APPALACHIAN
Research in Business Symposium

Proceedings of the Appalachian Research in Business Symposium

11th Annual Conference

April 4-5, 2024

Marshall University

Huntington, West Virginia

Edited by:

Boniface P. Yemba

Marshall University

2024 Appalachian Research in Business Symposium

Conference Committee:

Jason Xiong, Appalachian State University

Kristen Wilson, Eastern Kentucky University

Julia Graham, Eastern Kentucky University

Prasun Bhattacharjee, East Tennessee State University

Nancy Lankton, Marshall University

Boniface Yemba, Marshall University (Conference Chair)

Zachary A. Collier, Radford University

Ethan Cheng, Western Carolina University

It is our pleasure to present the Proceedings of the Appalachian Research in Business Symposium at the 2024 conference. The conference was held on April 4-5, 2024, hosted by the Lewis College of Business at Marshall University.

The Appalachian Research in Business Symposium provides a venue for presenting new research, discovering contemporary ideas, and building connections among scholars at Appalachian State University, Eastern Kentucky University, East Tennessee State University, Marshall University, Radford University, and Western Carolina University. This year we had a participation of faculty and students from Morehead State University and Lander University as guests.

Acknowledgements:

The Conference Committee for the 2024 Appalachian Research in Business Symposium wishes to extend our gratitude to all authors, presenters, conference contributors, exhibitors, and volunteers for their time and effort in service to the conference. As always, we are grateful for the continued support from all for this engaging, research-driven conference.

Website, Registration, and Conference Planning:
Margie Phillips
Charlotte Boyce
Richard Bledsoe
Andrew Kesling
Zach Kincaid
Laurin Bentley
Liyah Bady
Vanessa Coleman

Reviewers:

Appalachian State University

Jason Xiong
Tanga Mohr

Eastern Kentucky University

Kristen Wilson
Michael Fore
John Harter
Beth Polin
Faridah Awang
James Kirby Easterling
Siwei Gao
Julia Graham

East Tennessee State University

Anca Traian
Prasun Bhattacharjee
David Saleh
Joseph Newhard
Kelly Atkins
Michelle S. Freeman
Ahmad Al Doulat
Emily Cokeley
Lorianne Mitchell
Ghaith Husari

Marshall University

Uday Tate
Alberto Coustasse
Yi Duan
Bo Feng
Uyi Lawani
Nabaneeta Biswas
Mohammad A. Karim
Mohammad Uddin
Alan Letton
Thomas Norton
Tim Brian
Amanda K. Thompson-Abbott
Kevin Knotts
Boniface Yemba
Jingran Zhang
Casey Baker
Deepak Subedi

Radford University

Liang Shao
Zachary Collier
Ben Biermeier-Hanson
Thomas Duncan
Mike Chatham
Jennifer Sobotka Elias
Luke Liska
Molly Minnen Sloan

Western Carolina University

Dr. Heidi Grappendorf
Erica Thompson
Angela Dills
Steve Ha
Brian Whelan
Ethan Cheng
Anna Dai
Kadie Otto
Bukola Bakare

Table of Contents

ROMANCE IN (OR OUT) OF THE WORKPLACE? A MODEL EXAMINING EMPLOYEE OUTCOMES

Sunny Barboj
Industrial-Organizational Human Resource Management
Appalachian State University
Campus Box 4095
barbojs@appstate.edu
786-266-8144

Jim Westerman
James E. Holshouser Professor of Business Ethics
Walker College of Business
Department of Management
Appalachian State University
Campus Box 4095
westermanjw@appstate.edu
828-262-7475

Keywords: Workplace romance, attachment style, employee satisfaction, employee commitment

Introduction

Romance and attraction are a fundamental part of our existence, we are social creatures. Naturally, this leads to romance being an expected outcome in most social settings, including the workplace. A Workplace romance (WR) is defined as a relationship between two members of the same organization that includes some sort of mutual romantic or sexual attraction (Dillard & Witteman, 1985). It is important to note that this is different than workplace sexual harassment or socio-sexual behavior. A sizeable portion of the population has engaged in or are currently engaged in a workplace romance. Surveys find that between 30% and 60% of working adults admit to being involved (past and present) in a workplace romance (Main & Hansen, 2023; Gurchiek, 2022). In the work environment, there exists a wide range of approaches used to deal with workplace romance. A few companies enact strict "no romance or fraternization policies" either out of fear of perceived bias/favoritism or sexual harassment claims (Biggs et al. 2012). However, it is much more common for employers to not require disclosure of a workplace romance (Gurchiek, 2022). In fact, some companies expect their employees to date. For example, Ben & Jerry's host holiday functions and subsidize hotel rooms for employees to share, a personnel manager noting "We expect that our employees will date, fall in love, and become partners" (Boyd, 2010). It remains difficult to stop people from interacting and developing feelings for one another. However, whether engaging in a workplace romance (WR) is beneficial or not for organizations is hotly debated, and is the purpose of this study. This manuscript proposes a testable theoretical model examining the effects of WR on organizational outcomes, based on an employee's attachment style. Our model specifically suggests that a WR moderates the relationship between anxious attachment styles and relationship satisfaction as a result of the increased propinquity to a partner that exists in a WR.

Literature Overview

Romance and attraction are fundamental to human experience, and responsible for our existence via propagation as a species, and the idea of romantic love is culturally universal (Jankowiak, 2008). Simply put, it is human nature. If a group of people are in regular contact with one another, there is a high statistical probably that one or more of these individuals will develop romantic feelings towards one another. This is also referred to as the "propinquity effect" (Festinger et al., 1950; Shin et al., 2019). This most often happens in places where people have a great deal of shared time and experience, such as in school and the workplace. The average time of a work week is 34 hours, that amount of continuous contact is bound to spark some feelings, so it should not be surprising that some individuals develop attraction and romantic feelings for one another (BLS, 2023). A survey done by the Society for Human Resource Management (SHRM) found that around 33 percent of the 550 U.S workers they surveyed said they are or have been romantically involved with a colleague in 2022 (Gurchiek, 2022). Some other studies have reported that the number to be as high as 60% (Main & Hansen, 2023).

Romance is often depicted as a "mysterious force" and something that just happens and exists without any scientific understanding for the mechanisms that underlie why humans are attracted to each other and form and maintain such intimate relationships. Through the lens of a science, particularly from an evolutionary standpoint, romance can be viewed as a "commitment device designed to encourage people to invest in one another and help raise future generations" (Gonzaga & Haselton, 2008). Romantic relationships involve "an intense passionate desire to be in the presence of one's romantic partner; a shared exchange of personal disclosures, affection and respect, experiences, pleasant emotional states such as need satisfaction, happiness, sexual gratification, and physiological arousal; and the desire for sexual acts such as kissing, petting, and intercourse with one's partner" (Hatfield, 1988).

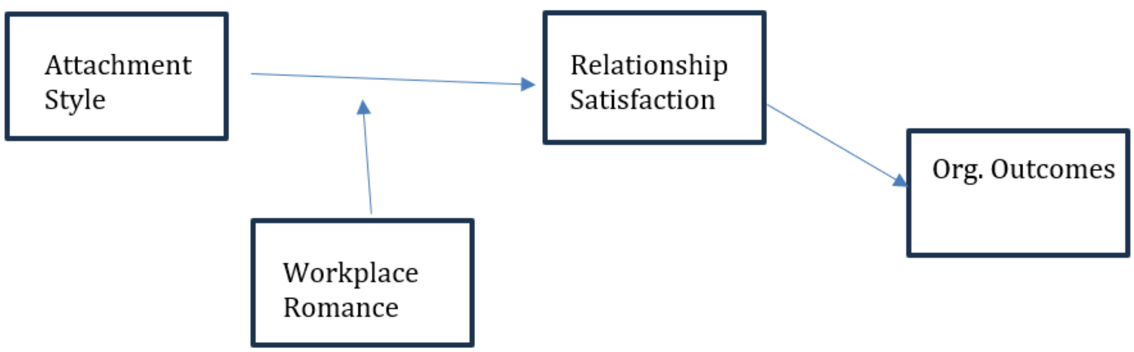
The initial attraction stage can involve a wide range of different factors, from the psychological to the physiological. However, once the initial 'honeymoon phase' passes, the question of how to maintain the romantic relationship remains. The answer lies in the degree of satisfaction experienced by each participant in the relationship. According to Cahill et. al (2020), romantic relationship satisfaction can be described as an "emotional state of being content with the interactions and experiences of one's relationship". Relationship satisfaction can be defined as the measurement of a person's feelings and thoughts about their marriage or similar intimate relationship (Hendrick, 1988). Higher levels of relationship satisfaction are associated with high levels of relationship stability, lower rates of separation, and better physical and mental health compared to those who are alone or in unstable relationships (Cahill et al., 2020).

A workplace romance (WR) can be defined as simply a consensual relationship between two members of the same organization that includes some sort of mutual romantic or sexual attraction (Dillard & Witteman, 1985). Individuals involved in a workplace romance bring different attachment styles formed in childhood and adolescence. Attachment styles appear in three categories: secure, avoidant, and anxious (Ainsworth et al., 2015). Individuals with a secure attachment style bond with a figure who can be relied upon, trusted with personal thoughts, and a desire to be present. This creates a positive and secure relational atmosphere (Bowlby, 1969), which becomes a guide for adolescents to create meaningful relationships and eventual romances with their peers and society as a whole. If the attachment figure isn't available, responsive, or engaged, the individual in question can become anxious or avoidantly attached (Bowlby, 1973). Individuals who are anxiously attached tend to be clingy, and constantly worried about their attachment figure abandoning them (Bowlby, 1973). Anxious individuals tend to fear rejection and abandonment, and essentially become paranoid or even distrustful of their partners and are vigilant for signs of disinterest or betrayal (Ainsworth et al., 2015; Bowlby, 1973). Alternatively, those who are avoidantly attached take an opposite approach. They distrust others, prefer to keep their distance, and tend to disengage emotionally (Bowlby, 1973). Due to being abandoned or neglected by their primary caregiver, the child feels that they do not have anyone to rely on, and they learn to avoid seeking help and attention from their caregiver or other adult figures. This attachment style can influence other behaviors as the individual reaches adolescence and adulthood, including decreased physical expressions of affection, which has negative implications for relationship security (Bowlby, 1973).

The consensus is that a secure attachment style correlates positively with relationship satisfaction and insecure attachment styles correlates negatively (Candel & Turliuc, 2019; Hadden et al., 2014; Li & Chan, 2012; Simpson, 1990). Those who are anxiously attached to their partner are fearful of being "left behind" or their partner "finding someone better". Those employees who are anxiously attached are more likely to suffer in long-distance relationships and separation from their partner in comparison to those who are avoidantly or securely attached. These fears turn into jealousy, distrust, and overall, negatively affect the individual's relationship satisfaction.

A summary of the rationale behind our model is as follows: a large part of the negative relationship satisfaction from individuals who are insecurely attached comes from the fact that they are constantly worried about their partner not being there for them, particularly in the case of those who are anxiously attached (Ainsworth et al., 2015). Being involved in a WR provides those individuals the opportunity to spend more time around their partner (propinquity). Seeing their partner at work (having more contact with a partner) leads to them feeling more confident in their relationship, therefore increasing their relationship satisfaction. The increased satisfaction coupled with the fact that their partner also works with them would increase their affective and continuance commitment, to the extent that workplace romances have more positive organizational outcomes than traditional non-workplace romances. The proposed model is indicated in Figure 1.

Figure 1: Workplace romance and organizational outcomes



Methodology

The goal of this study is to observe if participating in a workplace romance moderates the relationship between anxious attachment styles and relationship satisfaction because of the increased propinquity to their partner. Attachment style falls under one of three categories, secure attachment (considered the healthy and desired outcome), anxious attachment (always feeling like they need to prove themselves to their partner), and avoidant attachment (is very closed off and tend to avoid touch behaviors with their partner). We propose the following propositions to test this model in Figure 1:

P1: An employee with a secure attachment style will possess greater relationship satisfaction than those with anxious or avoidant attachment styles.

P2: Employees who are anxiously attached and involved in a workplace romance will possess higher relationship satisfaction than employees who are anxiously attached and not engaged in a non-workplace romance.

P3: Employees currently involved in a workplace romance spend more time with their partners each day than employees engaged in a non-workplace romance.

P4: Employees involved in a workplace romance have greater relationship satisfaction than employees engaged in a non-workplace romance due to increased propinquity.

P5: Employees involved in a workplace romance have better organizational outcomes (satisfaction and commitment) than employees who are involved in a non-workplace romance due to greater propinquity and relationship satisfaction.

Participants could be instructed to complete a survey which includes a few screening questions (making sure the participants are over the age of 18 and are also in a committed romantic relationship) and complete measurement instruments for attachment style (Fraley, 2000), and relationship outcomes (Funk & Rogge, 2007). Participants could also be asked how many hours in a week they spend with their partner, as well as identifying if the relationship they are currently in is a workplace romance or a non-workplace romance.

Results and Implications

The comparison between the relative effects of workplace romances in comparison to non-workplace romances on employee attitudes and performance is currently unexamined. As workplace romance is a fundamental part of the human condition, it is important that organizations understand how it effects employee outcomes to guide policy.

Conclusion

Our theoretical model is the first to suggest that workplace romance results in more beneficial organizational outcomes for employees than non-workplace romances, contingent on propinquity and employee attachment style. We provide propositions to guide future research in examining these important questions to guide policy towards enhancing employee performance in the workplace.

References

Ainsworth, M. D., Blehar, M., Waters, E., & Wall, S. (2015). *Patterns of attachment: A psychological study of the stranger situation.* New York, NY: Routledge.

Biggs, D., Matthewman, L., & Fultz, C. (2012). Romantic relationships in organizational settings: Attitudes on workplace romance in the UK and USA. *Gender in Management: An International Journal*, *27*(4), 271-285.

Boyd, C. (2010). The Debate Over the Prohibition of Romance in the Workplace. *Journal of Business Ethics*, 97, 325–338. https://doi.org/10.1007/s10551-010-0512-3

Bowlby, J. (1969). *Attachment and loss: Vol. 1. Attachment and loss.* New York: Basic Books.

Bowlby, J. (1973). *Attachment and loss: Vol. 2. Separation: anxiety and anger.* New York, NY: Basic Books.

Bureau of Labor Statistics (2023). *News Release, November 2023*. https://www.bls.gov/news.release/pdf/empsit.pdf

Cahill, V. A., Malouff, J. M., Little, C. W., & Schutte, N. S. (2020). Trait perspective taking and romantic relationship satisfaction: A meta-analysis. *Journal of Family Psychology*, 34(8), 1025–1035. https://doi-org.proxy006.nclive.org/10.1037/fam0000661.supp

Candel, O. S., & Turliuc, M. N. (2019). Insecure attachment and relationship satisfaction: A meta-analysis of actor and partner associations. *Personality and Individual Differences*, 147, 190-199. https://doi.org/10.1016/j.paid.2019.04.037

Dillard, J. P. and Witteman, H. (1985). 'Romantic relationships at work: Organizational and personal influences', *Human Communication Research*, 12, 99-116.

Fraley, R. C., Waller, N. G., & Brennan, K. A. (2000). An item-response theory analysis of self-report measures of adult attachment. *Journal of Personality and Social Psychology*, 78, 350-365.

Festinger, L., Schachter, S., Back, K., (1950) "The Spatial Ecology of Group Formation", in L. Festinger, S. Schachter, & K. Back (eds.), *Social Pressure in Informal Groups*, 1950. Chapter 4.

Funk, J. L. & Rogge, R. D. (2007). Testing the ruler with item response theory: Increasing precision of measurement for relationship satisfaction with the Couples Satisfaction Index. *Journal of Family Psychology*, 21, 572-583

Gonzaga, G. C., & Haselton, M. G. (2008). The evolution of love and long-term bonds. In J. P. Forgas & J. Fitness (Eds.), Social relationships: Cognitive, affective, and motivational processes (pp. 39 –54). Hove, England*: Psychology Press*

Gurchiek, K. (2022, February 7). *Romance continues to flower at work*. SHRM. Retrieved November 27, 2022, from https://www.shrm.org/hr-today/news/hr-news/pages/romance-continues-to-flower-at-work.aspx#:~:text=One%2Dthird%2C%20or%2033%20percent,%22unofficial%2C%22%20SHRM%20found.

Hadden, B. W., Smith, C. V., & Webster, G. D. (2014). Relationship duration moderates associations between attachment and relationship quality: Meta-analytic support for the temporal adult romantic attachment model. *Personality and Social Psychology Review*, 18(1), 42-58. https://doi.org/10.1177/1088868313501885

Hatfield, E. (1988). 'Passionate and companionate love'. In: Sternberg, R. J. and Barnes, M. L. (Eds) The Psychology of Love, *Yale University Press*, New Haven, CT, pp. 191-217.

Hendrick, S. S. (1988). A generic measure of relationship satisfaction. *Journal of Marriage and the Family*, 50(1), 93–98. https://doi.org/10.2307/352430

Jankowiak W. R. (2008). *Intimacies: Love and sex across cultures*. Columbia University Press.

Li, T., & Chan, D. K. S. (2012). How anxious and avoidant attachment affect romantic relationship quality differently: A meta-analytic review. *European Journal of Social Psychology*, 42(4), 406-419. https://doi.org/10.1002/ejsp.1842

Main, K., & Hansen, L. (2023). Workplace romance statistics: Survey shows employees regularly engage in office relationships. *Forbes*. https://www.forbes.com/advisor/business/workplace-romance-statistics/#:~:text=Workplace%20romance%20statistics%20show%20that,t%20likely%20to%20go%20anywhere.

Shin, J., Suh, E. M., Li, N. P., Eo, K., Chong, S. C., & Tsai, M.-H. (2019). Darling, get closer to me: Spatial proximity amplifies interpersonal liking. *Personality and Social Psychology Bulletin*, *45*(2), 300–309. https://doi-org.proxy006.nclive.org/10.1177/0146167218784903

Simpson, J. A. (1990). Influence of attachment styles on romantic relationships. *Journal of Personality and Social Psychology*, 59(5), 971-980. https://doi.org/10.1037/0022-3514.59.5.971.

ENVIRONMENTAL SUSTAINABILITY IN 3D PRINTED CLOTHING

Wei Xie
Department of Computer Information Systems
Walker College of Business
Appalachian State University
416 Howard Street
Boone, NC 28608
xiew1@appstate.edu
828.262.8898 (Contact Author)

Charlie Chen
Department of Computer Information Systems
Walker College of Business
Appalachian State University
416 Howard Street
Boone, NC 28608
chench@appstate.edu

William Anderson
School of Communication
Elon University
Elon, NC 27244
banderson11@elon.edu

Keywords: sustainable fashion, 3D printed clothing, diffusion of innovation, imitate other.

Introduction

The fashion industry represents 2 percent of the world's gross domestic product and is valued at $3 trillion (fashinnovation.nyc, n.d.). It is also the second-most polluting industry in the world (Rathinamoorthy, 2019). The fashion industry's focus has recently centered on the harmful environmental consequences stemming from consumption and conventional production methods (Mukendi et al., 2020). In response to these challenges, sustainable fashion has arisen as a concept encompassing clothing and practices aimed at minimizing harm to both people and the environment (Niinimäki, 2017). Sustainable fashion seeks to steer the industry toward heightened ecological responsibility (Grazzini et al., 2021; Orminski et al., 2020). This movement has been driven, in part, also by consumers. In the 2019 and 2020 CGS study involving participants aged 18 to 65 from the USA and the U.K., consumers displayed a greater inclination to purchase products from companies that commit to environmental sustainability and that Sustainability significantly influences demand and fosters customer loyalty, particularly among younger generations. A separate survey found that 87% of U.S. Millennials expressed a willingness to pay a premium for sustainable fashion, with many prioritizing eco-friendly brands when making their purchasing decisions (Garcia, 2018).

Against the backdrop, fashion companies are striving to generate profits and address environmental and social issues (Kotler et al., 2021). The 3D printing technology is particularly evident in benefiting the fashion industry (Spahiu, 2020). Since the debut of the first 3D-printed dress (Kilbert, 2016), the innovation has paved the way for pioneering trends, offering consumers the potential for personalized clothing customization while minimizing the waste of resources (Xiao, 2022). Consumers are increasingly aware of 3D-printed clothing. Spahiu et al. (2020) found that 89% of survey respondents were familiar with 3D printing, 60% recognized the benefits of 3D printing in fashion, and 79% expressed a willingness to do a 3D-printed dress.

However, fashion sustainability is a complex issue that covers three essential aspects: environmental, social, and economic (Daukantiene, 2023). In the context of environmental benefits to society and economic profits to businesses, the social aspect of engaging customers in 3D-printed fashion and clothing is equivalently important. Thus, comprehending the factors that influence consumers' intention to wear and purchase is a crucial first step, especially during the early stage when consumer knowledge and awareness are limited, as they remain poorly understood (Frank & Brock 2018; Kozlowski et al., 2016). When future behaviors are difficult to capture, intentions offer critical insights and predictions (Ajzen, 1991; Jeyaraj et al., 2023). Given the innovative nature of 3D-printed fashion, the Diffusion of Innovation (DoI) provides a fitting theoretical framework to study the dissemination and adoption of new ideas, products, or technologies that society adopts (Rogers et al., 2014). This study presents a psychometric intention model that lays the groundwork for a more profound understanding of customer adoption of 3D-printed fashion and clothing innovations. The theory has five direct adoption precursors: relative advantages, Compatibility, trialability, Complexity, and observability (Rogers et al., 2014). Our research questions ask how each precursor influences consumers' adoption intention.

Literature Overview & Hypothesis

Relative Advantage in Environmental Protection

Relative advantage refers to the extent to which an innovation can surpass other options (Rogers 2014). When people acknowledge the relative advantages gained from engaging in a particular behavior, they tend to respond positively to that behavior (Ajzen & Fishbein, 1980). Conversely, if individuals perceive that a behavior carries more drawbacks, they might develop a negative attitude toward it. Relative advantage stands out as a key predictor of behaviors (Kim, 2008), as well as innovations in products or services (Laukkanen 2016; Müller-Stewens 2017). For this study, the relative advantage of 3D-printed clothing revolves explicitly around the capability for environmental protection, including reducing waste and chemicals, being considered environmentally friendly, and protecting the climate. We hypothesize:

> **H1:** Relative advantage in environment protection (AdvEn) positively correlates to the intention to use 3D printed fashion.

Compatibility

Compatibility refers to the degree to which an innovation is perceived to be consistent with existing values, needs, and experiences of potential adopters (Rogers 2014). Several studies show the positive direct effects of Compatibility on behavioral intention (e.g., Nordhoff et al. 2021). For instance, Cui et al. (2022) concluded that Functional, Expressive, and Aesthetic (FEA) consumer needs effectively predict satisfaction with 3D printing integrated apparel products. This study views Compatibility as consistency and suitability with one's existing style, presumed comfort to wear, and self-expression. We hypothesize:

> **H2:** Compatibility (Cpat) positively correlates to the intention to use 3D printed fashion.

Complexity (Ease of Use)

Complexity is the degree to which the innovation is seen as difficult to understand or use; consumers are less likely to adopt hard-to-use or complex products (Rogers 2014). On the opposite end of Complexity is the ease of use or understanding (Davis, 1989). Moore and Benbasat (1991) suggested 'Ease of Use' to measure the perceived Complexity more effectively with less conceptual confusion. We hypothesize:

> ***H3:*** *Ease of Use (EoU)*positively correlates to *the behavioral intention to use* 3D printed fashion.

Trialability

Trialability is the extent to which an innovation can be tried and experienced before its adoption (Rogers 2014). We expect a positive relationship between trialability and the behavioral intention to use 3D-printed fashion. The supposition is that individuals who value experiencing 3D-printed fashion in trials before adoption are more inclined to use 3D-printed fashion. We hypothesize:

> ***H4:*** *Trialability (Tb)* positively correlates to *the behavioral intention to use 3D printed fashion.*

Imitate Others (Observability)

Moore and Benbasat (1991) pointed out the ambiguity of the original definition of observability. 3D-printed fashion is also rarely-observable. Sun (2013) develops an 'imitate others' construct and proposes that imitation behaviors are provoked primarily by observing priors and others (Sun, 2013). This study incorporates 'imitate others' as a proxy for observability, which refers to individuals observing and emulating the clothing choices of their significant figures. For example, when people watch others incorporate sustainable and cutting-edge smart clothing into their repertoire, they are more inclined to follow suit (Johnstone & Lindh, 2022; Ko et al., 2009). We hypothesize:

> ***H5:*** Imitating others (observability) (Imi) positively correlates to *the behavioral intention to use* 3D-printed fashion.

Figure 1 is our research model. Our dependent construct is users' intention to adopt 3D-printed Fashion (IW).

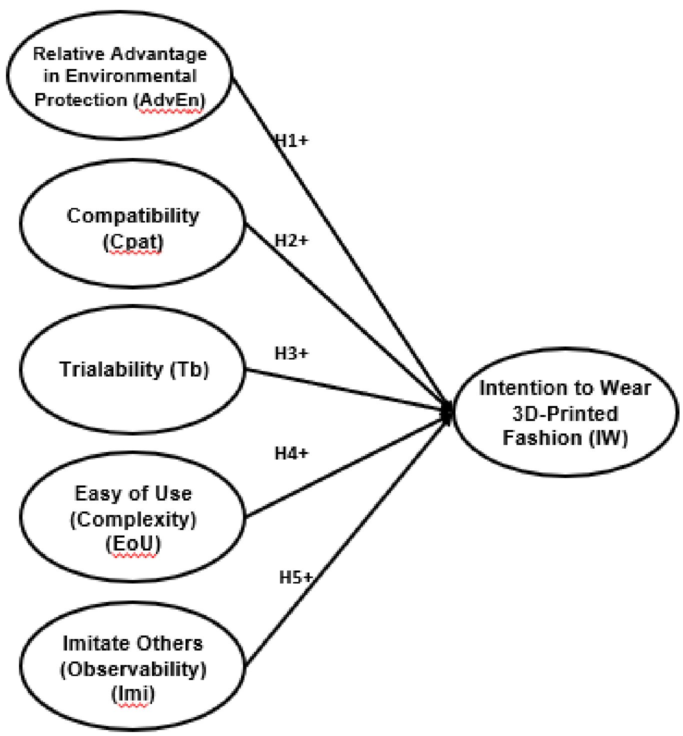


Figure 1. Research Model

Methodology

We developed a survey instrument rooted in DoI to evaluate our proposed constructs and hypotheses. Each construct comprises measurement questions adapted from prior studies. We employed multi-item scales to enhance the validity and reliability of the constructs within the research model, following the approach suggested by MacKenzie et al. (2011). Item responses were gathered using a seven-point Likert scale, ranging from 1 = "strongly disagree" to 7 = "strongly agree." Subsequently, we employed Partial Least Squares – Structural Equation Modeling (SmartPLS V.4.0.9.6) to scrutinize our exploratory measurement and structural models and validate the hypothesized relationships among the constructs (Hair et al., 2021).

Before taking the survey, the respondents watched a 2-minute video about 3D-printed clothing that reflects the research context and constructs, including generating 3D-printed clothing, the significance of social impact, environmental protection, personalization, and the style and functions offered. We collected 222 data from Prolific, with 221 admissible data after careful checking, verifying that participants on Prolific were more likely to pass various quality checks (Douglas et al., 2023; Peer et al., 2022). Table 1 includes the demographics. Figure 2 shows the monthly shopping frequency of respondents.

Table 1. Demographics

Demographics (221 total)	Statistics	Count	%
Gender	Female	103	47%
	Male	113	51%
	Prefer not to answer	5	2%
Age	GenZ (born 1995 - 2012)	118	53%
	Millennials (born 1980 - 1994)	76	34%
	GenX (born 1965 - 1979)	21	10%
	Boomer (born 1946 - 1964)	6	3%
Ethnicity	Asian	7	3%
	Black or African American	22	10%
	Hispanic or Latino	32	14%
	White	156	71%
	Others	4	2%
Education	Less than high school	1	0%
	High school diploma	57	26%
	Associate degree	11	5%
	Undergraduate degree	76	34%
	Graduate degree	71	32%
	Others	5	2%
Household Income	Poverty (< $20,000)	63	29%
	low income ($20,000 - $50,000)	79	36%
	middle class ($50,000 - $150,000)	47	21%
	high income (> $150,000)	8	4%
	Prefer not to answer	24	11%
Employment Status	Full-time	111	50%
	Part-time	29	13%
	Unemployed	37	17%
	Retired	3	1%
	Self-employed	18	8%
	Prefer not to answer	23	10%

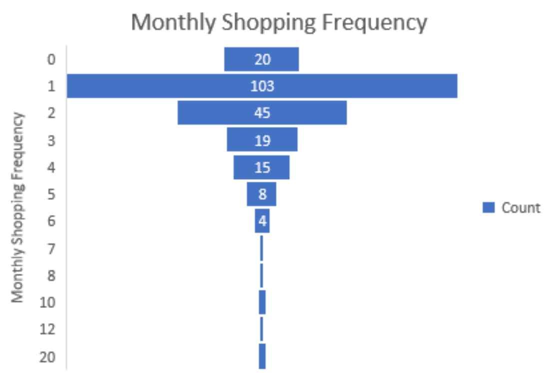


Figure 2. Shopping Frequency

Results

Measurement Model Estimation

The measurement model estimates the reliability and accuracy of measurable items (variables), the relationships between the measured items, and the latent constructs these items represent. To ensure item commonality, all item loadings surpass the established threshold value of 0.70 (Chin, 1998); to ensure no item redundancy, item loadings should not be larger than 0.95 (Hair et al., 2021). Model Cronbach's α and the composite reliability have values larger than 0.7, demonstrating robust internal consistency in items' reliability, measuring what they are supposed to measure reliably (Hair et al., 2021). Convergent validity is evaluated by assessing the average variance extracted (AVE) (Chin, 1998; Fornell & Larcker, 1981), with values exceeding the recommended minimum threshold of 0.50 (Fornell & Larcker, 1981), accurately measuring the underlying latent variables. The discriminant (divergent) validity ensures that each construct is empirically unique, and items only measure their associated constructs. Henseler et al. (2015) propose a more constrained HTMT with a threshold value of 0.85, if the constructs in the path model are conceptually more distinct. All values of HTMT are smaller than 0.85, except for 0.87 between the intention and Compatibility, indicating distinctions of all constructs (Hair et al., 2021). Table 2 shows all the measurement model results.

