-off between customer service level and fulfillment costs is critical. Schneider and Klabjan (2013) investigated different inventory control policies for omni-channel retailers in order to determine optimal base stock and (s, S) inventory policies.

Given the significant fulfillment costs and lower gross margins associated with store fulfillment of online orders, researchers have sought methods to maximize the effectiveness and profitability of omni-channel fulfillment strategies that include this channel. One of the first published works on the topic was from Alptekinoğlu and Tang (2015), who modeled a retail distribution system that incorporated both online and in-store channels. Aksen and Altinkemer (2008) created a retail decision model to determine which stores should fill online orders, based on fixed operating and last-mile delivery costs. Their model took demand from both channels and assigned it to different DCs based on total transportation and inventory costs. Mahar et al. (2012) investigated the fulfillment strategy of filling online orders through retail stores, with orders either pulled from DCs and shipped to stores and pulled directly from in-store inventory. They found that it was best to form subsets of retail stores within a region for online order fulfillment rather than consider all retail stores. Ishfaq and Bawja (2019) determined the effects of fulfillment methods and alternative logistics process structures on retailer's online sales profitability. Difrancesco et al. (2021) used a simulation-based approach, along with exploratory modeling, to determine the optimal batching time, number of pickers, number of packers, and associated performance metrics under multiple sources of uncertainty. The effectiveness of an omni-channel fulfillment strategy that incorporates store fulfillment must consider both the internal metrics to be optimized and the external customer service requirements.

Inventory competition between fulfillment channels may also be introduced with the addition of store fulfillment. Geng and Mallik (2007) utilized a game theoretic model to model inventory stocking decisions between a manufacturer's direct channel and its independent retailer for the same product. They found that an equilibrium condition exists whereby the manufacturer may short a retailer's order even when production capacity exists to fill the order in full, in order to grow total supply chain profit. Difrancesco and Huchzermeier (2020) determined that the refund rate, the values of the return rate, and online order appeal defined the conditions under which a Nash equilibrium exists between competing omni-channel retailers, assuming online order returns (with a restocking fee) but no brick-and-mortar returns. The choice of fulfillment option is also impacted by shipment consolidation opportunities and the resultant decrease in shipping costs via economies of scale. Torabi et al. (2015) built a mixed-integer programming to optimize customer order fill while minimizing associated logistics costs.

From the consumer's perspective, the in-store shopping experience is still valued and remains a viable choice in demand fulfillment options. Early in the history of e-commerce, Ranganatham and Ganapathy (2002) identified security and privacy issues as factors that made consumers hesitant to buy online. In the choice between omni-channel retailers, Gowar and Hoberg (2019) found that price was the leading consumer decision criteria, followed closely by lead time and convenience. The perception of convenience may shift when multiple fulfillment options are available, leading to fulfillment channel shifts (Gallina and Moreno, 2014). In-store shopping also offers benefits other than the purchase of goods, such as entertainment, opportunities for social interaction and physical movement, and trip chaining (Mokhtarian, 2004). It is therefore important that consumer behavior and preferences be understood in order to create an effective omni-channel fulfillment strategy (Ehmke and Campbell, 2014). Because in-store shopping opportunities remain a valued shopping option for consumers, efforts by retailers to capitalize on their investments in retail outlets for multiple fulfillment options are worthwhile.

Dual-Channel Retail Distribution with Store Fulfillment

Figure 1, below, provides a framework for a dual-channel retail fulfillment strategy that incorporates store fulfillment. In this framework, online orders can be filled with inventory from either a dedicated direct-to-consumer fulfillment center (DC) or a brick-and-mortar retail store (RS) utilizing 3PL parcel shipping services for final delivery.

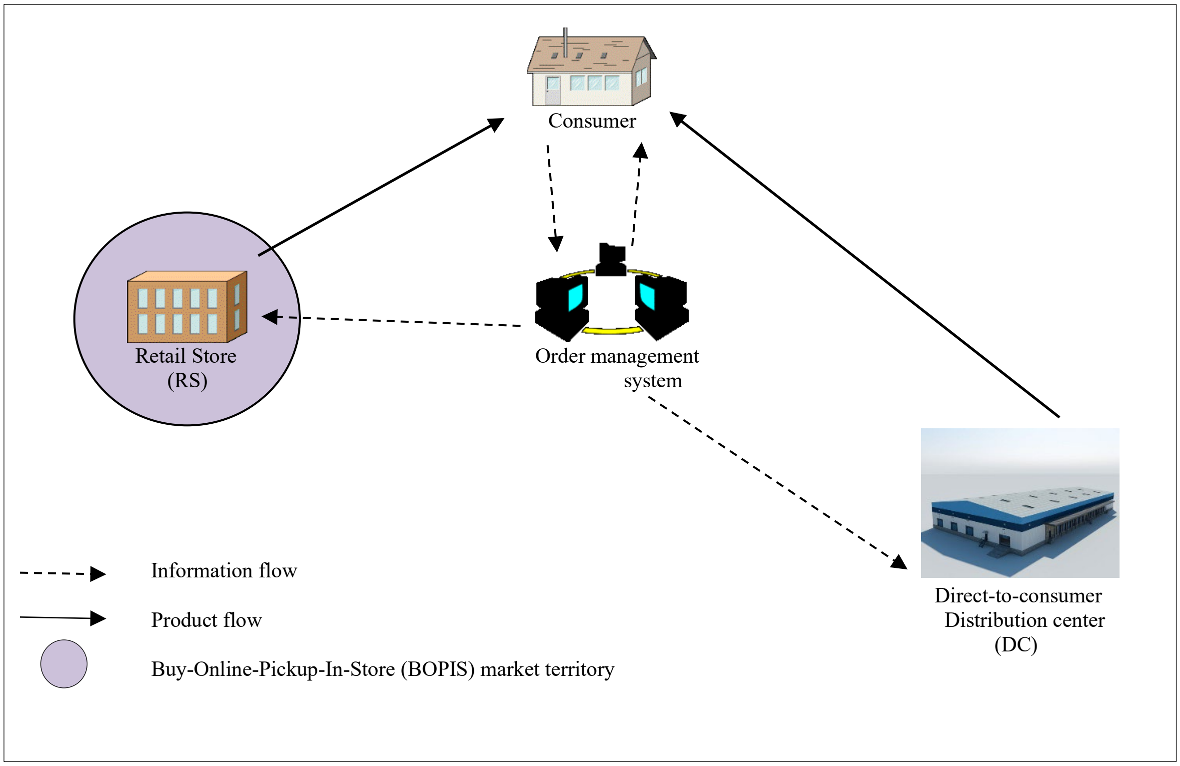

Figure 1: Dual-Channel Retail Fulfillment Framework with Store Fulfillment

An order management system is utilized to process online orders, send fulfillment instructions to participating fulfillment facilities, and communicate order status information back to the customer. Customers that reside within the market territory of the retail store (indicated by the circle in Fig.) may buy-online-pickup-in-store (BOPIS). Fulfillment decisions are based on the proximity of the customer to the retail store (for potential BOPIS fulfillment) and order pick, pack, and ship costs from each facility to the customer's address. Inventory allocation decisions also consider inventory carrying costs, labor costs, and capacity considerations at each facility.

Given the stochastic nature of product demand, order pick and pack time, and shipping time to a customer's address, the dual-channel fulfillment framework described above can best be modeled and optimized using discrete-event simulation. Discrete-event simulation is "the process of codifying the behavior of a complex system as an ordered sequence of well-defined events. Each event occurs at a particular instant in time and marks a change of state in the system" (Kiran, 2019). For this research, a case analysis approach is used to determine the optimal inventory allocation between the distribution center and retail store for the online order fulfillment of a given retailer.

Case Analysis

Lawson Clothiers, a regional clothing retailer, operates one brick-and-mortar retail store (RS) and one direct-to-customer distribution center (DC) within a 200 square mile area in the Northern Alabama / Southern Tennessee region. Local online shoppers living within 30 miles of the retail store order online and pickup at the store (BOPIS), while regional online customers outside the 30-mile radius of the store shop order online and have their items shipped directly to them. All regional online customer orders are filled from the DC, if inventory is available, to take advantage of quicker order pick time and lower shipping costs. If inventory is not available there, the retail store inventory is tapped for ship-from-store (SFS) order fulfillment. Local shoppers' online orders are filled from the retail store rack inventory; no additional backroom inventory storage is available. Consequently, local shoppers' online orders are filled by the DC if the retail outlet is out of stock. Only if inventory in unavailable in both locations are shortages recorded for ordered items.

Within the 200-square mile N. Al / S. Tenn region, the retail store is located at coordinates (34, 50) miles (with the local market region enclosed in the circle) and the distribution center at (100, 150) miles, as shown in Figure 2, below:

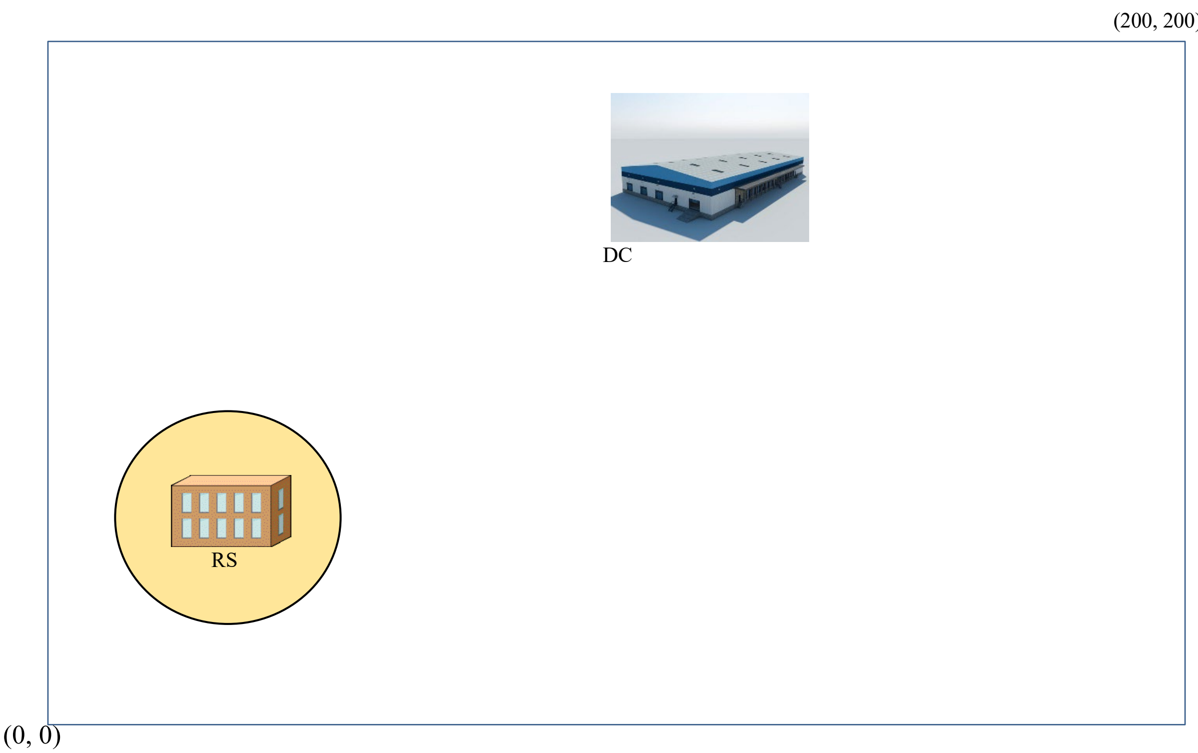

Figure 2: Location of Retail Store and Distribution Center
within 200 Sq. Mile Omni-Channel Fulfillment Region for Lawson Clothiers

Two of the winter season's high-demand items are a particular fleece hoodie jacket and its matching jogger pants, which retail for $60 and $40, respectively, a retail markup of 55% over the cost of merchandise sold (Claypoole, 2019; Thomas et al., 1999). One order is placed for the season but shipped in partial segments, with shipments arriving weekly and available for distribution first thing Monday morning. Customers either purchase just the jacket or both the jacket and pants.

The stochastic characteristics of this order fulfillment system at present include the time between orders and the order pick and package times. These characteristics are given in Tables 1 and 2, below.

Item	Time between Orders
Jacket only	Normally distributed, NORM(4, 0.2) hours
Jacket / Pants set	NORM(3, 2) hours

Table 1: Time Between Orders for Order Options

Facility	Garment	Order Pick and Pack (OPP) Time
Retail Store	Jacket	NORM(0.4, 0.1) hrs
	Pants	NORM(0.3, 0.1) hrs
Distribution Center	Jacket	UNIF(0.25,0 .4) hrs
	Pants	UNIF(0.25, 0.4) hrs

Table 2: Order Pick and Pack Time per item for each facility

Order pick and pack (OPP) fees (excluding storage and shipping) are assumed to be $3.13 per item at the distribution center (WarehousingAndFulfillment.com, 2022) and $5.92 at the retail store (Fit Small Business, 2021). Inventory carrying cost percentages (ICC) for these items are 25% of unit cost at the distribution center and 40% at the retail store (Ganeshan, 1999; Fares and Tebbett, 2015). Shortage costs are estimated as the gross profit per item short (Lack, 2017), which are $21.92 and $14.19 for the jacket and pants, respectively. The fleece hoodie and jacket have a two-month Fast Fashion selling season, which is 9 weeks long.

Research Objective 1: Minimize Order Fulfillment Costs, Shipping Cost Not Considered

Lawson management first wants to determine the best inventory replenishment policy for these items at both the retail store and the distribution center to minimize average order fulfillment costs/day, which includes the combined holding, shortage (Kelton, et al, 2015), and order pick costs at the two facilities. Shipping costs are not considered, and total shipping time is assumed constant and equal to one business day (15 hours) for both facilities, to all destinations within the region. Order fulfillment costs are calculated as follows:

$$\text{Avg. order fulfillment cost / day} = \text{Avg. order pick cost/day} + \text{Avg. holding cost/day} + \text{Avg. shortage cost/day}, \quad (1)$$

where

$$\text{Avg. order pick cost/day} = \text{Avg. number of orders filled/day} \times \text{order pick cost/order}$$
$$= OPC_{DC}(n_{J,DC} + n_{P,DC}) + OPC_{RS}(n_{J,RS} + n_{P,RS}) \quad (2)$$

with

OPC_{DC} ≡ Order pick cost at DC = $3.13
OPC_{RS} ≡ Order pick cost at RS = $5.92
$n_{J,DC}$ = avg. number of jacket orders filled/day at DC
$n_{J,RS}$ = avg. number of jacket orders filled/day at RS
$n_{P,DC}$ = avg. number of pants orders filled/day at DC
$n_{P,RS}$ = avg. number of pants orders filled/day at RS

and

Avg. inventory carrying cost / day =

$$= ICC_{J,RS}(\mu_{J,RS}) + ICC_{J,DC}(\mu_{J,DC}) + ICC_{P,RS}(\mu_{P,RS}) + ICC_{P,DC}(\mu_{P,DC}) \quad (3)$$

with

$ICC_{J,RS}$ ≡ unit holding cost/day for jacket at RS $= 0.40(\$60/1.55) = \$15.48$
$ICC_{J,DC}$ ≡ unit holding cost/day for jacket at DC$= 0.25(\$60/1.55) = \$9.68$
$ICC_{P,RS}$ ≡ unit holding cost/day for pants at RS$= 0.40(\$40/1.55) = \$10.32$
$ICC_{P,DC}$ ≡ unit holding cost/day for pants at DC$= 0.25(\$40/1.55) = \$6.45$
$\mu_{J,RS}$ ≡ Time-persistent inventory level for jacket at retail store
$\mu_{J,DC}$ ≡ Time-persistent inventory level for jacket at DC
$\mu_{P,RS}$ ≡ Time-persistent inventory level for pants at retail store
$\mu_{P,DC}$ ≡ Time-persistent inventory level for pants at DC

and

$$\text{Avg. shortage cost / day} = SC_j \times \mu_{SL,J} + SC_P \times \mu_{SL,P} \quad (4)$$

with

SC_j ≡ unit shortage cost/day for jacket = \$21.72
SC_p ≡ unit shortage cost/day for pants = \$14.19
$\mu_{SL,J}$ ≡ time-persistent jacket shortage level
$\mu_{SL,P}$ ≡ time-persistent pants shortage level

To determine the optimal inventory allocation for this organization, a discrete-event simulation model was built using Arena © simulation software to model daily order fulfillment activities. A total of 10,000 replications of the two-month selling season for these garments were run for each inventory allocation strategy tested. Each facility (retail store and distribution center) was assumed to be open for online orders 7 days per week, 15 hours per day, and all shipping occurs during these hours. The details of the simulation model are provided in Appendix A.