Table 2. Measurement Model Results

Latent Variable	Indicators	Items	Convergent Validity: Loadings	Convergent Validity: Indicator Reliability	Convergent Validity: AVE	Internal Consistency Reliability: Cronbach's alpha	Internal Consistency Reliability: Composite reliability (rho_a)	Internal Consistency Reliability: Composite reliability (rho_c)	Discriminant Validity: HTMT
			> 0.7	> 0.5	> 0.5		0.7 - 0.9		< 0.85
AdvEN	AdvEn1	3D-printed clothing helps me reduce waste.	0.849	0.721	0.713	0.908	0.91	0.909	Yes
	AdvEn2	3D-printed clothing allows me to be more environmentally friendly.	0.879	0.773					
	AdvEn3	3D-printed clothing assists me in decreasing chemical pollutant.	0.846	0.716					
	AdvEn4	3D-printed clothing provides me better control in protecting the climate.	0.803	0.645					
Cpat	Cpat1	3D-printed clothing could be comfortable to wear.	0.775	0.601	0.651	0.882	0.882	0.882	Yes
	Cpat3	3D-printed clothing suits my dressing style.	0.810	0.656					
	Cpat4	3D-printed clothing fits well with my sustainability image.	0.830	0.689					
	Cpat5	3D-printed clothing is compatible with my customized clothing needs.	0.811	0.658					
EoU	Eou1	Using 3D-printed clothing does NOT require much effort. (R)	0.716	0.513	0.704	0.874	0.887	0.876	Yes
	EoU2	Using 3D-printed clothing would be simple.	0.873	0.762					
	Eou3	I expect using 3D-printed clothing with no difficulty.	0.916	0.839					
Imi	Imi3	I would choose to use 3D-printed clothing because many other people are using it.	0.854	0.729	0.782	0.876	0.879	0.877	Yes
	Imi4	I would use 3D-printed clothing because it is the best-selling product.	0.914	0.835					
Tb	Tb2	3D-printed clothing should be made available to me to test.	0.853	0.728	0.735	0.892	0.895	0.892	Yes
	Tb3	I could try 3D-printed clothing long enough to see what it could do.	0.911	0.830					
	Tb4	I should be allowed to experiment with 3D-printed clothing as necessary.	0.805	0.648					
IW	IW1	I intend use 3D-printed clothing in the future.	0.921	0.848	0.831	0.936	0.937	0.937	Yes
	IW2	Given the opportunity, I predict that I would use 3D-printed clothing.	0.900	0.810					
	IW3	The likelihood of me using 3D-printed clothing is high in the future.	0.914	0.835					

Path Model and Hypothesis Estimation

For the path model, first, all VIF values of constructs in the model are in the range of 1.488 to 2.978, below the cutoff value of 3, suggesting that variance is solidly attributed to each construct and that common method bias (CMB) and multicollinearity are unlikely to exert any undue influence on the study results (Kock & Lynn, 2012). Table 3 and Figure 3 below report all path coefficients in the model with their associated significance. To our surprise, the Environmental Advantage path is not supported. Imitating others to capture the observability in DoI is not significant as well. Other than these, Compatibility, Trialability, and Ease of Use are important predictors for 3D-printed clothing adopters. Further, we assess construct relationships' strength, significance, and model strength in R^2, Q^2, and F^2. R^2 of our model is deemed exceptionally strong, indicating that the 84.5% variance in the intention of users to adopt 3D-printed clothing could be explained by five DoI constructs (Hair et al., 2021). However, because R^2 is sensitive to the number of predictors in the model – the more predictors increase its size, the effect size of F^2 testing is consulted, which tells the change in the R^2 when a specific predictor is omitted from the model (Hair et al., 2021). Like the path model results, Environmental Advantage (0.008) is ineffective. In addition, only Compatibility (0.64) and Trialability (0.3) are effective predictors in the model, but not Ese of Use (0.08) and Imitating Others (0.02) (Kline, 2023). In terms of out-of-sample predictive power, Q^2 statistics of 0.743 indicate our model has strong out-of-sample predictive power (Hair et al., 2021), with the predictive power primarily attributed to Compatibility and Trialability constructs.

Table 3. Structural Model Results

Path	Coefficients	T statistics	P values	Support Hypothesis?
H1: AdvEn -> IW	0.044	0.875	0.382	No
*H2: Cpat -> IW ****	0.540	7.737	0.000	Yes
*H3: EoU -> IW ****	0.135	2.644	0.008	Yes
*H4: Tb -> IW ****	0.289	5.354	0.000	Yes
H5: Imi -> IW	0.076	1.434	0.152	No

*** p <= 0.01

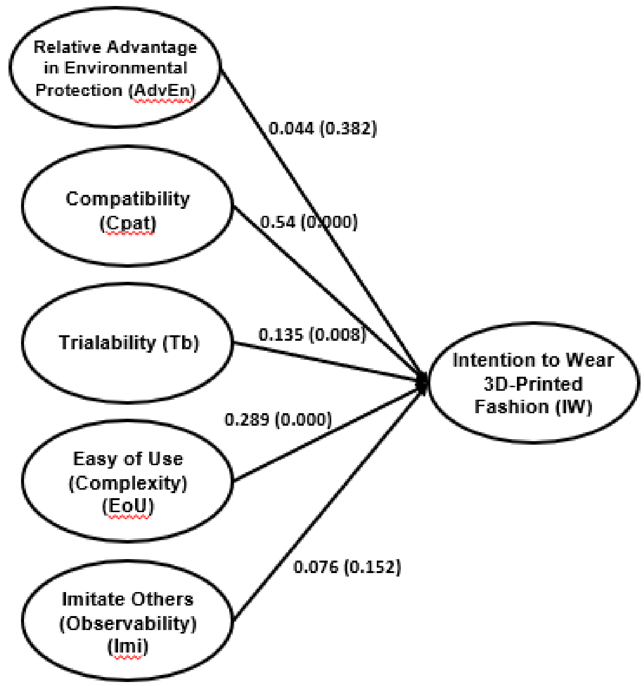


Figure 3. Model's Path Coefficients

Implications and Conclusion

This research demonstrates the power of DoI theory to explain and predict consumers' intentions to adopt 3D printing fashion. First, Compatibility, Trialability, and Ease of Use (Complexity) emerge as critical determinants with substantial influence on the model, positively shaping the intention to adopt 3D-printed clothing. This finding is consistent with the literature on fashion (Littrell & Miller, 2001). Second, imitating others to gauge observing others' behavior does not have an adoption influence either. When Lyu et al. (2018) applied the Technology Acceptance Model in their study of Millennials, they found that 'fashion leadership' fosters a positive attitude and intention toward 3D fashion products. Our results suggest that the observable behavior of influencers may need to go through extra mechanisms to engage imitation and ultimately increase consumers' adoption intention. Third, notably, the relative advantage in environmental protection that could be provided by 3D-printed clothing is not an adoption influencer at all. This intriguing result comes as a salient surprise that needs further investigation. It suggests that consumers may espouse environmental protection as a catchphrase at a superficial level, indicating 'more attitudinally green than behaviorally green' (e.g., Naderi & Steenburg, 2018; Park & Lin, 2020). It may also suggest that the advantage of environmental protection may exert its influence through other mediating variables. Presuming that the idea of environmental protection will automatically fly in consumers' choice and float a future innovative product or service is not sustainable. Future research may need to conceptualize and differentiate environmental protection as biospheric, altruistic, and egoistic value-specific, as environmental psychology suggests (Martin & Czellar, 2017; Stern & Dietz, 1994; Stern et al., 1993).

In conclusion, guided by the diffusion of innovation theory, this study builds a model to examine five theoretical factors and their differentiated effect on the diffusion of 3D-printed fashion. These findings underscore the multifaceted dynamics at play in adopting 3D-printed fashion. The results highlight the importance of Compatibility, Trialability, and Ease of Use in consumers' intention to adopt innovative 3D-printed clothing. This study contributes to enhancing and expanding the DoI theory into the sustainable fashion and 3D-printed clothing context, improving the understanding of the clothing industry's transformation toward sustainability and technological innovation. The fashion and clothing industry needs to comprehensively reevaluate the entire fashion system beyond the production aspects to reach the ultimate goal of sustainability, including educating consumers about the environmental implications of fashion.

References

Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes*, *50*(2), 179-211.

Ajzen, I., & Fishbein, M. (1980). Understanding attitudes and predicting social behavior. Englewood Cliffs: Prentice-Hall.

Chin, W. W. (Ed.). (1998). *The partial least squares approach for structural equation modeling*. Associates Publishers.

Cui, T., Chattaraman, V. and Sun, L. (2022), “Examining consumers’ perceptions of a 3D printing integrated apparel: a functional, expressive and aesthetic (FEA) perspective”, Journal of Fashion Marketing and Management, Vol. 26 No. 2, pp. 266-288. https://doi.org/10.1108/JFMM-02-2021-0036

Daukantienė, V. (2023). Analysis of the sustainability aspects of fashion: a literature review. *Textile Research Journal*, *93*(3-4), 991-1002.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 319-340.

Douglas, B. D., Ewell, P. J., & Brauer, M. (2023). Data quality in online human-subjects research: Comparisons between MTurk, Prolific, CloudResearch, Qualtrics, and SONA. *Plos one*, *18*(3), e0279720.

Fashion industry statistics: 4th gorgeous sector is clothing. Fashinnovation. (2023, November 13). https://fashinnovation.nyc/fashion-industry-statistics/#:~:text=Fashion%20Industry%20Statistics%3A%20General%20Data,Gross%20Domestic%20Product%20(GDP)

Frank, P. and Brock, C. (2018), “Bridging the intention-behavior gap among organic grocery customers: the crucial role of point-of-sale information”, Psychology and Marketing, Vol. 35, pp. 586-602.

Fornell, C., & Larcker, D. F. (1981). Structural equation models with unobservable variables and measurement error: Algebra and statistics. *Journal of marketing research*, 382-388.

Garcia, K. (2018), Do Shoppers Care about Sustainable Fashion? Millennials Are Thought to Be at the Forefront, but Results Are Mixed, [Online], eMarketer, available at: https://www.emarketer.com/content/do-shoppers-care-about-sustainable-fashion (accessed 01 October 2023).

Grazzini, L., Acuti, D. and Aiello, G. (2021), “Solving the puzzle of sustainable fashion consumption: the role of consumers’ implicit attitudes and perceived warmth”, Journal of Cleaner Production, Vol. 287, 125579.

Hair Jr, J., Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage publications.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the academy of marketing science*, *43*, 115-135.

Jeyaraj, A., Dwivedi, Y. K., & Venkatesh, V. (2023). Intention in information systems adoption and use: Current state and research directions. *International Journal of Information Management*, *73*, 102680.

Johnstone, L., & Lindh, C. (2022). Sustainably sustaining (online) fashion consumption: Using influencers to promote sustainable (un) planned behaviour in Europe’s millennials. *Journal of Retailing and Consumer Services*, *64*, 102775.

Kilbert, A. (2016). 3D printers could revolutionize fashion industry. Retrieved from http://www.duqsm.com/3d-printers-could-revolutionize-fashion-industry/. Accessed 2 October 2023.

Kim, D.J.; Ferrin, D.L.; Rao, H.R. A trust-based decision-making model in electronic commerce: The role of trust, perceived risk, and their antecedents. Decis. Support Syst. 2008, 44, 544–564.

Kline, R. B. (2023). *Principles and practice of structural equation modeling*. Guilford publications.

Ko, E., Sung, H., & Yun, H. (2009). Comparative analysis of purchase intentions toward smart clothing between Korean and U.S. consumers. *Clothing and Textiles Research Journal*, *27*(4), 259-273.

Kock, N., & Lynn, G. (2012). Lateral collinearity and misleading results in variance-based SEM: An illustration and recommendations. *Journal of the Association for information Systems*, *13*(7).

Kozlowski, Anika, Cory Searcy, and Michal Bardecki. "Innovation for a sustainable fashion industry: a design focused approach toward the development of new business models." Green Fashion: Volume 2 (2016): 151-169.

Laukkanen, T. Consumer adoption versus rejection decisions in seemingly similar service innovations: The case of the Internet and mobile banking. J. Bus. Res. 2016, 69, 2432–2439.

Littrell, M. A., & Miller, N. J. (2001). Marketing across cultures: Consumers' perceptions of product complexity, familiarity, and Compatibility. *Journal of Global Marketing*, *15*(1), 67-86.

Lyu, J., Hahn, K., & Sadachar, A. (2018). Understanding millennial consumer's adoption of 3D printed clothing products by exploring personal values and innovativeness. *Clothing and Textiles 5*, 1-24.

MacKenzie, S. B., Podsakoff, P. M., & Podsakoff, N. P. (2011). Construct measurement and validation procedures in MIS and behavioral research: Integrating new and existing techniques. *MIS quarterly*, 293-334.

Martin, C., & Czellar, S. (2017). Where do biospheric values come from? A connectedness to nature perspective. *Journal of Environmental Psychology*, *52*, 56-68.

Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information systems research*, *2*(3), 192-222.

Mukendi, A., Davies, I., Glozer, S., & McDonagh, P. (2020). Sustainable fashion: current and future research directions. European Journal of Marketing, 54(11), 2873-2909.

Müller-Stewens, J. Gamified information presentation and consumer adoption of product innovations. J. Market. 2017, 81, 8–24.

Naderi, I., & Van Steenburg, E. (2018). Me first, then the environment: Young Millennials as green consumers. *Young Consumers*, *19*(3), 280-295.

Niinimäki, Kirsi. Fashion in a circular economy. Springer International Publishing, 2017.

Nordhoff, Sina, et al. "A structural equation modeling approach for the acceptance of driverless automated shuttles based on constructs from the Unified Theory of Acceptance and Use of Technology and the Diffusion of Innovation Theory." Transportation research part F: traffic psychology and behaviour 78 (2021): 58-73.

Orminski, J., Tandoc, E.C., Jr and Detenber, B.H. (2020), "#sustainablefashion – a conceptual framework for sustainable fashion discourse on Twitter", Environmental Communication, Vol. 15, pp. 115-132.

Park, H.J. and Lin, L.M. (2020), "Exploring attitude–behavior gap in sustainable consumption: comparison of recycled and upcycled fashion products", Journal of Business Research, Vol. 117, pp. 623-628.

Peer, E., Rothschild, D., Gordon, A., Evernden, Z., & Damer, E. (2022). Data quality of platforms and panels for online behavioral research. *Behavior Research Methods*, 1.

Rathinamoorthy, R. (2019). Consumer's awareness on sustainable fashion. *Sustainable fashion: Consumer awareness and education*, 1-36.

Rogers, E. M., Singhal., A., & Quinlan., M. M. (2014). *Diffusion of innovations: An integrated approach to communication theory and research.*

Spahiu, T.; Canaj, E.; Shehi, E. 3D printing for clothing production. J. Eng. Fibers Fabr. 2020, 15, 1–8.

Stern, P. C., & Dietz, T. (1994). The value basis of environmental concern. *Journal of social issues*, *50*(3), 65-84.

Stern, P. C., Dietz, T., & Kalof, L. (1993). Value orientations, gender, and environmental concern. *Environment and behavior*, *25*(5), 322-348.

Sun, H. (2013). A longitudinal study of herd behavior in the adoption and continued use of technology. *Mis Quarterly*, 1013-1041.

Xiao, Y.-Q.; Kan, C.-W. (2022). Review on Development and Application of 3D-Printing Technology in Textile and Fashion Design Coatings, 12, 267.

ANALYZING THE DECLINE IN OFFSHORING IN CHINA

Dr. James Kirby Easterling (faculty mentor)
Assistant Professor-Global Supply Chain Management
Department of Management
EKU College of Business
Eastern Kentucky University
521 Lancaster Avenue
Richmond, KY 40475
859.622.7893

Michael Peake (undergraduate student)
EKU Honors Program
Eastern Kentucky University
521 Lancaster Avenue
Richmond, KY 40475
859.753.4288 (Contact Author)

Keywords : Offshoring, China, Total Cost of Ownership, Supply Chain Management

Introduction

The People's Republic of China (PRC) has become a global center of manufacturing. This is especially true in certain markets, particularly in consumer electronics. The surge in Chinese globalization has been a process which started in the 1980s and has surged as the world has increasingly globalized. This had turned China into a primary topic of discussion around the path of how globalization impacts under-developed markets.

In its simplest terms, *outsourcing* describes the decision for a company to take one of its business functions and pay another company to perform one of its business functions. A company can outsource a huge variety of its functions, ranging anywhere from manufacturing, raw materials, engineering, customer service, etc. *Offshoring*, which this paper primarily discusses, defines when a company outsources its processes to a company that is not native to the same country as the original company. In essence, offshoring refers to outsourcing in a different country. While this may seem more expensive, this is primarily done to gain advantages that are found in a foreign country and may be difficult or even impossible to replicate. The most common example is low costs of labor, with companies in developed countries choosing to offshore in developing countries since low expected incomes in those companies translates into lower costs of production. *Reshoring* describes when a company chooses to move manufacturing back to their home country after offshoring it. *Globalization* describes the global phenomenon of companies all over the world partaking in these processes, building a global economy. This began in the 1980s, leading to the globalized world we have today. China has been at the forefront of this for a variety of factors, but this has occurred across the planet.

The COVID-19 pandemic created a crisis across the global supply network, particularly in American supply chains. The global increase in costs, port blockages, and lead times crashed the delicate web of suppliers, producers, consumers, and freight forwarders that enabled the global economy (Labelle, Sancretau). This showed some of the critical weaknesses of offshoring most global manufacturing across the Pacific Ocean to China and throughout East Asia. Another event involved the trade war between the United States of America and China. Diplomatic tensions between the two combined with intense trade partnerships have created a conflict of tariffs and regulations, with both using their economic power to gain influence and control (Banguira, Choi, Swenson, Xu). These issues created the core research problem of whether or not we as a market can find a better solution than offshoring most manufacturing to China, and potential approaches that can create a better solution.

Literature Overview

Substantial literature exists regarding inexpensive wages as a primary motivator for domestic companies to offshore manufacturing to China. Feng, Bu, and Cai portray inexpensive wages as the exclusive motivator for this offshoring, portraying population density and a developing economy as the only geographic advantage has China has over other reason (Feng, Bu, Cai). Almost every source that discussed the Chinese economy discussed this within the lens of how expensive or inexpensive Chinese labor will become in the future. This theme was almost always given as the motivator for any foreign company to offshore any function into the Chinese market. Part of this stems from the importance of cost reductions to any supply chain decision, but especially offshoring.

Another theme prevalent in literature involves heavy labor abuses and corruption found within the Chinese manufacturing system. Most labor found in export-oriented factories is migratory labor, meaning people who move from rural regions in central China to urban parts of coastal China in order to pursue gainful employment, often in manual labor. Chan and Siu point out that these workers are heavily exploited and are often disregarded in labor standards. In their study, Chan and Siu studied 11 different factories and found that on average these factories overworked their employees by almost 100 hours over legal limits, with no form of overtime whatsoever (Chan & Siu). This occurs due to a number of factors mentioned including widespread corruption, low expected wages, and the Chinese housing system treating these citizens like second-class citizens. This literature suggests that Chinese labor costs are more than just a mathematical inevitability of the Chinese labor market, but also artificially kept inexpensive through a vicious cycle of exploitation and worker's abuse.

An alternative to this single-variable cost savings approaches initially proposed by Ellram was Total Cost of Ownership (TCO). TCO is a management philosophy that tries to consider every factor of the cost of a decision beyond the purchase price of the good (or service) itself, such as product sitting at port, risks taken in a certain decision, defective goods, opportunity costs, etc. TCO takes advantage of data collection methods via advanced technology to accurately assess total cost holistically (Ellram). This is in sharp contrast from earlier literature that really only considered one cost (labor), and instead argues that more needs to be considered to get a meaningful picture. While this still analyzes decisions through the metric of costs, TCO expands how a supply chain manager views purchase price versus total cost in a decision.

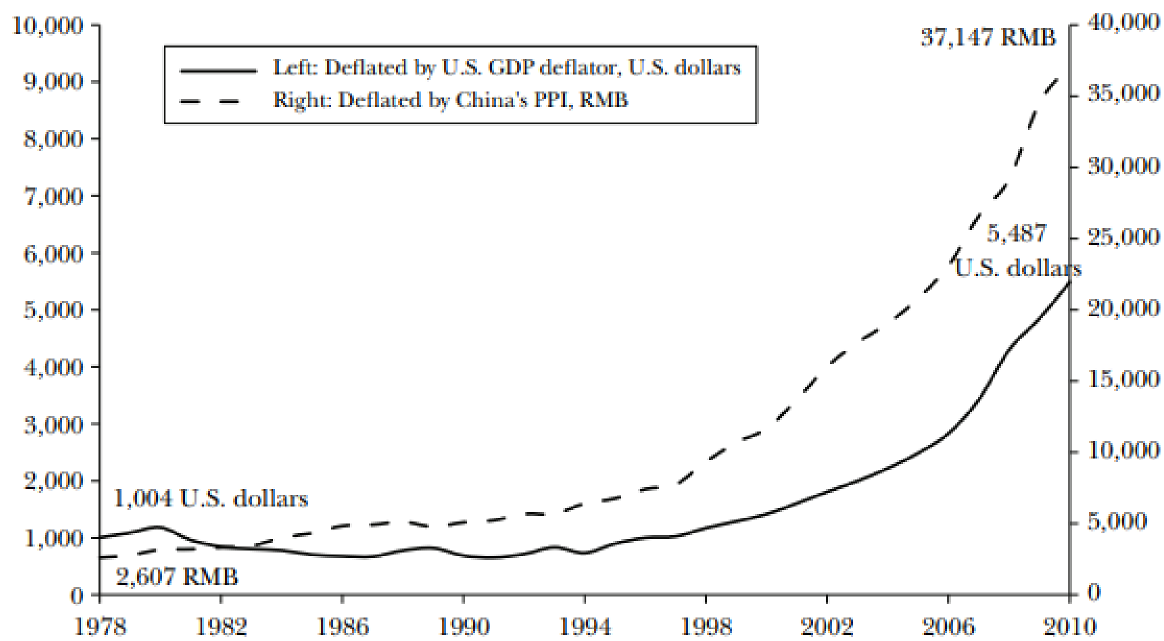
Methodology

Most empirical studies only focus on one specific problem or one factor that contributes to this broader issue of offshoring to China. This paper's primary objective is to bring together research in order to create a cohesive image and meaningful solutions to the problem stated in the introduction. Due to difficulties in translation, corruption, and censorship laws, considerable care had to be taken to find reliable Chinese sources to balance out Western sources and avoid the inherent bias of only using Western sources in a research piece about China. Almost half of these sources used for this study were Chinese in origin in order to limit this bias. This paper thus served as a case study of Chinese offshoring that has occurred in the last 40 years of western offshoring and foreign direct investment into China. To this end, various statistics and numbers from each of these studies were cross-examined to determine what all sources can collectively and meaningfully confirm as trends and numeric facts about the Chinese economy.

Results and Implications

The results of this study suggest that there is substantial evidence that points to a rising costs in the Chinese labor market, causing its infamously low prices to substantially rise. One of the first reasons given for this included the rural-to-urban demographic shifts and waves of migratory labor that defined the Chinese industrialization of past decades have slowed down as the Chinese economy has developed these interior rural areas and drained some of the population that was migrating to the more urbanized coast. The One Child Policy also limited the explosive demographic growth that once defined Chinese industrialization, slowing population increases until they began to decrease and fertility rates continually declined (Retherford, Choe, Chen, Xiru). Another reason for this decrease was found in speeds at which Chinese expected wages were increasing. As shown in the figure 1, expected wages are not increasing on a linear curve, but instead on an exponential one, only continuing to speed up as the Chinese economy develops and better and more gainful employment is more attainable for the average Chinese citizen.

Real Annual Wages of Chinese Urban Workers
(deflated to 2010 prices)



Source: China Statistical Yearbooks.
Note: PPI is producer price index.

As shown, real wages have increased fivefold since 1978 (Li and Li, Wu, Xiong, 57). This has failed to keep up proportionally with productivity, which has meant that factory owners are now paying more for the same amount of labor.

Another significant result found in this study is the noted gap in quality control between American and Chinese firms. On average, quality control in offshored manufacturing was found to be weaker than in the original firm pre-offshoring. This was found via a quantitative study comparing American manufacturing to firms doing similar work in Puerto Rico, where it was found that language differences made up a substantial challenge in controlling quality, which the researchers primarily explained by difficulties in communicating specifications. Examples of lawsuits involving firms that relied on Chinese manufacturing also recorded this phenomenon as a primary reason for the lax quality control that led to massive lawsuits (Ahsan).

Conclusion

This ongoing research will have impacts on the global economy and thus supply chain management as a field. It helps reframe how we view one of the largest and most influential members of the global economic value chain. This case study is an attempt to connect together different studies to derive a meaningful conclusion that supply chain managers can use in a modern globalized economy. This study also connects current methods of the study of supply chain management to a real application. While all of these factors have been separately researched, combining them together means that new conclusions can be reached, and more research can be done in light of this fact. This accompanies total cost of ownership which also asks for a holistic approach. By using TCO and other modern supply chain management approaches we can gain a more complete understanding of the advantages and disadvantages of offshoring, nearshoring, or reshoring. When initial decisions were made in the early days of globalization during the 1980s, supply chain management did not truly exist as a field of study (the term itself was only coined in the 1990s) so many managers did not have the ability, information, or the technology to completely analyze offshoring as a process or what that would means for their companies.

Future action will involve more research into globalization as a broader phenomenon. This research almost exclusively discusses China, since it is the largest example of an export-focused economy and best represents several major processes that can plague markets that primarily function through foreign direct investment, though more research should be done to examine how these phenomena impact other countries that will be in different contexts. It is also important to remember that the processes are still ongoing and will shift in our lifetime, so future research will inevitably be needed to see where this goes in this future. China will continue to play a central low to the global economy in the future, though this place is changing in the future.

References

Ahsan, K. (2013). Trend analysis of car recalls: evidence from the US market. International Journal of Managing Value and Supply Chains, 4(4), 1-16.

Benguria, F., Choi, J., Swenson, D. L., & Xu, M. J. (2022). Anxiety or pain? The impact of tariffs and uncertainty on Chinese firms in the trade war. Journal of International Economics, 137, 103608.

Feng, W., Gu, B., & Cai, Y. (2016). The end of China's one-child policy. Studies in family planning, 47(1), 83-86.

LaBelle, J., & Santacreu, A. M. (2022). Supply Chain Disruptions During the COVID-19 Recession. Economic Synopses, (2).

Li, Hongbin, et al. (2012). "The end of cheap Chinese labor." Journal of Economic Perspectives 26.4: 57-74.

Retherford, R. D., Choe, M. K., Chen, J., Xiru, L., & Hongyan, C. (2005). How far has fertility in China really declined?. Population and Development Review, 31(1), 57-84.

ASSESSING STUDENT ENGAGEMENT OF CAREER FAIRS AT REGIONAL UNIVERSITIES

Dr. James Kirby Easterling
College of Business
Eastern Kentucky University
521 Lancaster Avenue
Richmond, KY 40475
James.Kirby.Easterling@eku.edu
859.622.7893 (Contact Author)

Dr. Michael Fore
College of Business
Eastern Kentucky University
521 Lancaster Avenue
Richmond, KY 40475
Michael.Fore@eku.edu
859.893.1434

Dr. Kristen B. Wilson
College of Business
Eastern Kentucky University
521 Lancaster Avenue
Richmond, KY 40475
Kristen.Wilson@eku.edu
859.622.2103

Keywords: Regional Academic Institutions, Schools of Opportunity, Career Fair, Internship, Professional Development

Introduction

Regional colleges and universities (hereafter called *regional academic institutions*) primarily serve a specific geographical area and often have a different mission than research-oriented institutions (Bok, 2015). Regional academic institutions often state being a '*school of opportunity*' as part of their primary mission and tend to focus admittance decisions on who they include rather than who they exclude in providing higher education access to students who are first generation college students and/or come from low-income backgrounds (Eastern Kentucky University College of Business, 2022). Education opens doors to students and has the potential to change lives. Aside from the core functions of imparting knowledge and developing critical thinking and other key skills, regional academic institutions also have the potential (and perhaps duty and obligation) to expose college students to career opportunities, especially given many students come from families where professional networking is not common or accessible. One method of providing this type of exposure is via career fairs.

The Commonwealth of Kentucky's public higher education system includes eight (8) publicly funded ("State") universities, each with a specific service region (The Carnegie Classification of Institutions of Higher Education, n.d.). Eastern Kentucky University's service region, as example, comprises twenty-two south-eastern counties. Figure 1 shows the county-by-county service regions for each of the eight public universities.

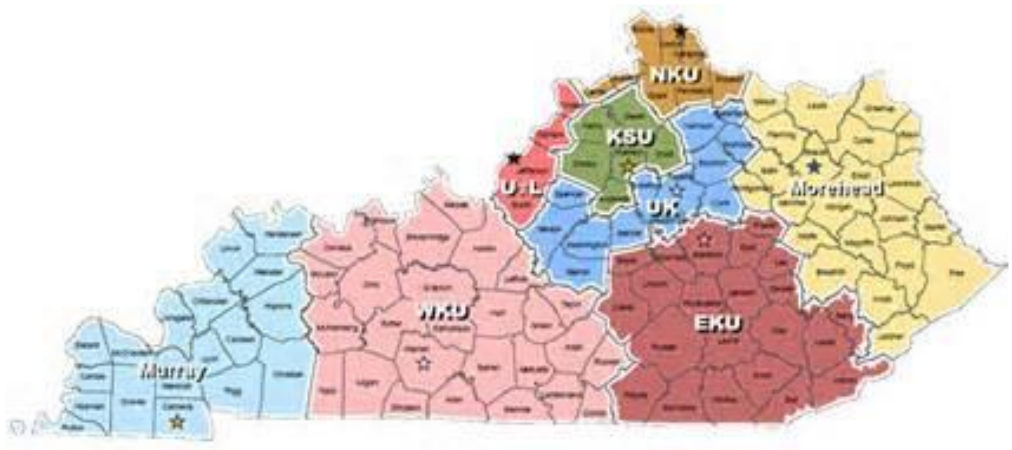


Figure 1. Service Regions for Kentucky Public Universities (KABHE, n.d.)

While perhaps no standard definition exists, career fairs provide opportunities for employers and prospective students to network in a setting that is often highly advantageous to students due to the events are often on or near campus. Career fairs provide an early educational opportunity for students to engage employers, distribute résumés, practice introducing oneself, and network with representatives from various companies and industries with low out-of-pocket expenses (i.e., minimal travel required). Career fairs may focus on parttime internships/co-ops, fulltime job opportunities for students nearing graduation, recent graduates with perhaps 2-3 years of experience, or some combination thereof. Further, practical experience allows application of classroom knowledge; for example, exhibiting effective résumé writing and interviewing skills taught in Business Communications courses. Regardless of scope, career fairs are a key element for many first-generation college students who come from families where professional networking may not exist. Many employers particularly like to recruit from regional academic institutions, given that many students have a strong work ethic due to partially or fully self-funding their education due to limited family financial support capability (National Center for Education Statistics, 2022). In sum, career fairs are an essential part of the undergraduate experience, particularly at regional academic institutions.

Career Fair Types

Career fairs vary in a number of different ways including scope and discipline focus (e.g., accounting, supply chain, etc.), among others. Three distinct categories of career fairs exist, as illustrated in Figure 2. Program specific (closed) career fairs focus on one program exclusively, whereas program specific (open) career fairs are open to all students (within a given college) with an interest in the discipline and/or exploratory students (i.e., those undecided or unsure of their major). College specific career fairs have the broadest scope of all, in that they are open to all students and all majors across a given college. As highlighted below, each career type has distinct advantages and disadvantages.

Career Fair Type	Example	Advantage	Disadvantage
Program Specific (closed)	Supply Chain Career Fair (Supply Chain Majors only)	Heightened focus on one program for students and employers	Discourages curious / exploratory students with an interest in the program
Program Specific (open)	Supply Chain Career Fair (open to all College of Business students/all majors)	Encourages curious / exploratory students with an interest in the program and/or specific employers	Employers may be seeking candidates with program-specific knowledge
College Specific	College of Business Career Fair (all College of Business majors)	Heightened opportunity for students to explore career tracks across various programs and employers	Can be inefficient for both students and employers due to scale and breadth of event

Figure 2. Career Fair Types

Study Overview

This study was conducted at an AACSB-accredited College of Business which regularly hosts a number of career fairs throughout the Fall semester. Career fairs are often organized by a faculty member(s) within a given major. This presents a significant outlay of faculty time in contacting employers, building corporate alliances, developing career fair agendas, arranging featured speakers, implementing marketing campaigns, coordinating parking and security, implementing check-in procedures, helping students prepare (e.g., résumé review, questions to ask, general coaching, etc.), collecting data from students and employers for future data analysis, and following-up with students regarding their experiences. In Fall 2023, during which the pilot survey was conducted, the College offered career fairs for Accounting, Sales and Marketing, Supply Chain, Banking and Financial Services, and Risk Management and Insurance (RMI).

Student Opinion Survey

The authors have and propose to continue to study student engagement and the role of career fairs, beginning at a regional university. This research will gain insights into student perceptions of career fairs, attempt to determine barriers to participation or success, and the role that fairs should play as part of a comprehensive education program at a regional academic institution.

To test the process, the authors initially surveyed a single, in-person section of junior year undergraduate students taking part in a professional development course. The survey instrument explored student opinions, participation, and preparedness for the career fairs offered. The subject institution requires students to complete professional development courses as part of their business curriculum. One course is required per year as part of the school's curriculum, with these classes focusing on development of soft or power skills, including integrity, communication, courtesy, responsibility, social skills, positive attitude, professionalism, flexibility, teamwork, and work ethic (Robles, 2012). Development of these skills are vital for success in any endeavor, but growth is even more essential for the first-generation and economically-disadvantaged populations. The annual professional development courses were designed in part to address this gap. Since all students are required to take the course at the same point in their education, this provides an excellent baseline population in which to study the role of career fairs. Moreover, the targeted population of juniors is in the midst of preparing for a transition from school to career.

Conducted during class on September 29, 2023, the survey produced a good response rate, with 36 of 39 students being present and completing the survey (n=36). The survey was conducted using Qualtrics.

Students were provided with a link and QR code to the instrument and completed it as the class day's closing activity.

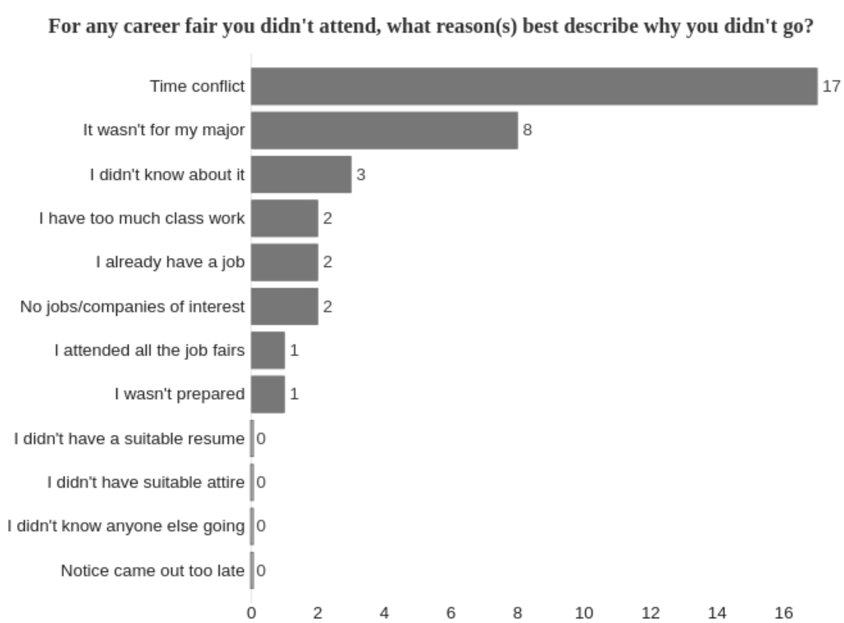
Student Background

Consistent with the population attending a regional academic institution, nearly two-thirds of respondents reported working while attending school (Q2). Consistent with their junior standing, 69.44% of respondents were "probably" or "definitely" confident in the field of work they intended to pursue. Students also provided additional background information on their major fields of study. Because the course provided the survey population, all respondents were of similar academic standing and progress, and all were undergraduate students pursuing a degree within a College of Business.

Results

Sixty-nine percent (69%) of respondents had or intended to participate in a career fair(s) while at the College that semester. Future work will cross-refence data regarding participation with student majors as well as a deeper dive into possible demographic characteristics that might drive or hamper participation. In particular, as students at regional academic institutions often work while attending school, the authors are interested in learning if working impacts participation across a larger sample. Are students with work experience more likely or less likely to recognize the importance and possible benefits of career fair participation? Or do the demands of balancing work and school hamper students from pursuing their future careers? If so, what steps can be taken to remove these barriers to participation? These will be topics for future research.

The pilot survey did seek information about reasons for student non-participation. Of all the reasons offered for nonparticipation, by far the largest reason students cited for non-participation was time conflict (47% of respondents; see Figure 3). Typically, the College in question has conducted career fairs during normal business hours, usually during a mid-day break when there are fewer courses in session. Future research will explore if this barrier exists more for working students or is a barrier for any other particular student group.



p.

Figure 3. Reasons for Not Attending Career Fairs

One potential challenge in building fair participation is student notice. However, lack of notice was only cited by three (8%) of responding students as a reason for their nonparticipation. Based on the very limited data, it appears the programs are doing an excellent job of making students aware of the career fairs (see Figure 4). Students reported that the most effective methods of providing notice were in-class and email announcements. Fewer students found posts on the college learning management system or college display monitors to be the most effective methods of letting them know about upcoming career fairs.

Please rate your evaluation of the relative effectiveness of each method of getting notice out about a career fair with 0 being not effective at all and 100 being the most effective method.

Field	Min	Max	Mean	Responses
Hearing about it from an advisor	0.00	100.00	54.53	34
Notices posted on the College of Business Monitors	1.00	100.00	66.31	35
Emails	19.00	100.00	82.11	36
Personal invitations	0.00	100.00	66.61	33
Announcements in class	46.00	100.00	85.42	36
Notices on the College of Business Blackboard web site	0.00	100.00	65.14	35
College of Business social media	0.00	100.00	64.03	34
Posts on class blackboard sites	0.00	100.00	78.31	35

Figure 4. Effectiveness of Career Fair Communication

One of the more potentially contentious issues regarding career fairs is inclusion versus targeting. Should major-centric career fairs be limited to participation of just students within those majors, our should they be open to all students within the college, regardless of major? Within the studied College, there have been very good arguments presented that some career fairs, such as those featuring accounting firms, should be limited to accounting-only students since that is the only population the employers expect to hire. However, other programs report tremendous success in cross-pollination of majors, with major corporations hiring qualified students regardless of major or students making valuable connections outside their immediate field of study.

Student opinions on the question were similarly split; see Figure 5. Fifty-four percent (54%) of students favored career fairs being open to all majors, while forty-six (46%) preferred they be limited to only the chosen field.

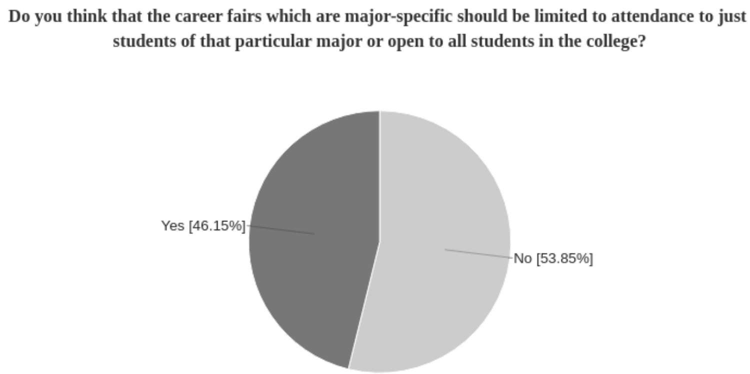


Figure 5. Targeting of Career Fairs

This is certainly a question that merits further research and discussion. Likely, the best answer to this question may vary by major, needs of employers, and student view.

Future Research

The initial pilot study is limited in size of survey base, representing only 36 respondents across a college of approximately 1,300 majors. The authors intend to follow-up on this preliminary work by conducting a similar study across all sections of the professional development courses mandated for juniors. This follow-on study is anticipated to consist of several surveys, spread over the course of an academic year, and will track student responses over the course of the fairs (before and after participation), as opposed to the initial study which was limited to a single snapshot in time.

The authors also intend to study the prevalence of cross-disciplinary employment—the phenomenon where students make a connection at a career fair outside their particular discipline that nevertheless leads to a career opportunity. This is particularly important given the debate in some fields as to whether fairs should be limited to particular majors or open to all students within the College. In addition, this work will lead the way for future studies to provide insights into how best to maximize the effectiveness of career fairs in creating full-time employment opportunities and enhancing the student experience. As such, research is necessary to focus and refine these efforts to maximize the student experience.

References

Bok, D. (2015). *Higher education in America*. Princeton University Press.

Eastern Kentucky University College of Business. (2022). *Path to excellence: College of Business strategic plan 2022-2027*. Richmond, KY.

KABHE Regions. Kentucky Association of Blacks in Higher Education. (n.d.). https://kabhe.wildapricot.org/page-1436642

National Center for Education Statistics. (2022). College student employment. *Condition of education*. U.S. Department of Education, Institute of Education Sciences. https://nces.ed.gov/programs/coe/indicator/ssa.

Robles, M. M. (2012). Executive perceptions of the top 10 soft skills needed in today's workplace. *Business Communication Quarterly*, *75*(4), 453-465.

The Carnegie Classification of Institutions of Higher Education (n.d.). *About Carnegie Classification*. Retrieved from http://carnegieclassifications.iu.edu/.

REVOLUTIONIZING BUSINESS CURRICULUM THROUGH TAILORED PROGRAMS

Dr. James Kirby Easterling
College of Business
Eastern Kentucky University
521 Lancaster Avenue
Richmond, KY 40475
James.Kirby.Easterling@eku.edu
859.622.7893 (Contact Author)

Dr. Kristen B. Wilson
College of Business
Eastern Kentucky University
521 Lancaster Avenue
Richmond, KY 40475
Kristen.Wilson@eku.edu
859.622.2103

Dr. Julia Graham
College of Business
Eastern Kentucky University
521 Lancaster Avenue
Richmond, KY 40475
Julia.Graham@eku.edu
859.622.1409

Keywords: Niche programs, program development, curriculum.

Introduction

The landscape of post-secondary business education is undergoing a transformative shift, with an increasing focus on specialized and niche programs tailored to meet evolving industry demands. This research paper delves into the revolutionary paradigm of business curriculum development, exploring the strategic implementation of tailored programs to address specific employment needs across various industries and regions. Traditionally, institutions have concentrated on disciplines like accounting, marketing, and management, but a surge in specialized programs, ranging from supply chain and banking to music business and cybersecurity, signifies a noteworthy departure from convention. This study explores the strategic considerations, challenges, and proven methodologies involved in revolutionizing business education. Additionally, the research introduces a comprehensive ten-step guide for successfully implementing specialized business programs, offering a navigational beacon for institutions seeking to bridge the gap between literature and practice.

Foundation for Research

Many post-secondary institutions offering undergraduate business programs focus on traditional disciplines such as accounting, marketing, and management. However, a recent shift has seen a rise in more specialized or niche business programs. These programs, tailored to specific industries such as supply chain, banking and financial services, professional golf management, entrepreneurship, business analytics, music business/marketing, information assurance, cyber security management, financial security and cybercrime, and corporate communication and technology, aim to address the evolving employment needs of various industries and regions. For instance, Belmont University, situated in Nashville, Tennessee, the renowned 'Country Music Capital of the World,' has successfully introduced a music business major. This major equips students with the knowledge and skills required for diverse careers within the music business, including record company operations, music publishing, artist management, publicity, concert promotion, and booking (Belmont University).

Frequently, corporations focus their recruitment efforts on academic institutions in close proximity to their corporate headquarters. As an example, Corning Incorporated, a global leader in specialty glass located near the Pennsylvania border in southwestern New York state, actively recruits from the nearby Penn State University. Similarly, Domino’s Pizza Inc., headquartered in Ann Arbor, Michigan, establishes strong recruitment ties with the University of Michigan and Michigan State University. However, given that many corporations have significant operational entities spread across various states, they often extend their recruitment initiatives to the regions where they operate, particularly if specialized programs are available. This strategic approach not only contributes to enhanced employee retention by minimizing turnover but also fosters diversity within the workforce. An illustrative example is Carhartt, which, with 13 locations in the Ohio Valley region, actively recruits students from Eastern Kentucky University's supply chain management program to support staffing needs across its global supply chain headquarters, distribution centers, manufacturing facilities, and retail outlets in the region (Eastern Kentucky University). Additionally, some corporate alliances organize key leadership meetings in collaboration with specific specialized programs hosted on college campuses, as highlighted by the Vice President of Quality at Carhartt (J. D. Long, personal communication, February 3, 2023).

In light of this knowledge, developing specialized programs can be an excellent way to meet both employment and economic needs of a region, state, or country. This can seem like a daunting task, especially for programs with little to no experience in developing tailored programs. Prior research is sparse, and the area largely focuses on the need and impact of specialized degree programs and courses (see examples in Gallager, 2012; Madhar, 2016; State Council of Higher Education for Virginia, 2006); however, little no to literature, pedagogical or otherwise, presents a model for actual development. With mounting pressures on university systems (e.g., state funding, performance-based funding, retention, job placement), offering both useful, specialized degrees that directly meet needs of employers has immense potential to address challenges. The purpose of this research project attempts to bridge the gap between literature and practice, offering a proven ten-step guide to implement such curricula.

Ten-Step Implementation

Below, the authors present an initial ten-step guide for implementing specialized business programs. It's important to recognize that certain steps, such as curriculum design, naturally occur earlier in the overall sequence, while others, like ongoing engagement with program graduates, typically unfold later. Meanwhile, some steps offer more flexibility in terms of timing. Consequently, it's crucial to understand that these steps are not intended to be strictly adhered to in a linear fashion but rather serve as directional guidelines. The fluidity in their execution allows for adaptability and ensures that the implementation process aligns with the unique needs and dynamics of the program being developed.

Step 1 – Ensure Alignment

Embarking on the initiation of a new academic program is a weighty undertaking that demands substantial and continual resources, both in terms of time and finances. Alignment is multifaceted, involving the integration of the new program with the institution's strategic plans. It also entails senior administrators, such as Deans, Chairs, departmental leaders, and program coordinators, appropriately allocating resources for the launch, both in faculty and staffing. Ultimately, alignment should extend to harmonize with the mission and vision of the academic institution across all levels.

Step 2 – Hire a Program Champion

Commencing a new academic program, irrespective of the discipline, demands commitment, perseverance, and enthusiasm. This endeavor requires dedicated time and focus, ideally facilitated by a full-time resource possessing expertise in the discipline and proficient project management skills. While the champion may traditionally emerge from an academic background, a contemporary approach involves hiring individuals with substantial industry experience, such as executives nearing retirement seeking an academic transition (Crane et al., 2009). Bringing on someone with industry insight accelerates the establishment of advisory boards and the formation of corporate alliances, leveraging pre-existing personal and professional networks for a quicker implementation process.

Step 3 – Build a Word-Class Curriculum

College educators encourage students to surpass mediocrity in their academic performance, and students should anticipate nothing less than world-class curricula. A valuable starting point is benchmarking against institutions offering similar programs. Input from industry leaders (refer to Step 6 below) is also highly beneficial in the curriculum design process. It is imperative that, irrespective of the discipline, the curriculum maintains a comprehensive and holistic approach, avoiding a narrow focus within the broader field.

Step 4 – Be Seen and Heard

Effectively narrating the narrative is a crucial aspect of introducing any new academic program. Given that more programs are often discontinued than established, considerable effort is essential in communicating with both internal and external stakeholders. Demonstrating the program's high demand and significant growth potential can garner internal support and increased resource allocation, such as additional funds for marketing. Internally, updates can be shared with boards of directors/regents, introduced in convocation meetings, discussed in campus-wide faculty forums, and featured in alumni reports. Hosting notable events enhances visibility for the program; for example, a Distinguished Speaker Series would be an excellent way to connect students with executives in a related industry. External communications may involve updates to civic organizations, such as Rotary International and Kiwanis International, offering opportunities for guest speakers.

Step 5 – Recruit Students

A significant hurdle in introducing specialized business programs lies in the lack of awareness among students about the field and its career prospects. The success or failure of program launches often hinges on effective student recruitment. Diverse recruitment strategies should be employed, beginning with engagements at local high schools, where presentations to relevant clubs can tap into existing minimal awareness of the field. Utilizing institutional social media accounts offers a cost-effective and impactful means to promote new programs. Furthermore, exploring conferences provides opportunities to address substantial audiences, particularly educators.

Step 6 – Implement an Advisory Board

Industry professionals readily offer substantial support to institutions that provide access to talent in specialized domains. Advisory board members from diverse industries, including manufacturers and service providers, contribute insights and perspectives with a focus on continuous improvement. This engagement creates significant networking opportunities among industry professionals, turning them into vocal advocates for the program. Advisory board members go beyond advocating within their companies, extending their support across external channels like suppliers and customers. Their invaluable contributions include insights into recommended curriculum changes, internship opportunities, job openings, and participation in supplier conferences and career fairs.

Step 7 – Build Alliances

Alliances refer to entities that consistently back program initiatives over time, encompassing both individual companies and professional organizations. These partnerships are frequently identified as companies actively offering internships, recruiting graduates, having senior executives serve as guest lecturers, participating in advisory boards, sponsoring internships, facilitating field trips, making program donations, and more. Achieving the status of an "employer of choice" for a specific specialized program is a prime example of a corporate alliance. Additionally, alliances may involve sustained collaboration with professional organizations.

Step 8 – Engage with Graduates

Establishing an enduring connection with graduates transitioning from entry-level to supervisory positions yields a substantial increase in internship and job prospects for current students. This trend becomes particularly evident approximately 6-7 years after the program launch, as the initial cohort of students progress through the program, graduate, and assume hiring roles. Sustaining and strengthening relationships with program graduates holds significance for various purposes, including scholarship support (both corporate and individual), field trips, and guest speaking opportunities. The impact intensifies when multiple graduates find employment with the same employer, leading to panhellenic effects—amplified sentiments arising from belonging to a shared program—as these graduates ascend into leadership positions. To effectively manage this step, compiling and managing data on graduates is key.

Step 9 – Communicate Progress

As emphasized in Step 2, Program Champions juggle various roles, one of which is that of a 'cheerleader.' Regular communication of progress is vital for new programs, with key performance indicators such as enrollment figures, internship placements, and graduation rates serving as common benchmarks. Additional metrics encompass industry visits, guest speaker engagements, average starting salaries, graduation job placement rates, and the number of on-campus special events. Periodic updates can take the form of a program newsletter, offering comprehensive insights into a variety of topics, including current student profiles, recent graduate profiles, upcoming events, new faculty hires, diversity initiatives, program modifications, marketing initiatives, and available internship opportunities.

Step 10 – Develop Upstream and Downstream Partners

Academic institutions can foster mutually beneficial collaborations rather than maintaining adversarial or competitive relationships. A case in point is Eastern Kentucky University's bachelor's degree program in supply chain management, which collaborates with various community college programs (upstream) to recruit students with associate degrees in supply chain. Simultaneously, it actively engages with the University of Kentucky (downstream), which recently introduced the state's first master's degree program in supply chain management. This collaboration results in a symbiotic relationship where multiple Eastern Kentucky University supply chain students come from the community college system, and numerous University of Kentucky master's degree supply chain students are graduates of Eastern Kentucky University's bachelor's degree program. Such partnerships facilitate increased internships, enhanced program integration, expanded student opportunities, and the sharing of faculty resources.

Conclusion

This research endeavor does not aim to encompass every conceivable step involved in initiating a specialized business program. Instead, it serves as a guiding framework—a navigational beacon, if you will—offering crucial insights for the effective implementation of programs. Furthermore, the outlined steps in this study are theoretically applicable to the establishment of academic programs across various disciplines. Whether in education, social sciences, or other fields, the proposed ten-step approach can be adapted to enhance the success of program launches. Consequently, the findings of this research possess broad applicability to academic program introductions in any discipline and at any level, be it associates, bachelor's, master's degree, and so forth. Future research will further develop this pedagogical study with a fully developed framework intended to help higher education institutions develop niche programs.

References

Belmont University, Curb College of Entertainment and Music Business. (n.d.). *Music Business, BBA*. https://www.belmont.edu/academics/majors-programs/music-business/.

Crane, B., O'Hern, B., & Lawler, P. (2009). Second career professionals: Transitioning to the faculty role. *The Journal of Faculty Development*, *23*(1), 24-29.

Eastern Kentucky University, College of Business. (n.d.). *Global Supply Chain Management*. https://www.eku.edu/business/gscm/.

Gallagher, P. (2012). Specialized degree programs rise in popularity. *Westchester County Business Journal*, *48*(5), 13.

Madhar, M. A. (2016). Business programs in logistics and supply chain management its relevance, importance and application in higher educational institutions (HEIs) in Sultanate of Oman. *Journal of Business Research*, *1*(22), 78-82.

State Council of Higher Education for Virginia. (2006). *Report on the Analysis of Education Demand in Southside Virginia and Recommendations for Action*. https://files.eric.ed.gov/fulltext/ED498150.pdf.

DO THE MATH II: BUILDING A MATH MENTALITY

Stephen Shackelford
College of Business
Eastern Kentucky University
521 Lancaster Avenue
Richmond, KY 40475
stephen.shackelford@eku.edu
859.622.4984 (Contact Author)

Dr. Julia Graham
College of Business
Eastern Kentucky University
521 Lancaster Avenue
Richmond, KY 40475
Julia.Graham@eku.edu
859.622.1409

Dr. Kristen B. Wilson
College of Business
Eastern Kentucky University
521 Lancaster Avenue
Richmond, KY 40475
Kristen.Wilson@eku.edu
859.622.2103

Keywords: Math anxiety, problem solving skills, pilot study.

Introduction

Math anxiety is acknowledged as a tangible and impactful phenomenon, posing constraints on students' capabilities and prospects for success in both advanced academic pursuits and adulthood (Shackelford & Mahaney, 2023). This proposal moves the discussion forward toward better understanding this phenomenon and completing a pilot study to gather initial data to refine the instrument for data collection in upcoming terms. While the primary emphasis of the proposed study is on undergraduate students pursuing business-related majors, the insights gleaned are likely to have broader applicability across various disciplines. Although existing research has examined students in fields such as statistics and engineering, a notable gap exists in the exploration of math anxiety within the context of business studies. This initial exploration underscores the significance of delving into this domain, highlighting its potential for yielding valuable and productive outcomes.

This research aims to employ a methodology for investigating math anxiety, exploring the potential effectiveness of quantitative problem sets in addressing this issue. The proposed approach involves examining the pre- and post-class perceptions of students enrolled in the "Problem Solving with Excel" course at a southern regional university to seek insights into the suitable methods and steps for overcoming math anxiety. A persuasive argument is put forth for an approach rooted in the adage "practice makes perfect," asserting that the most effective strategy for alleviating math anxiety involves consistent engagement in mathematical exercises. The premise is that through repeated practice, students can cultivate self-confidence, ultimately transforming mathematical skills into routine and familiar components of their academic repertoire.

Literature Overview

Math anxiety is characterized by negative feelings toward one's own ability to complete mathematical work (Ashcraft & Kirk, 2001). This "fear" limits students' ability to undertake quantitative business disciplines such as finance and accounting and many STEM disciplines (Shackelford & Mahaney, 2023; Jenifer, Levine, & Beilock, 2023).

The origins of math anxiety in college students have been traced back to math-averse parents and/or early childhood teachers (Elliott, Bachman, and Henry, 2020; Lin, et al., 2017). According to this research, if young students see adults exhibiting math-averse behaviors, they are more likely to develop those behaviors themselves.

Regardless of the origins of math anxiety in college students, the effect of this phenomenon limits students' potential for success (Shackelford & Mahaney, 2023). The above-mentioned "practice makes perfect" approach as an intervention is the focus of the current research.

Methodology

The current proposal aims to conduct a phenomenological study addressing key inquiries surrounding math anxiety; specifically, how math anxiety impacts students, contributing factors to its development, assessing the efficacy of math interventions in overcoming this anxiety, and exploring the potential reduction in math anxiety feelings. Specifically, these were studied with students enrolled in a college-level "Problem Solving with Excel" course following classroom interventions, as described below.

Leveraging the established Math Anxiety Rating Scale (MARS) survey questions, this proposal employed an adapted version in a preintervention survey to categorize students into high and low math anxiety levels (Richardson & Suinn, 1972). As such, students enrolled in the pilot study section were classified as high- or low-level anxiety and contributing factors were identified based on responses to a pre-assessment given early in the semester.

It is of note that in future data collections 'interventions' in improving math skills will be given to enrolled students through seven question sets of ten questions each. These question sets were patterned after word problems similar to those that might appear on a standardized college entrance exam such as the ACT or the SAT. Students will be asked to interpret the problems, for each problem determine what was known, and develop equations to solve for what was unknown. Afterward, a post-assessment (same questions as pre-assessment) will be given to the same students to evaluate whether math anxiety levels diminished, with a focus on discerning any differential impact on high versus low anxiety students.

This particular proposal discusses a pilot study conducted in the Fall 2023 semester to prepare for full data collection in upcoming terms. Specifically, the assessment (post, in the case of this data collection) will be used to further refine the instrument as tailored to the in-class instruction and interventions toward improving math anxiety.

Pilot Study Results

In this section, we delve into a review of the data collection process employed in our pilot study, with a specific emphasis on assessing the validity of the measurement scale utilized. The effectiveness and reliability of any study hinge significantly upon the accuracy and relevance of the data collected. As such, our examination goal is to ensure the validity of the chosen scale, providing insights into future data collections and the extent to which they align with the research objectives.

The authors employed a convenience sampling method to gauge the math preparedness and anxiety levels of students attending a regional southern United States university pursuing a Bachelor of Business Administration degree. Identical pre- and post-assessments were administered to all students enrolled in multiple sections of a "Problem Solving with Excel" course in the Fall 2023 semester (see Appendix A). The study included 58 participants, encompassing diverse majors, classifications, and other demographic characteristics within the student population.

The survey scales underwent re-coding for several items due to their reverse-scored nature. This adjustment was necessary because, when amalgamating variables into a comprehensive composite scale, it is crucial for them to be coded in the same direction. This ensures that the results are both relative and comparable to other item responses (Robert & Dennis, 2005). Specifically, nine items were subjected to re-coding to reverse their scoring, aligning the positive answer selection (Agree/Positive Expression) with a representation of 5, while the negative answer selection was represented by 1. Responses in between varied. For reference, Table 2 contains the names of the re-coded scale items.

First, exploratory factor analyses were conducted to assess the discriminant validity for the scale used in each of the pilot study. Overall, two individual items (Questions 14 and 15; see Appendix) were removed from the model due to low or cross loadings between scale items and two factors emerged. All remaining factor loadings well exceeded the recommended cutoff of 0.50 to be interpreted as significant (Hair et al. 2006). Two factors emerged, classifying the pilot study scale into questions surrounding efficacy and apprehension. For classification purposes, these factors were named Math Confidence and Math Anxiety based on the question content within. These analyses are shown in Table 1.

	Factor Loadings*	
Assessment Question	**1 Math Confidence**	**2 Math Anxiety**
1. I believe I can complete all the assignments in a math course.	0.849	
2. I believe I can do the math in a math course.	0.873	
3. I believe I can do well on a math test.	0.868	
4. I believe I can learn well in a math course.	0.889	
5. I believe I can think like a mathematician.	0.854	
6. I believe I can understand the content of a math course.	0.942	
7. I get nervous when asking questions in a math course.		0.631
8. I get nervous when I have to use math outside of school.		0.517
9. I get tense when I prepare for a math test.		0.706
10. I have been able to understand math.	0.777	
11. I have been happy in math courses.	0.691	
12. I have done well in math courses.	0.683	
13. I have enjoyed math.	0.792	
14. I worry I do not know enough math to do well in future math courses.		0.590
15. I worry I will not be able to understand math.		0.720
16. I worry that I will not be able to do well on math tests.		0.767
17. I worry I will not get a good grade in math classes.		0.776
18. Working on math homework is stressful for me.		0.747

**Minimum residual extraction method was used in combination with a Varimax rotation*

Table 1. Factor Loadings

Next, global scales for both factors were calculated using the average responses of each individual question within for remaining scale items. Cronbach alphas were calculated for each factor respectively and as a global measure for the models. These results are presented below in Table 2.

	Cronbach's α
Global Scale Reliability	**0.928**
Math Confidence *(if item dropped Cronbach alpha listed below in italics)*	**0.955**
I believe I can complete all the assignments in a math course.	*0.949*
I believe I can do the math in a math course.	*0.948*
I believe I can do well on a math test.	*0.948*
I believe I can learn well in a math course.	*0.948*
I believe I can think like a mathematician.	*0.949*
I believe I can understand the content of a math course.	*0.946*
I have been able to understand math.	*0.953*
I have been happy in math courses.	*0.956*
I have done well in math courses.	*0.955*
I have enjoyed math.	*0.951*
Math Anxiety *(if item dropped Cronbach alpha listed below in italics)*	**0.887**
I get nervous when asking questions in a math course. [a]	*0.881*
I get nervous when I have to use math outside of school. [a]	*0.889*
I get tense when I prepare for a math test. [a]	*0.875*
I worry I do not know enough math to do well in future math course. [a]	*0.884*
I worry I will not be able to understand math. [a]	*0.869*
I worry that I will not be able to do well on math tests. [a]	*0.859*
I worry I will not get a good grade in math classes. [a]	*0.860*
Working on math homework is stressful for me. [a]	*0.863*

[a] *reverse scaled item*

Table 2. Reliability Analyses

The analysis of the data collection process in our pilot study substantiates the validity of the amended measurement scale. Exploratory factor analyses revealed the emergence of two distinct factors: Math Confidence and Math Anxiety, each demonstrating high factor loadings. The calculated Cronbach alphas for both global scales and individual factors further affirm the reliability of the scale. The findings support the use of this amended pilot study scale for future data collections, offering a robust foundation for continuing research endeavors.

Conclusion & Future Research

This research initiative on building a math mentality has made significant strides in understanding and addressing math anxiety among undergraduate students, particularly those pursuing business-related majors. The proposal successfully conducted a pilot study in the Fall 2023 semester, employing a methodology focused on class perceptions of students enrolled in a "Problem Solving with Excel" course. In essence, this research provides a solid foundation for future data collections and interventions aimed at addressing math anxiety. The findings underscore the importance of refining the instrument based on the insights gained from the pilot study, paving the way for continued research endeavors to enhance students' math confidence and mitigate math anxiety across diverse academic disciplines. Future research and data collections will help map the relationship between math confidence and math anxiety and identify specific changes in these levels after classroom interventions.

References

Ashcraft, M. H., & Kirk, E. P. (2001). The relationships among working memory, math anxiety, and performance. *Journal of Experimental Psychology: General*, *130*(2), 224–237.

Elliott, L., Bachman, H. J., & Henry, D. A. (2020). Why and how parents promote math learning with their young children: A mixed-methods investigation. *Parenting: Science and Practice*, *20*(2), 108-140.

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., and Tatham, R. L. (2006) *Multivariate Data Analysis*. Pearson Prentice Hall.

Jenifer, J. B., Levine, S. C., & Beilock, S. L. (2023). Studying while anxious: Mathematics anxiety and the avoidance of solving practice problems during exam preparation in college calculus. *ZDM–Mathematics Education*, *55*(2), 359-369.

Lin, Y., Durbin, J. M., & Rancer, A. S. (2017). Perceived instructor argumentativeness, verbal aggressiveness, and classroom communication climate in relation to student state motivation and math anxiety. *Communication Education*, *66*(3), 330-349.

Richardson, F. C., & Suinn, R. M. (1972). The mathematics anxiety rating scale: Psychometric data. *Journal of Counseling Psychology*, *19*(6), 551-554.

Robert, L., & Dennis, A. (2005). Paradox of richness: A cognitive model of media choice, *Professional Communication, IEEE Transactions, 48*(1), 10-21.

Shackelford, S., & Mahaney, R. C. (2023). Do the math: Overcoming math anxiety. In *2023 Appalachian Research in Business Symposium Conference Proceedings* (Vol. 2, p. 175).

Appendix – Math Confidence Survey Instrument

Please complete this survey which will take approximately 6 minutes. Your participation is appreciated.

Dear Students:

Math Anxiety and Math Confidence levels of incoming business students greatly impact their choices of major and employment after graduation. We are studying the levels of math confidence/anxiety among College of Business students. We kindly request your participation in this research, and please feel free to respond honestly. Your contribution is greatly appreciated and will be kept anonymous. Participation in this survey will in no way influence your grade in this class, as your survey results are completely anonymous. Only the researchers will have access to the data.

Please select an answer for each statement below*:

1. I believe I can complete all the assignments in a math course.
2. I believe I can do the math in a math course.
3. I believe I can do well on a math test.
4. I believe I can learn well in a math course.
5. I believe I can think like a mathematician.
6. I believe I can understand the content of a math course.
7. I get nervous when asking questions in a math course.
8. I get nervous when I have to use math outside of school.
9. I get tense when I prepare for a math test.

10. I have been able to understand math.
11. I have been happy in math courses.
12. I have done well in math courses.
13. I have enjoyed math.
14. I have worked hard in my math courses.
15. I worry that I will have to use math in a future career.
16. I worry I do not know enough math to do well in future math courses.
17. I worry I will not be able to understand math.
18. I worry that I will not be able to do well on math tests.
19. I worry I will not get a good grade in math classes.
20. Working on math homework is stressful for me.