The model parameters (independent variables) varied for cost minimization purposes in Research Objective 1 include the weekly inventory allocation of each garment during the 9-week season in both facilities: Number of jackets at the retail store (J RS), number of pants at the retail store (P RS), number of jacket at the distribution center (J DC), and the number of pants at the distribution center (P DC).

The results of the simulation trials for Research Objective 1 are shown in Tables 3 through 5. Decisions about candidate inventory allocation levels were made between trials and based upon the total order fulfillment cost shown in Table 3, as well as the average inventory levels shown in Table 4.

	Inventory Holding Cost / Day				Shortage Cost / Day		OPP Cost / Day		Total
Inventory Allocation (J RS, P RS, J DC, P DC)	J, RS	P, RS	J, DC	P, DC	J	P	RS	DC	Avg Order Fulfillment Cost / Day
(16, 12, 49, 26)	\$487.64	\$339.92	\$201.60	\$67.26	\$0.03	\$0.84	\$10.84	\$24.82	\$1132.95
(12, 7, 49, 28)	221.96	154.02	201.55	78.17	0.48	1.15	9.71	25.73	692.76
(5, 4, 39, 18)	43.70	13.52	127.72	31.43	51.84	32.30	6.52	18.51	325.54
(5, 4, 31, 16)	36.89	11.66	80.78	24.87	111.26	41.92	6.78	15.49	329.65
(5, 4, 34, 18)	39.57	13.53	97.18	31.47	86.13	32.35	6.75	17.19	324.18
(5, 4, 36, 18)	41.26	13.43	108.90	31.45	71.38	32.46	6.63	17.72	323.21
(5, 4, 37, 18)	42.05	13.47	114.99	31.44	64.56	32.34	6.60	17.98	323.44

Table 3: Avg. Daily Order Fulfillment Costs for Given Inventory Allocation Strategies

Inventory Allocation (J RS, P RS, J DC, P DC)	$\mu_{J,RS}$	$\mu_{P,RS}$	$\mu_{J,DC}$	$\mu_{P,DC}$	Avg. Jacket Shortage Level	Avg. Pants Shortage Level
(16, 12, 49, 26)	31.50	32.94	20.83	10.43	0.0012	0.0592
(12, 7, 49, 28)	14.34	14.92	20.82	12.12	0.022	0.081
(5, 4, 39, 18)	2.82	1.31	13.19	4.87	2.36	2.28
(5, 4, 31, 16)	2.38	1.13	8.35	3.86	5.076	2.951
(5, 4, 34, 18)	2.56	1.31	10.04	4.88	3.930	2.28
(5, 4, 36, 18)	2.67	1.30	11.25	4.88	3.26	2.29
(5, 4, 37, 18)	2.72	1.30	11.88	4.87	2.95	2.28

Table 4: Time-Persistent Inventory Levels at Four Inventory Allocation Points

Inventory Allocation (J RS, P RS, J DC, P DC)	J RS BOPIS CT	J RS SFS CT	J DC CT	J and P RS BOPIS CT	J and P RS SFS CT	P DC CT
(16, 12, 49, 26)	0.900	15.399	15..324	1.198	15.699	15.324
(12, 7, 49, 28)	0.900	15.399	15.324	1.197	15.699	15.324
(5, 4, 39, 18)	0.899	15.399	15.324	1.138	15.700	15.324
(5, 4, 31, 16)	0.899	15.399	15.324	1.104	15.693	15.324
(5, 4, 34, 18)	0.900	15.399	15.324	1.134	15.696	15.324
(5, 4, 36, 18)	0.899	15.399	15.324	1.137	15.698	15.324
(5, 4, 37, 18)	0.899	15.399	15.324	1.133	15.700	15.324

Table 5: Order Fulfillment Cycle Time for all Fulfillment Points

The results of these simulation trials showed that the best weekly inventory allocation strategy for (J RS, P RS, J DC, P DC) was (5, 4, 36, 18), with an average daily fulfillment cost of $323.21. Further inventory allocation strategies modeled resulted in higher daily fulfillment costs. Table 5 shows that order fulfillment cycle time remained consistent for each inventory allocation strategy modeled, with slight variation seen in order fulfillment options when two items were purchased.

Research Objective 2: Minimize order fulfillment cycle time, with stochastic shipping time

Lawson management is also interested in minimizing order fulfillment cycle time, which is defined here as the time from order placement to order receipt or delivery. The current order pick and package times (with current staffing levels and packaging facilities) were given in Table 2 and the cycle times for the Research Objective 1 simulation trials were shown in Table 5.

In Research Objective 1, it was assumed that shipping time was constant and exactly equal to 15 hours for each facility. Constant ship time resulted in high consistency in the cycle times for each fulfillment portal in Table 5, but it does not reflect true shipping operating conditions. For Research Objective 2, this assumption is relaxed, with shipping time now assumed to vary with the last mile delivery distance and set parcel pickup times at each facility. It is now assumed that parcel pickup occurs every hour at the DC and every 2 hours at the RS. The assumed shipping times are now defined as

$$CT_{RS} = WT_{PPU,RS} + DT_{RS,Cust}$$

where

$$CT_{RS} \equiv \text{Delivery cycle time from retail store}$$
$$WT_{PPU,RS} \equiv \text{Wait Time for parcel pickup at retail store} = 2 \text{ hours}$$
$$DT_{RS,Cust} \equiv \text{Delivery time to customer} = \text{Distance to customer} \times 45 \text{ mph}$$

and

$$CT_{DC} = WT_{PPU,DC} + DT_{DC,Cust}$$

where

$$CT_{DC} \equiv \text{Delivery cycle time from distribution center}$$
$$WT_{PPU,DC} \equiv \text{Wait Time for parcel pickup at distribution center} = 1 \text{ hour}$$
$$DT_{DC,Cust} \equiv \text{Delivery time to customer} = \text{Distance to customer} \times \text{vehicle speed}$$

The optimal inventory allocation strategy of (J RS, P RS, J DC, P DC) = (5, 4, 36, 18) was used for Research Objective 2 optimization via simulation. Table 6 contains the simulated cycle time results for five different average vehicle speeds.

Vehicle Speed	J RS BOPIS CT	J RS SFS CT	J DC CT	P DC CT	J and P RS BOPIS CT	J and P RS SFS CT
40	0.909	5.754	4.081	5.082	1.109	6.060
45	0.852	5.381	3.775	4.776	1.052	5.687
50	0.807	5.083	3.530	4.531	1.016	5.388
55	0.770	4.840	3.330	4.330	0.982	5.144
60	0.739	4.636	3.163	4.163	0.954	4.940

Table 6: Average Order Fulfillment Cycle Time Results (in hours) for Various Delivery Vehicle Speeds and Set Parcel Pickup Times for the Retail Store and Distribution

Table 6 illustrates the customer advantage of utilizing BOPIS options for online order fulfillment speed. For example, local customers who purchase a jacket from the retail store and elect to utilize curbside pickup would, on average, receive their order almost four hours before a delivered item would arrive. Even for local customers, delivery must follow the pickup and delivery schedule of the parcel service utilized.

The cycle time predictive capabilities of the model could be further enhanced by using stochastic delivery time that incorporates traffic delays impacted by urban density. Total order fulfillment in that case would incorporate both stochastic order pick and pack time and stochastic ship time. Order fulfillment times, from both facilities, could then be compared for individual customers at specific locations.

Opportunities for Further Research

Discrete-event simulation provides a valuable tool for evaluating order fulfillment strategies in omni-channel retailing. For the Lawson Clothiers case, the lowest-cost inventory allocation strategy can be determined for the independent variables defining fulfillment costs, order pick and pack times, and order ship time. If per-unit fulfillment or inventory costs change, a new inventory allocation strategy could easily be determined using the model.

The simulation model for Lawson Clothiers could also be utilized to evaluate other factors in total order fulfillment cost. For example, labor costs for order pick and pack could be added to the total cost of fulfillment, with additional labor cost incurred to lower order pick and pack time. Backroom storage could be added to the retail store, with associated costs, to increase customer service to local customers in densely populated areas. Shipping costs, and the associated value of parcel delivery contracts, could be considered within the total cost framework as well, especially in decisions regarding point of fulfillment (RS or DC). With the model in place, any number of fulfillment options could be considered, with the costs, cycle times, and any other performance metric of interest, tracked for optimization purposes.

Conclusion

The rapidly changing retail landscape has brick-and-mortar retailers rethinking their approach to demand fulfillment and the idea of what constitutes a retail shopping experience. Now that omni-channel fulfillment has been fully embraced by consumers, retailers must find low-cost ways to meet customer demand with high customer service. Simulation modeling provides a valuable tool to assess omni-channel fulfillment strategies in the presence of every-changing demand patterns and customer preferences. By incorporating store fulfillment within the list of fulfillment options, traditional brick-and-mortar retailing may remain a viable shopping option long into the future.

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Appendix A
Discrete-Event Simulation Model Details

Arena © simulation software was used to create the discrete-event simulation model for the Lawson Clothiers case dual-channel fulfillment process. Inventory arrival for the jacket and pants items, at both the retail store and the distribution center, was modeled via Create flowchart modules to describe interarrival times, as detailed in Table 1, and the number of entities per arrival, which defined the replenishment strategies (number of sourced items arriving at a time) tested for the case. Assign modules were used to reset the global Shortage Level value to 0 before inventory was stored. The subsequent storage of these items in inventory was modeled by Hold modules, and the time-persistent average number in the queue of each Hold was used to reflect average inventory levels for both items in each facility. The inventory loops used for this purpose in the model are shown in Figure 3.

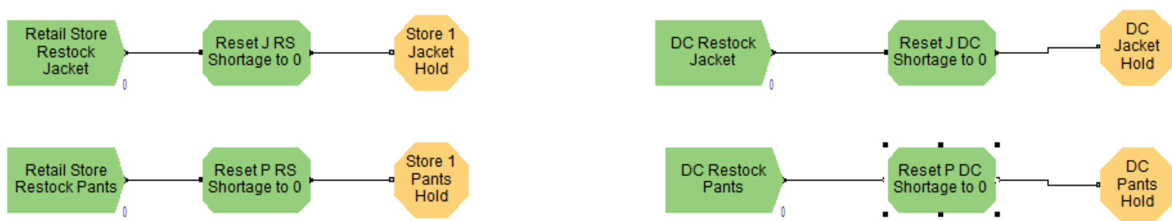

Figure 3: Screenshot of Inventory Replenishment Hold section of model

A second section of the model represented customer arrival, determination of order fulfillment point, removal of inventory for order, and shipment/pickup of order. Two create modules begin this section, each creating a customer for either a jacket-only or jacket-and-pants order. Upon arrival, each customer was randomly assigned an address within the 200 x 200 sq. mile region, then the distances to the retail store and the distribution center were calculated using Manhattan distance (Jaggia et al, 2021), which is defined as

$$\text{Manhattan distance to Retail Store} = |(x_i - x_{RS})| + |(y_i - y_{RS})|$$

and

$$\text{Manhattan distance to Distribution Center} = |(x_i - x_{DC})| + |(y_i - y_{DC})|$$

where (x_i, y_i) represents the location of customer i, and (x_{RS}, y_{RS}) and (x_{DC}, y_{DC}) represent the locations of the retail store and distribution center, respectively. Since one "customer" is created for each item purchased, customer purchase sets were batched per order before assigning addresses and distances to each order. The model section for customer arrival and attribute assignment is shown in Figure 4.

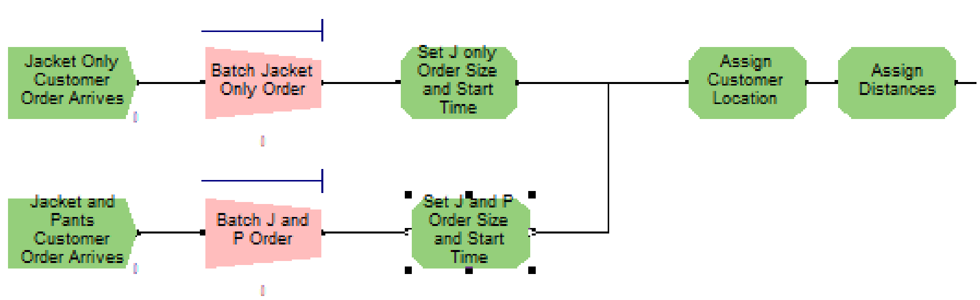

Figure 4: Customer Arrival and Attribute Assignment

After customer arrival and attribute assignment, orders are sent to different sections of the model based on order size. In each section, orders for customers within 30 miles of the retail store are assumed to be filled there, with customers buying online then driving to the retail store for pickup. Inventory is first checked at the retail store; if inventory is available, the purchased items are removed from the appropriate Hold inventories and time is allotted for order pick and pack and customer travel time. If retail store inventory is not available, inventory at the DC is checked; if inventory is available, the order is picked and packed for shipment, then time is allotted for shipment to the customer. All inventory checks are accomplished by assessing the current number in the queue in the appropriate Hold module, which represents the inventory of the given item at the facility being considered for fulfillment. Figure 5, below, shows the basic structure of the order fulfillment section of the model as it appears for jacket-only orders. The code structure is repeated in other sections of the model for jacket-and-pants orders, with code modifications included for split order fills between the retail store and the distribution center. Decision points are also incorporated based on customer distance to the retail store and the availability of the requested inventory at each location.

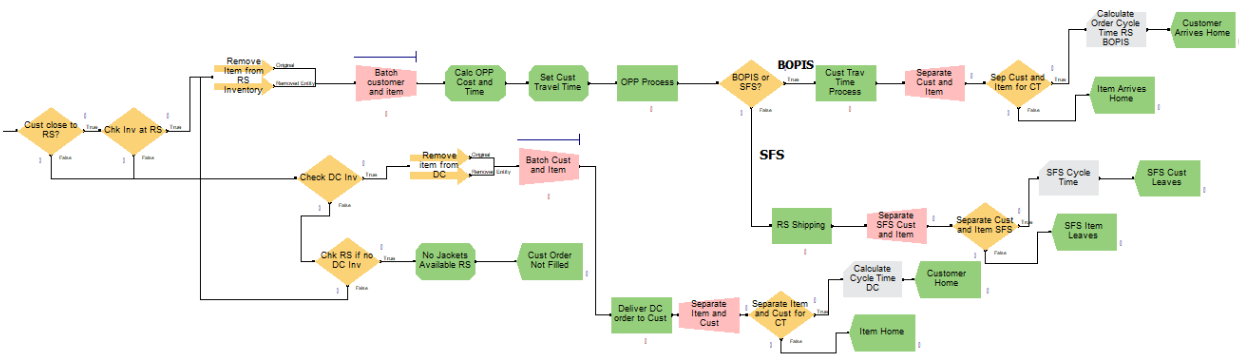

Figure 5: Order Fulfillment for Jacket-Only Orders

Model Results

A total of 10,000 replications of each candidate model structure were run, with summary statistics calculated automatically by Arena for entities, queues, resources, and user-defined statistics. For the Lawson Clothiers model, time-persistent statistics were also defined for inventory holding and storage costs at each location. Furthermore, output statistics were also defined for order pick and pack (OPP) costs at each facility and total order fulfillment costs.

Cycle times were calculated through the insertion of Record modules in the model. Cycle times were recorded for each possible fulfillment option within the dual-fulfillment strategy used by Lawson.

Evaluation of Research Objectives

Research Objective 1 focused on minimizing order fulfillment costs, with the independent variables defined as the restock quantity of each item at the two locations. Candidate restock quantities were evaluated methodically by observing the input costs and inventory levels (defined by the average number in the queue of each Hold inventory module) associated with total order fulfillment costs. Based upon the candidate replenishment strategies presented in Table 3 (and others run as part of this optimization effort), the lowest fulfillment cost strategy was found to be (J RS, P RS, J DC, P DC) = (5, 4, 36, 18). The cycle times for each order fulfillment point was found to be consistent, due to an assumed constant ship time of 15 hours (one business day).

For Research Objective 2, the assumption of constant shipping time was relaxed and changes in total cycle times were observed. The lowest fulfillment cost inventory replenishment strategy from RO 1 was used for inventory restock levels. In the model, shipping time was changed in the Ship Time variable used within the shipping Process modules in the model.

Well-Being of Global Virtual Teams

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Abstract

Much of the academic research on the health and wellness of organizational teams have been conducted in the context of co-located team members. However, the global trend in organizational team composition is moving toward more virtual teams. In the majority of virtual teams, half of the members are from different cultures. There is a lack of research on the impact of working as a part of a global virtual team has on the wellbeing of team members. For example, little is known about the effects of geographic disbursement and cultural differences on individual team member wellness.

More than two-thirds of professionals around the world telecommute at least once a week. This phenomenon will grow as the world becomes more interconnected through globalization and advances in computer-mediated communication (CMC) technology. These forces have given rise to Global Virtual Teams (GVTs). GVTs are comprised of culturally diverse people who are geographically and/or temporarily dispersed around the globe. These diverse teams communicate using information technologies to achieve organizational goals and objectives. There is a substantial body of knowledge on the impact that the GVT environment has on team performance, but there is a dearth of research on the effect it has on team wellness. Wellbeing has been defined as the experience of health, happiness, and prosperity—including good mental health, high life satisfaction, a sense of purpose, and ability to manage stress. Given that a high percentage of GVTs members are from different countries, the author posits that cultural and contextual factors influence the wellbeing of GVTs.

This paper explores the relationship between organizational and contextual factors on the wellbeing of global virtual teams. These findings will inform the development of a framework to be used in measuring and maintaining the welfare of global virtual teams.

Section 1: Global Intelligence

Global Intelligence (G.Q.) is "the ability to understand, respond to, and work toward what is in the best interest of and will benefit all human beings and all other life on our planet" (Spariosu, 2004). It consists of the skills and attributes needed work with people from different cultures and socioeconomic backgrounds on a global scale effectively. In his book, *Global Intelligence and Human Development* (2004), Spariosu points out that there is no one-size-fits-all approach to solving problems with people from different cultural backgrounds. The writers theorize that there is a positive correlation between wellbeing and three attributes of G.Q.: cultural competence, cultural intelligence (C.Q.), and global mindset (Figure 1).

Conversely, a lower G.Q. is associated with decreased wellbeing, which contributes to the formation of cultural silos within GVTs. Cultural silos take root when members of different cultures think and behave at cross-purposes to each other. These silos happen when team members fail to understand each other's unique values, beliefs, customs and perspectives. This lack of understanding can lead to misunderstandings, interpersonal problems and team conflict. These conditions create stress, low job satisfaction and poor performance, all of which are factors contributing to decreased team welfare (Adamovic, 2018).

Cultural Competence

"Cultural competence is about mindset: it is about being open, inquisitive, curious and respectful of different cultures" (Owen, 2017, p. 114). In practice, it is about accumulating knowledge, understanding, skill and attitude of different cultures. In the context of GVTs, there is a high probability that team members will hold different cultural values, beliefs, and perspectives that influence how they work together. Therefore, teams that lack cultural competence are at high risk for interpersonal conflict and a stressful work environment (Adamovic, 2018). A lack of wellbeing in this context may manifest as anxiety, as identified in a study of the longitudinal effects of CMC on virtual team interactions (Fuller, Vician, & Brown, 2016). The writers posit that cultural competence has the potential to increase trust, understanding, and respect between team members who might otherwise feel culturally isolated, alone and undervalued. These factors have a negative bearing on the wellbeing of GVTs.

Potential strategies to increase cultural competence on GVTs include:

1. Organize a face-to-face (F2F) meeting at inception and regularly after that. Meeting F2F allows team members to get to know each other personally, culturally and socially (Liao, 2016). These meetings help to establish and maintain a team rapport throughout the life cycle of the GVT.
2. Arrange virtual team-building exercises regularly (e.g., virtual staff parties) (Szewc, 2013).
3. Develop knowledge and understanding of the different cultural practices and worldviews of team members (Huang, 2015).
4. Develop cross-cultural skills such as understanding and respecting team members' customs, social norms, and work culture. Acknowledging different religious and civic holidays, and developing intercultural language skills such as "hello," "goodbye," and "thank you."

Cultural Intelligence

Cultural intelligence (C.Q.) refers to "a person's capability to adapt effectively to new cultural contexts" (Earley and Ang, 2003). C.Q. is not about knowing all there is to know about another culture. C.Q.

is about being able to learn and quickly adapt to different ways of working and thinking (Owen, 2017). It is not, "my way is best." At its core, C.Q. is about developing self-awareness and understanding of others' perspectives. Only by reflecting on one's values and beliefs can one be open to learning how others perceive, think and interact with the world around them. It is more than skin-deep knowledge of cultural traits. It is about understanding what drives behaviour in different social, cultural, industrial, and in this example, virtual contexts. As such, the writers believe that C.Q. increases a shared understanding of others' perspectives in a GVT environment. Also, cultural intelligence serves to control and regulate one's thought processes and emotions in response to culturally sensitive situations (Presbitero, 2019), a quality that can mitigate cultural conflict on teams.

Finally, C.Q. includes openness to drawing upon others' talents to collaborate, problem-solve and innovate. Diverse people bring different skills, mindsets and experiences to the situation. Leveraging this diversity will establish trust, which will make it is easier for the team to coalesce around a shared purpose, such as working toward the organization's objectives in a collaborative manner (Liao, 2016). As a result, GVT members will experience a sense of accomplishment by leveraging diversity as a unifying force that focuses the team on its goals and objectives. The outcome is that team members will feel valued for their diversity, and team wellbeing will increase.

Global Mindset

A global mindset is about building a frame of mind that seeks to understand others, not to judge. A global mindset is open to new ideas and new ways of working, can work with ambiguity, can adapt quickly to verbal and non-verbal behaviour that is appropriate to the cultural setting, and is humble and respectful of cultural differences (Owen, 2017). Teams with a global mindset are naturally curious to learn more about other cultures (Gourami, 2019). A global mindset requires an open mind, powers of perception, excellent listening skills, and self-reflection. Imagine the strength of this mindset on a GVT, with members from Europe, South East Asia and North America all wanting to learn about the unique cultural values, skills, and attributes that each member of the team can bring to a project. Now imagine if each member takes the initiative to embed themselves in their teammates' cultures. The collective knowledge and wisdom gained from these cultural exchanges would further deepen cross-cultural understanding and interpersonal bonds on the team. It would also increase empathy by having teammates metaphorically walking a mile in someone else's shoes. "This requires humility and an ability to engage with people from different cultures on a personal level" (Gourani, 2019, p. 1). With empathy, there is no room for judgment, prejudice or bias. Insight allows respect for others. This enlightenment opens new ways to see, learn and behave. In a GVT environment, it will lead to more effective ways of communicating and collaborating in alignment with the organization's goals and objectives (Gourani, 2019). As a result, team members will feel valued, and the team's sense of accomplishment will increase along with their wellbeing.

In summary, it is hypothesized that the wellbeing of GVTs increases on a continuum of global intelligence, which includes the core attributes of cultural competence, intelligence and a global mindset. Teams that possess all three attributes will experience the highest levels of wellness. Conversely, GVTs that operate in cultural silos will have the lowest wellness scores.

Section 2: Establishing trust in virtual teams

Corporations use GVTs for a variety of reasons. Still, in all cases, it is an opportunity to bring together individuals with the knowledge and skills that an organization might not otherwise be able to access. GVTs can accomplish a great deal using highly skilled and high-performance members. Still, they can also be hampered by the very feature that makes them desirable - they're global. That global feature makes it more challenging to bring together all aspects of teamwork, including time zones, cultures, languages and traditions.

GVTs have a high dependency on the communication and collaboration that is established by the team members and therefore, a significant element of trust in communication must be part of the GVT environment from the outset. Team members must share their knowledge and recognize that the success of the team must be of higher importance than their tendency to hoard knowledge (Alsharo, Gregg & Ramirez, 2017). A willingness to share knowledge and contribute to a team is a direct aspect of trust existing within that team. Co-located teams build trust by exposure to each other, consistent and predictable behaviours, and a feeling that they can believe or rely on someone for something. The absence of that face-to-face aspect makes the development of trust in a virtual team a more complex challenge.

Research on how trust works in GVTs is still relatively new. Still, it does appear to indicate that trust is not only linked to communications but also related to contributing factors such as a sense of fairness, competence and reliability (Benetytė & Jatuliavičienė, 2014). A 2014 study by D. Benetytė and G. Jatuliavičienė measured the trust between virtual team members across a short set of trust-related criteria. They ran two comparisons at different times and measured the changes to the trust criteria.

The initial testing identified that the lowest set of measures was about openness, honesty and concern for stakeholders. Standards for communications were put in place by management to try to address these poor results. Eventually, staff from the offices that participated in the study were divided into groups and then worked in the office of a colleague for five days. The result was that the post-visit results in all the previously weak test areas had improved. Although improvements were seen across the board, some improvements were more substantial than others, with an increase in the colleagues' impressions of openness and honesty being the largest (Benetytė & Jatuliavičienė, 2014). The Benetytė and Jatuliavičienė study concluded that communications were the most significant factor in improving the level of trust between the virtual team members. Their results showed that establishing communications standards, having scheduled communications points, and having communications outside the work environment has the potential to improve the levels of trust across teams significantly. It is reasonable to assume that the opportunity to briefly co-locate assisted in the rapid formation of trust within the group.

An alternate 2013 study by Chyng-Yang Jang investigated the difficulties virtual teams have in addressing a lack of awareness and in establishing trust relationships. Jang's research identified that the more significant the awareness team members had regarding the tasks being worked on by one another, the greater trust was established between them. This form of trust, again, comes back down to communications.

The path to greater trust within virtual teams is ensuring that there are clear lines of communication. Establishing some consistent rules around those communications, including frequency and a regular cadence, will help to facilitate a trust relationship.

Section 3: Interpersonal Virtual Team Dynamics

GVTs allows an organization to enlist strong skill sets required for high-performance results by employing talent from all over the world. Companies who can enable a GVT have the advantage of recruiting the best of the best to work on their projects. It does, however, present different challenges that are less prevalent in a co-located team situation. A great deal of energy must be spent on understanding cultural differences that impact work styles and preferences. Team leaders for a GVT must dedicate a significant amount of attention to subtle signals that would otherwise be more transparent to the team members if they were co-located. Those subtle details around team dynamics, if ignored, could significantly impact any team member's sense of belonging, respect and trust if not managed.

Further, the usual team wellbeing issues also remain a challenge, including how a team will work together around individual personality differences, work styles, communication preferences and conflict management styles. There is also the added complexity of not being able to resolve issues face-to-face or take subtle cues that are more easily read in person. Extraordinary effort must be expended to ensure that this team can understand each other to ensure success, as well as personal and group wellbeing.

Whether co-located or global, teams go through a variety of stages in their move from the unknown to the known. In the mid-1960s, Bruce Tuckman created a framework to identify the various stages of team development. This framework identifies the feelings and behaviours that team members have to understand why teams need to progress to the point of performing and providing sustainable and consistent results. Understanding why things on a team happen in specific ways can be an essential part of self-evaluating personal contribution, analyzing the input and performance of others, and identifying blocks to improved team performance (Tuckman, 1965). Understanding the stages of team development can help us analyze whether a team is merely moving through the regular steps to reach peak performance, or whether there are signals that indicate the emergence of a problem, which impacts GVT dynamics.

Tuckman's work was published in 1965, long before anyone imagined the type of global teamwork we are experiencing today. Today members spanning the globe can share ideas, collaborate on documents, share thoughts and ideas in real-time using digital tools like Microsoft Teams, Zoom, WebEx or Skype. Surprisingly, Tuckman's model adapts well when applied to virtual teams. In 1997 Lipnack and Stamps modified the Tuckman model to support virtual teamwork stages. In this model, the structure of Forming, Storming, Norming, Performing and Adjourning remain. However, Lipnack and Stamps suggest that virtual teams have a significantly shorter but more awkward first three stages before Performing. They also added the stages of Testing and Delivery to ensure that gaps that may result from more limited communication modes do not impact the result (Lipnack and Stamps, 1997).

With Tuckman, Lipnack and Stamps providing the team dynamics stages of development in mind, there are some real-world tips to deal with a variety of team interaction difficulties that impact overall wellness for virtual teams, including conflict management/resolution and communication management.

Conflict Resolution

Conflict arises in all teams, but even more pointedly in dynamic and high-performance teams. Individuals are selected to join a company for their significant knowledge and capabilities. A global group of high-performance individuals is highly susceptible to struggling with conflict management as members cannot sit down face-to-face and work out differences. Challenging someone's approach or thinking in a virtual setting is much harder to do. This difficulty arises when there is a set amount of direct team interaction, time zone differences that may impede further discussion, or in some cases, being the only remote player in a team of other people who are co-located. These conditions can drive a team member to feel that their issues are not being addressed because they are not "in the room." Conflicts may increase trust, respect, and confidence among employees within and across teams. The goal is to understand fundamental natures of workplace conflicts and find ways to make those conflicts productive and not destructive. Unresolved conflict can derail a project, disintegrate team morale and impact the overall wellness of the team dynamic (Daft, 2018).

The approach to conflict within a virtual team is dependent on the type of conflict experienced. Interpersonal conflict is a result of personalities or personal style issues being dependent on the parties and their approach to resolution. Some will tackle the issue head-on while others will practice avoidance of the other individual. In a virtual setting, conflict avoidance is more comfortable for those with a propensity to let issues fester due to the reduced interpersonal time and fewer opportunities to "clear the air." Without a resolution, these conflicts can lead to some members leaving virtual teams. The upside to reduced facetime in a virtual environment is that interpersonal conflict is rare because the team is remote and more focussed on the task at hand (Ferazzi, 2012). Simply put, less interpersonal time equates to less interpersonal conflict.

The other type of conflict is around the work itself – the tasks or plans around executing initiatives. Work-related conflicts are more straightforward to resolve than personal ones as there is a less personal investment, but they still exist. Because virtual teams tend to be more efficient in their discussions around work misalignments and approach, their interaction can often lead to better decision making and a better overall result for the team as there is less "noise" in their discussions. However, while issues around work conflict can be resolved more quickly, there tends to be more of them. This increase in disputes may be a result of less face to face interaction but can also create less empathy on the team, thus causing a quick escalation of tensions when issues remain unresolved (Ferrazzi, 2012).

Further, this lack of empathy increases the likelihood of communication breakdowns escalating to untenable levels when using channels like e-mail or instant messaging. This escalation is called the "online disinhibition effect" by psychologists because it is much easier to write in a sharp tone than it is to articulate frustration or disagreement verbally. As well, the lack of eye contact is a substantial factor in the level of conflict escalation (Lapidot-Lefler and Barak, 2012).

The keys to virtual team wellbeing and conflict resolution lie in several communication modes, including using online chat functions to nip conflict in the bud before it festers into a more significant problem. Further, encourage the entire team to provide viewpoints on all aspects of the project. Sometimes the best solutions come from someone who is further away from the gritty details of the issue. As well, transparency on a team builds the overall strength of the group as trust becomes greater as issues fall away (Ferrazzi, 2012).

Communication & Modes of Collaboration

Virtual global teamwork has never been more convenient than it is now. There is a multitude of ways to keep in touch with teammates and manage work. Microsoft Teams has become a leader in team collaboration, providing access to video and verbal methods to bring individuals together in real-time. Webex, Skype and Zoom all provide modes for team interaction that include video, chat, document and desktop sharing as well. Virtual team members have an innate need to be involved in the teamwork anywhere, anytime. Working in a virtual environment requires strong enough internet bandwidth to be able to use these modes of communication without freezing, staggering or dropping signals. If the communication relationship is not fluid and dependable, virtual team members can quickly become frustrated and feel disconnected (Petersen, 2014).

What's App, Slack, Skype all provide channels for real-time team connection. Document sharing platforms like One Drive, Google Drive and Sharepoint all provide collaboration opportunities, effectively eliminating the need for version control as edits can be made in documents by multiple players at any time. Some teams also utilize more informal, chat-board type tools such as Yammer or Slack that will allow for light discussions and non-business topics which help promote interpersonal relationships. Finally, telephone conversations are always an option, either for singular discussions or conference calls. The immediate connection provided by all these tools increases the feeling of commitment and support.

Although there are many ways to stay connected and communicate, there are still challenges with actual communication. Social and cultural differences, language differences, the lack of visual cues and personal communication styles remain challenges for virtual teams. Global virtual teams will almost always have members who have different cultural norms than others on the team. Those differences can lead to misunderstandings, feelings of mistrust and hesitancy to share viewpoints because cultural differences in language interpretations are not clearly understood. In 2016, Aleksandra Smal and Elina Jogeva, students of the University of Gothenburg, studied twelve project manager experiences leading global virtual teams to determine the most significant communication challenges faced in a virtually run project. Their study proposed that project managers perceive four types of communication challenges: those related to cultural differences, those related to distance, communication technology, and limited language competencies (Small and Jogeva, 2016). Language competence was found to be a significant barrier that isn't easily eradicated in a virtual setting. Efforts to have someone on the team that is multi-lingual would be a robust tool in managing cultural and language barriers.