*Each statement was presented with a five-point Likert scale – Never, Seldom, Sometimes, Often, Usually.

Demographic Questions

21. What is your Gender?

Male
Female
Non-binary
Prefer not to say

22. How many math classes did you have in high school?

1
2
3
More than 3

23. What is the highest math class you took in high school?

Algebra
Geometry
Pre-Calculus
Trigonometry
Statistics
Calculus
Other

24. What was your average grade in high school math classes?

F
D
C
B
A

25. What was your high school GPA?
0 - 1.0
1.1 - 2.0
2.1-3.0
3.1 - 4.0
4.1 or higher

26. How many math classes have you had in college?
0
1
2
3
More than 3

27. How many more math classes do you need to take in college?
0
1
2
3
More than 3

28. What was your average grade in college math classes?
F
D
C
B
A

ADVERSE CHILDHOOD EXPERIENCES AND FINANCIAL SECURITY: GENDER AND RACIAL DIFFERENCES

Cynthia Harter
College of Business
BTC 214
Eastern Kentucky University
521 Lancaster Avenue
Richmond, KY 40475
Cynthia.Harter@eku.edu
859.622.1390

John F.R. Harter
College of Business
BTC 214
Eastern Kentucky University
521 Lancaster Avenue
Richmond, KY 40475
John.Harter@eku.edu
859.622.1773 (Contact Author)

Keywords: Adverse Childhood Experiences, race and gender, food insecurity, housing insecurity, financial wellbeing

Introduction and Literature Review

It is well known that childhood trauma can have long-lasting impacts on a person's health (summarized by ACES Too High, 2019; Asmundson and Afifi, 2020; Merrick, Ford, Port, Guinn, Chen, Klevins, … & Mercy, 2019), both physical (Vig, Paluszek, & Asmundson, 2020) and mental (Sheffler, Stanley, & Sachs-Ericsson, 2020). Childhood trauma is even linked to many causes of death (Felitti, Anda, Nordenberg, Williamson, Spitz, Edwards, Koss, & Marks, 1998). More recently, childhood trauma has also been linked with economic wellbeing (Metzler, Merrick, Klevins, Ports, & Ford, 2017). Those who have suffered trauma when young are likely to earn less later in life (Schurer, Trajkovski, & Hariharan, 2019).

Financial wellbeing is more than just income, however. The Consumer Family Protection Bureau (CFPB, 2015) proposed a more interdisciplinary approach which incorporates aspects such as psychology and health concerns into economic analyses. This new definition contains four aspects: "(having) control over day-to-day, month-to-month finances; (having)the capacity to absorb a financial shock; (being) on track to meet your financial goals; and (having) the financial freedom to make the choices that allow you to enjoy life." (CFPB, 2015, 5) This is broader than the usual economic indicators of income or wealth. Figure 1 (included in the CFPB report) groups the aspects of the CFPB.

	Present	**Future**
Security	Control over your day-to-day, month-to-month finances	Future capacity to absorb a financial shock
Freedom of Choice	Financial freedom to make choices to enjoy life	On track to meet your financial goals

Table 1. The Four Elements of Financial Wellbeing (CFPB, 2015, p. 19)

From this definition of financial wellbeing, it is apparent that food and housing security are partial indicators of overall financial wellbeing. Food and housing security are apparent in the upper-left box of Figure 1 – control over the day-to-day and month-to-month finances. Food insecurity has been studied extensively, both in the United States (Gunderson and Ziliak, 2018) and around the world (Grimaccia and Naccarato, 2019). The relationship among food insecurity, gender, and race is particularly important. Food insecurity has been found to be higher for females (Broussard, 2019). Also, non-Hispanic blacks appear to be most likely to be food insecure (Balisterri, 2016) and also tend to be downwardly mobile in food security over time (McDonough, Roy, and Roychowdhury, 2020).

Childhood trauma is linked to food and housing insecurity (Lippert and Lee, 2021). Specifically, Harter and Harter (2022) found that the second-greatest negative predictor of escaping food and housing insecurity was exposure to childhood trauma. While having a relatively high income has the greatest impact on food and housing security, "the variable with the largest negative impact on the probability of escaping food and housing insecurity is being female." (Harter and Harter, p. 838) Adding the relationship between race and financial wellbeing mentioned above, we extend that work by investigating interactions between gender and race and how the link between childhood trauma and financial wellbeing differs among those characteristics.

Childhood trauma can be measured by utilizing Adverse Childhood Experiences (ACEs). The original ACEs study was conducted by the Centers for Disease Control and Prevention and Kaiser Permanente to study health-related issues (Felitti et al., 1998). ACEs consist of a set of traumas experienced prior to the age of 18. These traumas include physical abuse or neglect, emotional abuse or neglect, sexual abuse, or various forms of family disfunction.[i] Often, an ACE score is created by simply summing the categories of ACEs a person had been exposed to in childhood regardless of the frequency of exposure. Since a child's brain cannot distinguish among the various types of toxic stress, each type is thought to have the same impact. Childhood exposure to ACEs seems to lower resilience (Kelifa, Yang, Carly, Bo, & Wang, 2021) and leads to risky behaviors (Campbell, Walker, & Egede, 2016; Dube, Felitti, Dong, Chapman, Giles, & Anda, 2003) and disease (Anda, Brown, Dube, Bremner, Felitti, & Giles, 2008).

Methodology

We utilize data from the Centers for Disease Control and Prevention's Behavioral Risk Factor Surveillance System (BRFSS). BRFSS is an annual, state-based, random-digit-dial telephone (both landline and mobile phone) survey collecting data from non-institutionalized U.S. adults regarding health conditions and risk factors. Established in 1984 with 15 states, BRFSS is now administered in all 50 states, the District of Columbia, and three U.S. territories. The three sections of the survey are a core component with questions about demographics and current health behaviors, optional modules, and state-added questions. The core component questions are required of all health departments without modification in wording, but the additional modules are optional. This is the largest continuously conducted health survey system in the world with over 400,000 interviews completed annually (CDC, 2014).

The optional modules vary by year and state. An Adverse Childhood Experience Module was adapted from the original CDC-Kaiser ACE Study and was added in 2009. It includes questions about two categories of ACEs, namely child abuse and household challenges. A Social Context Module was added in 2012 and includes questions about respondents' worries about food security and payment for housing. This can demonstrate their beliefs about their socioeconomic vulnerabilities. For the purposes of this study, we searched for years in which states chose to administer both the Social Context Module and the ACE Module. In 2012, both North Carolina and Tennessee administered both optional modules, so we restrict our analyses to these states in that year.

In 2012, the BRFSS survey results were weighted using raking procedures to adjust the sampling weights based on known population characteristics. The aggregate BRFSS combined landline and cell phone dataset was built from the landline and cell phone data submitted for 2012 and includes data for 50 states, the District of Columbia, Guam, and Puerto Rico (CDC, 2014). Because the data were built using complex sampling methods, the sample is not random, and our estimation procedures are adjusted accordingly using sampling weights provided as part of the dataset.

From Figure 1, financial security is an aspect of financial wellbeing. We use food and housing security as an indicator of financial security. Specifically, we are using the data from two questions that were asked on the 2012 BRFSS Social Context Module:

How often in the past 12 months would you say you were worried or stressed about having enough money to pay your rent/mortgage? Would you say you were worried or stressed
Always
Usually
Sometimes
Rarely
Never

How often in the past 12 months would you say you were worried or stressed about having enough money to buy nutritious meals? Would you say you were worried or stressed
Always
Usually
Sometimes
Rarely
Never

We use descriptive analyses to examine the link among financial insecurity and gender and race. We investigate two measures of financial stress. The first is a measure of housing security (HouseSecure), and the second is a measure of food security (FoodSecure). These variables are constructed from the questions above where HouseSecure equals 1 if the respondent is always stressed about having enough money to pay for housing, 2 if usually stressed, and so on, such that 5 means the respondent is never stressed (or always secure) about having enough money to pay for housing. The variable FoodSecure is constructed in the same manner using the results from the question about stress related to the purchase of nutritious meals.

Results

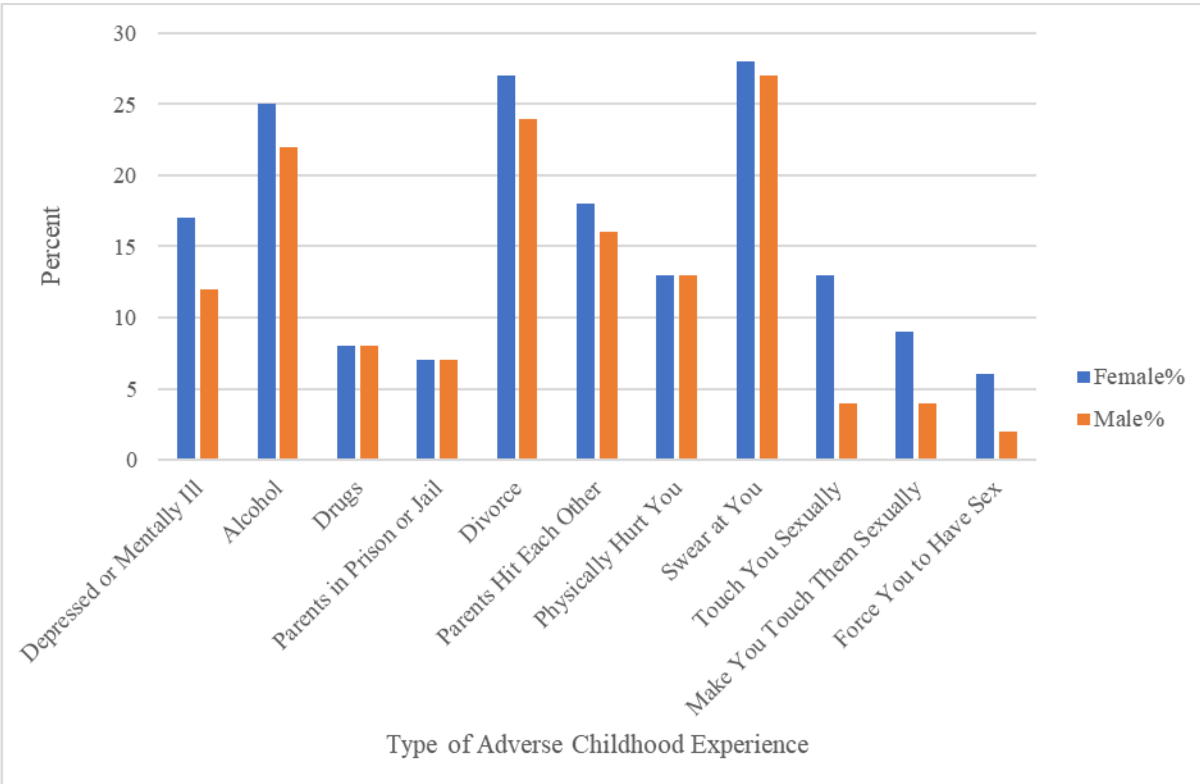


Figure 2. Percentage of Respondents by Gender Reporting ACEs by Type

Figure 2 illustrates the types of ACE included in the dataset and the percentage of respondents by gender who reported remembered occurrences of these adverse childhood experiences. There is no specific ACE where the percentage for males is higher than the percentage for females. Most striking is the difference for the last three types of ACEs, which involve inappropriate sexual activity. The percentages of females who experienced each of this type is more than double the percentage of males.

Turning to financial wellbeing in adulthood, we find differences between the genders as well. Figures 3 and 4 show that male respondents report higher levels of both housing security and food security as compared to female respondents. These results support others in the literature that show that females have lower levels of financial wellbeing (Broussard, 2019).

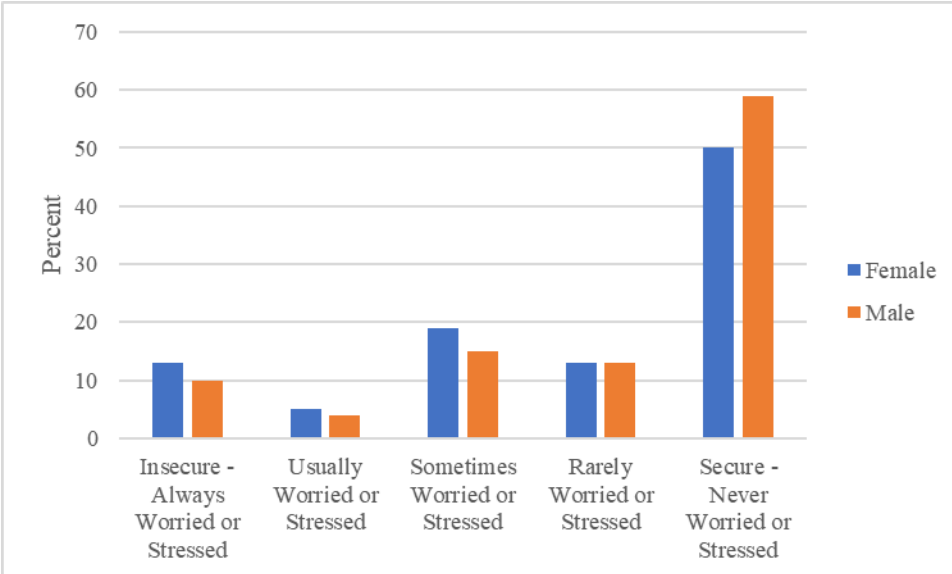


Figure 3. Levels of Housing Security by Gender

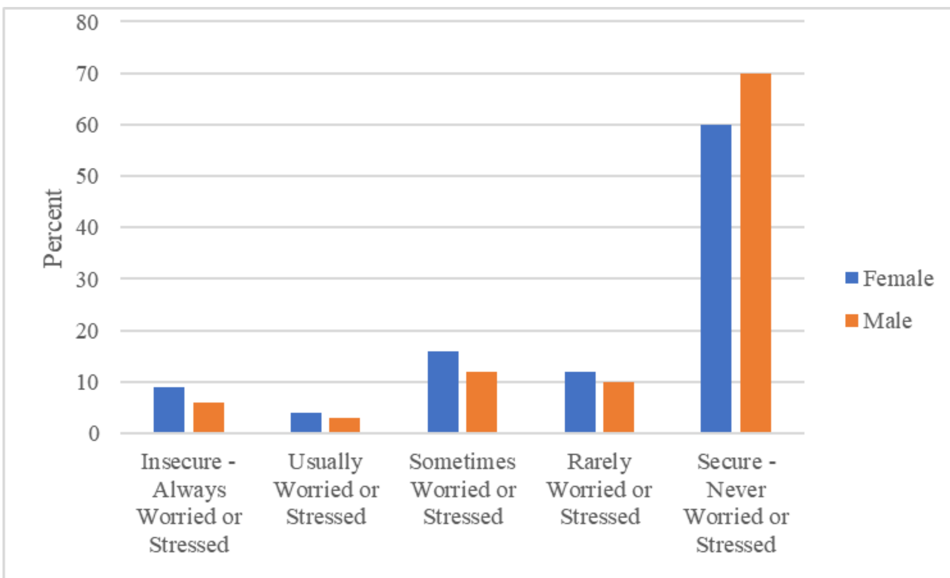


Figure 4. Levels of Food Security by Gender

To dig deeper into demographic differences, we now investigate female respondents divided by race. The survey asked which one or more of the following categories would the respondent say is their race: White, Black or African-American, Asian, Native Hawaiian or Other Pacific Islander, American Indian or Alaskan Native, and Other. We have omitted respondents who refused to answer this question, did not know or were not sure of their race, or reported that they are multi-racial, and their preferred race was not asked. Because some of the individual race categories had small numbers of responses, we are isolating our analysis to White and Non-White. Figure 5 illustrates the breakdown of types of ACEs for females by Race. The percentage for non-whites is equal to or higher for eight of the types – drugs, prison, divorce, parents hitting each other, physically hurting you, and all three of the sexual types of ACE.

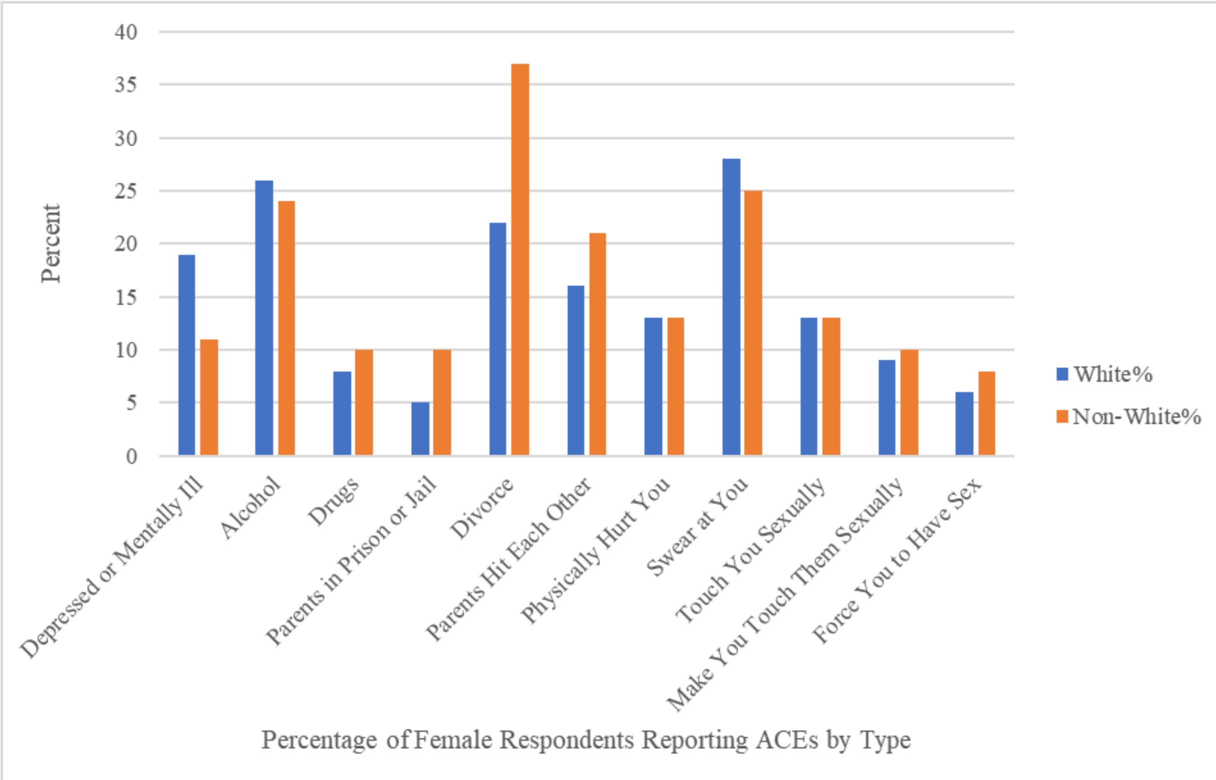


Figure 5. Percentage of Female Respondents by Race Reporting ACEs by Type

Turning to financial wellbeing of females in adulthood, we find differences by race as well. Figures 6 and 7 show that White respondents report higher levels of both housing security and food security as compared to Non-White respondents.

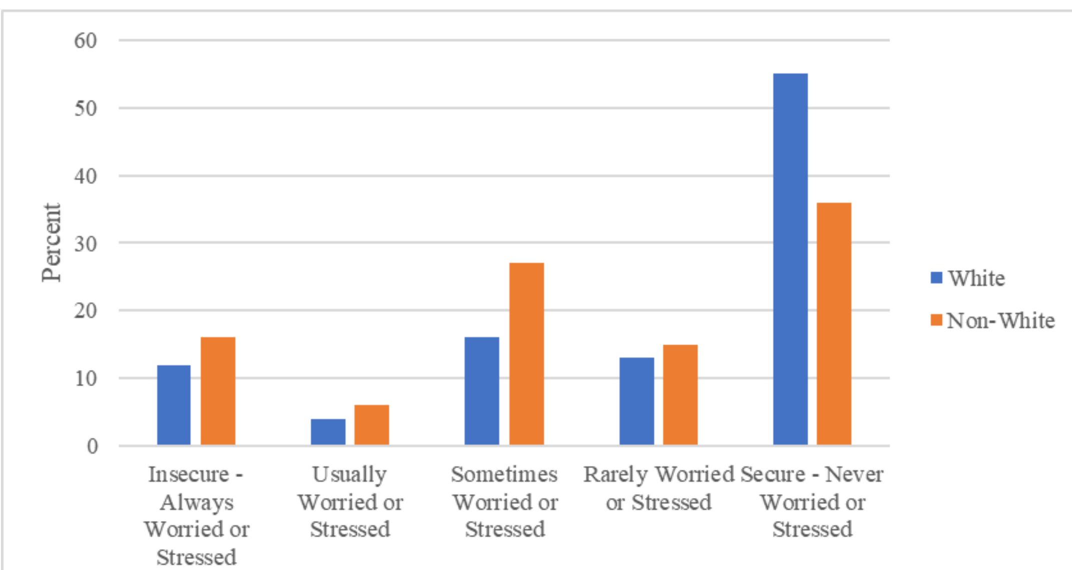


Figure 6. Levels of Housing Security for Females by Race

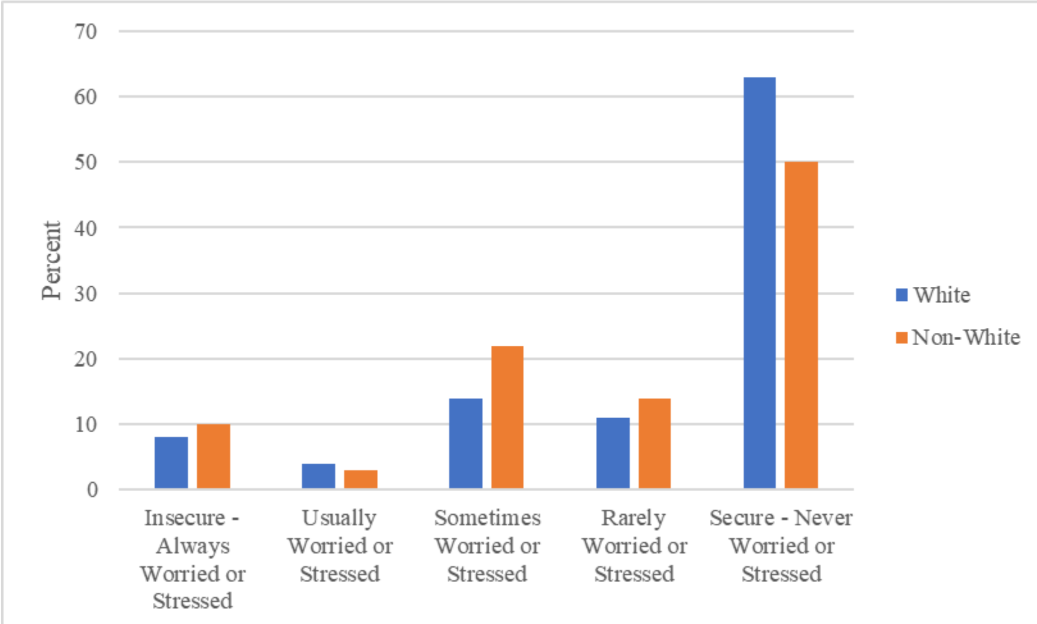


Figure 7. Levels of Food Security for Females by Race

Conclusion

Food insecurity and housing insecurity are common barriers to financial wellbeing since they inhibit a person's control over their finances. Harter and Harter (2022) found a link between Adverse Childhood Experiences and food and housing insecurity. They also found that being female was linked to food and housing insecurity. Being black has additionally been linked to food insecurity (Balisterri, 2016). This work extends to examine the interaction of these variables on wellbeing.

Being female increases the likelihood of food and housing insecurity, as does exposure to ACEs. Since females are more likely to be subjected to ACEs, that is an added barrier to financial wellbeing. This is especially true of non-White females, who are likely to experience even higher ACE scores. This combination of factors greatly increases the obstacles to financial wellbeing of non-White females.

Females, especially non-White females, face structural inequities and institutional biases in achieving financial wellbeing. In addition, these groups face higher numbers of ACEs, which has also been shown to be an impediment to financial wellbeing. This indicates that educators, therapists, social workers, and other professionals need effective strategies for preventing ACEs and building resilience. Kelifa et al. (2021) have shown that exposure to ACEs is linked with lower resilience, demonstrating an enhanced need for targeted policies to counteract the effects of childhood trauma.

References

ACES Too High. (2019). *PACEs Science 101*. https://acestoohigh.com/aces-101/

Anda, R.F., Brown, D.W., Dube, S.R., Bremner, D., Felitti, V.J., & Giles, W.H. (2008). Adverse Childhood Experiences and chronic obstructive pulmonary disease in adults. *American Journal of Preventive Medicine, 34(5)*, 396-403. https://doi.org/10.1016/j.amepre.2008.02.002

Asmundson, G.J.G, & Afifi, T.O. (Eds.). (2020). *Adverse Childhood Experiences: Using evidence to advance research, practice, policy, and prevention*. Elsevier Academic Press. https://doi.org/10.1016/c2017-0-03827-2

Balistreri, K.S. (2016) A decade of change: Measuring the extent, depth and severity of food insecurity. *Journal of Family and Economic Issues, 37(3)*, 373-382. https://doi.org/10.1007/s10834-016-9500-9

Broussard, N.H. (2019). What explains gender differences in food insecurity? *Food Policy, 83*, 180-194. https://doi.org/10.1016/j.foodpol.2019.01.003

Campbell, J.A., Walker, R.J., & Egede, L.E. (2016). Associations between Adverse Childhood Experiences, high-risk behaviors, and morbidity in adulthood. *American Journal of Preventive Medicine, 50(3)*, 344-352. https://doi.org/10.1016/j.amepre.2015.07.022.

Center for Disease Control and Prevention. (2014). *Behavior risk factor surveillance system 2012 survey data and documentation*. https://www.cdc.gov/brfss/annual_data/annual_2012.html.

Consumer Financial Protection Bureau. (2015). *Financial well-being: The goal of financial education*. https://files.consumerfinance.gov/f/201501_cfpb_report_financial-well-being.pdf

Dube, S.R., Felitti, V.J., Dong, M., Chapman, D.P., Giles, W.H., & Anda, R.F. (2003). Childhood abuse, neglect, and household dysfunction and the risk of illicit drug use: The Adverse Childhood Experiences study. *Pediatrics, 111(3)*, 564-572. https://doi.org/10.1542/peds.111.3.564

Felitti, V.J., Anda, R.F., Nordenberg, D., Williamson, D.F., Spitz, A.M., Edwards, V., Koss, M.P., & Marks, J.S. (1998). Relationship of childhood abuse and household dysfunction to many of the leading causes of death in adults: The Adverse Childhood Experiences (ACE) study. *American Journal of Preventive Medicine*, *14*(4), 245–258. https://doi.org/10.1016/s0749-3797(98)00017-8

Grimaccia, E., & Naccarato, A. (2019). Food insecurity individual experience: A comparison of economic and social characteristics of the most vulnerable in the world. *Social Indicators Research*, *143*, 391-410. https://doi.org/10.1007/s11205-018-1975-3

Gundersen, C., & Ziliak, J. P. (2018). Food insecurity research in the United States: Where we have been and where we need to go. *Applied Economic Perspectives and Policy*, *40*(1), 119-135. https://doi.org/10.1093/aepp/ppx058

Harter, C.L., & Harter, J.F.R. (2022) The link between Adverse Childhood Experiences and financial security in adulthood, *Journal of Family and Economic Issues*, *43*, 832-842. https://doi.org/10.1007/s10834-021-09796-y

Kelifa, M.O., Yang, Y., Carly, H., Bo, W., & Wang, P. (2021). How Adverse Childhood Experiences relate to subjective wellbeing in college students: The role of resilience and depression. *Journal of Happiness Studies, 22*, 2103-2123. https://doi.org/10.1007/s10902-020-00308-7

Lippert, A.M., & Lee, B.A. (2021). Adult and child food insecurity among homeless and precariously-housed families at the close of the twentieth century. *Population Research and Policy Review*, *40*, 231-253. https://doi.org/10.1007/s11113-020-09577-9

McDonough, I.K., Roy, M., & Rowchowdhury, P. (2020). Exploring the dynamics of racial food security gaps in the United States. *Review of Economics of the Household, 18(2)*, 387-412. https://doi.org/10.1007/s11150-019-09456-z

Merrick, M.T., Ford, D.C., Port, K.A., Guinn, A.S., Chen, J., Klevins, J., … & Mercy, J.A. (2019). Vital signs: Estimated proportion of adult health problems attributable to Adverse Childhood Experiences and implications for prevention – 25 States, 2015-2017. *Morbidity and Mortality Weekly Report, 68(44)*, 999-1005. https://doi.org/10.15585/mmwr.mm6844e1

Metzler, M., Merrick, M.T., Klevins, J., Ports, K.A., & Ford, D.C. (2017). Adverse Childhood Experiences and life experiences: Shifting the narrative. *Children and Youth Services Review, 72*, 141-149. https://doi.org/10.1016/j.childyouth.2016.10.021

Schurer, S., Trajkovski, K., & Hariharan, T. (2019). Understanding the mechanism through which Adverse Childhood Experiences affect lifetime economic outcomes. *Labour Economics, 61*, 101743. https://doi.org/10.1016/j.labeco.2019.06.007

Sheffler, J.L., Stanley, I., & Sachs-Ericsson, N. (2020) ACEs and mental health outcomes. In *Adverse Childhood Experiences* (pp. 47-69). Academic Press. https://doi.org/10.1016/b978-0-12-816065-7.00004-5

Vig, K.D., Paluszek, M.M., & Asmundson, G.J.G. (2020) ACEs and physical health outcomes. In *Adverse Childhood Experiences* (pp. 71-90). Academic Press. https://doi.org/10.1016/b978-0-12-816065-7.00005-7

CORPORATE LEVERAGE DURING COVID-19

Tahsin Imtiazul Huq
Eastern Kentucky University
Email: tahsin.huq@eku.edu
ORCID: 0000-0002-2326-5699

M. Kabir Hassan
University of New Orleans, USA
Email: mhassan@uno.edu
ORCID: 0000-0001-6274-3545

Dung Viet Tran
Banking University Ho Chi Minh City
Email: tranvietdung.hvnh@gmail.com
ORCID: 0000-0002-3673-9160

Keywords: Pandemic; Capital Budgeting; Corporate; Leverage

Introduction

The COVID-19 pandemic has created economic uncertainty which resulted in an unprecedented decline in credit supply to corporations by banks across the globe. Colak and Oztekin (2021) report reduction in global bank lending in countries with greater health crisis due to COVID-19. Hasan et al. (2021) finds that during pandemic, borrowing costs are higher for financially constrained firms. As a result of these unprecedented shocks to credit supply, firms are less likely to rely on debt and adopt more conservative leverage structure.

Existing literature on corporate leverage argues uncertainty increases managerial conservatism, increases the cost of external financing, and exacerbates financial constraint of firms (Panousi & Papanikolaou, 2012; Gilchrist et al., 2014; Brogaard and Detzel, 2015). Empirical evidence suggests that increase in political uncertainty drives firms to lower their leverage ratios (Pan et al. 2019). Chen et al. (2019) finds that firms with higher stock liquidity have lower excess leverage.

Limited number of studies focus on investigating the effect of COVID-19 on capital structures of firms across the globe. Haque and Varghese (2021) examines the impact of the pandemic on the capital structure of U.S. firms, and find these firms decrease their leverage significantly compared to pre-COVID periods.

It is essential to understand the change in capital structure of firms due to pandemic in order to comprehend the barriers these companies experience on the road to recovery. Therefore, this paper aims to examine the impact of COVID-19 on firm leverage ratio around the world. This paper complements Haque and Varghese (2021) by analyzing how firms manage their leverage during the health pandemic. It also extends the growing literature strand on economic uncertainty; this is among the first studies which focuses on the most recent economic uncertainty created by the pandemic and its effects on global firm leverage.

This paper is organized as follows. Section 2 describes our data sample. Section 3 discusses our main findings. In section 4, we conclude our study.