The absence of non-verbal cues creates challenges in virtual team communications. No eye contact or body language is a distinct disadvantage, mainly because researchers estimate that 90% of our communication is nonverbal. There are ways to mitigate the absence of these non-verbal cues that include, if possible, conducting the first meeting in-person to allow the team to get to know who they will be working with and to establish a connection. Another mitigation tactic is to use appointed facilitators for each team meeting. The facilitator would ensure that each team member gets airtime, so they feel heard and that their ideas have been considered. Finally, even virtually, a team should celebrate successes through congratulatory e-mails, team picture sharing, or wrapping the project up with an in-person meeting (Beyerlain, 2014)

Section 4: Virtual Organizational Culture

Leaders need to be deliberate when considering virtual teams and building the organizational culture online to ensure an environment of wellbeing and health for all members of the group. Culture is the personality of the company and alignment of team members, while the organization fosters mutual respect, belonging. Team members aligned with virtual organizational culture will be more likely to experience "eustress," which is positive the stress that accompanies achievement and avoids burnout, which is the most severe workplace distress that manifests as frustration, productivity impacts and depression (Belcourt, 2016).

Cultural strength refers to the ability of employees to agree on specific values and ways of operating. "If widespread consensus exists, the culture is strong and cohesive; if little agreement exists, the culture is weak" (Daft, 2018). Virtual teams are working from all areas of the world and are empowered to work from where they live. Although there are several advantages to working virtually for all stakeholders, building a culture around a team that does not meet in person on a daily or regular basis, while potentially operating in various time zones, may present challenges. Virtual teams are attractive to employees who value mobility, autonomy and flexibility. "Building a culture across a company where there are no offices requires intentionality. While technology and tools are enabling companies to operate efficiently in a remote setting, it's important to focus on documenting culture first, then using tools to support" (@GitLab, 2019).

Tools for modality, organizational support, team building, training, development, and performance management enhance and contribute to a company's ability to maintain a strong virtual corporate culture. GitLab, an entirely virtual company, identifies that "there should be no unwritten rules in a remote culture." This rule means that tasks and communications are performed with intent, and documentation is essential to help a virtual team avoid dysfunction (@Gitlab, 2019). This intention of clearly defined values is the foundation for establishing what is critical to an organization and aligns the wellbeing of employees with determining a good fit. Virtual employees, likewise, with co-located teams, should resonate with what the company believes in to ensure a healthy mindset and wellbeing in their roles.

Alignment of values within all stages of leadership, organizational levels and decision-making processes ensure there is strength in the cultural meanings of what they believe to be a top priority. Walking the virtual walk instead of talking the virtual talk is what virtual team members will remember and understand as the real value to an organization. If the team's values coincide with the organization, employees will feel a sense of pride and belonging, further enhancing their sense of wellbeing in the global team environment. New employees to a virtual team are chosen based on their skills but are socialized into the corporate culture. Through this process, a new team member is exposed to the values, norms, perspectives, and expected behaviours helping them to be successful within the virtual group or organization (Daft, 2018).

Tools for Modalities

Leading an organization that has virtual teams offers challenges for leaders to generate an impression of the wellbeing of each team member as, in this situation, many of the communication processes that they typically rely on during the communication process are absent. Reliance on nonverbal cues such as body language, demeanour, and voice tonality requires additional factors. When using electronic means of communication, these usual messaging clues are absent. Virtual teams need to establish different sets of factors when trying to interpret and evaluate the thoughts and feelings of their virtual co-workers (Connelly, 2016). Communicating the organizational values of wellbeing and health through organizational culture can be achieved by sharing the voice of leaders within the organization. As was expressed by Daft (2018), leaders can communicate a shared corporate narrative by frequently repeating messages and illustrating a company's core believes and values through their actions.

Establishing health and wellness plans and checkpoints that are easily accessible to employees through tools such as Employee Assistance Programs, provides opportunities for team members to seek support when needed anonymously. That help may come in the form of mental health, work-life balance, financial or even personal services such as guidance on legal services. These invaluable tools ensure employees have an opportunity to balance work-life demands, starting from a place of wellbeing. Leaders of virtual teams also need to establish review and response plans that respect the virtual nature of the group. These plans should include establishing a regular cadence where they work with team members to review virtual arrangements and wellbeing. This information enables a leader to develop a wellbeing baseline against which they can trend the wellness of team members over time. This baseline measurement provides leaders with an early warning system that will trigger corrective actions to improve the wellbeing of the team members (Kearney, 2019).

Promotion of a safe work environment can help maintain a healthy online environment and culture. Although safe work practises and the workplace hazard identifications are less of a concern when individuals are working from home, creating a culture of safety and security through employee handbooks, policies, and rewards programs are all items critical to the wellbeing and health of the work team. Virtual organizations should maintain clearly defined health and safety practises including guidelines and policies around emergency contingency plans, crisis management teams and workplace harassment policies, all built towards the emotional and physical health of the team members. Ergonomics should be a significant factor in consideration of the health and wellness of the team. Companies need to understand the practice of matching the features of products and linking ergonomics to safety. Ergonomics improve the efficiency of work while supporting the comfort, health and performance of virtual team members. Ergonomics yields positive returns on investment by minimizing repetitive strain injuries and optimizing productivity and health.

Global teams require a Global Compensation System that acknowledges the total compensation of the team members. A system should provide everyone equitable compensation, medical care, security, training, and benefits, but with a flexibility that allows for variances within geographical regions. Offering customized benefit programs to what employees want or need most could help hourly employees. A survey conducted by FRACTL, a digital marketing company, determined that the most desirable benefits include health/dental and vision insurance, flexible hours, more vacation time and work-from-home options. Three of the top four desired benefits are focused on work-life balance (Fractl, 2018). Different demographics of employees may have different needs for safety and security, which a corporation can meet to varying means to ensure a healthy, secure workforce. Flexible Benefits enable employees to select the benefits that are the most relevant to them and provides organizations with a feature to attract and retain top employees. Benefits do have an impact on an organization's competitive advantage of employee wellbeing.

Organization Support

Having a systemic understanding and support from the organization on wellbeing and health for virtual teams requires that team members are supported through all levels of the organization and the online cultural environment. GitLab found a way to strike a balance between the level of process needed to support their culture. They found that even with unlimited vacation, there was a fear of taking time off if there were no suggestions or a framework that supported it (@Gitlab, 2019). Structurally, the team's wellbeing can be enhanced by having clear guidelines, expectations, and policies and procedures for team members to follow. GitLab has found that documentation that reinforced their culture has been beneficial and supportive of their team members. The documentation creates good habits that they feel help to create a strong culture moving forward. (@Gitlab, 2019). Clear communication maintains a sense of connection to the workplace. Without this, employees feel helpless, frustrated and disconnected from the team. This disconnection may happen when a significant change has occurred, or there is an absence of information being shared with the team.

Cultural Audits are another way that quality of work-life balance can be assessed for its contribution to the health and wellbeing of virtual team members. Organizations can determine gaps in employee wellbeing by understanding how team members spend their time and exploring how they feel about the organization. Additionally, managers can assess additional differences through employee interactions with other members of the team: how they think the organizational values are exhibited, how they respect leadership, their understanding of team objectives, and assessing how employees' values align with company culture. The input of employees into the creation of a wellbeing plan helps organizations be transparent about their concern for virtual teams. Everyone's situation and role will be different. Leveraging their experiences and knowledge can help promote well being through identifying their needs and building a system that addresses their concerns (Kearny, 2019). Multidimensional problems require multidimensional thinking. This approach is known as the Law of Requisite Variety and states, "only variety destroys variety" (weforum.org). Essentially, to defeat problems experienced by virtual teams, a single frame of thinking will not suffice. To match the complexity of global team problems, they require the right people, with the proper role, in the right place of the organization, business units, levels of hierarchy, diversity, power, authority, expertise and all other factors and characteristics of the team dynamics. In summary, for teams to have the required organizational support to maximize output, leaders must take ownership and create groups with a variety of resources from within and around their organization. To this end, there are three primary objectives: uniting a team, alignment on co-created plans, and clarity on goals (Benjamin, 2020)

Team Builder

Team building takes time, and a single individual does not create all the problems. So, it only stands to reason that the associated issues cannot be solved by a single individual (Benjamin, 2020). The traditional functions of team building—forming, storming, norming and performing—need to occur in the absence of nonverbal cues. Organizational culture assimilates employees and stakeholders, so they learn how everyone in the organization is relating to one another, while adapting to the business environment. Corporate culture provides employees a way to identity and understand how best to work together (Daft, 2018). Peter Senge suggests that teams need time to interact and practice together to establish a collective intelligence (I.Q), thus enabling organizations to operate at a higher level than any single I.Q. (Senge, 2006). What this does for building team dynamics in the virtual team environment is that it yields practical results for working more effectively for a team. This style of team building intends to remove team members' assumptions by initially having only dialogue and no decisions. This emphasis on dialogue helps the team practice and understand everyone's style of communication and sets guidelines for interactions. This methodology, when all members of the virtual team participate, may be an effective way to establish ground rules for team communication, strategies to resolve conflict, and individual accountability to the wellbeing of the collective (Senge, 1990).

Leaders investing time, energy and resources into building a team environment can expect to have healthier, supportive online workplaces. Team members who perceive they are well treated, and have a better connection with their teammates, tend to have increased performance (Lin and Huang, 2010). Involving the team members in many decision making situations, and being open to opinions on team building activities or social aspects of online working teams, could increase buy-in and engagement throughout the group. Regardless of how an organization decides to increase their engagement with virtual teams, they need to seek out a variety of perspectives to inform decision making and involve people in making the decisions. This participation and commitment help to keep critical people focused and aligned (Benjamin, 2020).

Talking to team members about health and wellbeing identifies it as a cultural value within the organization. Reinforcing wellbeing during individual meetings as well as emphasizing health and wellness as a shared team objective, builds a shared understanding of importance throughout the team and encourages healthy team-building behaviours (Kearney, 2019).

Facilitating team touchpoints and human connection is key to leading with health and wellness in mind for virtual teams. For self-managed teams, it can be difficult for a personal contribution to be recognized. The social exchange within the virtual team helps team members feel supported, and their contributions noticed (Chidambaram and Tung, 2005). Connection with other team members helps establish organizational processes and behavioural skills through participative forums. Avoiding isolation is good for wellbeing and fosters both social and work relationships. Humans are social beings that crave a connection to their tribe. Regular team check-ins or small and frequent conversations allow for this "interconnectedness" to flourish in the context of a globally dispersed team (Kearney, 2019).

Training and Development

Training and Development are interconnected, and both are needed for success, growth, and maintenance of forward-facing organizations. Training is the foundation for building, maintaining and strengthening the core values, competencies and abilities within the workplace. Training is required as the team is being built, and steps are taken towards attaining the organization's strategic goals. The fast pace of changes to systems, technology, and expectations within roles and responsibilities requires multiple levels of training for team members so they can enhance their skills, awareness, and abilities to perform their tasks. Among the skills needed by virtual team members is the need to understand systems and software, communication, relationships and the technical aspects of the team's role. As team members build skills, they will be developing their abilities.

Although they are interconnected, training and development are not the same things. Training is a way for their associates to learn in a variety of methods and focuses on addressing short term performance issues or plans. Development involves increasing skills for future responsibilities and career growth. Training fits a current need or trend in the organization and, as a result, can fix a short term need without aligning to long term strategic goals. Employers can help virtual teams to foster learning and a feeling of accomplishment by providing cultural awareness and intelligence training, succession planning, and learning how to track and evaluate their performance at a distance. Continuous reassessment of team needs, intrinsic motivation and alignment with organizational culture will help maintain an engaged, healthy team with a competitive advantage. Remote workers run the risk of being isolated or feeling less connected to the broader group, so they need to have work that is appealing and rewarding. Pre-emptively checking-in to gauge their level of engagement, interest in their work and their level of enjoyment will help leaders address potential issues early on (Kearney, 2019). Fostering an environment of self-help and providing skills-training that benefits the needs of individuals will motivate the team in a manner that promotes its health and wellbeing.

Conclusion

Global virtual teams are comprised of individuals from different cultures and nations around the world. Team members may share different values, beliefs and perspectives. In addition, they may speak different languages and have different ways of communicating with each other. Even in co-located, multicultural teams, these differences can create stressful working relationships that negatively affect team performance and wellbeing. In a virtual environment where team members are scattered physically and temporarily across the globe, it is that much harder for team members to understand how the other is thinking, perceiving and behaving. Virtual platforms simply do not provide the same richness of verbal and non-verbal communication that a face-to-face meeting offers, nor does it convey the cultural context of other team members. This lack of reference has the potential to lead to misunderstandings, team conflict, and poor performance. The wellbeing of the team suffers as a result.

The writers posit that the wellbeing of GVTs is influenced by four forces: virtual organizational culture, interpersonal team dynamics, global intelligence, and trust. Cultural and contextual factors influence each of these components. Evaluating these forces as a whole will assist organizations in monitoring, trend and measure the wellbeing of global virtual teams.

Empirically verification of the writers' hypothesis should be conducted through a qualitative ethnographic study into each of the four forces that comprise the framework for assessing the wellbeing of

GVTs.

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The Economic Impact of Supply Chain Disruption Resulting from the COVID-19 Pandemic: An Investigation of the Impact on the Publishing Industry

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Abstract:

As the world recovers from the coronavirus pandemic, the economic impact of the past two years is far-reaching, and every industry will feel the effect for years to come. This study will investigate the implications of the supply-chain interruption created by the shutdown during the COVID-19 pandemic of 2020. Every aspect of the economic process is experiencing shortages and hyper-increases in the cost of raw materials, production, transportation, and delivery. There are innumerable contributing factors to these shortages and consequent price increases. This study begins with a review of the pandemic events starting in the Spring of 2020. This investigation details the major contributing factors to the disruption of the supply chain and just-in-time delivery systems crucial to economic success and subsequent increases in the cost of doing business. This study examines the impacts specific to the publishing industry. It concludes with suggestions for publishers to minimize the impact of the disruption and continue to operate and thrive within the current environment and in a post-pandemic world.
Keywords: COVID-19 pandemic; economic impact; supply chain disruption; publishing industry

Introduction

At the beginning of 2020, the 2019 variant of the SARS-COV-2 virus, commonly referred to as COVID-19, spread worldwide, triggering a global pandemic. As cities, states, and nations implemented stay-at-home orders and outright quarantines to slow the spread of the virus and keep their citizenry safe, the economic impact of those orders affected every industry to some degree. Shortages in household products such as toilet paper, cleaning supplies, and hand sanitizer were common. On a larger scale, the disruption forced manufacturers to assemble products with the resources they had on hand once the government lifted the stay-at-home order. Businesses reopened with the stock they had on hand with no assurance of incoming inventory as the flow of parts and raw materials trickled back into the assembly plants (Ferguson & Drake, 2021). As of late 2020, 89% of manufacturers report a direct business impact because of COVID-19, including lower sales, increased cost of materials and production, and canceled or delayed product launches (News&Trends, 2020)

Because the transportation industry had shut down for weeks, resupplying manufacturers, distribution centers, and retail outlets became a daunting task. The lack of transportation forced manufacturers that rely upon just-in-time (JIT) resupply for parts and materials to put the assembly on hold until the needed parts could be delivered. Countless thousands of incomplete automobiles sit in veritable boneyards (Affelt, 2021; Murray, Curran, & Chipman, 2021), awaiting computer chips from China to make them work. Tons and tons of food rotted and went to waste, as there were no drivers available to take the fresh produce to market, let alone have consumers willing to venture out into public spaces to purchase the food.

Background

Every manufacturer relies on raw materials from a host of providers to assemble and produce their product. The manufacturers then rely upon retailers to display and sell their products. Transportation is required upstream to get the raw materials to the manufacturer and downstream to get the finished product to market. Enter the global pandemic, which affected every aspect of the transportation industry, sometimes to the second and third-order (Ferguson & Drake, 2021). As of the end of 2021, the United States has opened back up for regular business. There has not been a stay-at-home order since the government lifted the original order in 2020, and most, if not all, local governments have lifted mask mandates (Wu, Si, & Chiwaya, 2021). Restaurants can operate at total capacity (Fortney, 2021), and grocery stores are open during regular business hours. Supermarkets have suspended special hours for elderly and immunocompromised patrons as of mid-2020.