Data

We collect data on non-financial firms across the globe using Thomson Reuters database. Our policy measure data comes from Oxford COVID-19 Government Responses Tracker. To focus on the effects of pandemic on global firms' change in leverage, our sample period is from January 2020 to March 2021. We delete firms with missing variables and winsorize at 1% and 99% to mitigate any outlier effects. Table (1) reports the summary statistics and Table (2) shows the correlation between variables.

Empirical Results

We estimate the following regression to examine the impact of COVID-19 pandemic on firm leverage:

$$\mathrm{LEV_{it}} = LnCVD_{i,t-1} + \mathrm{z_{i,t-1}} + \mathrm{\pi_i} + \mathrm{\theta_t} + \mathrm{\varepsilon_i} \tag{1}$$

where, $\mathrm{LEV_{it}}$ is proxy for the total leverage of firms *i* at time *t*. We control for size, firm's growth opportunities, return on assets, capital expenditure, total accounts payable, cash, and standard deviation of firm's profit. All independent variables are lagged one period to address the endogeneity concerns. The model includes firm-, time- fixed effects.

Table 3 reports our results for baseline regressions. Column (1) shows a significantly negative relationship between leverage and the number of affected cases reported,[1] indicating that firms are reducing their total debt as the number of COVID-19 cases reported increase because they anticipate limited financial support through external sources due to the pandemic. These findings are corroborated by exiting studies. For example, Vo et al. (2022) shows that countries severely affected by COVID-19 outbreak adjust their target leverage faster than countries less severely affected by the pandemic. Additionally, we find that firms there is a reduction in cash by firms which means that these companies are using internally generated capital to reduce their outstanding debt. These results are consistent with the findings of Duong et al. (2020).

Furthermore, we want to investigate what type of debt these firms are trying to reduce. To examine this, in columns (2) and (3), we use the firms' total long-term (LT debt) and short-term debt (ST debt) as dependent variables. We find that the increase in reported cases of COVID-19 motivates firms to reduce both types of leverage. In column (4), we use excess leverage which is measured as the difference between firm leverage and the average of the industry in each country as dependent variable and find similar results. Finally, in column (5), we replace COVID-19 cases with the number of deaths from COVID-19 and our results remain consistent.

Phan et al. (2020) shows that a firm's financial constraint can influence it to lower its leverage in presence of political uncertainty. Hence, to check for this issue, we divide our sample between financially unconstrained and constrained firms following Phan et al. (2020). In Table (4), columns (1) and (2), we use the Whited-Wu index as proxy for financial constraint and find that financially constrained firms are reducing their debt more compared to non-financially constrained firms due to the pandemic[2].

Columns (3) and (4) we use firms' earnings volatility as proxies and see that firms with lower volatility reduce their leverage more compared to firms with higher volatility.

Overall, we find that firms are lowering their leverage ratio in order to survive economic uncertainty created by the pandemic.

Conclusion

This paper examines the impact of pandemic on global firm leverage from 2020-2021. The empirical findings show that firms are reducing their leverage after economic uncertainty created by the pandemic. As COVID-19 limited external funding opportunities, firms are using internal capital to reduce debt. Further analysis indicates that this effect is significant for financially constrained firms. The results are robust to

[1] In unreported tests, we include additional variables such as world policy uncertainty, standard deviation of change of profits, and obtain similar results.
[2] In unreported tests, we use size as proxy and find similar results.

different proxies. This paper provides novel insights into the way firms are rearranging their leverage structure which has important policy implications.

Reference

1. Brogaard, J., & Detzel, A. (2015). The asset-pricing implications of government economic policy uncertainty. *Management science*, *61*(1), 3-18.
2. Chen, Zilin, Kang Gao, and Weiwei Huang, 2020, Stock liquidity and excess leverage, *Finance Research Letters* 32, 101178.
3. Çolak, G., & Öztekin, Ö. (2021). The impact of COVID-19 pandemic on bank lending around the world. *Journal of Banking & Finance, 133*, 106207.
4. Duong, H. N., Nguyen, J. H., Nguyen, M., & Rhee, S. G. (2020). Navigating through economic policy uncertainty: The role of corporate cash holdings. *Journal of Corporate Finance*, *62*, 101607.
5. Gulen, H., & Ion, M. (2016). Policy uncertainty and corporate investment. *The Review of Financial Studies*, *29*(3), 523-564.
6. Hasan, I., Politsidis, P. N., & Sharma, Z. (2021). Global syndicated lending during the COVID-19 pandemic. *Journal of Banking & Finance*, *133*, 106121.
7. Haque, S. M., & Varghese, M. R. (2021). The COVID-19 Impact on Corporate Leverage and Financial Fragility. *International Monetary Fund*.
8. Pan, W. F., Wang, X., & Yang, S. (2019). Debt maturity, leverage, and political uncertainty. *The North American journal of economics and finance*, *50*, 100981.
9. Panousi, V., & Papanikolaou, D. (2012). Investment, idiosyncratic risk, and ownership. *The Journal of finance*, *67*(3), 1113-1148.
10. Phan, H. V., Nguyen, N. H., Nguyen, H. T., & Hegde, S. (2019). Policy uncertainty and firm cash holdings. *Journal of Business Research*, *95*, 71-82.
11. Tran, D., Nguyen, C., & Hoang, H. V. (2023). How do banks manage their capital during uncertainty?. *Applied Economics Letters*, *30*(2), 195-199.
12. Vo, T. A., Mazur, M., & Thai, A. (2022). The impact of COVID-19 economic crisis on the speed of adjustment toward target leverage ratio: An international analysis. *Finance Research Letters*, *45*, 102157.

Variable	Mean	Std. Dev.	Min	Max
LEV	0.313	0.195	0	0.888
CVD	13.504	2.815	4.963	17.232
SIZE	8.877	2.522	2.631	16.669
GROWTH	0.003	0.323	-1.12	1.148
ROA	-0.008	0.204	-1.24	0.404
CAPEX	0.043	0.051	0	0.409
TRADE	0.093	0.087	0	0.459
CASH	0.149	0.182	0	0.957

Table 1: Summary Statistics

Variables	LEV	CVD	SIZE	GROWTH	ROA	CAPEX	TRADE

CVD	0.01	1					
SIZE	0.195***	-0.382***	1				
GROWTH	-0.015***	0.052***	-0.028***	1			
ROA	-0.021***	-0.134***	0.338***	0.104***	1		
CAPEX	0.078***	-0.037***	-0.014***	0.036***	0.075***	1	
TRADE	-0.258***	-0.017***	-0.014***	0.018***	0.171***	-0.163***	1
CASH	-0.375***	0.131***	-0.361***	0.029***	-0.450***	-0.159***	-0.059***

Table 2: Correlations

	Baseline model	LT Debt	ST Debt	Excess leverage	CVD (Cases deaths)
	(1)	(2)	(3)	(4)	(5)
CVD	-0.003***	-0.003***	-0.000***	-0.001**	-0.002***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
SIZE	-0.002	-0.014***	0.000	-0.008	-0.003
	(0.007)	(0.005)	(0.002)	(0.007)	(0.007)
GROWTH	-0.003*	-0.001	-0.001	0.000	-0.004**
	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
ROA	-0.033***	-0.022***	-0.001	-0.021***	-0.033***
	(0.002)	(0.004)	(0.002)	(0.003)	(0.002)
CAPEX	-0.026	-0.039	0.003	-0.023	-0.018
	(0.035)	(0.031)	(0.004)	(0.019)	(0.033)
TRADE	0.028	0.012	0.000	0.010	0.038
	(0.032)	(0.025)	(0.011)	(0.033)	(0.032)
CASH	-0.090***	-0.020	-0.007	-0.061***	-0.095***
	(0.018)	(0.015)	(0.008)	(0.013)	(0.018)
Constant	0.386***	0.425***	0.020	0.093	0.374***
	(0.064)	(0.043)	(0.019)	(0.060)	(0.063)
Obs.	5,341	5,340	5,333	5,341	5,337
Adj R^2	0.043	0.018	0.006	0.012	0.038
FE	Yes	Yes	Yes	Yes	Yes

Table 3: Baseline Multivariate Regression

	WW			
	UC	FC	Low risk (Earnings volatility under median)	High risk (Earnings volatility higher than median)
	(3)	(4)	(5)	(6)
CVD	-0.002***	-0.004***	-0.005***	-0.001***
	(0.001)	(0.001)	(0.001)	(0.000)
SIZE	-0.024*	0.008	-0.021***	0.040***
	(0.012)	(0.010)	(0.003)	(0.014)
GROWTH	-0.004***	0.001	0.002	-0.008***
	(0.001)	(0.002)	(0.004)	(0.001)
ROA	-0.032***	-0.034***	-0.046***	-0.023***
	(0.002)	(0.003)	(0.003)	(0.002)
CAPEX	-0.027	-0.020	0.014	-0.038
	(0.016)	(0.055)	(0.032)	(0.051)
TRADE	-0.020	0.010	0.164***	0.068
	(0.042)	(0.037)	(0.028)	(0.047)
CASH	0.013	-0.137***	-0.065***	-0.107**
	(0.036)	(0.025)	(0.014)	(0.051)
Constant	0.621***	0.313***	0.530***	0.008
	(0.123)	(0.073)	(0.026)	(0.123)
Obs.	2,544	2,382	2,428	2,422
Adj R^2	0.053	0.053	0.075	0.025
FE	Yes	Yes	Yes	Yes

Table 4: Robustness Tests

Variables	Description	References
LEV	Total debt over lagged total assets	
Excess leverage	The difference of firm leverage at time t and the average leverage of the industry at time t	
LT Debt	Long-term debt over lagged total assets	
ST Debt	Short-term debt over lagged total assets	
CVD	Natural Logarithm of number of covid infected cases	
CVD (Cases deaths)	Natural Logarithm of number of covid death cases	
SIZE	Ln (Total assets)	
GROWTH	Growth rate of total assets over quarter	
ROA	EBIT over lagged total assets	
CAPEX	Capital expenditure over total assets	
TRADE	Total accounts payable over lagged total assets	
CASH	Cash and short-term investments over lagged total assets	
SD_DPROFIT	The within-quarter cross-sectional standard deviation of firm-level profit growth (quarter-on-quarter change in net profit divided by average sales.)	Gulen et al. 2016 RFS
UC_WW	WW index = −0.091*CF − 0.062*DIVPOS + 0.021*TLTD − 0.044*LNTA + 0.102*ISG −0.035*SG, where CF is the ratio of cash flow to the book value of assets; DIVPOS is a dummy variable that equals to one if the firm pays cash dividends in a given year, and zero otherwise; TLTD is the ratio of the long-term debt to the book value of assets; LNTA is the natural log transformation of the book value of assets; ISG is the firm's three-digit SIC industry sales growth; and SG is the firm's sales growth.	Phan et al. 2019 JBR
FC_WW	WW index = −0.091*CF − 0.062*DIVPOS + 0.021*TLTD − 0.044*LNTA + 0.102*ISG −0.035*SG, where CF is the ratio of cash flow to the book value of assets; DIVPOS is a dummy variable that equals to one if the firm pays cash dividends in a given year, and zero otherwise; TLTD is the ratio of the long-term debt to the book value of assets; LNTA is the natural log transformation of the book value of assets; ISG is the firm's three-digit SIC industry sales growth; and SG is the firm's sales growth.	Phan et al. 2019 JBR

Table A1: Variables Definitions

COMPARATIVE ANALYSIS OF LEARNING OUTCOMES IN ONLINE VS. FACE-TO-FACE COMPUTING COURSES AT A FOUR-YEAR UNIVERSITY

Ghaith Husari
Department of Computing
College of Business and Technology
East Tennessee State University
227 Sam-Wilson Hall | PO Box 70686
Johnson City, TN 37614
husari@etsu.edu

Brian T. Bennett
Department of Computing
College of Business and Technology
East Tennessee State University
227 Sam-Wilson Hall | PO Box 70686
Johnson City, TN 37614
bennetbt@etsu.edu

Chelsie M. Dubay
Department of Computing
College of Business and Technology
East Tennessee State University
227 Sam-Wilson Hall | PO Box 70686
Johnson City, TN 37614
dubayc@etsu.edu

Keywords: Student Performance, Online Learning, Face-to-face, Graduate, Undergraduate.

Introduction

Online education at the undergraduate and graduate levels has been growing at a dramatic rate at colleges and universities (St-Hilaire et al., 2021). According to Allen and Seaman (Allen & Seaman, 2011) more than 6.7 million students across 2,800 universities are enrolled in at least one online class. While many universities resisted full online education in the past, the COVID-19 pandemic required an urgent shift from face-to-face to online education. This shift caused institutions to quickly investigate and adopt strategies and technologies to support online teaching and learning.

Now that institutions have gone (or are still going) back to the ‘norm’, the online (or asynchronous) learning experience showed that such teaching modality provides an excellent opportunity to seek online degrees. The online modality is convenient to many students due to its flexibility to fit into the schedules of busy students--especially, graduate students and non-traditional students who might have full-time jobs or obligations that make face-to-face learning inconvenient (Schmidt, 2012).

The steep shift of teaching modalities from face-to-face to online due to the COVID-19 pandemic prompted a very important question. How effective is online teaching and learning when compared to the face-to-face teaching modality? Some degrees pose a significant challenge to adopt online learning modalities (Brazina et al., 2014; Verhoeven et al., 2011). Degrees that involve clinical lab work and require using expensive machines or hardware for the learning process might be very hard (if not impossible) to change to online education. Other degrees that involve software teaching activities, such as computer coding, can be done remotely and are facilitated as simply as creating an account on a remote server to write and execute computer code and submit the required deliverables (findings).

For these reasons, most of the existing research has arrived at different conclusions comparing face-to-face to online teaching modalities and learning experiences (St-Hilaire et al., 2021; Adedoyin et al, 2023). However, various research works agree that quantitative courses such Data Analytics need more research to investigate the difference between face-to-face and online modalities (Brazina et al., 2014; Schmidt, 2012). For this reason, in this work, we conduct and present a comparative analysis for the course Data Analytics for the undergraduate and graduate levels, delivered in a face-to-face modality and in an online modality. In this analysis, we investigate the influence of the teaching modality on the student's ability to absorb the concepts and achieve the learning outcomes compared to the face-to-face modality.

The aim of this paper is to quantitively compare and contrast the learning outcomes of the Data Analytics class provided via two popular teaching modalities (face-to-face and online). This quantitative investigation also incorporated a comparative analysis between the four-year undergraduate and the graduate students. We used the course final grade to assess the achieved student learning outcomes for 229 students.

The Data Analytics class offers 3 credit hours for both sections (online and face-to-face). They are both higher level analytics courses that focus on data cleaning, descriptive analytics, predictive analytics, and machine learning model evaluation. This course is designed to teach students how to use data to answer business questions and derive insights and business wisdom in a systematic manner. The assignments in this class included weekly (approximately 14) knowledge quizzes, practical labs, written assignments, a midterm and a final test.

To minimize confounding variables, both sections, over three years, posted assignments and tests that were available to take online with the same deadlines. The face-to-face section included active learning strategies such as "learn by doing" and the professor answered students' questions in class. The online asynchronous section included videos that were specifically recorded and edited for the online modality. Office hours were offered both on the ground and online.

Analytical Approach and Findings

The objective of this approach is to compare student learning outcomes (assessed by final grades) induced by face-to-face and online (asynchronous) teaching modalities for an "Introduction to Data Analytics" course. The analysis of this research was conducted on a dataset of 229 students from a four-year public university in the U.S. from 2020 to 2022. The assignments and exams were identical, and students registered online or face-to-face based on preference. The only exception is in one semester of this study, the second part of the course for the face-to-face section had to continue online as most universities in the U.S. closed its physical campus due to COVID-19 restrictions.

The size of the data analytics class ranged from 33 to 61 students. The average number of undergraduate students over the three-year period of this study was approximately 34 students per section. Where the average number of graduate students was 11 students per section. The total number of undergraduate students was 173 students, and the number of graduate students was 56 students.

Research Question 1: Is there a statistically significant difference between the teaching modality and the final grade?

To investigate if the teaching modality (online or face-to-face) has an impact on the final grade, we conducted an independent samples t-test between online and face-to-face (F2F) students. Figure 1 shows the distributions of final grades for the two groups of the different teaching modalities.

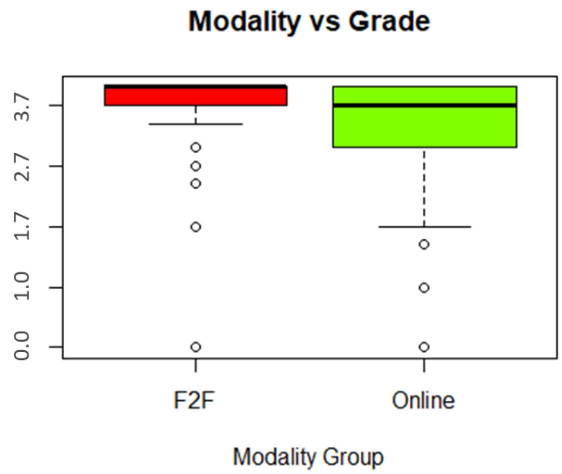


Figure 1: The Distribution of Student Final grades in Each Teaching Modality: Face-to-face (F2F) and Online

In this t-test, the test variable was the mean of the final grades, and the grouping variable was the teaching modality. The test showed that there a statistical significance (p-value <0.05) between the average final grade of face-to-face students from their online counterparts. This initial analysis showed that face-to-face students performed better on average than online students. However, these two groups contained two sub-groups within them, these were the graduate student's group and the undergraduate students. This test indicates that more analysis is needed on these sub-groups to understand the relationship between the final grades and the teaching modality.
To this end, we conducted a t-test of independent samples to investigate if there is a significant difference between the final grades of graduate and undergraduate student groups. Figure 2 shows the distributions of final grades for the two groups of students (Graduate and Undergraduate).

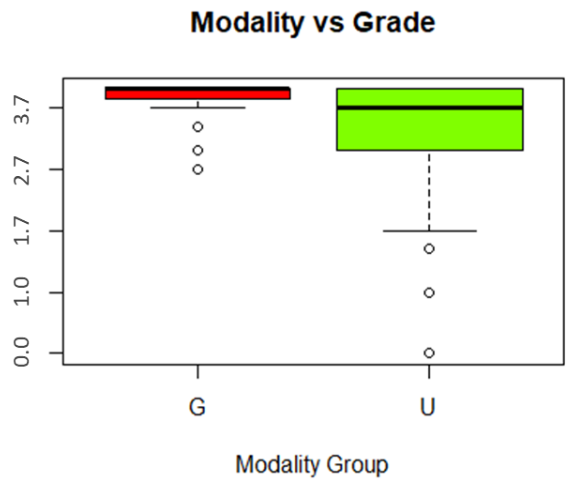


Figure 2: The Distribution of Student Final grades in Each Student Group (G = Graduate and U = Undergraduate)

This t-test revealed that there is a significant difference between the final grades of graduate students and undergraduate students (p-value <0.05). The results of this t-test showed that the statistically significant difference of the first analysis (online vs. face-to-face) might be caused by a confounding variable of graduate and undergraduate students.
For this reason, we split our dataset of 229 students into two separate sets of 173 undergraduate students and 56 graduate students. Then, we conducted two independent samples t-tests: (1) a t-test that included only graduate students' final grades and the two teaching modalities (online and face-to-face), and (2) a t-test for undergraduate students' final grades and the two teaching modalities.

The t-test for the graduate student dataset showed a statistically significant difference between online and face-to-face (p-value <0.05) which indicates that graduate students who attended face-to-face achieved consistently higher final grades than students who attended online. We believe this could be due to various reasons which will be addressed later in the discussion section of this paper.

On the contrary, the t-test for undergraduate student dataset of 173 subjects was not significant (p-value > 0.05). The results of this t-test indicated that undergraduate students who attended face-to-face on average achieved about the same final grade as their online counterparts. This result was surprising because face-to-face students attended classes and labs and actively participated and asked questions on how to resolve coding issues or how to interpret the generated analytics, an opportunity that is not readily available for online students who used emails and discussion forums for their questions. This finding led to another research question regarding the change (decline or increase) of student performance over time. The next part discusses this question in detail.

Research Question 2: Is there an impact for participating in online education over time (online fatigue)?

To investigate if enrolling in online classes over longer period (over 2 years) has an impact on the final grade, we conducted an independent samples t-test between online and face-to-face students for only the last academic year (semester 4 and 5) of 66 undergraduate student. Figure 3 shows the distributions of final grades for the two groups of the different teaching modalities.

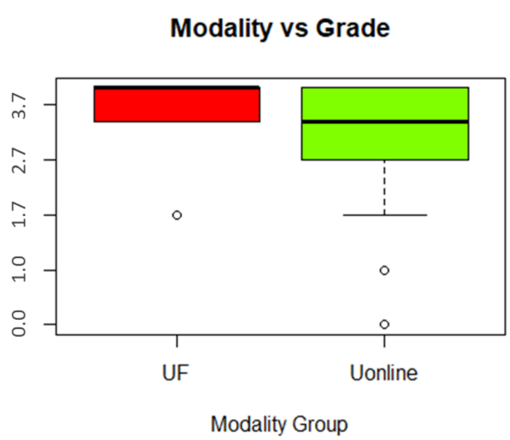


Figure 3: The Distribution of Student Final grades in Each Teaching Modality Group (UF = Undergraduate Face-to-face, Uonline = Undergraduate Online)

The t-test for the undergraduate student dataset of the latest two semesters (66 students) showed a statistically significant difference between online and face-to-face (p-value <0.05) which indicates that undergraduate students who attend face-to-face achieved mostly higher final grades than students who attended online. To illustrate the impact of online education over extended periods of time on students, we compiled the average final grades for every semester in the three years of this study. Figure 4 depicts the average final grades of four groups:

1. Undergraduate face-to-face students (UF)
2. Undergraduate online students (UO)
3. Graduate face-to-face students (GF)
4. Graduate online students (GO)

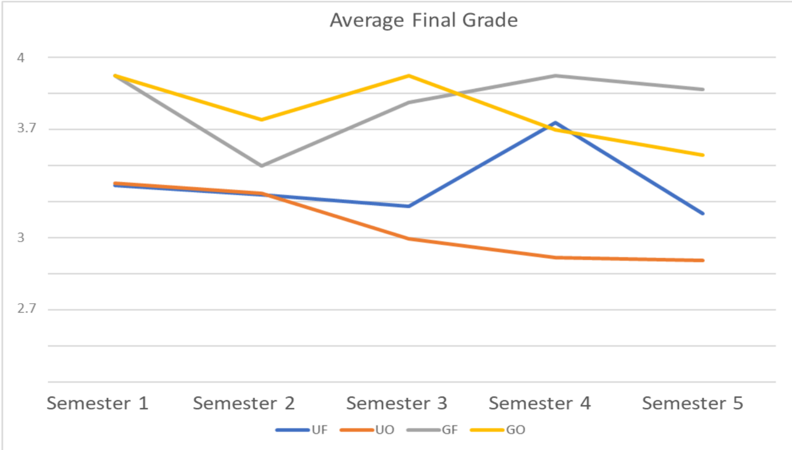


Figure 4: The Average Final Grade Over 5 Semesters for Undergraduate Face-to-face (UF), Undergraduate Online (UO), Graduate Face-to-face (GF), and Graduate Online (GO)

As illustrated by Figure 4, the undergraduate online students (UO) is the only group that continues to decline over time. This is evidenced by the significant difference between the average scores of Semesters 4 and 5 and Semesters 1 and 2. We can see that for the undergraduate students (Semesters 1 and 2) the online and face-to-face sections averaged about the same final grades. However, after Semester 3, the undergraduate online students started to average less final grade scores from the face-to-face sections and from the undergraduate online sections in semesters 1 and 2.

The reason behind the decline in the final scores for online undergraduate students can be attributed to various reasons. We believe online fatigue may serve as a primary explanation for this trend and be one of the main reasons that explain this trend. Another possible explanation for this decline is that the negative impact of COVID-19 (e.g., financial, personal, etc.) started to show more with the passage of time.

There are multiple factors contributing to the decrease in the overall scores of online undergraduate students. We believe that online fatigue may serve as a primary explanation for this trend as shown by other studies (Labrague & Ballad, 2021).

Conclusion

This study is one of few that focus on a comparative analysis of online and face-to-face course delivery in Data Analytics where all the course deliverables are online including the quizzes and exams. This aspect is important to mitigate the confounding variables that may affect the learning process in one of the teaching modalities. The data shows statistically significant evidence that students in the face-to-face teaching modality achieve higher grades than students in the online modality on the graduate (Master's) level. Conversely, students at the undergraduate level did not show a statistically significant difference in final grades in both teaching modalities, face-to-face and online.

Further analysis of the data over time showed that there is a decline in the final grades of undergraduate online students. After conducting further analysis, the tests showed evidence that undergraduate students achieve lower grades when they continue to enroll in online classes for several semesters.

One potential direction of this work is to collect more information about the study environment of online students. This could be a significant factor influencing their academic performance as on-campus students have access to quiet, well-equipped study spaces and the university library where online students may not have a similar access. Collecting such data can lead to a more in-depth analysis that could offer insights for enhancing online education in the future.

References

St-Hilaire, F., Burns, N., Belfer, R., Shayan, M., Smofsky, A., Vu, D. D., ... & Kochmar, E. (2021, June). A Comparative Study of Learning Outcomes for Online Learning Platforms. In International Conference on Artificial Intelligence in Education (pp. 331-337). Cham: Springer International Publishing

Faidley, J. K. (2021, March). A comparison of learning outcomes from online and face-to-face accounting courses at a four-year university. In ARBS 2021 Proceedings 8th Annual Conference Held Virtually on March 26, 2021 Hosted by Eastern Kentucky University Richmond, KY (Vol. 2, p. 44)

Adedoyin, O. B., & Soykan, E. (2023). Covid-19 pandemic and online learning: the challenges and opportunities. Interactive learning environments, 31(2), 863-875

Albacete, P., Jordan, P., Katz, S., Chounta, I.A., McLaren, B.M.: The Impact of Student Model Updates on Contingent Scaffolding in a Natural-Language Tutoring System. In: International Conference on artificial Intelligence in Education, pp. 37{47. Springer (2019)

Allen, I. E., & Seaman, J. (2011). Going the distance: Online education in the United States 2011. Babson Survey Research Group, Babson College. Retrieved on June 7, 2023 from https://eric.ed.gov/?id=ED529948

Schmidt, S. (2012). The rush to online: Comparing students' learning outcomes in online and face-to-face accounting courses. (Doctoral dissertation). Retrieved on June 7, 2023 from http://search.proquest.com/docview/1039150240

Brazina, P. R., & Ugras, J. Y. (2014). Growth and changes in online education. Pennsylvania CPA Journal, 85(3), 34-38. Retrieved on June 7, 2023 from http://onlinedigeditions.com/ publication /?i=224615&article_id=1807358&view=articleBrowser

Verhoeven, P., & Wakeling, V. (2011). Student performance in a quantitative methods course under online and face-to-face delivery. American Journal of Business Education, 4(11), 61-66. Retrieved on June 7, 2023 from https://login.iris.etsu.edu:3443/login?url =http://search.proquest.com.iris.etsu.edu:2048/docview/1697501263?accountid=10771

Labrague, L. J., & Ballad, C. A. (2021). Lockdown fatigue among college students during the COVID-19 pandemic: Predictive role of personal resilience, coping behaviors, and health. Perspectives in psychiatric care.

THE OPTION TO TRUST: MODELING CONTINGENT HIRING DECISIONS AS REAL OPTIONS

Zachary A. Collier
Department of Management
Davis College of Business and Economics
Radford University
701 Tyler Avenue
Radford, VA 24142
zcollier@radford.edu (Contact Author)

Molly M. Sloan
Department of Management
Davis College of Business and Economics
Radford University
701 Tyler Avenue
Radford, VA 24142
mminnen@radford.edu

Keywords: Trust, options, flexibility, hiring.

Introduction

Management researchers have long evaluated the antecedents and consequences of trust in the workplace (e.g., Dirks, 1999; Celani et al., 2008). Classical definitions of trust highlight the relationship between trust and risk. For example, Mayer et al. (1995) defined trust as “the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party” (p. 712). Trust involves risk because the trustee may not live up to the expectations of the trustor (Gambetta, 2000) due to opportunistic behavior or because the trustee lacks competence in performing the expected action (Inkpen & Currall, 2004).

The decision whether to trust has been modeled using tools from decision analysis, where trust is described as a subjective probability assessment that the trustee will perform a particular action in alignment with the expectations of the trustor (Gambetta, 2000). The trustor can either place trust in the trustee or walk away from the relationship. If the trustor chooses to place trust in the trustee, there is uncertainty about whether the trustee will cooperate or not (Huang & Fox, 2005; Collier et al., 2022a,b). The uncertainty about the trustworthiness of the trustee is resolved only after the trustor makes the decision to trust, opening the trustor up to potential risk.

A second perspective by which we can view trust decisions is through options pricing theory. Copeland and Antikarov (2003) defined a real option as “the right, but not the obligation, to take an action (e.g., deferring, expanding, contracting, or abandoning) at a predetermined cost called the exercise price, for a predetermined period of time – the life of the option.” The theory of real options extends the idea from finance to other settings where one can gain value from building flexibility into the decision. In this paper, we apply the notion of optionality to trust decisions related to hiring, where the hiring firm has uncertainty about the future performance of the potential employee.

Job recruitment and selection can be thought of as a process in which the hiring firm decides whether to place trust in the candidate (Klotz et al., 2013). According to the Society for Human Resource Management (SHRM), the average cost to hire an employee is $4,129, and on average it takes 42 days to fill a position (SHRM, 2016). Delays in hiring that leave vacant positions unfilled are related to decreases in organizational performance and increases in turnover among current employees (Papay & Kraft, 2016). It can also be costly to hire the wrong employee as firing costs average around 21.4% of the employee's salary (Boushey & Glynn, 2012) and the organization must again incur the costs of hiring a replacement. To stimulate hiring, some nations promote employment trial periods (Chappell & Sin, 2016), allowing employers to assess the employee's skills in the job during a period with reduced hurdles for dismissal (Volosevici, 2021; Chappell & Sin, 2016).

Such employment trial periods can be framed as real options, in which the hiring company has a right, but not an obligation, to extend the employment contract with the employee at the end of the trial period. Such arrangements allow firms to limit risk by granting them the option to defer the hiring of permanent employees and the option to abandon temporary workers (Foote & Folta, 2002). While several authors have identified the optionality embedded in the use of contingent hiring practices (Byrne & Pecchenino, 2019; Bhattacharya & Wright, 2004; Foot & Folta, 2002), they did no attempt to quantify the value of the flexibility afforded by the option.

Methodology

Suppose a trustor (i.e., employer) at time t_0 has the option to enter into a trust relationship with a trustee (i.e., job candidate). The trustee will cooperate (i.e., demonstrate acceptable job performance) with probability p and betray (i.e., demonstrate unacceptable job performance) with probability $(1-p)$, and each of these states of nature are associated with monetary payoffs. If at t_1 the trustee is judged to be trustworthy, the trustor can enter into a trust relationship (i.e., hire the job candidate). However, if at t_1 the trustor does not find the trustee to be trustworthy, the trustor can let the option expire as worthless (i.e., not hire the job candidate).

Extending the Cox, Ross, Rubenstein (CRR) option pricing model (Cox et al., 1979) which is based on binomial trees, Figure 1 shows the values of the underlying asset (in this case, the trust relationship) and the value of the option on that asset. Following the CRR model, the value of the underlying asset at time t_0 is S_0, S_u is the value after an up jump at t_1, and S_d is the value after a down jump at t_1. Similarly, C_0, C_u, and C_d represent the value of a call option at time t_0, after an up jump, and after a down jump, respectively.