Still, shortages are not hard to find. Empty spaces on grocery shelves where the store cannot restock a sold-out item are not hard to find. Restaurants continue to operate with limited menu items and staffing because suppliers cannot guarantee the ingredients (West, 2021). Even fast-food chains ration condiments such as ketchup packets (Maynard, 2021) because they cannot ensure JIT delivery should they run out. Prices on new cars are at an all-time high due to the shortage of new cars rolling off the assembly line. Most of these issues can be traced back to some disruption in the supply chain (Murray, Curran, & Chipman, 2021).

While the United States is recovering faster than most, many countries in Asia and Europe operate at limited capacity.

Compared to pre-pandemic rates, goods from China are coming out at a veritable trickle (Fisher, 2020), causing manufacturers to rethink their reliance on parts from overseas markets (News&Trends, 2020; Francis, 2020). When countries started to reopen, demand for raw materials and components from manufacturers quickly overburdened the sources (Francis, 2020). Once the manufacturer completes the product, the product often sits in warehouses because there are either too shipping containers available (Affelt, 2021) or few dock workers to load the cargo onto the ships (Murray, Curran, & Chipman, 2021). Once the shipment is on board the vessel, the shipping company needs a captain to pilot the boat. Once the boat arrives at its destination, it may be anchored off the coast, potentially for weeks at a time (Affelt, 2021), waiting for a berth in the port to offload the cargo. The disruption to the existing process has created an impossible lag in inventory flow.

Problem Statement

The publishing industry is by no means immune to the effects of either upstream or downstream delays in the supply chain. Publishing companies that produce paper journals and magazines utilize high-quality glossy paper as their print stock. South Korea mills much of the paper stock, with raw materials coming through the ports in China. With the transportation backlog in China and South Korea and the west-coast ports such as Los Angeles, the stock typically delivered in 2-3 days now takes 3-4 weeks and costs 40% more than pre-pandemic prices (Murray, Curran, & Chipman, 2021).

When the supply of any product becomes scarce, the price naturally increases, and there will be a tendency to hoard and panic-purchase that product (Rejeb, Rejeb, & Keogh, 2020). That was evident at the beginning of the pandemic with toilet paper, cleaning supplies, and hand sanitizer. As grocery stores and other outlets could restock their shelves, they had to enact price controls and purchase limits to prevent, or at least discourage, customers from hoarding those products and ensure everyone had a fair chance to buy these items (Francis, 2020; Shih, 2020). No such controls exist in the paper industry. Some companies will overbuy the raw materials needed and rent warehouses for storage to access those materials when needed (Murray, Curran, & Chipman, 2021). There is anecdotal evidence of printing businesses doing much the same thing; placing portable storage units on their property to store as much paper as they can hold to keep their presses rolling.

A third-order effect of the pandemic further exacerbates the lack of available paper. Because of the increase in the already booming e-commerce industry, companies like Amazon pay a premium to paper mills to produce boxes and shipping containers. Paper mills have converted their production focus from paper to milling cardboard boxes exclusively for use by online retailers, further reducing the availability of paper to printers.

Once the publisher can print their journals, delivery to their customers takes longer. Slowdowns and backups at the United States Postal Service (USPS) continue well into 2022, with the USPS publishing new standards for the delivery, extending the time the postal workers can deliver letters and packages to customers (Genovese, 2021). International delivery is even slower; European and Asian postal services are experiencing similar slowdowns in their delivery due to the speed of their recovery.

Solutions

It is evident that changes to the distribution of goods and services are necessary for businesses to survive during and post-pandemic (Rejeb, Rejeb, & Keogh, 2020). Several potential solutions are available to publishing companies to alleviate the financial and supply chain issues. First, the company can do nothing. Ride out the storm and wait for the supply chain issues to resolve and return to normal. If the company is big enough and has a sufficient cash reserve to cover the cost, that is possible (Fisher, 2020), assuming the crisis is short-lived. Most companies do not have the liquidity to maintain the status quo. Even large companies accountable to their stockholders and boards of directors must continue to show a profit or risk going out of business.

Second, the company can reduce or even eliminate the number of printed copies of their publication. Companies can do this by offering a digital version of the journal in either PDF or flipbook format on the internet. Flipbook publications act just as print publications do, benefiting search features and hyperlinking to advertiser websites or other online resources. Animation, video, and audio segments may also be included in such online publications, adding a multimedia experience for the reader. Electronic journals can be accessed online in perpetuity, thereby increasing the perceived value of an electronic subscription to the journal. Researchers desiring access to previously published manuscripts will have immediate access.

In contrast, print subscribers would have to research and purchase once printed publications at a premium if they are still in stock. Electronic publications are immediately available to subscribers; readers no longer have to wait for their magazine to arrive in the mail or risk the Post Office losing the periodical in transit (News&Trends, 2020). A final side benefit of electronic publications is the reduced environmental impact. Less paper means less recycling and less potential landfill use.

On the downside, some readers prefer the print version of a journal. The feel of the paper encourages readers to pick up a printed copy and read. Also, readers may not be able to dogear pages or make notes in the margins of an electronic publication like they would a print copy. The ability to take notes depends on the software used to create the magazine and the abilities of the technology the reader uses. Advertisers in the journal may also balk at being in a digital publication versus a print publication left on a coffee table or in a waiting room to be seen by the general public. One advantage to the advertiser is the ability to hyperlink their ad to the advertiser's website, so the reader merely needs to click or tap on the ad to access their website.

The final course of action is to purchase a large quantity of paper at the current market price and store it with the printer (Murray, Curran, & Chipman, 2021). The publisher may be able to secure a bulk discount with the mill with a large enough order, but hiring a storage unit to store the paper may offset the savings benefit. The publisher would have to arrange with the printer to use only the publisher's paper for their publication and nothing else. While the publisher may see initial cost savings, they are just delaying the price increase for their next paper purchase. With rates increasing 40% annually, it is not likely that the publisher would realize a financial benefit with this strategy. The only advantage to this strategy would be the guarantee that paper would be available to them on a JIT basis (Shih, 2020).

Recommendation

There are too many risks involved with maintaining the status quo or attempting to purchase large quantities of paper. The publisher can adopt a blended approach, encouraging new and existing subscribers to opt for digital subscriptions over a print subscription by offering discounts and incentives to the digital subscriber. The publisher should also invest in a modest amount of paper stock, perhaps enough for two or three editions of the print journal, so long as a feasible storage arrangement can be met (Shih, 2020). The blended solution seems to be a popular solution throughout the industry; 87% of businesses are transforming digital delivery into a high priority because of the pandemic (News&Trends, 2020)

Conclusions

Disruptions to supply chains can take years to remedy. We may not yet realize the second and third-order effects of the recent pandemic on our way of life, let alone how we do business. The pandemic of 2020 has fundamentally transformed our ideas about trade and commerce, allowing – or, instead, mandating – people to work, shop, communicate, educate, and learn from home, proving that the workforce is adaptable on a scale. That transformation should continue to manifest itself in traditional brick-and-mortar businesses such as the printed word. We should no longer be beholden to the convention of ink and paper but embrace the opportunity to broaden the concepts presented in electronic communication.

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The Effects of Government Spending on the Economic Growth in the U.S.

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Abstract
This paper performs empirical analysis to identify the effects of government expenditure on economic growth using a time series data from the U.S. over 61 years. Our results suggest that there is a positive relationship. To address the potential for reverse causation, we also provide instrumental variable (IV) analysis. Our empirical results are significant and robust.

1. Introduction

Governments around the world turn to fiscal stimulus packages to support economies when economies were in trouble. For example, the U.S. spent almost $800 billion dollars during great recession and total about $5 trillion during the pandemic.

What might be the effect of government spending on the economic growth? According to Keynesian theory, an increase in government spending boosts real GDP and create jobs by increasing aggregate demand with a multiplier effect. However, the crowding – out effect could hinder the effects of the multiplier effect. Government spending crowds out private investment and slow the economic growth. So, from a theoretical viewpoint then, the matter is ambiguous. the question is ultimately empirical.

A large literature explores how government spending have impacted the economy. Part of this literature considers the effects of government spending on the business cycles in the U.S. (levinson [1998] and Wincoop [2001]). Several papers focus on the fiscal spending on the economic growth in high income countries including the U.S. (Auerbach and Gorodnichenko [2012] and Atems [2019]). Both of these two papers use vector autoregressions (SVAR) models. There are limitations with this kind of approach.

This paper examines the empirical linkages between government spending and economic growth in the U.S. with simple OLS model.

2. Empirical model

Our empirical specification takes this simple form:

$$GGDP_t = \alpha + \beta GGOVT_t + \gamma GI_t + \epsilon_t \quad (1)$$

Where $GGDP_t$ and $GGOVT_t$ denote our measures of the real GDP growth rate and the growth rate of government expenditure in time t respectively. GI is the measure of investment growth rate in time t.

The purpose of this study is to discover the sign and size of the coefficient β. If estimates of β are positive, bigger government spending is associated with higher economic growth rate. On the other hand, if estimates of β are negative, then bigger government spending is associated with lower economic growth rate. This implies that possibly the crowding-out effect of government spending is bigger than the multiplier effect.

In order to address the possible simultaneous causation in equation (1), instrumental variable estimation will also be employed. Some possible instrumental variables include particular government revenue and expenditure variables from the public finance literature (e.g., Clark and van Wincoop [2001], Lan and Slywester [2013], and Lane [2003]). Lan and Slywester [2013] use expenditure variables as instrumental variables because they believe that government revenues could more depend on the strength of the economy. The instrumental variable we use is government spending on Public order and safety because this spending is part of government spending and we also assume that such spending is less driven by the economy.

For robustness check, we use consumer spending as our dependent variable. Simple OLS and instrumental variable estimators are employed.

3. Data

Annual data from 1961 to 2021 for US on government spending on public order and safety, GDP and its components: consumption, investment, government spending, export, and import are collected from U.S. Bureau of Economic Analysis (www.bea.gov) and all data series are in real term.

Each growth rate is computed as the first difference in the log of that variable. For example: growth rate of GDP is the first difference in the log of real GDP.

4. Empirical results and main findings

Before estimating the model, we conduct routine diagnostic unit root tests. We test stationarity of our variables by using Augmented Dickey-Fuller (ADF) and Kwiatkowski, Phillips, Schmidt and Shin (KPSS) methods.

We reject the null of a unit root for the first difference of the log in all variables at conventional test sizes. Given these results, we find the first differences for all to be stationary.

Now, we turn to our findings. Table 1 reports coefficients of β from equation (1). The first row presents the OLS estimate. The coefficient is positive and significantly different from zero at the one percent level, suggest that higher government spending is associated with higher GDP growth rate. One percent increase in government spending leads to 0.31percent increase in GDP growth.

The second row provides the estimates from IV. The coefficient is again positive and statistically significant at one percent level. Of note is that the coefficient estimate is smaller than its OLS counterpart and this is expected. Because employing IV technique to “remove” the effect from economic growth to government spending should then result in less positive coefficient estimate.

The third row considers consumer expenditure (which accounts for about two - thirds of GDP) as dependent variable. The coefficient is again positive and statistically significant at one percent level.

Table 1 Estimates of β

OLS	0.310126**
	(0.05)
IV	0.126512**
	(0.03)
Robustness	0.239077*
	(0.08)

Standard errors are given in parentheses. Coefficients significantly different from zero at 0.05 (0.01) level marked with one (two) asterisk(s).

5. Conclusions

We find a statistically significant positive correlation between government spending and economic growth in US from both OLS and IV estimations. These results suggest that government spending contribute to economic growth. Our results complement those in the literature and provide support to the Keynesian view. Government spending can boost real GDP by increasing aggregate demand

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Grade Point Average and Retention at a Southern Regional University[1]

Abstract

In this paper I investigate the association between GPA and retention at a small regional university in Alabama using Probit and Logit models. It is found that, after controlling for several other factors, GPA has a high positive association with retention. The average partial effects and partial effects at the average of an extra GPA point on the probability of registering in the next academic year are 23.5% and 18.9% respectively in the Probit model and 24.3% and 18.6% in the logit model. The effect of GPA is considerably larger than any of the other covariates included in the model.

JEL codes: C25, D12
Keywords: Probit, logit, education, retention.

Introduction

In this article I analyze the association between college students' grade point average and their likelihood of registering for the next academic year (in the education literature this measure is called student retention). Many small liberal arts colleges and regional public universities have been struggling financially lately because of reduced enrolment. The pandemic has accelerated the poor financial outlook of many small colleges and as a consequence it is believed that many will have to merge with other institutions or close permanently. See Hess (2021) for a discussion of this topic. Even though student retention has always been a concern of small universities and colleges across the US, now it has become a critical factor to measure the success of college governance. Consequently, university authorities have put tremendous emphasis and resources in improving student retention. This paper is relevant from the point of view of university administrators since most factors that affect enrolment are exogenous, that is, outside the control of university decision makers. However, it is likely that many factors that determine retention are directly or indirectly under their control. For example, many schools have created survey courses for freshmen designed to ease the transition from high school to college. The literature has shown mixed results with respect to their effectiveness, see Choudhury and Runco (2020). Another important aspect of retention is the performance of students during their freshmen year, result that is supported by the statistical analysis below. In this paper I analyze the association between freshmen grade point average and the likelihood of registering for the sophomore year at a small public regional university in Alabama.

Related Literature

The literature on retention is quite extensive, thus in this paper I mention just the articles that are particularly relevant for our purposes. Tinto (2006) is a survey that explores the ways in which our thoughts with respect to student retention have changed over the years. Another in-depth survey of the literature related to student retention is Habley and McClanahan (2004). Lau (2003) identified many aspects that help encourage student retention such as funding, academic support, academic environment, physical facilities, the role and involvement of faculty on providing high quality teaching and student support, and finally the role of student responsibility and accountability. Manyanga, Sithole and Hanson (2017) analyzed several models of retention and recognized the difficulty in deriving general conclusions due to the diverse characteristics of institutions of higher education. However, they observed that the empirical evidence suggest that some variables play a big factor in student success, such as intention to persist, academic achievement, academic history, high school experience, and social integration. Wetzel, O'Toole and Peterson (1999) found that at a public university the factors that had the largest influence on retention were GPA, falling into an academic at-risk classification, and the ratio of credit hours earned to those attempted. Financial variables had an effect on retention but smaller than the previous ones.Craig and Ward (2008) examined student retention and success at a large public community college in New England. They found that maintaining an above average GPA, having few unearned credits by not dropping courses once enrolled and enrolling in college immediately after high school graduation have a positive effect on retention. They found that student demographic factors such as age, gender and ethnicity/race were not related to student retention.

Dataset and Model

The data was collected in the year 2017. The number of students in the sample is 2,526 and all of them were freshmen. The dataset includes students who registered in the Fall of 2012, 2013 and 2014. Together with GPA at the end of their

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first year and whether or not they registered for the next academic year, the following covariates were included: age, gender, ethnicity and composite ACT scores.
Since the dependent variable is binary (whether or not the student registers for the next academic year) I will estimate probit and logit models. The main independent variable of interest is GPA and I will include the covariates mentioned above. The model is thus

$$P(registered = 1|X) = G(\beta_0 + \beta_1 gpa + W\beta)$$

Grade point average is the variable of interest and W is the vector of covariates. In the probit model the function G(z) is the standard normal cumulative distribution

$$G(z) = \int_{-\infty}^{z} \phi(v)dv$$

And in the logit model the function G(z) is the logistic function

$$G(z) = \frac{\exp(z)}{1 + \exp(z)}$$

The coefficients of the model are obtained using Maximum Likelihood estimation where the coefficients are chosen to maximize the log likelihood function

$$\sum_{1}^{n} L_i(\beta; x_i, y_i) = y_i \log(G(X\beta) + (1 - y_i)\log(1 - G(X\beta))$$

I estimate several specifications. First I start estimating one model for each cross section for years 2012, 2013 and 2014. Then I estimate a pooled cross section of the three years, including a time dummy variable to account for trends in the likelihood of registration that cannot be explained by the variables included.
Partial effects at the average (PEA) and Average partial effects (APE) are calculated for both models in all different specifications. The Partial effect of variable j at the average is given by $g(\bar{x}\hat{\beta})\widehat{\beta_J}$ and the Average partial effect of variable j is $[n^{-1}\sum_1^n g(x_i\hat{\beta})]\ \widehat{\beta_J}$.
Below is a summary of the results. One star signifies statistical significance at the 5% level, two stars at the 1% level.