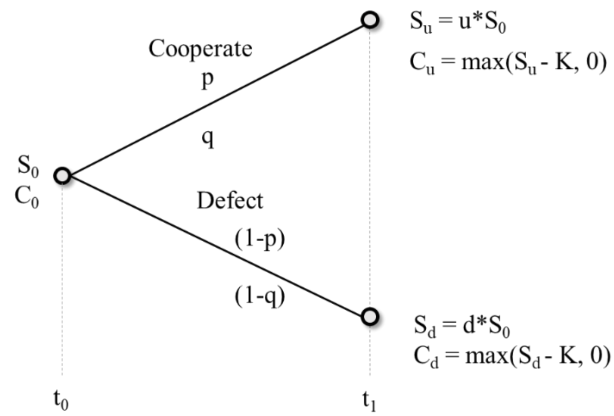


Figure 1. The Option to Trust as a One-Step Binomial Tree

Typically for financial assets, the value of S_0 is known and the magnitude of an up or down jump can be estimated based on the volatility of the asset. However, for our case, we cannot estimate the volatility of the trustee, so instead we estimate the final payoffs S_u and S_d, and then we can naively estimate the value at S_0 as the probability-weighted average of the payoffs S_u and S_d, given an a priori assessment of the probability, *p*, that the employee will cooperate. We can use S_u, S_d, and S_0 to derive the magnitudes of an up and down jump, *u* and *d*, respectively. Thus, the magnitude of an up jump, *u*, would simply be equal to S_u/S_0.

Following the CRR model, the value of a call option at the up node is $C_u = \max(S_u - K, 0)$ and the value of a call option at the down node as $C_d = \max(S_d - K, 0)$, where *K* is the exercise, or strike, price. The strike price can be conceptualized in this case as the price of waiting and gathering additional information over the trial period.

We then use the values of C_u and C_d to calculate the value of the option for the trustor, discounted back to time t_0. Following a risk-neutral pricing approach (Copeland & Antikarov, 2003), we define the risk-neutral probability *q* of an up jump as:

$$q = \frac{e^{rt} - d}{u - d} \tag{1}$$

where *r* is the risk-free rate and *t* is the time. The value of the call option at t_0 is then:

$$C_0 = [qC_u + (1 - q)C_d]/e^{rt} \tag{2}$$

Example: Trial Periods in Hiring

In this example, assume an employee has applied for a role making \$75,000 annually, and the hiring decision will be made after a 3-month trial period (*t*=0.25). The strike price, *K*, is equal to three months of the employee's salary, i.e., \$18,750. If the employee turns out to be a good (trustworthy) employee, the annual revenue generated by the employee is estimated as \$139,000, based on data quoted by Bryan and Zanini (2005). Adjusting the annual revenue from 2005 to 2023 dollars using a Consumer Price Index factor of 1.5688 (U.S. Bureau of Labor Statistics, 2023), we obtain an annual revenue of \$218,063.10. At the 3-month mark, the firm will have accrued a fourth of the annual revenue, therefore we let S_u=\$54,515.77. If the employee is bad (untrustworthy), the employee will be terminated after the 3-month trial period. We estimate firing costs of S_d=\$16,050, based on 21.4% of an employee's salary to fire and replace an employee (Boushey & Glynn, 2012). Finally, assume a risk-free rate, *r*, of 4.5%, with continuous compounding.

Let the employer's initial estimate of the probability that the employee will be good be *p*=0.5. The resulting option valuation is shown in Figure 2. The value of the flexibility afforded by the option during the trial period is equal to the expected value of the employment arrangement with the flexibility minus the expected value of the employment arrangement without the flexibility (Copeland & Antikarov, 2003), and is equivalent to the expected value of perfect information (Herath & Park, 2001). The expected value of the decision without the flexibility (Figure 3) is $[\max([p(S_u - K) + (1-p)(S_d - K)], 0)]/e^{rt}$.

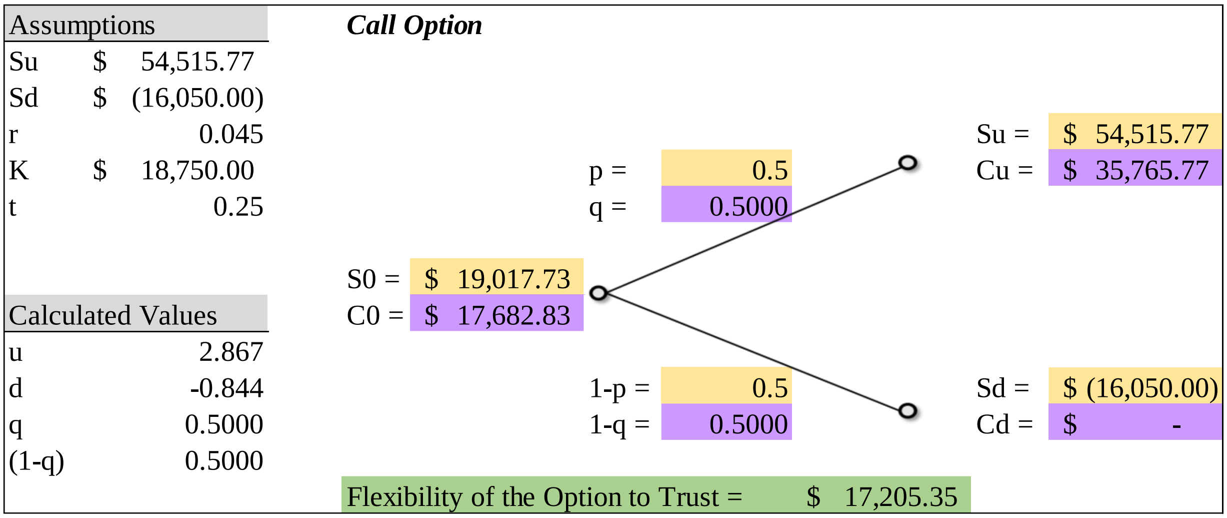


Figure 2. Real Option Valuation of Trial Hiring Period

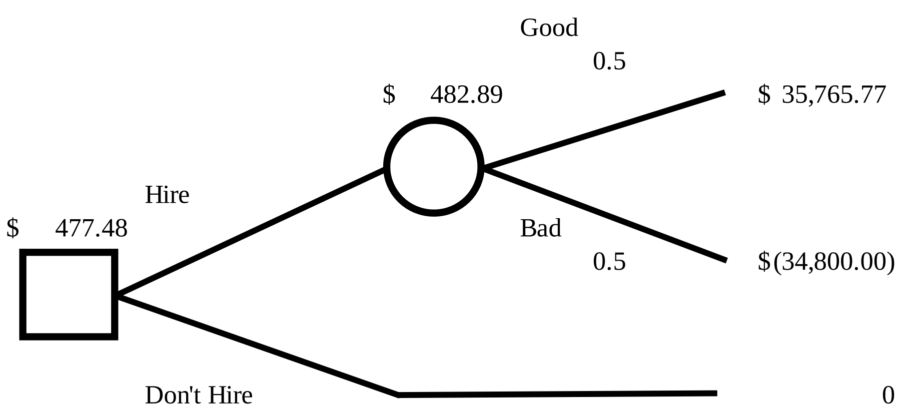


Figure 3. Hiring Decision without Trial Period

Figure 4 shows the results of a sensitivity analysis as the value of *p* is varied from 0 to 1. The closer the employer is to certainty (i.e., *p*=0 or 1), the lower the value of the flexibility afforded by the option. This is reasonable, since if the employer knew with certainty that the employee would be either bad or good, there would be no need for the trial period. The value of flexibility reaches a maximum around *p*=0.49, which happens to be the value at which the employer would be indifferent between hiring or not hiring the employee in the absence of the trial period:

$$p^{indiff} = \frac{0-(-34{,}800)}{35{,}765-(-34{,}800)} \approx 0.49$$

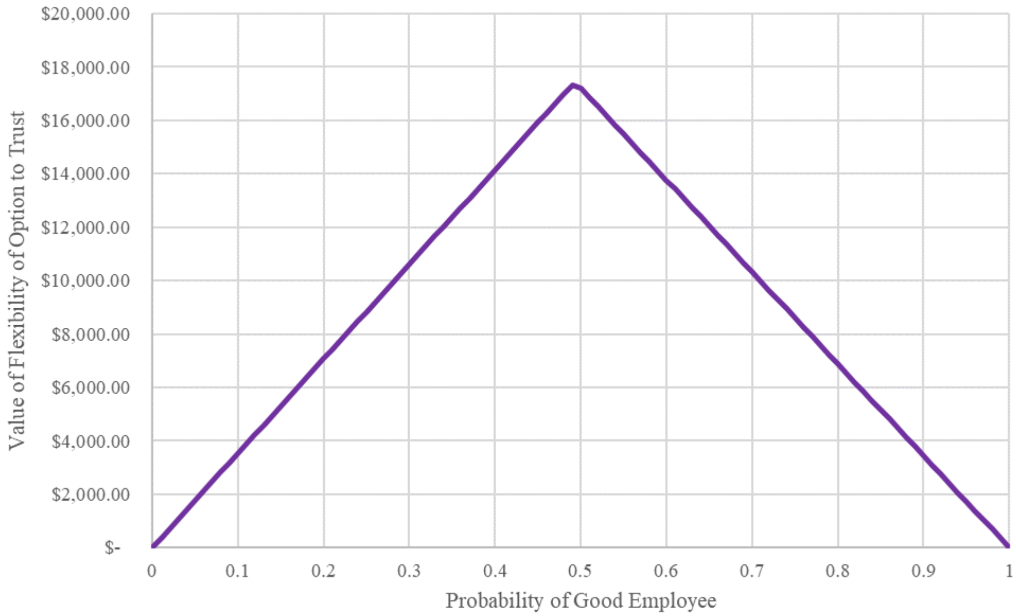


Figure 4. Sensitivity Analysis of the Value of Flexibility

Conclusion

In this paper, we described how trial periods in hiring can be modeled using real options analysis. On a broad level, Figure 4 suggests that the value of creating flexible options to hire and fire employees goes up when the uncertainty about their performance increases. We now consider future directions for the application and development of this model through social and behavioral research.

While organizations would prefer to hire candidates with highest likelihood of success given their scores on a traditional selection assessment (e.g., measures of personality and ability), factors such as the availability of qualified workers and salary budgets impact which candidates apply and accept a job. While organizations may not be able to hire ideal candidates, they are still likely to try to hire quickly due to the costs of leaving vacant positions unfulfilled (Papay & Kraft, 2016). The model presented in this paper may be used as a practical tool to limit risk associated with hiring a less-than-ideal candidate by allowing organizations to consider the value of a temporary hiring period (Figure 4) in mitigating the risk of hiring an unsuccessful employee. We believe this tool will be particularly useful to organizations when applicant pools are lean, and organizations are motivated to hire candidates with lower scores on selection assessments.

While the model presented in this project may be coupled with traditional selection measures and allow organizations to make more informed hiring choices, this model may not be inclusive of the costs of utilizing a probationary hiring period. A significant source of these costs may stem from employee perceptions of the organization when they are asked to engage in a probationary period. By definition, an employee has less trust that the organization will employ them long-term if they are in a probationary role as opposed to a permanent role. This lower level of trust in the organization can relate to lower levels of job performance and organization commitment (Ozyilmaz et al., 2018), meaning employees in probationary positions may perform worse at their job and be more likely to quit as compared to employees in permanent positions. Lower levels of trust may also impede socialization (process through which employees learn the norms, rules, and expectations of their role and organization; Weiss, 1977), which is considered crucial for the development of organizational commitment and sustained job performance (Cohen & Veled-Hecht, 2008; Heck & Wolcott, 1997; Nguyen et al., 2020). As a counterpoint, Chappell and Sin (2016) suggest that a probationary period does not significantly impact employee behavior or organizational trust because the probationary period is not perceived to be optional and because employees often do not truly understand what the probationary period is. Very little research has considered employee reactions to a probationary period, thus the costs (or lack thereof) of probationary periods for employee perceptions of the organization remains a fruitful area for future work.

The sunk cost of training during the probationary period may also influence the value of a probationary period. For example, if on-job training is fast and cheap, the cost of firing and re-hiring a new employee may be well below average. However, for specialized jobs in which new hires require several months of training and support, the cost of firing and re-hiring after a probationary period may be prohibitively high. While this sunk cost of training can likely be calculated and incorporated into selection processes, high training costs may cause managers to feel as though they *must* hire all temporary workers into permanent positions because the perceived loss of the training investment is so high (sunk cost fallacy; Garland & Newport, 1991). This may represent a hidden cost in which organizations believe the probationary period is providing decision flexibility, but in reality, managers do not execute on the option to not permanently hire, and the benefit of the probationary period is lost. The potential application avenues and unrecognized costs explored here represent fruitful directions for future research.

References

Bhattacharya, M., & Wright, P. M. (2004). Managing human assets in an uncertain world: Applying real options theory to HRM. Working Paper 04-03, Cornell University Center for Advanced Human Resource Studies.

Boushey, H., & Glynn, S. J. (2012). There are significant business costs to replacing employees. Center for American Progress, Washington, DC, USA.

Bryan, L. L., & Zanini, M. (2005). Strategy in an era of global giants. *McKinsey Quarterly*, https://www.mckinsey.com/capabilities/strategy-and-corporate-finance/our-insights/strategy-in-an-era-of-global-giants

Byrne, J., & Pecchenino, R. A. (2019). Heigh ho, heigh ho: Flexible labor contracts with real option characteristics. *Business Economics*, *54*, 25-34.

Celani, A., Deutsch-Salamon, S., & Singh, P. (2008). In justice we trust: A model of the role of trust in the organization in applicant reactions to the selection process. *Human Resource Management Review*, *18*(2), 63-76.

Chappell, N., & Sin, I. (2016). The effect of trial periods in employment on firm hiring behavior. New Zealand Treasury Working Paper 16/03, New Zealand Treasury, Wellington, NZ.

Cohen, A., & Veled-Hecht, A. (2010). The relationship between organizational socialization and commitment in the workplace among employees in long-term nursing care facilities. *Personnel Review*, *39*(5), 537-556.

Collier, Z. A., Wood, M. D., & Henderson, D. A. (2022a). Balancing risk and trust for strategic alliance formation decisions. *Journal of Strategy and Management*, *15*(4), 509-523.

Collier, Z. A., Guin, U., Sarkis, J., & Lambert, J. H. (2022b). Decision model with quantification of buyer-supplier trust in advanced technology enterprises. *Benchmarking: An International Journal*, *29*(10), 3033-3056.

Colquitt, J., LePine, J., & Wesson, M. (2023). *Organizational Behavior: Improving Performance and Commitment in the Workplace* (8^{th} ed). McGraw-Hill Education.

Copeland, T., & Antikarov, V. (2003). *Real Options: A Practitioner's Guide*. Texere, New York.

Cox, J. C., Ross, S. A., & Rubenstein, M. (1979). Option pricing: A simplified approach. *Journal of Financial Economics*, *7*, 229-263.

Dirks, K. T. (1999). The effects of interpersonal trust on work group performance. *Journal of Applied Psychology*, *84*(3), 445-455.

Foote, D. A., & Folta, T. B. (2002). Temporary workers as real options. *Human Resource Management Review*, *12*, 579-597.

Gambetta, D. (2000). Can we trust trust? In Gambetta, D. (Ed.), *Trust: Making and Breaking Cooperative Relations*, Electronic edition, Department of Sociology, University of Oxford, Oxford, pp. 213-237.

Garland, H., & Newport, S. (1991). Effects of absolute and relative sunk costs on the decision to persist with a course of action. *Organizational Behavior and Human Decision Processes*, *48*(1), 55-69.

Heck, R. H., & Wolcott, L. P. (1997). Beginning teachers: A statewide study of factors explaining successful completion of the probationary period. *Educational Policy*, *11*(1), 111-133.

Herath, H. S. B., & Park, C. S. (2001). Real options valuation and its relationship to Bayesian decision-making methods. *The Engineering Economist*, *46*(1), 1-32.

Huang, J., & Fox, M. S. (2005). Trust judgement in knowledge provenance. *Proceedings of the 16th International Workshop on Database and Expert Systems Applications (DEXA'05).*

Inkpen, A. C., & Currall, S. C. (2004). The coevolution of trust, control, and learning in joint ventures. *Organization Science*, *15*(5), 586-599.

Klotz, A. C., Da Monta Veiga, S. P., Buckley, N. R., & Gavin, M. B. (2013). The role of trustworthiness in recruitment and selection: A review and guide for future research. *Journal of Organizational Behavior*, *34*, S104-S119.

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. *Academy of Management Review*, *20*(3), 709-734.

Newman, D. A., & Lyon, J. S. (2009). Recruitment efforts to reduce adverse impact: Targeted recruiting for personality, cognitive ability, and diversity. *Journal of Applied Psychology*, *94*(2), 298.

Nguyen, T. N. T., Bui, T. H. T., & Nguyen, T. H. H. (2021). Improving employees' proactive behaviors at workplace: The role of organizational socialization tactics and work engagement. *Journal of Human Behavior in the Social Environment, 31*(6), 673-688.

Ozyilmaz, A., Erdogan, B., & Karaeminogullari, A. (2018). Trust in organization as a moderator of the relationship between self-efficacy and workplace outcomes: A social cognitive theory-based examination. *Journal of Occupational and Organizational Psychology*, *91*(1), 181-204.

Papay, J. P., & Kraft, M. A. (2016). The productivity costs of inefficient hiring practices: Evidence from late teacher hiring. *Journal of Policy Analysis and Management*, *35*(4), 791-817.

Ryan, A. M., & Ployhart, R. E. (2014). A century of selection. *Annual Review of Psychology*, *65*, 693-717.

SHRM (2016). 2016 Human Capital Benchmarking Report. Society for Human Resource Management, Alexandria, VA, USA.

U.S. Bureau of Labor Statistics (2023). BLS Data Viewer. https://beta.bls.gov/dataViewer/view

Volosevici, D. (2021). Some considerations on the trial period in the employment agreement. *Journal of Law and Administrative Sciences*, *16*, 47-54.

Weiss, H. M. (1977). Subordinate imitation of supervisor behavior: The role of modeling in organizational socialization. *Organizational Behavior and Human Performance*, *19*(1), 89-105.

U.S. CONSUMERS AND SMALL BUSINESSES CONTINUE TO NAVIGATE UNCERTAIN ECONOMIC CONDITIONS

Robert J. Lahm, Jr., Ph.D.
Professor of Entrepreneurship
College of Business
Western Carolina University
Cullowhee, NC 28723
rjlahm@wcu.edu
828.227.3295
(Contact Author)

Lane Graves Perry, III, Ph.D.
Assistant Professor of Entrepreneurship
College of Business
Western Carolina University
Cullowhee, NC 28723
laneperry@wcu.edu
828.227.2643

Keywords: Economy, inflation, consumer confidence, small business, entrepreneurship

Introduction

With the advent of the COVID-19 global pandemic, numerous problems presented themselves in what could be described as a chain reaction. The pandemic was not only a health crisis (Gopinath, 2020); calamity ensued as store shelves were stripped bare (Ahmed et al., 2020) in many consumer product categories such as food, and hygiene, making the interdependencies of labor shortages and supply chains glaringly clear. Inflation arose when labor shortages (Ferguson, 2022) led to upward pricing pressures (Ball et al., 2022; DeSilver, 2022; Hernandez, 2023). Supply has normalized to a substantial degree, but rising prices persist.

U.S. consumer debt – as well as public debt – have increased to record levels (Caporal & Albright, 2022; *Quarterly report on household debt and credit: Q3 2023.*, 2023) and the conditions seem to be pointing towards longer-term impacts. At the same time, consumers have increasingly been tapping into 401k accounts making hardship withdrawals (Anderson, 2023). In some industry sectors, substantial layoffs (Henney, 2022) have occurred (although some of these, particularly in the tech sector, have been attributed to over-hiring during the pandemic). As the Federal Reserve continues to work to moderate inflation through sustained interest rate increases, the consumers and businesses of the U.S. economy continue to find ways to navigate these uncertain economic conditions.

In the four years since the global pandemic unleashed itself most virulently in the spring of 2020, several records were set in the United States, e.g., gasoline and diesel fuel prices, credit card debt, inflation at 9.1 percent (*Consumer Price Index - June 2022*, 2022) in June 2022 – a forty-year high – which presented uncertainties for consumers, small businesses, and those trying to discern impacts. This research chronicles and further analyzes the economic indicators that are informing – as well as driving – consumer behavior and small business decisions.

Methodology

Reflecting on relevant trends associated with small business economies post-pandemic, this research is supported by several databases (with items collected across time), from which 266 artifacts informing this present work were derived. Database collections including those from *Ebsco ABI/INFORM and ProQuest* have been accessed. Reports from research organizations (e.g., NFIB Research Foundation); consulting firms with research arms or that sponsor research (e.g., Goldman Sachs); and data from government agencies has also been collected. In some instances, popular press sources have been useful as a starting place, especially where up-to-the-minute news is concerned. Secondary qualitative data methods have been identified as a promising resource for understanding dynamic circumstances (Rabinovich & Cheon, 2011).

Audience and Relevance

The ability to recognize wider economic conditions is imperative to the success of new business ventures and the entrepreneurs who navigate them (Dunkelberg & Wade, 2022; *Financial stability report*, 2022; Tegarden et al., 2000). As economic conditions evolve (abruptly in the case of the past four years), practitioners, student entrepreneurs, and educators must assess conditions stymieing or encouraging success. Conditions (entrepreneurial ecosystems) and opportunity (entrepreneurial response) go hand-in-hand (Sharma, 2020; Smith, 2020).

References

Ahmed, R. R., Streimikiene, D., Rolle, J.-A., & Duc, P. A. (2020). The COVID-19 pandemic and the antecedants for the impulse buying behavior of US citizens. Journal of Competitiveness, 12(3), 5-27. https://doi.org/10.7441/joc.2020.03.01

Anderson, B. (2023, August 8). 401(k) balances up in 2023, but so are hardship withdrawals, loans. https://401kspecialistmag.com/401k-balances-up-in-2023-but-so-are-hardship-withdrawals-loans/

Ball, L. M., Leigh, D., & Mishra, P. (2022). Understanding U.S. inflation during the COVID era. National Bureau of Economic Research.

Caporal, J., & Albright, D. (2022, September 20). Average American household debt in 2022: Facts and figures. Retrieved October 28 from https://www.fool.com/the-ascent/research/average-american-household-debt/Consumer Price Index - June 2022. (2022, July 13). Bureau of Labor Statistics. Retrieved July 13 from https://www.bls.gov/news.release/archives/cpi_07132022.pdf

DeSilver, D. (2022, June 15). In the U.S. and around the world, inflation is high and getting higher. Pew Research Center https://www.pewresearch.org/short-reads/2022/06/15/in-the-u-s-and-around-the-world-inflation-is-high-and-getting-higher/

Dunkelberg, W. C., & Wade, H. (2022). NFIB: Small business economic trends. (August). Retrieved October 22, from http://www.nfib-sbet.org/wp-content/uploads/2022/09/SBET-August-20221.pdf

Ferguson, S. (2022, July 15). Understanding America’s labor shortage. Retrieved July 24 from https://www.uschamber.com/workforce/understanding-americas-labor-shortage
Financial stability report. (2022, May). Board of Governors of the U.S. Federal Reserve System. Retrieved October 28 from https://www.federalreserve.gov/publications/files/financial-stability-report-20220509.pdf

Gopinath, G. (2020). The great lockdown: Worst economic downturn since the Great Depression. International Monetary Fund. Retrieved January 16 from https://blogs.imf.org/2020/04/14/the-great-lockdown-worst-economic-downturn-since-the-great-depression/

Henney, M. (2022, December 2). Layoffs mount as job market gets murky. Retrieved December 7 from https://www.foxbusiness.com/economy/layoffs-mount-job-market-gets-murky

Hernandez, R. (2023, January). What caused inflation to spike after 2020? U.S. Bureau of Labor Statistics. https://www.bls.gov/opub/mlr/2023/beyond-bls/what-caused-inflation-to-spike-after-2020.htm

Quarterly report on household debt and credit: Q3 2023. (2023, November). Federal Reserve Bank of New York. Retrieved January 2 from https://www.newyorkfed.org/medialibrary/Interactives/householdcredit/data/pdf/HHDC_2023Q3.pdf?sc_lang=en

Rabinovich, E., & Cheon, S. (2011). Expanding horizons and deepening understanding via the use of secondary data sources. Journal of Business Logistics, 32(4), 303-316. https://doi.org/https://doi.org/10.1111/j.0000-0000.2011.01026.x

Sharma, S. (2020, December 18). Industries thriving during the pandemic. Retrieved February 15 from https://www.forbes.com/sites/forbestechcouncil/2020/12/18/industries-thriving-during-the-pandemic/?sh=253fccd57a03

Smith, R. (2020). Innovation signals hope amid the pandemic. Research Technology Management, 63(5), 59. https://doi.org/10.1080/08956308.2020.1790257

Tegarden, L. F., Echols, A. E., & Hatfield, D. E. (2000). The value of patience and start-up firms: A re-examination of entry timing for emerging markets. Entrepreneurship: Theory & Practice, 24(4), 41. http://search.ebscohost.com/login.aspx?direct=true&db=bth&AN=3679483&site=bsi-live

EXPLORING MANAGEMENT CONSULTING VALUE CREATION FOR MICROENTERPRISES

Mariano Garrido-López
School of Economics, Management, and Project Management
College of Business
Western Carolina University
1 University Drive
Cullowhee, NC 28723
mglopez@email.wcu.edu
828.227.2889 (Contact Author)

Lane Graves Perry, III
School of Marketing, Entrepreneurship, Sports Management, and Hospitality & Tourism
College of Business
Western Carolina University
1 University Drive
Cullowhee, NC 28723
laneperry@email.wcu.edu
828.227.2825 (Contact Author)

Yue Hillon
School of Economics, Management, and Project Management
College of Business
Western Carolina University
1 University Drive
Cullowhee, NC 28723
ycai@email.wcu.edu
828.227.3588 (Contact Author)

Joshua Downs
School of Economics, Management, and Project Management
College of Business
Western Carolina University
1 University Drive
Cullowhee, NC 28723
jdowns@email.wcu.edu
828.227.3009 (Contact Author)

Keywords: Microenterprises, management consulting, value creation, practices, praxis

Introduction

Microenterprises represent over 80% of all businesses in the U.S. The challenges faced by these types of firms range from poor knowledge of strategy and competition, to limited financial and human resources. In this paper, we adopt the U.S. Small Business Administration definition of a microenterprise or microbusiness, as an employer with fewer than 9 employees. The aim of this paper is to explore some of the main challenges faced by microenterprises and how consultants, or business support services, can create value for and with them.

Many microenterprises fail over time or never embark upon a growth path (e.g., including expansion, impact, or market share) due to their inability to overcome on their own some of the challenges they face. Most microenterprises are reluctant to engage the support of Management Consulting firms. They either find them too costly, or do not necessarily believe in the value they can help them create.

This research took a deep dive into the Management Consulting practices used during interventions with microenterprises and identified practices that work best for such companies. Drawing from researcher-practitioners' own consulting experiences working with four microenterprises in diverse industries and sectors, both for profit and non-for-profit, this paper explores lessons learned from the application of Management Consulting practices in microenterprises; it also examines how these practices may differ or be similar to the approaches used in larger scale interventions (e.g. with large MNCs), as well as explores "how-to" questions about possible ways of improving praxis going forward.

Some of the questions to be explored in this paper include:

- What are some of the main challenges faced by microenterprises?
- How is value created in the interplay between microenterprises and Management Consultants?
- What are some of the Management Consulting practices and tools used during interventions with microenterprises and which ones work best for such companies?
- How do these Management Consulting practices and tools differ or align with the approaches used in larger scale interventions (e.g. with large MNCs)?

Literature Overview

Global market complexity and the recent pandemic have urged organizations of all types to lift the "bell jar" that limits their perspectives and did not allow them to see all the possibilities. It also encouraged them to be brave enough to challenge the status quo in a way that they may have never done before, breaking down dichotomies and habits that may be keeping them stuck and unable to move forward into new growth. This disruption of the status quo can lead to a reframing of engagement and informing of decisions (Fritz, 1996). SMEs, and especially microenterprises tend to be rather conservative (Achtenhagen, Ekberg, & Melander, 2017) or risk adverse, and therefore usually find the idea of breaking out of habitual ways of doing business challenging. Management Consultants can play a critical role in supporting the organizations' strategic agendas and help them unleash their existing growth potential efficiently and effectively.

This paper adopts U.S. Small Business Administration definition of a microenterprise or microbusiness, as an employer with fewer than 9 employees. Today, according to Census 2020 Statistics of US Businesses (SUSB) on economic distribution by industry and enterprise size, 99.66% of all firms in the U.S. are considered small businesses (with < 500 employees) employing 45.92% of the total U.S. workforce. Of which, 78.97% these firms (82.73% of total # of firms) are microenterprises (with 1-9 employees) employing 20.51% of all small businesses' workforce in the U.S. Interestingly, during and post-COVID (from 2020-2023), small businesses in the U.S. have continued to grow at a faster rate than pre-pandemic and small business (alongside no-propensity businesses) represent the source of the most accelerated growth (Lahm & Perry, 2023).

Small businesses are the economic foundations creating jobs, encouraging innovation, and fostering competitiveness to stimulate economic growth. Although small businesses are thought to be more nimble and adaptive to changes, global competition continues to exert pressure on them (Moutray, 2008). Technology advancements are shifting the economic structure, innovation, governance, and trade, thus giving new meaning to terms such as "global village" and "global competition" (Markman, Devinney, Pedersen, & Tihanyi, 2016). Therefore, more than ever, small businesses need to have a clear understanding of the competitive environment in which they operate. However, with scarce marketing budgets, dated marketing techniques (Jelfs & Thomson, 2016), and limited time, resources, and expertise, small businesses cannot afford competitive intelligence programs for long-term strategic planning (Prescott & Miree, 1998). Thus, a lack of a strategic plan is one of the crucial weaknesses of small businesses, especially in family-owned businesses (Ward, 2016).

A healthy regional, particularly rural, entrepreneurial ecosystem with a strong entrepreneurial culture, talents, resources, intersections and so on is vital to microentrepreneurship success (Potter, 2020). Banc and Messegham (2020) noted that these micro-ecosystems describe interconnected entrepreneurial activity in a localized open system that is directly influenced and responsive to the greater entrepreneurial ecosystem (a sort of nestedness). Concurrently, microenterprises also need to fully understand at any point in time their organizational resources and capabilities while cultivating an internal and external strategic focus to improve performance (Harris, Gibson, & McDowell, 2014). A strong national economy and an enterprise's ability to penetrate new markets are considered the top two most important success factors by microenterprise entrepreneurs, but also major challenges. Simultaneously, having a trained workforce, product diversification, access and ability to use the internet, and ability to manage healthcare costs, tax burden, and state/federal regulation are equally important organizational capabilities for success (Monahan & Mattare, 2011). Digital innovation created opportunities for microenterprises, especially for rural microenterprises, but a lack of digital competencies prevented entrepreneurs' ability to take advantage of this digital competitiveness (Raisanen & Tuovinen, 2020).

Microenterprises lack of systems and routines, use of non-formalized methods, usual one person-centered organizational structure and overall limited financial and human resources (Achtenhagen et al., 2017), among other factors, represent great challenges for microenterprises to be able to define and drive their strategic agendas. Additionally, many of these microenterprises exist in areas with institutional voids. Narooz and Child (2017) noted that the institutional void perspective suggests that in addition to a lack of institutional support (e.g., actions and infrastructure) for entrepreneurial efforts within a defined ecosystem, uncertainty is also perpetuated by inadequate or unclear rules (Khanna & Palepu, 2010). Most entrepreneurs running these types of companies struggle and/or are unable to overcome these challenges on their own and eventually fail. Do Management Consultants have a legitimate role to play in support of microenterprises' future success and could they be supportive assets in contrast to institutional voids that exist within rural ecosystems specifically?

Management Consulting firms' role in supporting small firm's competitiveness and success continues to be a controversial topic (Christensen & Klyver, 2016; Whittle, 2006). On the one hand, small firms rarely use management consulting services due to a perception of high cost, as well as their limited understanding of their specific challenges, leading to advice of little to no use to them. On the other hand, some management consultants argue that SMEs usually lack strategic focus and are managed in an unprofessional manner (Stevenson & Sahlman, 1988). This clearly represents another disconnect worth exploring.

Most management consulting services are considered primarily geared towards large organizations. However, there is sufficient evidence to support that these services can be extremely valuable for microenterprises (Bathgate, 2013), to help them overcome some of the challenges highlighted in this proposal. The Management Consulting practices commonly used in the practitioner world originated from experiences with large corporations (Christensen & Klyver, 2006). This could represent a challenge if they were to be applied "as is" to different contexts like microenterprises. To these ends, a respect for the heterogeneity of microenterprises needs to be considered; therefore, there is a need to critically assess the validity of such practices, as well as develop approaches conducive to supporting the specific needs of microenterprises (Salvador, 2017).