Coefficients and Standard Errors

	Probit	Logit	Probit	Logit	Probit	Logit	Probit	Logit
	2013	2013	2014	2014	2015	2015	Pooled	Pooled
GPA	.686** (.068)	1.18** (.127)	.57** (.05)	.95** (.089)	.622** (.046)	1.03** (.08)	.613** (.03)	1.03** (.05)
ACT	-.0025 (.02)	-.002 (.035)	.031 (.018)	.054 (.03)	.023 (.016)	.037 (.028)	.02 (01)	.035 (.018)
White	.0138 (.2)	-.003 (.33)	-.196 (.227)	-.326 (.39)	.038 (.182)	.081 (.31)	-.025 (.115)	-.047 (.19)
Black	.117 (.209)	.171 (.34)	-.278 (.228)	-.46 (.39)	.05 (.182)	.096 (.31)	-.02 (.116)	-.038 (.196)
Female	.126 (.123)	.20 (.21)	.093 (.106)	-.137 (.18)	.113 (.1)	.19 (.17)	.049 (.062)	.087 (.10)
Age	-.04* (.039)	-.07 (.069)	-.064* (.027)	-.105* (.04)	-.074* (.029)	-.12* (.05)	-.061* (.018)	-.10** (.03)
t_2014							-.29** (.08)	-.48** (.14)
t_2015							-.423** (.08)	-.71** (.14)
Pseudo R2	.215	.219	.179	.17	.194	.19	.1934	.194
Correctly Predicted	73.8%	73.8%	74.4%	74.6%	72.9%	72.9%	74.2%	74.3%
Log-likelihood	-296.5	-295.17	-399.9	-399.4	-483.9	-484.3	-1186.0	-1184.2

In none of the previous models we can reject the null hypothesis that the coefficient for both White and Black are jointly equal to zero at the 5% level (Actually, the lowest p-value in all of those tests is .44). So it is clear that race has no effect whatsoever on retention in this dataset.
Below I include the marginal effects at the average of some regressors on the likelihood of retention. I include only the variables that are statistically significant at the 5% level or better. The values are interpreted in the following way (I use the pooled Probit as an example): An increase in GPA of one point leads to an increase in the likelihood of registering for the next academic year of 23 percentage points. Moreover, the year dummy variable t_2014 shows that relative to the year 2013, there was a reduction in the likelihood of retention of 11 percentage points, controlling for all the other factors.

Marginal Effects at Average

	Probit	Logit	Probit	Logit	Probit	Logit	Probit	Logit
	2013	2013	2014	2014	2015	2015	Pooled	Pooled
GPA	.248 (.024)	.257 (.027)	.213 (.019)	.217 (.02)	.244 (.018)	.25 (.02)	.23 (.012)	.24 (.01)
Age			-.24 (.01)	-.02 (.01)	-.029 (.011)	-.03 (.01)	-.023 (.007)	-.02 (.007)
t_2014							-.11 (.03)	-.11 (.03)
t_2015							-.16 (.03)	-.17 (.03)

Below I calculate the average marginal effects. Both the probit and logit models are highly nonlinear, thus it is important to determine the average marginal effects and not rely solely on marginal effects at a single value (such as the mean of the covariates).

Average Marginal Effects

	Probit	Logit	Probit	Logit	Probit	Logit	Probit	Logit
	2013	2013	2014	2014	2015	2015	Pooled	Pooled
GPA	.198 (.013)	.197 (.01)	.175 (.011)	.172 (.01)	.193 (.01)	.19 (.01)	.187 (.006)	.186 (.006)
Age				-.02 (.008)	-.023 (.009)	-.02 (.01)	-.019 (.005)	-.019 (.005)
t_2014							-.089 (.025)	-.09 (.02)
t_2015							-.13 (.025)	-.13 (.024)

We can see that both the marginal effects at the average and average marginal effects are similar in magnitude.

Conclusion

In this paper I have estimated several limited dependent variable models to understand the role that GPA and other variables play on retention by freshmen. I have used a novel dataset from a small southern university and found that GPA is highly correlated with the likelihood of registering for the sophomore year. Moreover, all other factors included in the models such as age, gender, race, ACT scores play no roles on retention. This is consistent with what other researchers have found in other institutions.
It is important to notice that we are determining the correlation between GPA and retention. In no way I am claiming that higher GPA causes retention to increase by the percentages mentioned in the results section of the article. This is due to the fact that the models suffer from omitted variables bias since GPA is correlated with omitted factors such as motivation, intelligence, etc. Therefore the estimated coefficient is biased. We can assume that motivation and intelligence will increase the likelihood of retention, therefore the estimated coefficient of GPA is probably biased upwards (i.e. the true causal effect is smaller than I report here)
Recommendations based on this study: Like some other papers we have found a clear correlation between GPA and the likelihood of retention. Actually, GPA during the freshmen year has by far the largest effect on retention among the covariates included in this dataset. Therefore, the policy recommendation for administrators involves the use of university resources to encourage students to improve performance during freshmen courses. Such resources may be close

monitoring and alerts when students obtain poor grades, extensive tutoring by advanced students, closer guidance by faculty members, etc.

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Revisiting Woodland & Woodland's (2015) "The National Football League Season Wins Total Betting Market: The Impact of Heuristics on Behavior"

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Abstract

Woodland & Woodland, in their 2015 paper titled "The National Football League Season Wins Total Betting Market: The Impact of Heuristics on Behavior", studied 12 seasons of betting lines (1998 to 2010) and found that the NFL wins total betting market was highly inefficient, with many opportunities for profitable wagering for astute and rational bettors. Our paper examines if the conclusions of their 2015 article still hold, by studying 12 seasons of wins total betting lines from the years 2009 to 2020. We find that the market is now markedly more efficient, with little opportunity for profitable wagering. The market appears to have adjusted to the proposed betting strategies and move toward efficiency, a phenomenon which is not unlikely, as it has been observed in other sports betting markets as well.

Introduction

Sports betting markets are of interest to academics, since the participants (bettors and bookmakers) operate outside a controlled environment, guided mainly by their own intuition and understanding of the market. Generally, economists expect for these markets to be efficient. However, Woodland and Woodland (2015), henceforth referred to as WW, found the National Football League (NFL) wins total betting market, "…to be highly inefficient, providing several opportunities for profitable wagering." They write, "We believe these inefficiencies are a consequence of the representativeness heuristic. Most significantly, there is evidence that bettors, when considering teams with strong records in the previous season, overreact to historical performance and fail to recognize the statistical phenomenon of regression to the mean."

The findings in WW (2015) are surprising, as they find strategies with positive average earnings over a sustained period. In this article, we hypothesize that the rules formulated in WW (2015) no longer remain profitable, as the market should adjust to the representativeness heuristics and the lack of bettors recognizing regression to the mean, among other things. This would mean that the market no longer presents favorable returns for those strategies, and ultimately is efficient.

Subjective probabilities, commissions, and data

In their 2011 paper, Woodland and Woodland discuss and provide derivations for the subjective win probabilities and commissions used for wins total markets. Additionally, they use a unique approach to define a unit bet. They write, "Let ρ represent the subjective probability that the underdog team wins and c is defined to be the commission, which is the net receipts divided by the total number of unit bets, as given by

Woodland and Woodland (1994). For the money line ($-\beta_1 100$, $+\beta_2 100$), β_1 and β_2 denote the favorite and underdog prices. For the favorite team, the WW approach defines a unit bet as $\$\beta_1$ to win \$1." The subjective odds and commissions result from the solution of the following equations:

$$\$\beta 2\,\rho + (-\$1)\,(1-\rho) = -\$c$$
$$\$1(1-\rho) + (-\beta 1)\,\rho = -\$c$$

Solving each pair of equations yields,

$$c = \frac{\beta 1 - \beta 2}{\beta 1 + \beta 2 + 2}, \quad \rho = \frac{1}{\frac{\beta 1 + \beta 2}{2} + 1}$$

We use the WW approach for calculating the subjective probabilities and commissions in this paper. We similarly follow their approach regarding the definition of a unit bet.

WW (2015) use data from the 1998-2010 seasons, while missing data for the 2001 season (12 seasons). This research uses 12 consecutive seasons of betting lines for the 2009-2020 seasons.

Summary statistics for the data used in the current analysis are provided in Table 1. Of the 384 lines posted in this 12-year time-frame (2009-2020), there were 17 occurrences of push bets. This research will consider the remaining 367 lines. The data were retrieved from the website Sports Odds History (www.sportsoddshistory.com), with an exception for a season retrieved from the website The Spread (www.thespread.com).

Table 1. Summary statistics for the 2009-2020 seasons

Number of lines	**384**
Number of pushes	**17**
Remaining lines for analysis	**367**
Average wins	**7.970**
Standard deviation	**3.165**
Average closing line	**8.150**
Closing line standard deviation	**1.677**
Minimum closing line	**3.5**
Maximum closing line	**12.5**
Minimum actual wins	**0**
Maximum actual wins	**15**

Betting Rules

WW (2015) formulated a series of rules to test for deviations from market efficiency and the potential for profitable wagering. In their paper, *Z* testing of efficiency examined if average returns were significantly greater than $-\bar{c}$, where $\bar{c}$ was the average commission. *Z* testing of profitability examined if average returns were greater than zero.

In this section, we replicate these rules, however, our a priori assumption is that the market is efficient following the publication of their rules, and hence we do not expect the rules to be profitable for the seasons we analyze. Hence we expect the strategies to return negative average profits for bettors and test if average returns are less than zero. We test for market efficiency by comparing the average returns to less than $-\bar{c}$.

Rule 1

Rule 1 in WW (2015) examines whether bettors in the football wins total market root for wins rather than scoring. We test for the same and calculate the average returns. For the 367 games, the average returns for betting the under for all teams is -0.008. It is an efficient market with a p-value of 0.789, which is in line with our hypothesis. This result is similar to that of WW who found the market to be efficient in regards to this rule.

Rule 2

The second betting rule, as explained in WW (2015), is "…a simple, technical trading strategy derived from the weak-form test of market efficiency". Their findings suggest betting on the under when the wins total line (WTL) is at least 8 games and betting the over when the line is less than 8 games.

Rule 2O: Bet the over when the WTL is at most D*, or WTL ≤ D*, for D*=7.5, 7, …,0.
Rule 2U: Bet the under when the WTL is at least D*, or, WTL ≥ D*, for D*=8, 9, …,16.

Table 2. **Rule 2 Results**

Approach	**D***	**Average Return**	**N**	**Z efficiency**	***p*-Value**	**Z Profitability**	***p*-Value**
WW	**7.5**	**-0.169**	**148**	**-1.178**	**0.119**	**-1.777**	**0.038**
WW	**7**	**-0.147**	**108**	**-0.807**	**0.210**	**-1.308**	**0.095**
WW	**6.5**	**-0.039**	**80**	**0.134**	**0.553**	**-0.297**	**0.383**
WW	**6**	**-0.095**	**54**	**-0.240**	**0.405**	**-0.592**	**0.277**
WW	**5.5**	**-0.356**	**32**	**-1.414**	**0.079**	**-1.686**	**0.046**

Rule 2O: Bet the Over if WTL ≤ D*, where WTL is the Wins Total Line.

Approach	**D***	**Average Return**	**N**	**Z efficiency**	***p*-Value**	**Z Profitability**	***p*-Value**
WW	**8**	**-0.039**	**219**	**0.202**	**0.580**	**-0.509**	**0.305**
WW	**8.5**	**-0.072**	**189**	**-0.216**	**0.414**	**-0.889**	**0.187**
WW	**9**	**-0.002**	**128**	**0.549**	**0.708**	**-0.016**	**0.494**
WW	**9.5**	**-0.027**	**96**	**0.248**	**0.598**	**-0.230**	**0.409**
WW	**10**	**0.042**	**68**	**0.692**	**0.756**	**0.298**	**0.617**
WW	**10.5**	**-0.085**	**46**	**-0.176**	**0.430**	**-0.488**	**0.313**

Rule 2U: Bet the Under if WTL ≥ D*.

Our results are summarized in Table 2 above. Average returns for all but one value of D* are negative. We also find that the *Z* values for efficiency do not reject market efficiency at conventional levels of statistical significance. Negative profits are clearly more prevalent, with any instances of statistical significance at the

5% level indicative of negative earnings. While WW (2015) found positive profits for most values of D*, none were significant at the 5% level.

Rules 3, 4 and 5, to quote WW (2015), are "…semi-strong tests that are designed to take advantage of errors in judgement by bettors, that may result from the representativeness heuristic".

Rule 3

Define $D_t = WTL_t - W_{t-1}$.
Rule 3O: Bet the over when $D_t \geq D^*$,
Rule 3U: Bet the under when $D_t \leq -D^*$,
Where, D* = 0.5, 1, … 3.

Rules 3O and 3U are in accordance with the assumption that bookmakers are more informed about the change in a team's ability than the bettors. Suppose the team won more games in the previous season than the posted total in the current season. Bookies recognize that the team may not be as strong as it was in the previous year, but bettors are slower to react to this information. The rule suggests betting the under for maximum profit. WW found consistent positive profits for rule 3, with statistically significant profits for many average returns for rule 3U (the bottom half of Table 3). Our results are presented in Table 3.

Table 3. **Rule 3 Results**

Approach	D*	Average Return	N	Z efficiency	*p*-Value	Z Profitability	*p*-Value
WW	**0.5**	**-0.117**	**186**	**-0.712**	**0.238**	**-1.377**	**0.084**
WW	**1**	**-0.096**	**142**	**-0.419**	**0.338**	**-0.991**	**0.161**
WW	**1.5**	**-0.043**	**116**	**0.115**	**0.546**	**-0.398**	**0.345**
WW	**2**	**0.027**	**89**	**0.670**	**0.749**	**0.219**	**0.587**
WW	**2.5**	**0.044**	**72**	**0.733**	**0.768**	**0.327**	**0.628**
WW	**3**	**-0.015**	**54**	**0.263**	**0.604**	**-0.092**	**0.463**

Rule 3O: Let $D_t = WTL_t - W_{t-1}$. Bet the Over when $D_t \geq D^*$, where WTL_t is the wins total line
in the current season and W_{t-1} is the number of games won in the previous season.

Approach	D*	Average Return	N	Z efficiency	*p*-Value	Z Profitability	*p*-Value
WW	**0.5**	**-0.120**	**145**	**-0.661**	**0.254**	**-1.240**	**0.107**
WW	**1**	**-0.101**	**124**	**-0.442**	**0.329**	**-0.967**	**0.167**
WW	**1.5**	**-0.067**	**108**	**-0.105**	**0.458**	**-0.594**	**0.276**
WW	**2**	**0.040**	**84**	**0.747**	**0.772**	**0.313**	**0.623**

For teams with losing records in the previous season ($W_{t-1} < 8$), bet the Over when $D_t \geq D^*$. For D* > 2, results are identical to those above and are not reported. All teams with D* > 2 had losing records in the previous season.

Table 3 continued

Approach	D*	Average Return	N	Z efficiency	*p*-Value	Z Profitability	*p*-Value
WW	-0.5	-0.023	165	0.356	0.639	-0.263	0.396
WW	-1	-0.029	138	0.268	0.606	-0.298	0.383
WW	-1.5	-0.096	105	-0.374	0.354	-0.868	0.193
WW	-2	0.103	73	1.193	0.884	0.783	0.783
WW	-2.5	0.076	60	0.868	0.807	0.512	0.696

Rule 3U: Let $D_t = WTL_t - W_{t-1}$. Bet the Under when $D_t \le -D^*$, where WTL_t is the wins total line in the current season and W_{t-1} is the number of games won in the previous season.

Approach	D*	Average Return	N	Z efficiency	*p*-Value	Z Profitability	*p*-Value
WW	-0.5	-0.086	143	-0.335	0.369	-0.911	0.181
WW	-1	-0.082	121	-0.272	0.393	-0.795	0.213
WW	-1.5	-0.106	98	-0.450	0.326	-0.926	0.177
WW	-2	0.108	71	1.212	0.887	0.805	0.790

For teams with winning records in the previous season ($W_{t-1} > 8$), bet the Under when $D_t \le -D^*$.
For $-D^* < -2$ results are identical to those above and are not reported. All teams with $-D^* < -2$ had winning records in the previous season.

We find that overall, and for teams with winning and losing records, the average returns are mostly negative, despite implementing the betting strategy outlined in rule 3. Those instances of positive average profits are not statistically significant at reasonable levels. However, it is somewhat surprising that for rule 3U, D* = -2 returns positive profits of 0.103 and 0.108, suggesting average returns of over 10%. The lack of statistical significance may not rule out consideration of this type of bet as Fodor et al. (2013) note, "A failure to find such significance does not negate the opportunity for informed bettors to profit."

Rule 4

WW (2015) state the basis for rule 4 is bettors being "…unaware of the phenomenon of regression to the mean"; they may observe a trend and then overreact. If a team improves in terms of the number of wins from a previous season, the rule states that bettors should bet the under to secure more profits. We test this rule to see if it remains profitable over the more recent period.