Methodology

Using a multi-case study, this paper explores the main challenges faced by micro enterprises and how consultants can create value for and with them. Two for-profit and two non-for-profit organizations were selected to provide as much variability as possible in terms of research contexts. Case studies fit well when dealing with real life research contexts (Yin, 2002). This research method allows us to gain insights from various micro enterprises and their experiences with management consulting, providing a rich and diverse dataset for this exploratory research. The strengths of the multi-case study method include its ability to generate comparative in-depth and detailed insights, as well as its potential for theory development and generalizability. However, it is important to acknowledge the weaknesses of this research method, such as the potential for researcher bias, the time and resource-intensive nature of data collection and analysis, and the limited ability to establish causality. Next, we will discuss the main results and implications of our study.

Results and Implications

In the following section four case studies discussing microenterprises' are presented. These microenterprises are situated in various industries/sectors (e.g., nonprofit, transportation, brewing/manufacturing, etc.) and located in the same rural region in the Southeastern part of the U.S. Each case is briefly framed and an emphasis is placed on the consulting techniques and tools that were leveraged to help each organization address a real-time pressing need or opportunity. Please see Table 1 located in section Emergent Themes and Implications for a cross-case analysis of the tools and praxis adopted to facilitate consultations with microenterprises.

Case 1: Nonprofit Microenterprise Strategic Planning and Goal Setting

This nonprofit microenterprise was incorporated in 2013 with the goal of ending interpersonal violence in the community. The nonprofit is focused on prevention, intervention, and educational services addressing domestic violence. The main challenges voiced by the organization included: strategic planning; organization development; and coaching. Thus, the project objectives included:

- evaluating past achievements and actions to identify impact after 10 years of work;
- reimagining mission, goals, purpose, and next steps;
- developing a road map charting key focus areas for the future using the SOAR Strategic Planning Model (strengths, opportunities, aspirations, and results) and frame results using SMART Goal method.

The strategic planning workshop was facilitated over a 2-day period. In preparation, organization documents, and assessments were provided to the facilitator to provide context of the organization's history and impact. Every board member, staff member, and team member was present. Value was co-created through the process leading to the refinement of the organization's mission, core values, and next step road map built on the organization's strengths to chart what success looks like over the next 3+ years.

The pluses of the management consulting practices used during project/intervention included: providing a needed space to reflect on program effectiveness, a chance to celebrate strengths, recognize opportunities, clarify aspirations, and convert aspirations into measurable goals. Facilitated space for collective visioning and meaning-making helps clarify purpose and refine organization identity. In this case, that seemed to be impactful. Through this process over 50 actionable "next-steps" across 5 aspirational directions helped reinforce the nonprofit's mission and vision.

In reflection, nonprofit microenterprises are unique as they typically have 1) limited resources in the form of infrastructure (e.g., tech systems, space acquisition, location, improvements), funding, human capital, access to consultants, a specific/localized geographic service area which narrows reach, and a social mission that can narrow focus. Concomitantly, 2) consulting practices that are tailored to nonprofit microenterprises must be responsive to the exogenous impacts associated with sustainable funding, a focused social mission, and an alternative to the one-and-done consulting model. Consultants should have appropriately 3) developed follow-up protocol in place to check in with their clients through a formalized quarterly review process. 4) Intentionally focusing on strengths through an asset-based approach can keep the consultation positive and productive. Balanced with a well-prepared organization, tailored consultation efforts for nonprofit microenterprises can be effective.

Case 2: Biological Field Station Strategic Repositioning

Located in the Southern Appalachians, the field station was established in 1927 as a museum for public natural history education. Taking advantage of regional biodiversity, it stimulates place-based teaching/learning and serves as an outpost for biological science education, research, and training. It also provides diverse outreach programming for K-12 schools and local community life-long-learners. As a research non-profit, it is supported by the foundation and a consortium of regional universities.

As the field station continued to grow, the organization encountered growing pains: 1) administrative shifts created new complexities; and 2) core proposition disagreements among key constituents. The foundation desired more outward facing activities, while the scientific board desired increased research capabilities, and university administration expected an increase in education activities. However, the field station lacked adequate resources to accommodate all areas.

To help the field station craft a sustainable strategic plan, consulting engagement main objectives included: 1) find common grounds across diverse perspectives; 2) reevaluate core propositions; 3) define strategic priorities (immediate-, short-, and long-term) that best reflect these core propositions; 4) explore challenges prohibiting strategic momentum; and 5) develop an actionable roadmap.

It was a journey of collective learning: environmental scan and industry analysis to identify opportunities and threats, and socio-economic learning of organizational dynamics using the Socio-Economic Approach to Management (SEAM) methodology. The process not only discovered organizational strengths, more importantly embedded hidden challenges and potential through a series of listening sessions. Unique to a micro non-profit, the consulting team was able to document every constituent's voice, where only a small percentage can be heard in large corporations. This collective knowledge resulted in a strategic planning retreat that brought together individuals with a common vested interest and diverse knowledge, and ultimately better awareness of organizational dynamics, core values, and renewed strategic priorities.

Traditional organizational learning often concludes with an analysis of the most frequently communicated experiences. A process that might overlook the fact that these experiences are in fact symptoms of something deeper and more fundamental. In this case of the field station, through a series of story mapping of the diverse organizational challenges, the consulting team was able to uncover the root causes to many of the embedded issues, which were unclear long-term direction and a lack of effective personnel management system. A common underlying challenge for microenterprises.

In conclusion, when working with microenterprises, it is important for management consultants to recognize that 1) rather than expert telling, value creation is more meaningful and impactful through learning together; 2) consultants are companions to the life of the organization with a great deal of influence, not the director; 3) tools and processes are used to help add value, they are not the value themselves; and 4) agility is built on socially responsible improvements to the bottom line.

Case 3: Consultancy as a Vehicle to Move a Microenterprise Forward

This case involved a recreational vehicle rental company that primarily serviced visitors to the Smoky/Blue Ridge Mountain area. Employees included the owner/founder, who had extensive subject-area experience as a user entrepreneur (Shah & Tripsas, 2007), but lacked formal business training and experience, and a part-time employee assisting with vehicle pickups/drop-offs and turnover. The fleet included two firm-owned vehicles and three vehicles owned by contracting third parties. The firm did well during the COVID-era, serving essential workers requiring accommodation without hotels. Client's challenges included the decline of COVID-related demand, emerging threat of a listing-by-owner platform, and uncertainty about future growth.

The approach consisted of conducting a broad internal/external analysis, applying frameworks such as PESTLE, 5 Forces, 3 Circles, Business Model Analysis, SWOT, and VRIO to guide the scope of data acquisition and analysis. Primary research included semi-structured interviews with the owner and netnography for customer sentiment and competitor benchmarking purposes. Secondary research involved accessing data and reports that were cost and time prohibitive to the firm to access and assimilate. Client discussions included preliminary conclusions, and the narrowing of project scope to six additional areas to audit and provide recommendations. Foci included: operations, additional revenue streams, marketing, website/social media strategy, and fleet management.

Each area provided valuable recommendations which the client would likely not have reached alone. One recommendation involved a shift in framing the new platform as a competitor, instead viewing it as a source for identifying potential partners. Thus, the client could grow their fleet through contracting with vehicle owners as opposed assuming the risks and costs associated with growth through ownership. This highlights a primary issue with microenterprises that may be addressed by consultants, myopia and the lack of bandwidth afforded to microenterprises perpetuating that myopia. Consultants offering an outsider perspective can frame the organization's problems differently and systematically discover solutions otherwise missed.

A unique challenge discovered in consulting with this microenterprise was that its niche status defied straightforward application of industry classifications, complicating research efforts. Most reports compiled by third parties are primarily applicable to MNCs established in an industry, thus these data required filtering to keep what was relevant and remove non-pertinent details that could lead to ill-informed recommendations. Also, while MNC's typically have the capabilities to understand recommendations and develop and implement proprietary tools required to carry out the recommendation, for this client, solutions had to be in a form that was (at least partially) applicable out-of-the-box with clear instructions on how to implement them. For this case, an excel-based tool to project the financial impact of fleet additions included minimal variables and clear instructions on how to plug in the numbers.

In summary, this microenterprise benefitted from the application of frameworks and research from data sources that are typified with a standard consulting approach, with some adaptation. The absence of in-house expertise placed an emphasis on low-complexity, turnkey solutions. Myopia was a significant issue given the lack of internal capacity and perspectives, though the low number of internal stakeholders also made the recommendations provided easier to adopt by the organization. Finally, a pragmatic approach to research was required to filter out data that was applicable to firms that were well-established in a standard industry category, but much less relevant to the microenterprise defined less by industry category and more by the niche within that it inhabits.

Case 4: A Micro-Brewery Journey

The last case focuses on a micro-brewery located in the heart of the WNC mountains. The business has been in operation since 2016 and is on track to a million dollars in sales. Beyond the financial challenges faced (i.e. to support growth), the case company lacked a formalized vision, mission, and core values statements. Since its inception, the brewery has grown organically; its owner lacked the necessary business know-how to effectively grow the organization, which continued to represent a challenge. Other challenges contributing to many operational inefficiencies included the brewery's lack of a formalized strategic plan, rudimentary and disjointed marketing tactics, and lack of foundational infrastructure capabilities.

The micro-brewery engaged the support of a team of consultants to help them address some of the critical challenges, as well as develop a strategic growth plan for the organization. The consulting team created value for the brewery by conducting a comprehensive strategic analysis of the organization, applying a number of key strategic practices and tools designed to assess its external and internal environments. The team also facilitated the development of the top priorities for the next 3-5 years, articulated in a strategic action plan and roadmap, with clearly defined objectives, strategies, and measures. Additionally, the team conducted numerous deep dives into top priority areas identified through this process (e.g. conducted extensive market research, developed a digital marketing strategy and plan, created a master production plan, etc).

The consulting team leveraged consulting practices that are commonly used with organizations of all sizes, including MNCs, but tailored them to the context and idiosyncrasies of the client organization. Both primary and secondary research methods were used to support this process (e.g. review of organization documents, semi-structured interviews with multiple stakeholders, employee and customer surveys). Operational process walkthroughs were also done, to better understand the day-to-day operations of the brewery. Key financial, customer, process, and employee data were gathered to assess current performance.

In summary, beyond developing a strategic growth roadmap for the brewery, the other main (unspoken) goal of this engagement focused on knowledge transfer / competency development and capability building, so that the client organization can continue to use these new practices and tools with minimal to no support. The consultants brought their expertise to the table (including best practices) and facilitated the knowledge transfer process and capability buildout with client support. There was more listening involved than telling, to allow for the tailoring of practices and tools to the client context. As a result of this engagement, a number of playbooks (e.g. strategic planning process, branding guidelines, …), dashboards and other assets were built together with the client that have now become a part of the brewery's core (infrastructure) capabilities. This was a perfect example of harmonious value co-creation!

Emergent Themes and Implications

Cross-case analysis of the four microenterprises illuminates commonalities and idiographic conditions contributing to each applied consultancy experience. It is evident that many of the typically found tools in the toolbox of a consultant were leveraged to support the microenterprises' needs (tools for internal/external analyses, strategic planning/doing processes, and forecasting/near-future focused planning). Additionally, application of proven consultancy practices and tools were also ubiquitously adopted in praxis (e.g., strategic planning retreats, virtual/in-person meetings, facilitation, current state assessment, future state visioning session, etc.).

An emergent theme codified across the cross-case analysis demonstrated an appreciative approach by the consultant team that was constructive, collaborative, and listening-centered (consultant to client). Another theme (client to consultant), is framed as the TIE Assertation, which describes the importance of the client (microenterprise) being prepared for the consultancy experience by ensuring they are in a position to dedicate the Time & Space, Information & Data, and Energy & Effort in order to ensure that the consultancy experience is effective. The consultancy experience, to be effective, must be a two-way street that is mutually beneficial, collaborative, and dialogical. Finally, user-friendly tools, turn-key solutions, and plug-and-play plans alongside follow-up outreach were emphasized as being key to the success of the plans described. In order to demonstrate effectiveness of the consultancy interventions, follow-up outreach and access to sustained funding to support implementation was recognized as being critical to success.

Table 1 presents the main consulting practices, tools, and dispositions that emerged from the four case studies on microenterprises.

Main Consulting Practices & Tools Used	Case Organization(s)
Strategy Framework Guiding Engagement: AFI – Analysis, Formulation, Implementation, SEAM	1, 2, 3, 4
Strategic Analysis Tools (external): PESTEL, Industry Analysis, Market Analysis, Porter's Five Forces, Competitive Benchmarking	2, 3, 4
Strategic Analysis Tools (internal): Value Chain Analysis, Capability Analysis, VRIO	1, 3, 4
Strategy Formulation Tools: SWOT, Ansoff, BCG	1, 3, 4
Strategy Implementation Tools: OGSM, Strategic Action Plan, Strategic Implementation Roadmap, Prioritization Matrix	1, 2, 4
Organization's Vision, Mission, and Core Values Statements	1, 4
Long-range planning (3-5-year strategic plan)	1, 2, 4
Business Model Canvas	2, 3, 4
SEAM Analysis	2
Market research	2, 3, 4
Listening sessions	1, 2, 4
Story mapping/relationship mapping	2
Root cause analysis	2
Production Planning and Control (e.g. Master Production Plan)	4
Supply chain management systems	4
Quality management tools (e.g. Six sigma – FMEA, SPC)	4
Lean manufacturing tools (e.g. 5S, value stream mapping)	4
Workforce management tools	1,
Process mapping and flowcharts	1, 2, 4
Project management tools	1, 4
Forecasting 3-5 years	1, 2
Revenue Analysis	2, 4
Branding strategy	1, 4
Social media marketing strategy and plan	3, 4
Customer journey mapping	4
Customer survey	4
Employee survey	1, 4
User-friendly tools, turn-key solutions, plug-and-play, minimal expertise	3, 4

Table 1. Cross-Case Analysis Highlighting the Main Consulting Practices and Tools Used.

Conclusion

In reflection, through an thematic analysis of the four cases presented, we saw that all consulting projects incorporated multiple consulting practices and tools. Some of which carried over well into microenterprises (or nonprofits) from larger corporations, while some presented unique challenges that required incremental or radical adaptation of approaches to accommodate microenterprise consulting (see Table 2).

Consulting practices that worked well in microenterprises	• Alignment of strategic goals and objectives* • Harmonious integration of external and internal strategic learning • Participation of diverse constituents in the consulting process* • Remember consultants are facilitators, NOT directors* • Ensure organization's self-discovery & ownership* • Financial measures of behavioral/intangible indicators are necessary • Flexible and scalable frameworks*
Consulting practices required better management in microenterprises	• Help organizations differentiate between strategy and strategic tools • It is an involved process and take time, thus need for "strategic" patience* • Certain tools (e.g. time study) should only be used to help develop managerial skills during consulting, not to evaluate employees
Ways to improve consulting praxis with microenterprises	• Leverage "holistic" management approaches, NOT a single practice* • Ensure development/change ownership resides in the organization, NOT consultants* • Less storytelling and more story listening* • Understand unity of business and personal identities • Differentiate fundamental vs. symptomatic phenomenon before investing in solutions* • Use a metrics-driven (qualitative, quantitative, & financial) approach* • Set the right level of governance (e.g. operational and strategic steering) • Drive change with work organization and communication* • Increase economic sensitivity of the entire team - empower managers' economic impact • Eliminate isolation and provide courage/support (e.g. multi-office)* • Recognize organizational development is bi-directional (vs. inward-out)* • Focus on long-term socially responsible sustainability instead of short-term gains/savings*

Table 2. Implications for Practitioners (*=shared reflections).

The goal of this study is not to be prescriptive in dictating how to approach microenterprise consultation, but to be descriptive of the types of experiences had by various consultation-based efforts with microenterprises. The four cases across a range of sectors and industries do not present an exhaustive picture of all conditions impacting these phenomena, which may continue to emerge through future case-based inquiry similar to that conducted here. The notable ways to improve management consulting praxis with microenterprises warrant future inquiry. Future research could also limit cases to shared sector and/or industry membership to control for factors not shared across the clients featured in our study. Finally, further inquiry could define the scope of case-study clients by certain relevant attributes, such as size, to see if further distinctions can be made within the microenterprise classification.

References

Achtenhagen, L., Ekberg, S., & Melander, A. (2017). Fostering growth through business development: Core activities and challenges for micro-firm entrepreneurs. Journal of Management & Organization, 23, 167-185.

Association for Enterprise Opportunity. (2010). Microenterprise business statistics in the United States. Retrieved December 19, 2019, from https://aeoworks.org/wp-content/uploads/2019/03/aeo_microbusiness_fact_sheet_landscape.pdf

Banc, C. & Messeghem, K. (2020). Discovering the entrepreneurial micro-ecosystem: The case of a corporate accelerator. Thunderbird Int. Bus. Rev, 62, 593– 605.

Bathgate, I. K. (2013). The role of the consultant in enterprise development. In Ndubisi, N.O., & NuanKwo, S. (Eds), Enterprise development in SME and entrepreneurial firms: dynamic processes. Business Science Reference.

Christensen, P. R., & Klyver, K. (2016). Management consultancy in small firms: How does interaction work?. Journal of Small Business and Enterprise Development, 13, 299-313.

Edgcomb, E. L. (2002). What makes for effective microenterprise training?. Journal of Microfinance/ESR Review, 4(1), 8.

European Commission. (2015). Definition of micro enterprises. Retrieved December 19, 2019, from https://ec.europa.eu/regional_policy/sources/conferences/state-aid/sme/smedefinitionguide_en.pdf.

Fritz, C. E. (1996). Disasters and mental health: Therapeutic principles drawn from disaster studies.

Harris, M. L., Gibson, S. G., & McDowell, W. C. (2014). The impact of strategic focus and previous business experience on small business performance. Journal of Small Business Strategy, 24(1), 29-44.

Jelfs, A., & Thomson, H. (2016). Marketing small and medium sized enterprises in the digital age: Opportunities and challenges. Teaching Business & Economics, 20(1), 4-7.

Khanna, T. & Palepu, K.G. (2010). Winning in emerging markets: A road map for strategy and execution. Boston, MA: Harvard Business Press.

Lahm, R. J., Jr., & Perry, L. G., III. (2023). Small business and economic conditions: Navigating volatility. Global Journal of Entrepreneurship, 7(1), 14, 18-40.

Markman, G., Devinney, T. M., Pedersen, T., & Tihanyi, L. (2016). Global entrepreneurship: Assessment and challenges. In Global entrepreneurship: Past, present & future: 35-43. Emerald Group Publishing Limited: Leeds, UK.

Monahan, M., Shah, A., & Mattare, M. (2011). The road ahead: Micro enterprise perspectives on success and challenge factors. Journal of Management Policy and Practice, 12(4), 113-125.

Moutray, C. (2008). Looking ahead: Opportunities and challenges for entrepreneurship and small business owners, A working paper for the Office of Advocacy U.S. Small Business Administration.

Narooz, R. & Child, J. (2017) Networking responses to different levels of institutional void: A comparison of internationalizing SMEs in Egypt and the UK. International Business Review, 26(4), 683-696.

Potter, J. (2020). Micro businesses, macro challenges: Rebooting start-up policy. OECD. https://www.oecd-forum.org/posts/micro-businesses-macro-challenges-rebooting-start-up-policy

Prescott, J. E., & Miree, C. E. (2015). Small business solutions: Building and leveraging a competitive intelligence capability without going broke. Journal of Small Business Strategy, 9, 57-76.

Räisänen, J., & Tuovinen, T. (2020). Digital innovations in rural micro-enterprises. Journal of rural studies, 73, 56-67.

Salvador, E. (2017). The difficult relationship between the consultancy market and SMEs: Inspiring insights for future improvement. Conference paper presented at XXVIe Conférence Internationale de Management Stratégique.

Servon, L. J. (2006). Microenterprise development in the United States: Current challenges and new directions. Economic Development Quarterly, 20(4), 351-367.

Shah, S., & Tripsas, M. (2007). The accidental entrepreneur: The emergent and collective process of user entrepreneurship. Strategic Entrepreneurship Journal, 1(1-2), 123-140.

Stevenson, H. H. & Sahlman, W. A. (1988). How small companies should handle advisors. Harvard Business Review, March-April, 28-44.

Townsend, L., Wallace, C., Smart, A., & Norman, T. (2016). Building virtual bridges: How rural micro-enterprises develop social capital in online and face-to-face settings. Sociologia Ruralis, 56(1), 29-47.

Ward, J. (2016) Keeping the family business healthy: How to plan for continuing growth, profitability, and family leadership. Springer: NYC.

Whittle, A. (2006). The paradoxical repertoires of management consultancy. Journal of Organizational Change Management. 19: 424-436.

Yin, R. K., (2002) Case study research: Design and methods, 3rd ed. SAGE Publications: Thousand Oaks, CA.

CHANGING CAPTAIN AHAB'S DIRECTION: A LOOK AT SURVIVING TOXIC WORKPLACES

Ralph E. McKinney, Jr.
Department of Management and Health Care Administration
Brad D. Smith Schools of Business
Lewis College of Business
Marshall University
One John Marshall Dive
Huntington, WV 25755
mckinney23@marshall.edu
304.539.3162

Alan Letton
Center for Economic & Community Development in Black Appalachia & Isolated Communities
Marshall University
One John Marshall Drive
Huntington, WV 25755
letton@marshall.edu
304.696,2663

Key words: Toxic leadership, ethics, hostile work environment, destructive leadership

Introduction

In the 1851 book by Herman Melville entitled *"Moby Dick or The White Whale"*, a story unfolds that describes a sea captain's obsession with the relentless pursuit of an elusive Sperm Whale (Melville, 1892). Through this pursuit, Captain Ahab uses his ship the Pequod and his crew only to serve his obsession with getting this whale. His demands are unreasonable as he pushes this crew beyond their abilities to work, he ignores advice of his officers, and he his narrowly focused decisions are driven by emotions. Ultimately, he sacrifices his ship, his crew, and his life to this obsession. The one survivor, Ishmael, is left to tell this story.

Although this story of Captain Ahab is a fictional depiction, it was inspired by the earlier events in 1820 of an encounter between a whale and a ship named Essex (National Geographic, n.d.). Nonetheless, the story of Captain Ahab can be applied to similar situations of toxic work environments. The purpose of this paper is to conceptualize Melville's classic story as a case for identifying toxic environments and potentially surviving those environments.

Literature Overview

According to Tavanti (2022, p. 127), *"…toxic leaders are a painful but common reality in many organizations. Their destructive behaviors and dysfunctional personal characteristics often generate enduring poisonous effects on those they lead."* It is important to correctly identify a toxic leader. In some instances, managers correcting behaviors may be incorrectly perceived as toxic. Identification of toxic managers must include more information and details about their overall behaviors and actions. For example, toxic leaders tend to leverage a dependance relationship upon their actions as a means to establish the power of control over stakeholder. Their communications focus on selective and manipulative of information and of events to illustrate their power and control of the situation. Additionally, incompetence in subordinate supervisors ensures that their power though dependence is ensured. Thus, they may encourage incompetence to foster their position of power and control. Moreover, toxic managers may consistently disrespect an individual's rights and dignity to demoralize, reduce job satisfaction, and impact work performance to assert control.

In applying these concepts as expressed by Tavanti (2022), Captain Ahab engages his crew through demoralizing actions and demands that create fear in the crew. He illustrates their inadequacies to illustrate his superiority. He ignores the advice of his subordinates and his crew. These actions are consistent with fostering and maintaining a hostile work environment (cf. Alterman *et al*., 2013). Alterman *et al*. (2013, p. 667) states *"…that poor psychosocial work environment (e.g., high work pressure, autocratic management style, and role conflict) may create and sustain conditions that are conductive to bullying…"* and sustain a hostile work environment. It is apparent that Ahab's autocratic commands to his crew create a high stress environment where limited resources further exacerbate individual emotions and moods that may lead to role and task conflicts.

Since the Pequod is at sea, the crew literally have few options to escape their employment. This additional pressure may give rise to a work-life imbalance (Alterman *et al*., 2013). Understanding and maintaining a work-life balance is essential to retaining employees and increasing job satisfaction among the employees (Castro *et al*., 2023). When managers alter the characteristics of the working environment, these changes can have spillover effect to an employee's emotion, psychological, and physical well-being. Toxic managers modify the employment conditions to promote their control and solidify their power (Alterman *et al*., 2013). Modifications may be through policy changes, contractual obligations, and organizational practices. While these changes are presented as positive changes that support organizational goals, these are used by toxic managers to subjugate the workers. With Ahab, the constant disruption and shifting of crew duties along with demands of constant improved performance in an inescapable environment.

Methodology

This paper frames the Melville (1851) story as a case study to examine toxic business practices. A case study is appropriate in this instance as it intently focuses on a single organization (i.e. Pequod), its management (i.e. Captain Ahab), and its organizational culture (*see* Stake, 2005; Yin, 2003). This case applies various theoretical constructs from literature that can add meaning to the action and practice of the characters within Melville's novel.

Results and Implications

This practical applications of this paper is that this case can foster discussions surrounding business ethics, toxic environments, psychological safety, and ways to navigate through bad actors. This is designed to serve as a teaching aid that supports ethical behaviors and developing positive practices that understand the needs of the employees that serve the organization.

Conclusion

This is a developing concept that seeks to build a case using Melville's novel to illustrate how a manager can create a toxic environment. Using literature to connect the theoretical concepts to the actions and inactions of the characters is an important consideration in presenting this as a case.

References

Alterman, T., Luckhaupt, S. E., Dahlhamer, J. M., Ward, B. W., & Calvert, G. M. (2013). Job insecurity, work-family imbalance, and hostile work environment: Prevalence data from the 2010 National Health Interview Survey. *American Journal of Industrial Medicine*, *56*(6), 660-669.

Bader, B., Schuster, T., & Dickmann, M. (2020). Managing people in hostile environments: lessons learned and new grounds in HR research. In Danger and risk as challenges for HRM (pp. 1-22). Routledge.

Castro, E., Bostic, S., McDonald, P., Fukuda, R., & McKinney, R.E., Jr. (2023). Millennials: A profile of desired employer values. *SAM Advanced Management Journal*, *88*(3), 75-92. https://journal.samnational.org/archive/vol88ed03/vol88ed03r04/

Melville, H. (1892). *Moby Dick or The White Whale*. C.H. Simonds Company: Boston, Massachusetts. (The original publication was in 1851. This edition has copyright in 1892 by Elizabeth S. Melville and issued to The St. Botoph Society).

National Geographic. (n.d.). Nov 20, 1820 CE: Tragedy of the Whaleship Essex. Accessed on 2024 February 1 from https://education.nationalgeographic.org/resource/tragedy-whaleship-essex/

Stake, R. E. (2005). Qualitative case studies. In N. K. Denzin & Y. S. Lincoln (Eds.), *The Sage handbook of qualitative research (Third Edition)*, (pp. 443-466). London: Sage Publications, Ltd.

Tavanti, M. (2011). Managing toxic leaders: Dysfunctional patterns in organizational leadership and how to deal with them. *Human Resource Management, 2011*, 127-136.

Yin, R. K. (2003). *Case study research: Design and methods (Third Edition)*. *(Volume 5 in the Applied Social Research Methods Series).* London: Sage Publications, Ltd.

ENGAGING STUDENTS THROUGH A FINANCIAL LITERACY FAIR: INCORPORATING PEER-TO-PEER LEARNING, INDUSTRY ENGAGEMENT, AND FUN

Maggie Abney
College of Business
Eastern Kentucky University
521 Lancaster Ave.
Richmond, KY 40475
maggie.abney@eku.edu
859.622.8998 (Contact Author)

Cynthia Harter
College of Business
Eastern Kentucky University
521 Lancaster Ave.
Richmond, KY 40475
cynthia.harter@eku.edu
859.622.1390

Tahsin Huq
College of Business
Eastern Kentucky University
521 Lancaster Ave.
Richmond, KY 40475
tahsin.huq@eku.edu
859.622.4985

Key words: Financial literacy, diversity, collaboration, peer-to-peer learning, industry engagement

Introduction

Today's college students are increasingly acquiring student loans to cover rising costs of higher education. According to a 2022 Financial Wellness Student Voice survey of college students conducted by Inside Higher Ed (2024), student loans were the most common type of loan with 54% of respondents reporting this type of debt. Fifty percent of respondents either were unaware of the amount of their student loans or were aware of the total but not of the monthly payments that would be required. When asked whether their college or university offers a program or class on financial literacy, 67% of respondents were not sure. Beginning in 2022, faculty from Eastern Kentucky University's College of Business have collaborated to offer an annual, campus-wide Financial Literacy Fair to increase student knowledge about financial decisions and about resources that are available when information is needed. To encourage participation in the optional event, the fair is a low-stakes, fun environment where students are encouraged to attend with friends. Demographic characteristics of those who attended the 2023 event as compared to the campus as a whole indicate more diversity among attendees. While 19% of the EKU student population reporting their race responded that they were non-white, 28% of fair attendees reported their race as non-white. This is particularly compelling in light of studies such as Artavanis and Karra (2020) that indicated that minority students have lower levels of financial literacy (24%) when compared to the sample as a whole (39.5%)

and Al-Bahrani, Weathers, and Patel (2019) that showed positive benefits of participating in financial literacy education but higher effects for whites than that for minorities.

Literature Overview

Financial literacy is an important component of individuals' financial wellbeing (Panos and Wilson, 2020), and, according to Harnisch (2010), a lack of financial understanding has even contributed to economic downturns such as the 2008-09 Great Recession. Today's college students face a complex system of rising costs of college and varied funding options. Increasingly, students are choosing student loans to help pay for their education (Board of Governors of Federal Reserve System, 2016). While student debt can be a helpful tool for increasing human capital, it can also lead to financial instability and reduced well-being (Modigliani, 1966; Rothstein and Rouse, 2011). In fact, students may sacrifice some of the positive impacts of postsecondary education on reducing inequality when they increase their debt load (Cherney, Rothwell, Serido, and Shim, 2020). Artavanis and Karra (2020) find that students with lower levels of financial literacy are more likely to underestimate future student loan payments. They also find lower levels of financial literacy particularly among female, minority, and first-generation college students. Another study by Tergesen (2019) found that 11% of student loan borrowers default on their student loans within 3 years of graduation.

Financial stress is also a primary reason that students drop out of college (Joo, Durband, and Grable, 2008). We have developed a Financial Literacy Fair event to help alleviate some of the stress about finances, to raise awareness of the importance of financial literacy, and to provide students with helpful information. Providing this type of support could also increase attachment to EKU and improve retention. In creating the event, we incorporated three factors that have been shown to increase financial literacy knowledge in other university financial literacy programs: peer-to-peer learning (Ma and Feng, 2018), industry engagement (Migliaccio, 2021), and financial incentives (Taylor, Serna, Eguiluz, and Marois, 2023). In addition, we included the element of fun through a welcoming atmosphere including giveaways, food, and t-shirts in order to attract students and to promote engagement and a sense of community on campus.

According to Shook and Keup (2012), peer-to-peer training programs benefit the student participants, the student trainers, and the community. These activities could ultimately contribute to a healthier economy for the Commonwealth. We have incorporated a research project to compare demographic information about students who attend the event with demographic information about the overall student population to help us reach a diverse group.

Methodology

This project was approved by the Eastern Kentucky University Institutional Review Board, and the data were obtained from EKU's Office of Institutional Research. The research objective is to identify demographics of those students who participate in the Financial Literacy Fair event to help us reach more students moving forward. All students attending EKU during the spring of 2023 were invited to the Business and Technology Center for the 2023 Financial Literacy Fair.

The faculty committee consulted with the university branding department to design a logo for the event to carefully plan the event branding. The logo selected was a Ferris wheel, to help the students associate fun with financial literacy and shape the atmosphere of the event around fun. Before the event, students were invited to participate in a TikTok contest where they made short TikTok videos offering financial advice to college students. At the beginning of the fair, winners of the contest were announced, contest videos were shown, and prizes were awarded. Attendees were invited to participate in other activities related to financial knowledge, and additional prizes were awarded.