Define $D_t = W_{t-1} - W_{t-2}$.
Rule 4O: Bet the over when $D_t \le -D^*$
Rule 4U: Bet the under when $D_t \ge D^*$,
Where, D* = 1, 2, ... 6.

Table 4. Rule 4 Results

Approach	-D*	Average Return	N	Z efficiency	*p*-Value	Z Profitability	*p*-Value
WW	-1	-0.081	163	-0.266	0.395	-0.886	0.188
WW	-2	-0.119	125	-0.587	0.279	-1.136	0.128
WW	-3	-0.206	93	-1.237	0.108	-1.727	0.042
WW	-4	-0.225	65	-1.149	0.125	-1.551	0.061
WW	-5	-0.023	37	0.187	0.574	-0.117	0.454
WW	-6	-0.070	23	-0.049	0.480	-0.281	0.389

Rule 4O: Define $D_t = W_{t-1} - W_{t-2}$. Bet the Over when $D_t \leq D^*$, where W_{t-1} is the number of wins in the previous season and W_{t-2} is the number of wins two seasons ago.

Approach	D*	Average Return	N	Z efficiency	*p*-Value	Z Profitability	*p*-Value
WW	1	0.005	158	0.687	0.754	0.061	0.524
WW	2	0.036	122	0.907	0.818	0.356	0.639
WW	3	0.019	78	0.595	0.724	0.153	0.561
WW	4	-0.036	59	0.135	0.554	-0.253	0.400
WW	5	-0.101	41	-0.255	0.399	-0.579	0.281
WW	6	-0.032	25	0.098	0.539	-0.140	0.444

Rule 4U: Define $D_t = W_{t-1} - W_{t-2}$. Bet the Under when $D_t \geq D^*$.

Results are presented in Table 4. WW (2015) report positive average returns for the above table. We find see that the average returns are mostly negative for the more recent seasons, with few values indicating positive returns, and these are rather small, for the under-bettor. The Z values for profitability are mostly negative, not significant, and consistent with the average returns for the bettors. Additionally, market efficiency cannot be rejected at even the 10% level for any of the values of D*.

Rule 5

This is a final rule employed by WW (2015) to capitalize on possible overreaction by bettors. They hypothesize that if a team performs significantly better than the posted total wins in the last season, bettors overemphasize this improvement without recognizing regression to the mean and overreact in the subsequent season, leading to an inflated money line. Hence WW theorize that under-betting in such a scenario is profitable.

Define $D_t = WTL_{t-1} - W_{t-1}$.
Rule 5O: Bet the over when $D_t \geq D^*$,
Rule 5U: Bet the under when $D_t \leq -D^*$
Where, $D^* = 0.5, 1, \ldots 4$.

We test to see if the market continued rewarding rule 5. Results are summarized in Table 5, where, similar to rule 3, the data is first considered as a whole and then partitioned according to the team's winning or losing record in the previous season.

Table 5. Rule 5 Results

Approach	D*	Average Return	N	Z efficiency	*p*-Value	Z Profitability	*p*-Value
WW	0.5	-0.176	180	-1.386	0.083	-2.033	0.021
WW	1	-0.146	150	-0.952	0.171	-1.550	0.061
WW	1.5	-0.136	127	-0.776	0.219	-1.330	0.092
WW	2	-0.084	104	-0.242	0.404	-0.745	0.228
WW	2.5	-0.099	84	-0.327	0.372	-0.774	0.219
WW	3	-0.186	68	-0.903	0.183	-1.303	0.096
WW	3.5	-0.176	53	-0.736	0.231	-1.089	0.138
WW	4	-0.006	36	0.272	0.607	-0.028	0.489

Rule 5O: Define $D_t = WTL_{t-1} – W_{t-1}$. Bet the Over when $D_t \geq D^*$, where in the previous season, WTL_{t-1} is the wins total line W_{t-1} is the number of games won.

Approach	D*	Average Return	N	Z efficiency	*p*-Value	Z Profitability	*p*-Value
WW	0.5	-0.125	134	-0.687	0.246	-1.243	0.107
WW	1	-0.084	121	-0.261	0.397	-0.789	0.215
WW	1.5	-0.148	108	-0.814	0.208	-1.315	0.094
WW	2	-0.072	94	-0.127	0.449	-0.598	0.275
WW	2.5	-0.083	78	-0.190	0.425	-0.618	0.268

For teams with losing records in the previous season ($W_{t-1} < 8$), bet the Over when
$D_t \geq D^*$. For D* > 2.5, results are identical to those above and are not reported.
(All teams with D* > 2.5 had losing records in the previous season.)

Table 5 continued

Approach	D*	Average Return	N	Z efficiency	*p*-Value	Z Profitability	*p*-Value
WW	**-0.5**	**-0.052**	**173**	**0.039**	**0.516**	**-0.606**	**0.272**
WW	**-1**	**-0.030**	**146**	**0.269**	**0.606**	**-0.323**	**0.373**
WW	**-1.5**	**-0.028**	**118**	**0.259**	**0.602**	**-0.270**	**0.394**
WW	**-2**	**-0.085**	**89**	**-0.251**	**0.401**	**-0.714**	**0.238**
WW	**-2.5**	**-0.078**	**74**	**-0.177**	**0.430**	**-0.591**	**0.277**
WW	**-3**	**-0.024**	**53**	**0.208**	**0.582**	**-0.149**	**0.441**
WW	**-3.5**	**-0.032**	**42**	**0.137**	**0.554**	**-0.180**	**0.429**

Rule 5U: Define $D_t = WTL_{t-1} - W_{t-1}$. Bet the Over when $D_t \leq D^*$, where in the previous season, WTL_{t-1} is the wins total line W_{t-1} is the number of games won.

Approach	D*	Average Return	N	Z efficiency	*p*-Value	Z Profitability	*p*-Value
WW	**-0.5**	**-0.123**	**140**	**-0.719**	**0.236**	**-1.288**	**0.099**
WW	**-1**	**-0.108**	**125**	**-0.531**	**0.298**	**-1.063**	**0.144**
WW	**-1.5**	**-0.076**	**109**	**-0.198**	**0.422**	**-0.699**	**0.242**
WW	**-2**	**-0.074**	**86**	**-0.157**	**0.438**	**-0.605**	**0.273**
WW	**-2.5**	**-0.092**	**73**	**-0.289**	**0.386**	**-0.699**	**0.242**

For teams with winning records in the previous season ($W_{t-1} > 8$), bet the Under if $D_t \leq - D^*$. For $-D^* < - 2.5$, results are identical to those above and are not reported. All teams with $-D^* < - 2.5$ had winning records in the previous season.

The results in Table 5 are unlike those of WW (2015), who report positive average returns for all values of D* in the table. We find average returns are negative, implying that the market may have evolved to take the overreaction bias into consideration and reach efficiency.

As noted by WW (2015), rules 4 and 5 do not take into consideration the total wins line in the current season, and hence they conclude that bets can be made prior to the posting of the lines. In our analysis, however, we find that the average returns are negative, reflecting that these strategies are no longer profitable.

Conclusion

This work revisits Woodland and Woodland's (2015) paper to investigate whether their findings hold true over the next twelve-year time frame (2009-2020). Several of their betting strategies were motivated by the representativeness heuristic. They showed that individuals may tend to overreact and fail to recognize certain natural phenomenon like regression to the mean. This left room for rational bettors to take advantage of the market inefficiency and place profitable wagers.

In our analysis, however, we find the strategies devised by WW, many of which were shown to yield profits over the 1998-2010 seasons, were broadly unprofitable over the 2009-2020 seasons. Contrary to WW (2015) we find the NFL wins total market to be generally efficient, with none of the proposed rules providing statistically significant positive average profits. However, betting the under for rule 3U when D* = -2 remained profitable, with an average return in excess of 10%, but this was not statistically significant at generally recognized levels.

The NFL wins total betting market moving toward efficiency is in line with our a priori assumption. The improved efficiency may be a result of the publication of WW (2015). Other reasons may include the increased prevalence of betting information on websites, the rise of sportsbook software applications, also know as apps, and increased television exposure regarding sports betting. This likely led to an increased number of bettors, with greater efficiency due to the wisdom of the crowd. Moore (2021) provides a more thorough justification along these lines in a discussion regarding increased market efficiency in regards to the NBA points total betting market.

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Altcoin Prices In Cryptocurrency Bear Market in 2018

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Abstract

Due to the increase in cash liquidity since 2020, capital has been rushing into the investment market recently. In addition to this phenomenon, the price of Cryptocurrencies tends to rise sharply due to quantitative easing. However, we have already witnessed another surge in prices and a consecutive collapse in 2017. Since so-called Altcoins have lower market volume than Bitcoin, investors are more sensitive to the signal of a price drop. Studies on Altcoin are insufficient, so it is difficult to predict price drops or recommend a reasonable investment strategy during bear markets.

Therefore, we present a realistic prediction model in this study by comparing several machine learning algorithms for four types of Altcoins: Zcash, Litecoin, Ripple, and Dash. We analyzed the sentiments of the comments of potential investors from Reddit by applying Linguistic Inquiry and Word Count (LIWC) and merged the price fluctuation data of Bitcoin and Ethereum and each Altcoin's trade volume data to the dataset created by the sentiment analysis. Then we train the model using Neural Net, Classification and Regression Tree, Random Trees, and Extreme Gradient Boosting Regression Tree (XGBoost). Using relative error, XGBoost is shown to outperform the others. We recommend XGBoost as a prediction model since it shows a small Root Mean Square Error (RSME).

1. Introduction

Cryptocurrency is a virtual currency that employs encryption to enable the secure transfer and exchange of digital tokens in a distributed and decentralized manner. These tokens can be exchanged for fiat currencies at market rates. Bitcoin was the first and most well-known cryptocurrency, and it began trading in January 2009. All other coins that differ from Bitcoin are referred to as alternative coins (Altcoins) (Li et al. 2019).

A bear market occurs when a market's price decreases for an extended period of time. It usually refers to a situation where crypto values have fallen 20% or more from recent highs due to widespread pessimism and poor investor sentiment. A number of events can trigger a bear market. The bear mark results from expected bad, falling, or slow economy. The examples of the price trend of the cryptocurrencies in a bear market are illustrated in Figure 1.

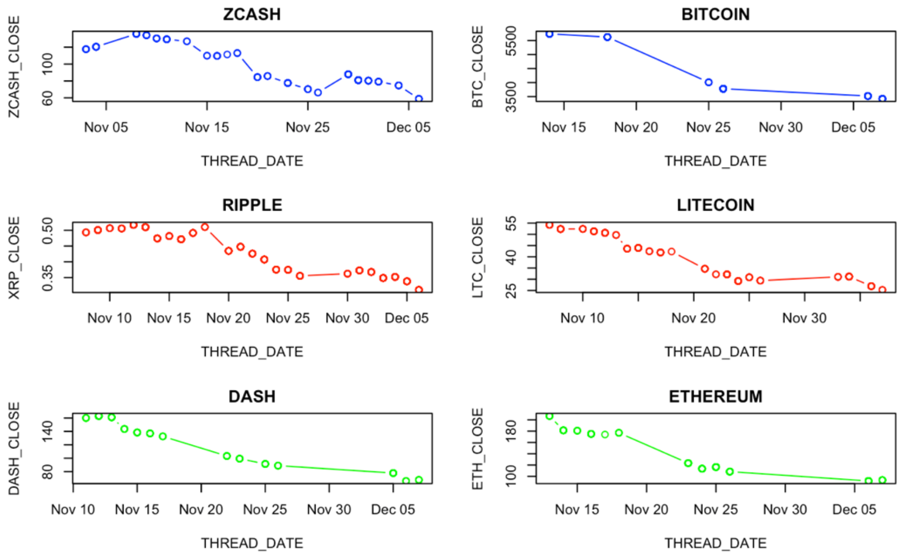


Figure 1. Examples of Price Trend of the Cryptocurrencies in a Bear Market.

Reddit is a social news aggregation, web content rating, and discussion website that allows users to watch live stream content. Reddit threads are created by Reddit users and can be commented on by other Reddit users. We created programs to collect data from the internet semi-automated (Reddit). We have cryptocurrency-related data that spans online social networks and pricing history. People use words in their everyday lives to reveal their beliefs, fears, thought processes, social relationships, and personalities. Figure 2 depicts the frequency of each term in our datasets as a word cloud. The larger the keyword appears in the graphic generated, the more it appears in the text being analyzed. As shown in figure 2, the word "bitcoin" is bigger than the word "zcash", indicating that it is discussed more frequently in the Reddit comments.

Figure 2. Word Cloud of The Cryptocurrencies

The cryptocurrency market, as well as its patterns, is exceedingly volatile. Researchers are drawn to it in order to capture the volatility and predict its next move. Market analysts research market behavior and devise buy and sell strategies based on their findings. Most investors base their decisions on information offered in the news regarding a particular coin.

In this study, we aim to find the relationships between sentiments and Altcoin prices.We use the sentiments of potential investors on Reddit and other cryptocurrency instruments to forecast the price fluctuations of four leading Altcoins in this paper: Zcash, Litecoin, Ripple, and Dash.

2. **Literature review**

2.1. Cryptocurrency

Cryptocurrency is a compound word of 'crypto-' meaning encryption and 'currency' meaning currency. It is a virtual and digital asset safely transmitted through public-key encryption on a distributed ledger. It can easily prove ownership using a hash function. In general, cryptocurrencies operate on a distributed ledger based on a blockchain or DAG (Directed Acyclic Graph).

The first cryptocurrency was Bitcoin. Based on the paper' Bitcoin: A Peer-to-Peer Electronic Cash System' (Nakamoto and Bitcoin 2008) published on October 31, 2008, the first block was created on January 3, 2009. In the early days, cryptocurrencies such as Bitcoin were referred to as electronic money such as b-money or Bit Gold (Dai 1998). Since Bitcoin was first known to the public in 2013, various media have used Bitcoin as virtual currency.

2.1.1. Altcoins

As Bitcoin has attracted attention as a monetary transaction and investment asset, many similar cryptocurrencies were invented. Legacy financial institutes or developer forums introduce some other cryptocurrencies (Chaum 1994; Nakamoto and Bitcoin 2008; Szabo 1996, 2008). Starting with Litecoin, which was first distributed on October 7, 2011, several Bitcoin-inspired digital assets were born, starting with cryptocurrencies that underwent several modifications in the Bitcoin codebase. It was called an Altcoin because of its character. Later, Vitalik Buterin came up with the idea of applying a smart contract devised by Nick Szabo in 1994 (Szabo 2008) - a set of promises expressed in digital form - to the blockchain, and Ethereum was born.

In the early days when it began to attract attention, standards and evaluations for value were divided in various ways. Some people want to take advantage of these points to cause artificial surges and plunges, so it is not fulfilling the expected role of safe assets. Suppose it is recognized and melted into life by many countries over time. In that case, eventually, countries with colossal capital will lead the reasonable price in consideration of various criteria such as the cost of mining, demand, and the total amount of money. Similarly, it is expected that fluctuations will occur according to changes in the value of money, such as an increase in interest rates or inflation.

2.1.2. Zcash

Zcash is a privacy coin family of cryptocurrencies that guarantee anonymity. Zcash uses zero-knowledge cryptography technology to protect an individual's transaction information completely. In Zcash, payments are made on a public blockchain, but the sender, receiver, and transaction amount remain private. In the case of public blockchains such as Bitcoin and Ethereum, it is not known who the account owner (wallet) is, but since all transaction details of the account are public and can be traced, privacy issues may arise. Zcash was born to solve this traceability problem. As of August 2018, Zcash's market capitalization was $600 million, or about 610 billion won, making it the 20th largest cryptocurrency by market capitalization. The monetary unit of Zcash is ZEC.

2.1.3. Ripple

Ripple's market capitalization is the 6th largest among cryptocurrencies and the second largest cryptocurrency among non-mining cryptocurrencies. It has long been called the top three cryptocurrencies along with Bitcoin and Ethereum and briefly handed over the top rankings to Bitcoin Cash, Litecoin, and IOTA in 2017. However, in December 2017, it increased tenfold, overtaking all of them and re-overtaking them again. It became the 3rd most significant currency leader.

On December 8, 2017, the Ripple operator adjusted the volume and value by escrowing 55 billion XRP, close to half of the maximum issuance. Eventually, tweets that SBI was experimenting with international remittances emerged, significantly overtaking IOTA and putting it on par with Bitcoin Cash. This became similar to dispersing issuance rights that were concentrated only on Ripple. However, since the amount circulating in the market was 38 billion XRP, it is not clear how much effect it will have.

2.1.4. Dash

A focus on anonymity characterizes dash. Existing Bitcoin is surprisingly inferior in anonymity because the sender and receiver are recorded on the blockchain. Dash guarantees better anonymity by providing the PrivateSend function and improved Coinjoin technique. Dash also has the advantage of sending money within 1 second. People have to pay a fee to use this feature. However, they can send money quickly while temporarily locking the transaction while preventing double payments.

2.1.5. LiteCoin

Litecoin is an open-source blockchain project released on October 7, 2011, by Charlie Lee, a software engineer at Google, with several modifications from the Bitcoin codebase. It has a block time of 2 minutes and 30 seconds, which is 1/4 of Bitcoin, so the maximum issuance is 84,000,000 LTC, four times that of Bitcoin. It uses a mining algorithm called Scrypt, and for a while, it was not possible to efficiently implement Scrypt-only ASICs and FPGAs, so graphics card mining lasted longer than Bitcoin. However, from the end of 2014, Litecoin ASIC miners started to be released, and by the end of 2015, they were utterly transferred to ASICs.

2.1.6. Etherium

Ethereum is a public blockchain platform created by Vitalik Buterin on July 30, 2015, and is the name of the platform's currency. The most significant difference between Bitcoin and Ethereum is the scope of application. Whereas Bitcoin focuses on payment or transaction-related systems, that is, functions as money, Ethereum transparently supports transactions and payments and various applications such as contracts, SNS, e-mail, and electronic voting based on blockchain, which is a core technology. It provides scalability for operation. In other words, it is a platform that allows anyone to create and use a decentralized application called dApp (DApp) for other purposes and money. It supports most major programming languages such as C++, Java, Python, and Go, which is quite versatile. Thanks to the high utility of Ethereum, various Ethereum-based tokens have been created. Representative examples include Basic Attention Token (BAT), created by the founder of Firefox, GOLEM, created by the early developers of Ethereum, and AUGUR, a prediction market platform. All of them are promising coins that are actively traded on exchanges such as Upbit. This alone suggests the high utility of Ethereum. Ethereum is considered one of the most potent coins that can beat Bitcoin in the future. Although the recognition is much lower than that of Bitcoin, it is incomparably high compared to other altcoins and has high versatility.

2.2. XGBoost

The Extreme Gradient Boosting (XGBoost) model and other tree-based models are widely used machine learning approaches that have shown to be effective in various applications. XGBoost builds an ensemble of shallow and weak successive trees, each learning and improving on the previous. In contrast, random forests generate an ensemble of deep independent trees. When these numerous weak successive trees are joined, they form a powerful "committee" that is typically difficult to beat with other methods. For the following reasons, the XGBoost model is particularly well suited for use with our data:

- Frequently gives exceptional predictive accuracy.
- Lots of flexibility - can optimize on a variety of loss functions and has various hyperparameter tuning options, making the function fit quite versatile.
- There is no need to preprocess data; it typically works well with categorical and numerical values as is.
- Imputation is not required to handle missing data.

The goal is to minimize:

$$L(\varphi) = \sum_{i} l(\hat{y}_i, y_i) + \sum_{k} \Omega(f_k) \quad (1)$$

$$\Omega(f) = \gamma T + \frac{1}{2} \lambda \|\omega\|$$

where $l(\hat{y}_i, y_i)$ is the loss function, $\Omega(f_k)$ is a regularization that penalizes each tree for having too many leaves and ensures smooth final learned weights ω is coefficient at each node and T is the number of leaves in the tree.

The greedy Algorithm 1 generates the regression tree forest F as initially implemented in (Chen and Guestrin 2016) to minimize the above equation.

Algorithm 1: Greedy Algorithm for split finding used in our price prediction model.

```
input : I, instance set of current node input : d, feature dimension
gain → 0
G ← Σ_{i∈I}, H ← Σ_{i∈I} h_i
for k = 1 to m do
G_L ← 0, H_L ← 0
for j in sorted (I, by x_jk) do
    G_L ← G_L + g_i, H_L ← H_l + h_j
    G_R ← G - G_L, H_R ← H - H_l
    Score ← max( score, G_L^2/(H_L+λ) + G_R^2/(H_R+λ) − G^2/(H+λ))
end
end output: Split with max score
```

In many studies and practices, XGBoost has been adopted by many researchers and practitioners as the classifier of their models (Gumus and Kiran 2017). In many competitions in Kaggle, XGBoost provided successful performances (Ogunleye and Wang 2020). In academia, (Gumus and Kiran 2017) and (Nobre and Neves 2019) applied XGBoost for the prediction of oil price and the trade signal prediction, respectively. In addition, XGBoost is adopted for the diagnosis of epilepsy (Torlay et al. 2017), Chronic Kidney Disease (Ogunleye and Wang 2020), and Intrusion Detection System (Dhaliwal et al. 2018). As seen in the literature, the XGBoost has the potential to provide a higher classification performance in various tasks, so it is employed as the classifier of the study.

2.3. Linguistic Inquiry and Word Count (LIWC)

LIWC was created in the early 1990s by psychologists Pennebaker, Booth, and Francis to automate the psychological analysis of written expression. It is now the most widely used automated sentiment detection method in psychology and the computer sciences.

It extracts emotions from a text by calculating the proportion of words that belong to each sentiment class. An example of LIWC is provided in Figure 3. The words in italic (six in number) in Figure 3 are identified as positive in the first statement, while no word was detected as negative. The total number of words is 39; hence the positive sentiment is scored as $\frac{6}{39} \times 100 \approx 15$ while negative sentiment is scored $\frac{0}{39} \times 100 = 0$. LIWC's biggest flaw is misclassifying that should be classified as "negative" as "positive." that is, its inability to identify sarcasm, a common linguistic schema on social networking platforms.

	LIWC	
	Pos	**Neg**
Sounds like a ***good challenge*** - to be proven or disproven. I'm ***happy*** if it can be shown to go further using closed cubic polynomial solutions. The ***nice*** thing about these are that they are ***pretty easy*** to test numerically –in "Exact trigonometric constants"	15	0
Seems you have not yet seen female ***lover*** after having sex who do not wish to have sex with the same ***lover*** any more **:)** Once you've seen it, you understand very *well* what ***war*** **of Venus means compared to** ***war*** **of Mars.** –in "House (astrology)"	6.8	4.5
What about the whirlie hazing, the alcohol ***abuse***, the ***emotional*** **poverty**, the **suicide** in 1995/6, the biotech plans which were stopped by pitzer ***protests*** –in "Harvey Mudd College"	4	8

Figure 3. Example of the Application of LIWC

3. Methods

This study aims to propose a model predicting the price fluctuations of four leading Altcoins by using the sentiments detected from Reddit comments. Therefore, the study model includes two parts: 1) data preprocessing – the extraction of sentiments from Reddit comments and the merge of Ethereum and Bitcoin data; 2) the prediction of the fluctuation of Altcoins using XGBoost classifier.

In the first step, we employ a text analysis application called LIWC to extract the many emotional, cognitive, and structural components found in individuals' spoken and written speech samples from the Reddit comments. Once the comments from Reddits are applied as input, the LIWC provides the 80 output variables. Among the outputs from LIWC, we selected four features: Comment Positive, Comment Negative, Textbody Positive, Textbody Negative. To the semtiment features, we added coin-related features: Ethereum fluctuation, Bitcoin fluctuation, and each Altcoin's trade volume. Because Bitcoin and Ethereum affect the price fluctuation of Altcoins, we included the features in the dataset. As the result of the preprocessing, we prepared the dataset having seven features: Comment Positive, Comment Negative, Textbody Positive, Textbody Negative, Ethereum fluctuation, Bicoin fluctuation, and each Altcoin's trade volume. We standardized the data to ensure that each feature contributes roughly equally.

As the next step, the dataset created in the preprocessing step is used as the classifier's input to predict the Altcoin prices. Among various classifiers, we selected XGBoost for our model because it provides enhanced performances in many applications such as Kaggle (Ogunleye and Wang 2020) by adopting the column sub-sampling, the additive application of weak learner sub-models, and the regularization for the prevention of overfitting. The high-level view of the model of this study is presented in Figure 4.

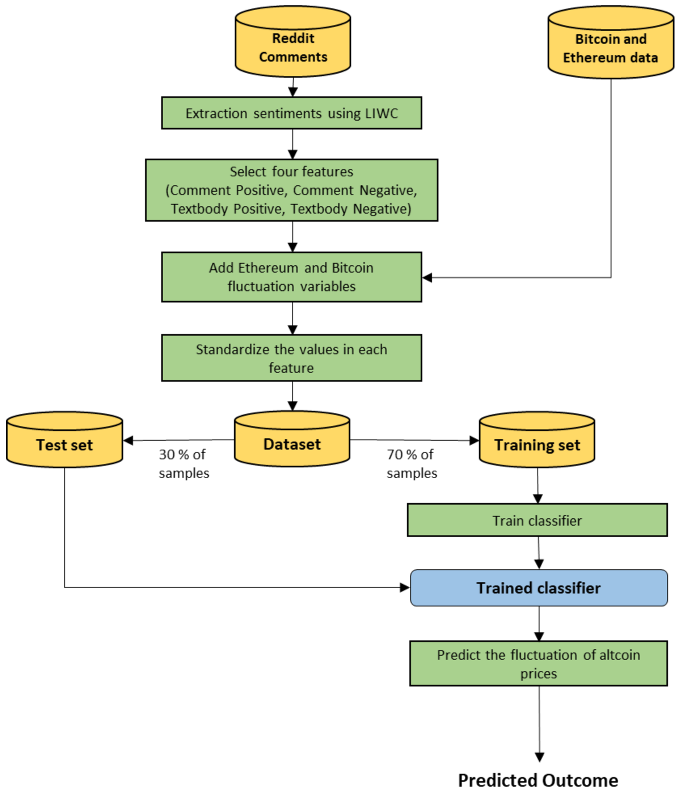


Figure 4. The Method of the Study

4. Experiment and Result

4.1. Experiment Setup

In the experiment, we used the data collected from Reddit comments about Altcoins and the fluction data of Bitcoin and Ethereum. The period for which the comments are collected are four weeks (between 11/5/2018 and 12/5/2018), and the number of collected comments are 1,258. The numbers of each Altcoin's samples are: Zcash 129, Bitcoin 157, Litecoin 200, Ripple 458, Dash 150, Ethereum 164.

Among the samples, 70% of samples are used for the training, and remaing samples (30%) are used for the test. We performed a grid search with 5-fold cross validation that returns the minimum training error and minimum number of trees to find the number of trees, and the model found is used for the training. For the performance comparison of our model, we selected Neural Net (NN), Classification and Regression Tree (C&R), Random Trees, and Extreme Gradient Boosting Regression Tree (XGBoost), and the relative errors are adopted as the performance metric. The relative error is defined as the absolute value of the ratio of the error to the actual observed value as below:

$$Relative\ error = |\ (actual\ price - predicted\ price) / actual\ price\ | \qquad (2)$$

For the application of LIWC, we used the website providing LIWC 2015 version, and R machine learning package is used for the classifiers.

4.2. Experiment Result

In the experiment, XGBoost provided the best performance among the classifiers when applied to Zcash. As can be seen in Table 2, XGBoost has the smallest relative error (0.003) among the classifier. The result implies that the XGBoost is the best classifier among the classifers in the experiment to fit our model. However, the random tree takes the least time to build a trained model (< 1 minute) while other classifiers require more than two minutes. After the training of the model, we plotted the prediction of our model.

Table 1. Model Comparison

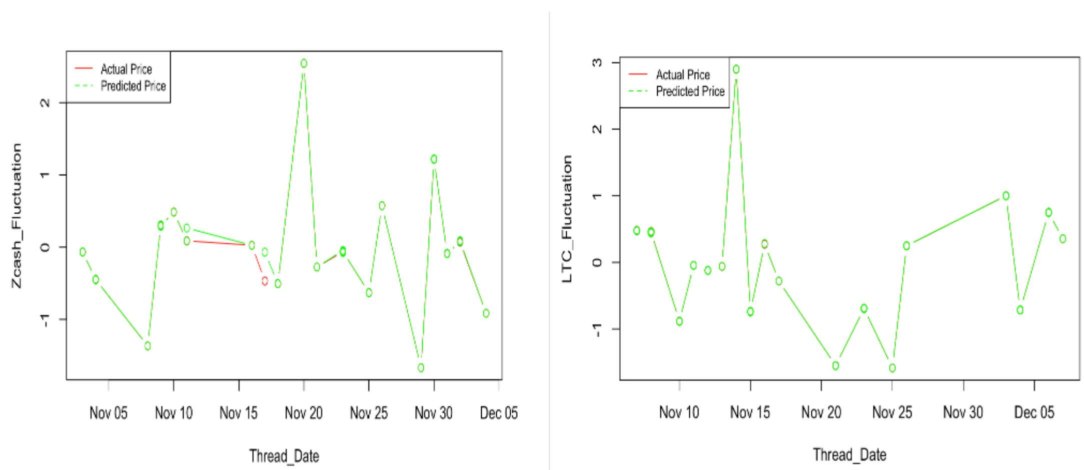
Classifier	Relative Error (unit: dollars)	Build Time (mins)
Neural Net	0.070	2
C&R	0.013	2
Random Trees	0.012	< 1
XGBoost Trees	0.003	2

In addition to the small relative errors, our model has a small RMSE and MAE in all types of Altcoins when tested against the actual test data (see Table 3). Also, our model generated pricing data that closely mirrored actual fluctuations based on the small relative error as depicted in Figure 6.

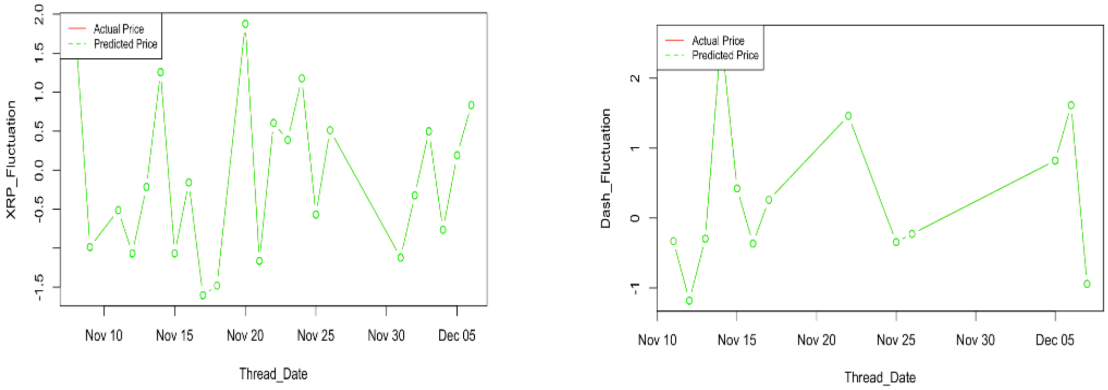
As a result, our model provides a feasible way for predicting price fluctuations and implies that statistical studies based on Reddit sentiment may be applied in analyzing price fluctuations in other cryptocurrencies. It is also worth noting that, despite the price model's comparable directionality to actual price fluctuation of Zcash, there appears to be an approximately $0.07 price difference between the actual and predicted prices. It is presumed that this could result from not having a large dataset to train and test the model. However, the model's overall predictability remains strong enough, implying that the model will produce a more accurate set of predictions if the models were trained on large datasets.

Table 2. Prediction Results for Altcoins

Altcoin	Number of Trees Used	RMSE (unit: dollars)	MAE (unit: dollars)	Most Influential Variable
Zcash	1197	0.07085279	0.01734792	*BTC Fluctuation*
Litecoin	145	0.004210568	0.001942391	*ETH Fluctuation*
Ripple	36	0.0001626887	0.00009389679	*ETH Fluctuation*
Dash	109	0.0001882867	0.0001655502	*ETH Fluctuation*



(a) (b)



(c) (d)

Figure 5. Prediction Plot of the Altcoins

5. Discussion and Conclusion

In this study, the model using XGBoost can predict price variations in the cryptocurrency bear market by evaluating Reddit sentiment, Bitcoin and Ethereum fluctuation, and each Altcoin's trade volume. As a result, given the lack of studies in this field, our model demonstrates that social media platforms can gather investor sentiment, and the sentiment can predict future price fluctuations of Altcoins. Other social media sites or data, such as Google Search results, Facebook postings, and tweets, could improve our pricing model even more. Finally, it would be interesting to train and evaluate our model over a more extended period. Our analysis was limited to a data set that encompassed four weeks. However, our findings point to the need for further resources and investments to enable us to test our pricing model over a more extended period and with other cryptocurrencies.

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