According to Migliaccio (2021), low-to-middle income individuals can benefit substantially not only from financial literacy programs, but also engagement with financial institutions and industry experts. Industry engagement was incorporated into the event by hosting a panel of bankers during the auditorium session. The floor was opened for students to ask the bankers any questions they had about financial literacy. The students were very receptive to this in-person access to financial literacy knowledge from industry experts. Students asked excellent and sometimes complex financial questions that were situation specific. The banker panelists, some of whom were alumni of the University, provided thorough and helpful answers to the students. Anecdotal data collected from students after the event indicated that students overwhelmingly enjoyed the banker panel and requested that it last for a longer time period at the next event.

After the auditorium session, students were dismissed to an open area where College of Business student organizations served as financial literacy ambassadors at the event. They worked at booths to engage attendees in games and activities to promote awareness of and knowledge about a variety of financial literacy topics. This type of peer-to-peer learning was shown by Ma and Feng (2018) to improve college student knowledge of financial literacy concepts while Borden (2023) showed that college students respond well to a financial education program that is relevant, simple to sign up for, and led by friendly and communicative staff. Along the way, attendees were also provided information to take with them about where to go for help with financial issues. The preparation and training that student ambassadors completed prior to the event and their leadership with the activities also improved their own financial literacy.

An additional component of the event was incentives offered to participants. Taylor et al. (2023) found that monetary incentives are a strong motivator for participation and completion of financial literacy programs for students. During the Financial Literacy Fair, students were offered several opportunities to win gift cards, prizes, and tickets for meals at multiple popular food trucks if all event activities were completed.

To track participation, upon arrival all participants were provided with an attendance card on which they were asked to record their student identification number (SIN). Students received stamps on these cards for taking part in the various games, and they could submit the cards at the end of the event to receive an event t-shirt and coupons to use at food trucks that were located outside. On the card, they were asked to opt in or out for allowing us to use their SIN to access demographic information from the Office of Institutional Research. Of 110 cards submitted, 105 students (95%) provided access. There were also a few students who attended for at least part of the event and did not submit a card. After the event, the Office of Institutional Research sent us a report that included the demographic information for those students who provided access and also averages for those same demographic variables for the entire university population.

Results and Implications

In comparing the university demographics with those of fair attendees, we find that most of the students who attended the fair were business majors. While business majors made up about 12% of the university dataset, 61% of the fair attendees were business majors. Since the event was hosted by the College of Business in our building and our student organizations were involved in the event, this is not surprising. About the same percentage (59%) of the EKU student population and of the fair attendees identified as female. As shown below in Figure 1, there were higher percentages of sophomores and juniors who attended the event as compared to the overall student population. This may be explained by the large portion of students that graduate from the College of Business who are transfers or have changed their major to business after they are at EKU. Also, given that the event is held late in the spring semester, seniors might be busy with internships, job searches, or other activities related to upcoming graduation.

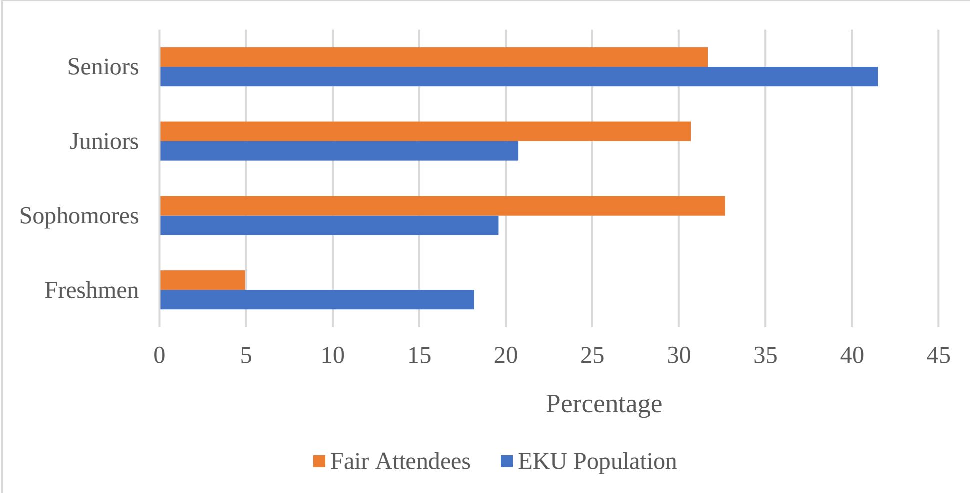


Figure 1. Percentages for Student Year of Progress

In addition, while 19% of the EKU student population were non-white, 28% of fair attendees were non-white. Some of this difference can be explained by the use of percentages along with the small sample of 105 students who attended the event as compared to nearly 11,000 students who completed questions for the university dataset. Nonetheless, it is an interesting outcome especially considering research findings of lower levels of financial literacy among minority students. This type of event that incorporates peer-to-peer learning, industry engagement, financial incentives, and fun might be an effective combination for engaging a diverse student population.

Conclusion

College students need financial education to prepare them to make good decisions after finishing their postsecondary education. This study provides a description of a research-informed Financial Literacy Fair created by a collaborative team of business professors at Eastern Kentucky University to provide more content knowledge and knowledge of where to find important resources for making financial decisions. The program incorporates industry collaboration by introducing students to professionals who can provide direction on basic topics such as budgeting, credit scores, and consumer loans. This research study shows that the event attracted a higher percentage of non-white students as compared to the overall percentage of non-white students at the university. This is positive news since studies have shown that minority students might struggle more with financial literacy than their counterparts.

The sample size in this study is small, so caution should be exercised in applying conclusions drawn at this time. However, the event has become an established annual event, and we will seek to invite more students and continue to collect data to measure success. It is important to note that this particular sample of students chose to attend the Financial Literacy Fair. This could mean that they are more interested in the topic and might have more knowledge than others who did not attend, but it could also mean that they are less knowledgeable and attended the event to learn more about a content area in which they were deficient. Either way, the results highlight the importance of devoting resources to equipping students with more knowledge in this critical area to improve lives and increase economic development in the Commonwealth.

References

Al-Bahrani, A., Weathers, J., & Patel, D. (2019). Racial differences in the returns to financial literacy education. *Journal of Consumer Affairs*, *53*(2), 572–599. https://doi.org/10.1111/joca.12205

Artavanis, N. & Karra, S. (2020). Financial literacy and student debt. *The European Journal of Finance*, *26*(4-5), 382-401. https://doi.org/10.1080/1351847x.2019.1711435

Cherney, K., Rothwell, D., Serido, J., & Shim, S. (2020). Subjective financial well-being during emerging adulthood: The role of student debt. *Emerging Adulthood*, *8*(6), 485-495. https://doi.org/10.1177/2167696819879252

Board of Governors of the Federal Reserve System. (2016). Student loan counseling challenges and opportunities: Findings from focus groups with financial aid counselors, retrieved from https://www.federalreserve.gov/consumerscommunities/files/student-loan-counseling-challenges-and-opportunities-2016.pdf, accessed January, 2024.

Borden, J.P. (2021). An innovative approach to improving financial literacy of college students. *Business Education Innovation Journal, 13*(2), 70-75.

Harnisch, T. (2010). Boosting financial literacy in America: A role for state colleges and universities. *Perspectives* (American Association of State Colleges and Universities), retrieved from https://aascu.org/resources/boosting-financial-literacy-in-america-a-role-for-state-colleges-and-universities/, accessed January, 2024.

Panos, G.A. & Wilson, J.O.S. (2020). Financial literacy and responsible finance in the fintech era: Capabilities and challenges. The European Journal of Finance, *26*(4-5), 297-301. https://doi.org/10.1080/1351847X.2020.1717569

Inside Higher Ed College Pulse with support from project partner Kaplan. (2024).
Student voice: Financial wellness, retrieved from https://reports.collegepulse.com/financial-wellness, accessed January, 2024.

Joo, S.-H., Durband, D. B., & Grable, J. (2008). The academic impact of financial stress on college students. *Journal of College Student Retention: Research, Theory & Practice*, *10*(3), 287–305. https://doi.org/10.2190/CS.10.3.c

Ma, G. & Feng, K. (2018). Evaluating Financial Literacy Student Ambassador Program: A student-led approach to promoting financial literacy. *Business Education Innovation Journal, 10*(2), 7-11.

Migliaccio, J.N. (2021). Taking the high ground on financial literacy. *Journal of Financial Services Professionals*, *75*(6), 12-18.

Modigliani, F. (1966). The life cycle hypothesis of saving, the demand for wealth and the supply of capital. *Social Research*, *33*, 160-217.

Rothstein, J., & Rouse, C. E. (2011). Constrained after college: Student loans and early-career occupational choices. *Journal of Public Economics*, *95*(1-2), 149-163. https://doi.org/10.1016/j.jpubeco.2010.09.015

Shook, J.L., & Keup, J.R. (2012). The benefits of peer leader programs: An overview from the literature. *New Directions for Higher Education*, *157*, 5-16, https://doi.org/10.1002/he.20002

Taylor, Z.W., Serna, K., Eguiluz, L., & Marois, M. (2023). "Not impossible to do": Why community college students participate and persist in voluntary financial education programs. *Critical Questions in Education*, *14*(3), 259-278.

Tergesen, A. (2019). Schools aim to teach teens financial savvy. *The Wall Street Journal*, March 23, 2019, retrieved from https://www.wsj.com/articles/schools-aim-to-teach-teens-financial-savvy-11553342401, accessed January, 2024.

RURAL HOSPITAL CLOSURES: UNRAVELING THE SOCIOECONOMIC, HEALTHCARE ACCESS, AND COMMUNITY IMPACT ON LOCAL COMMUNITIES

Jake Lestitian-Howard, MHAc
Healthcare Administration Program
Lewis College of Business, Marshall University
100 E. Peyton Drive,
South Charleston, WV, 25303

Chase Ooten, MHAc
Healthcare Administration Program
Lewis College of Business, Marshall University
100 E. Peyton Drive,
South Charleston, WV, 25303
ooten40@marshall.edu

Jay Poindexter, MHAc
Healthcare Administration Program
Lewis College of Business, Marshall University
100 E. Peyton Drive,
South Charleston, WV, 25303
poindexter20@marshall.edu

Colette Martin, MBA , DBA student
Lewis College of Business, Marshall University
100 E. Peyton Drive,
South Charleston, WV, 25303
martin967@marshall.edu

Alberto Coustasse, Dr.PH. M.D., MBA, MPH, **Contacting Author**
Healthcare Administration program
Lewis College of Business, Marshall University
100 E. Peyton Drive
South Charleston, WV 25303
coustassehen@marshall.edu

Introduction

Almost 60 million United States (U.S.) citizens lived in rural areas in 2020; since 2005, 162 rural hospitals have closed nationwide (Diaz & Pawlik, 2020). A 2018 congressional report found that the occupancy rates for urban hospitals were 66%, 40% for all rural hospitals, and 31% for rural hospitals with less than 50 beds (Corcoran & Waddell, 2019). It was also found that rural hospitals have smaller profit margins when compared to urban hospitals. On average, urban hospitals operate at a 5.5% profit margin, with rural hospitals operating anywhere from 2% to 2.6% (Corcoran & Waddell, 2019). Between 2010 and 2016, 75 rural hospitals closed, and 250+ were at risk of closure (Warden & Probst. 2017). In a 2,014 rural hospital service areas study, 3.8% experienced at least one hospital closure during the study period (Zahnd et al., 2023). Zero-point six percent of the hospitals experienced some closure, while 3.2% experienced full closure of all services (Zahnd et al., 2023). Over 100 rural hospitals have closed over the past decade, and more than 30% of the rural hospitals left in the country are at risk of closing (CHQPR 2023). Rural Health Information stated that in 2016, 673 hospitals in 42 states were at risk of closure. Among these hospitals, 68% were classified as critical access hospitals by CMS (Manlove & Whitacre, 2017).

Literature Overview

It was estimated that if all 673 hospitals were to close, there would be a loss of 99,000 jobs and a loss of $277 billion to the gross domestic profit (Manlove & Whitacre, 2017). Rural hospital closures have been linked to a percentage increase in the poverty level of their respective communities (Miller et al., 2021). Following hospital closures in a community, a 2% increase in the poverty level was seen (Miller et al., 2021). A study reported that after a rural hospital closure, the average time for a person to reach the nearest hospital was 20 minutes; some had to go across state lines to get to the nearest hospital post-closure (Wishner et al., 2016). Independent rural hospitals decreased from 68.9% in 2007 to 47% in 2019. Affiliated rural hospitals increased from 31.1% to 46.7% (Jiang et al., 2022). The number of rural hospitals that have experienced financial troubles increased by 5.2% from 2007 to 2019 (Jiang et al., 2022).

One study reported that 66% of rural hospital closures were in the southern part of the United States, while 22% of that was in the Appalachian Region; after the closure of the rural hospitals, the average E.R. visit increased by 10% in the respective communities (Ramedani et al., 2022). The average bystander admission in hospitals fell 5.7% before the hospital closure but rose 1.2% the year after (Ramedani et al., 2022). According to the National Rural Health Association Census 2015, 64% of hospital closures from 2010 to 2014 were in the Southern US, 19% in the Midwest, and 8.5% in the Northeast and Western regions (Kaufman et al., 2016). It was found that 66% of these closures resulted in states that neglected to participate in Medicaid expansion (Kaufman et al., 2016). A 2019 study conducted in Texas reported an 8.7% rise in inpatient mortality rates due to the increased transport times related to rural hospital closures (Falconnier & Hecht, 2022). Additionally, the community suffers a 4% decline in per-capita income and a 1.6% increase in the unemployment rate (Frakt, 2019).

Rural hospital closures have caused 1% of the population to travel 15 minutes or more to reach their nearest hospital. The most changes were located in the East South Central, which affected 178,478 residents, and the West South Central, which affected 197,660 residents (McCarthy et al., 2021). The healthcare sector supplied 10% of jobs in rural areas. One rural area reported a 14% reduction in jobs in the county after a hospital closure (Meline et al., 2022).

Methodology

This study aimed to analyze the effects of rural hospital closures on employment level, economic indicators, and availability of care for communities. The intended methodology for this qualitative study was an extended literature review following a systematic approach. The research used EbscoHost, Marshall Digital Scholar, PubMed, SAGE Journals, and Google Scholar databases. Throughout these databases, keywords were used, such as "rural hospital closure" AND "communities" AND "employment level" OR "income status" OR "population size" AND "availability of care" to find relevant sources. Using a PRISMA diagram, articles were included (N=42) if they described rural hospital closure and its effects on the local community.

Results

The research showed that rural hospital closures negatively impacted community economies and access to healthcare.

Employment and Economic Indicators

A study of 1,759 nonmetro counties had 109 that experienced hospital closure during their study period (Malone et al., 2022). The closures resulted in a 1.4% decrease in the labor force size and a 1.1% decrease in the population of the counties mentioned (Malone et al., 2022). Rural areas that have suffered hospital closure experienced a community unemployment rate that was 0.2% higher two years later than before the closure (Vogler, 2020). One study estimated that for every 100 hospital jobs lost due to a closure in a rural community, the surrounding community loses an additional 35 jobs (Adhikari, 2020). Researchers discovered a significant annual decrease in the supply of rural primary care physicians following the closure of a rural hospital (Adhikari, 2020). The employment rate grew by 0.8% per year in rural areas during the study period, while urban areas increased by 1.9% per year (GAO, 2018). Following the closure of rural hospitals, 10-12% of workers were no longer employed in healthcare jobs in their community (Alexander & Richards, 2021). Private sector jobs decreased by 2% after a rural hospital closure and did not recover for at least three years (Alexander & Richards, 2021).

In addition to employment, it was found that rural hospital closure affected other economic factors for the community. These closures resulted in a 2.7% decrease in per capita income and a 1.3% decrease in rent prices (Vogler, 2020). Closures of the only hospital in a rural area reduced the per-capita income by 4% and increased the unemployment rate by 1.6% (Rhoades et al.., 2023). There were 116 hospital closures between 2010 and 2019, and 76% of those hospitals were rural hospitals. A study from 2015 on the community effects of rural hospital closure found an average of 73 lost jobs and roughly $4.4 million in income, and another rural hospital closure resulted in the loss of 124 jobs and $3.3 million in labor income (Eilrich et al., 2015).

Healthcare Access

Access to care changed following a rural hospital closure. After a rural hospital closure, the number of patients forced to drive longer than 90 minutes increased 72 times, and the number of patients with commute times longer than 60 minutes increased seven times (Matsumoto et al., 2012). Rural hospital closures increased EMS transport times by 2.6 minutes on average and total activation time by 7.2 minutes (Miller et al., 2020). Another study showed a 76% increase in ambulance transportation times and Length of Stay (LOS) by 5.2% due to rural hospital closures (Gujral & Basu, 2019). Patients over the age of 64 who lived in rural areas had ambulance times increase from 13.9 minutes to 27.6 minutes, a 97.9% increase (Troske & Davis, 2019). Another study analyzed five rural hospital closures; one of the five hospital closures reported that patients had to drive an additional 13 minutes to reach the following emergency department (Smith et al., 2022). After the closure of a hospital pediatric unit, those under 18 in rural areas had to travel more than 40 minutes to reach the nearest pediatric care hospital (Tischler et al., 2023). the average distance traveled for inpatients before closures was 3.4 miles and 23.9 miles after closures; the average distance traveled for patients with alcohol or drug abuse treatment was 5.5 miles before closures and 44.6 miles after closures (GAO, 2020).

There were 4 million annual births in 2014, and 15% were in rural hospitals (Daymude et al., 2022). Despite the pressure of closure, many rural hospitals that remained open discontinued their obstetric care, leaving 54% of rural counties in the United States with no obstetric services (Daymude et al.., 2022). Nine percent of rural counties closed their obstetric services during the study period; an additional 45% of rural United States counties had no obstetric services at any point during the study period (Hung et al., 2017). The most isolated counties within the study had 59% of hospitals with no obstetric services. By the end of the study period, 10% of hospitals had lost obstetric services (Hung et al., 2017). Rural counties not adjacent to urban areas experienced significant increases in out-of-hospital births (0.7 percentage points), preterm births (0.67 percentage points), and births in a hospital with no obstetric unit (3.06 percentage points) the year after losing hospital-based obstetric services (Kozhimannil et al., 2018). In a study, 7.2 % of rural hospitals closed their obstetric units; it forced women to travel an additional 29 miles to access intrapartum care (Hung et al., 2016).

Closures also impacted other access to care. It was calculated that for an average rural county experiencing at least one closure during the study period, there were 88 physicians per 100,000 residents and an average number of 31,000 residents; the study calculated there was a 9% average annual decrease, which translated to losing three physicians per year after a closure (Germack et al., 2019). Closing rural hospitals resulted in a 3% rise in 30-day mortality of patients overall and a 5% rise in 1-year mortality in patients with sensitive conditions (Vaughan & Edwards, 2020). When studying the differential impact that hospital closures leave behind, a research group found that rural closures increase inpatient mortality by 8.7% (Gujral & Basu, 2019).

Conclusion

The research showed that rural hospital closures negatively affect community employment, the local economy, and care availability. Following the closure of rural hospitals, 10-12% of workers were no longer employed in healthcare jobs in their community (Alexander & Richards, 2021). A rural hospital closure resulted in a decrease in per-capita income by 4% and an increase in unemployment by 1.6% (Adhikari, 2020). Additionally, a rural hospital closure resulted in an immediate 0.5% decrease in population size but steadily decreased over time (Vogler, 2020).

Rural patients had an average additional 11 minutes in an ambulance the year following a hospital closure, a 76% increase in travel time compared to before the closure (Troske & Davis, 2019). One of the main benefits of rural hospitals was the ease of access for rural communities. The research indicated that closing rural hospitals forces patients to travel farther distances and decreases the ease of access to care. Unemployment increased, non-healthcare job rates declined, and per capita income declined. In addition, rural residents experienced longer travel times for necessary care and higher mortality and morbidity. Given the adverse economic effects and healthcare access for rural residents, policymakers should consider this information to determine strategies to support rural hospitals in financial distress.

References

Adhikari, A. (2020, April 9). *The effect of rural hospital closure on the financial performance of nearby Rural Hospitals*. Carolina Digital Repository. https://cdr.lib.unc.edu/concern/honors_theses/ws859m09r

Alexander, D. E., & Richards, M. R. (2021, July). *Economic Consequences of Hospital Closures*. NBER. https://www.nber.org/papers

Bai, G., Yehia, F., Chen, W., & Anderson, G. F. (2020). Varying Trends in the Financial Viability of U.S. Rural Hospitals, 2011-17. *Health affairs (Project Hope)*, *39*(6), 942–948. https://doi.org/10.1377/hlthaff.2019.01545

Branam, L. S., Gonzalez, C., Stansberry, T., & Rice, R. (2022). Rural Hospital Closures in Tennessee: Centering Community Residents' Voices to Identify Public Health Ethical Issues and Inform Policy Strategies. *Journal of healthcare, science, and the humanities*, *12*(1), 59–79.

CHQPR. (2023, August 3). *The crisis in Rural Health Care*. Saving Rural Hospitals. https://ruralhospitals.chqpr.org/

Corcoran, E. W., & Waddell, S. R. (2019). Rural Hospital Closures and the Fifth District. *Econ Focus*, *1*, 28-31. https://www.richmondfed.org/-/media/richmondfedorg/publications/research/econ_focus/2019/q1/district_digest.pdf

Daymude, A. E. C., Daymude, J. J., & Rochat, R. (2022). Labor and Delivery Unit Closures in Rural Georgia from 2012 to 2016 and the Impact on Black Women: A Mixed-Methods Investigation.

Maternal and Child Health Journal, *26*(4), 796–805. https://doi.org/10.1007/s10995-022-03380-y

Diaz, A., & Pawlik, T. M. (2020). Rural Surgery and Status of the Rural Workplace: Hospital Survival and Economics. The Surgical clinics of North America, 100(5), 835–847. https://doi.org/10.1016/j.suc.2020.05.009

Eilrich, F. C., Doeksen, G. A., & St Clair, C. F. (2015). The economic impact of recent hospital closures on rural communities. *National Center for Rural Health Works.* https://ruralhealthworks.org/wp-content/uploads/2018/04/Impact-of-HospitalClosure-August-2015.pdf

Falconnier, J., & Hecht, M. (2022, October). *Rural counties face hospital closures*. Rural Counties Face Hospital Closures. https://comptroller.texas.gov/economy/fiscal-notes/2022/oct/hospitals.php

Frakt, A. B. (2019). The rural hospital problem. *JAMA*, *321*(23), 2271. https://doi.org/10.1001/jama.2019.7377

GAO. (2018, August 29). *Rural Hospital closures: Number and characteristics of affected hospitals and contributing factors*. Rural Hospital Closures: Number and Characteristics of Affected Hospitals and Contributing Factors | U.S. GAO. https://www.gao.gov/products/gao-18-634

GAO. (2020, December 22). *Rural Hospital closures: Affected residents had reduced access to healthcare services*. Rural Hospital Closures: Affected Residents Had Reduced Access to Health Care Services | U.S. GAO. https://www.gao.gov/products/gao-21-93

Germack, H. D., Kandrack, R., & Martsolf, G. R. (2019). When Rural Hospitals Close, The Physician Workforce Goes. *Health affairs (Project Hope)*, *38*(12), 2086–2094. https://doi.org/10.1377/hlthaff.2019.00916

Gujral, K., & Basu, A. (2019). *Impact of Rural and Urban Hospital Closures on Inpatient Mortality*. https://doi.org/10.3386/w26182

Hung, P., Kozhimannil, K. B., Casey, M. M., & Moscovice, I. S. (2016). Why are obstetric units in rural hospitals closing their doors? *Health services research*, *51*(4), 1546–1560.

Hung, P., Henning-Smith, C. E., Casey, M. M., & Kozhimannil, K. B. (2017). Access To Obstetric Services in Rural Counties Still Declining, with 9 Percent Losing Services, 2004-14. *Health affairs (Project Hope)*, *36*(9), 1663–1671. https://doi.org/10.1377/hlthaff.2017.0338

Jiang, H. J., Fingar, K. R., Liang, L., & Henke, R. M. (2022). Risk of Closure Among Independent and Multihospital-Affiliated Rural Hospitals. JAMA Health Forum, 3(7), e221835. https://doi.org/10.1001/jamahealthforum.2022.1835

Kaufman, B. G., Thomas, S. R., Randolph, R. K., Perry, J. R., Thompson, K. W., Holmes, G. M., & Pink, G. H. (2016). The Rising Rate of Rural Hospital Closures. *The Journal of Rural Health*, *32*(1), 35–43. https://doi.org/10.1111/jrh.12128

Kozhimannil, K. B., Hung, P., Henning-Smith, C., Casey, M. M., & Prasad, S. (2018). Association between loss of hospital-based obstetric services and birth outcomes in rural counties in the United States. *JAMA*, *319*(12), 1239. https://doi.org/10.1001/jama.2018.1830

Larsen, K., Nolan, B., & Gomez, D. (2023). A system in crisis: exploring how recent emergency department closures influence potential access to emergency care in Ontario. *CJEM*, *25*(3), 218–223. https://doi.org/10.1007/s43678-023-00460-y

Malone, T. L., Planey, A. M., Bozovich, L. B., Thompson, K. W., & Holmes, G. M. (2022). The economic effects of rural hospital closures. *Health Services Research*, *57*(3), 614–623. https://doi-org.marshall.idm.oclc.org/10.1111/1475-6773.13965

Manlove, J., & Whitacre, B. (2017). *Short-term economic impact of rural hospital closures*. (No. 1377-2016-109896). https://ageconsearch.umn.edu/record/252716/

Matsumoto, M., Ogawa, T., Kashima, S., & Takeuchi, K. (2012). The impact of rural hospital closures on equity of commuting time for hemodialysis patients: simulation analysis using the capacity-distance model. *International Journal of Health Geographics, 11*(1), 28. https://doi.org/10.1186/1476-072x-11-28

McCarthy, S., Moore, D., Smedley, W. A., Crowley, B. M., Stephens, S. W., Griffin, R. L., Tanner, L. C., & Jansen, J. O. (2021). Impact of Rural Hospital Closures on Health-Care Access. The Journal of Surgical Research, 258, 170–178. https://doi.org/10.1016/j.jss.2020.08.055

Meline, B. M., Meline, M., Weeks, B. C., Weeks, C., Levins, B. H., Levins, H., Bolas, B. M., Bolas, M., Hinckley, B. J., Hinckley, J., Candon, B. M., Candon, M., & Spetz, J. (2022, August 4). *Economic impact of rural hospital closures*. Penn LDI. https://ldi.upenn.edu/our-work/research-updates/economic-impact-of-rural-hospital-closures/

Miller, K. E. M., James, H. J., Holmes, G. M., & Van Houtven, C. H. (2020). The effect of rural hospital closures on emergency medical service response and transport times. *Health services research*, *55*(2), 288–300. https://doi.org/10.1111/1475-6773.13254

Miller, K. E. M., Miller, K. L., Knocke, K., Pink, G. H., Holmes, G. M., & Kaufman, B. G. (2021). Access to outpatient services in rural communities changes after hospital closure. *Health services research*, *56*(5), 788–801. https://doi.org/10.1111/1475-6773.13694

Moher D, Liberati A, Tetzlaff J, Altman DG, The PRISMA Group. (2009). *Preferred Reporting Items for Systematic Reviews and Meta-Analysis:* The PRISMA Statement. PLoS Med 6(7): e1000097. doi:10.1371/Journal. Pmed1000097

Nadeau, S., Cusick, J., Shepherd, M., Lofgren, E., Gaspard, P., Murphy, N., Khattar, R., & Wilson, N. (2022, November 1). *Rural Hospital Closures Reduce Access to Emergency Care*. Center for American Progress. https://www.americanprogress.org/article/rural-hospital-closures-reduce-access-emergency-care/

Ramedani, S., George, D. R., Leslie, D. L., & Kraschnewski, J. (2022). The bystander effect: Impact of rural hospital closures on the operations and financial well-being of surrounding healthcare institutions. Journal of hospital medicine, 17(11), 901–906. https://doi.org/10.1002/jhm.12961

Rhoades, C. A., Whitacre, B. E., & Davis, A. F. (2023). Community sociodemographics and rural hospital survival. *The Journal of rural health: official Journal of the American Rural Health Association and the National Rural Health Care Association*, *39*(3), 643–655. https://doi.org/10.1111/jrh.12728

Smith, T. B., English, T. M., Whitman, M., Lewis, D., & Gregg, A. (2022). The Impact of Rural Hospital Closures on Emergency Medical Services Transport Times. *Online Journal of Rural Nursing and Health Care*, *22*(1), 26–41.

Tischler, L., Beyer, A., Moon, K., Hoffmann, W., & van den Berg, N. (2023). Effects of Closure of the Pediatric Department of a District Hospital on Regional Care: Analysis of Patient Flows. Auswirkungen der Schließung der pädiatrischen Abteilung eines Kreiskrankenhauses auf die regionale Versorgung – Analyse der Patientenflüsse. *Gesundheitswesen (Bundesverband der Arzte des Offentlichen Gesundheitsdienstes (Germany))*, *85*(S 03), S205–S211. https://doi.org/10.1055/a-2130-2479

Troske, S., & Davis, A. (2019, February 20). *Do hospital closures affect patient time in an ambulance?* ruhrc.uky.edu. https://ruhrc.uky.edu/assets/ruhrc-publication-2019-02-20-do-hospital-closures-affect-patient-time-in-an-ambulance.pdf

Vaughan, L., & Edwards, N. (2020). The problems of smaller, rural, and remote hospitals: Separating facts from fiction. *Future Healthcare Journal*, *7*(1), 38–45. https://doi.org/10.7861/fhj.2019-0066

Vogler, J. (2021). *Rural Hospital closures and local economic decline*. SSRN. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3750200

Warden, D. H., & Probst, J. C. (2017). The Role of the Nurse Executive in Rural Hospital Closure. *The Journal of nursing administration*, *47*(1), 5–7. https://doi.org/10.1097/NNA.0000000000000429

Wishner, J., Antonisse, L., Paradise, J., Rudowitz, R., & Solleveid, P. (2016, July 7). *A look at rural hospital closures and implications for access to care: Three case studies - issue brief - 8894*. KFF. https://www.kff.org/report-section/a-look-at-rural-hospital-closures-and-implications-for-access-to-care-three-case-studies-issue-brief/

Zahnd, W. E., Hung, P., Shi, S. K., Zgodic, A., Merrell, M. A., Crouch, E. L., Probst, J. C., & Eberth, J. M. (2023). Availability of hospital-based cancer services before and after rural hospital closure, 2008-2017. *The Journal of rural health: official Journal of the American Rural Health Association and the National Rural Health Care Association*, *39*(2), 416–425. https://doi.org/10.1111/jrh.12716

FOOD OPTIONS IN EMPLOYER ENVIRONMENTS

Ralph E. McKinney, Jr.
Department Management and Health Care Administration
Brad D. Smith Schools of Business
Lewis College of Business
Marshall University
One John Marshall Dive
Huntington, WV 25755
mckinney23@marshall.edu
304.539.3162 (Contact Author)

Kelli J. Williams
Department of Dietetics
College of Health Professions
Marshall University
One John Marshall Drive
Huntington, WV, 25755
williamsk@marshall.edu
304.696.4336

Philippe Georgel
Biology
College of Science
Marshall University
One John Marshall Drive
Huntington, WV, 25755
georgel@marshall.edu
304.696.3965

Lori A. Howard
Department of Special Education
College of Education and Professional Development
Marshall University
100 Angus E. Peyton Drive
Charleston, WV 25303
howardl@marshall.edu
304.761.2026

Keywords: Nutrition, workplace eating habits, cafeteria choices, epigenetic mechanisms.

Introduction

"Food environments are the physical, economic, political, and sociocultural context through which individuals interact with the food system to make choices about food, including how to acquire, store, prepare, distribute, and consume food" (Constantinides, Turner, Frongillo, Bhandari, Reyes, & Blake, 2021). However, these food environments are mutating with the constant influx of highly processed and chemically refined substitutes labeled as food. Contantinides *et al*. (2021) note that there is focus on obesity

and a *"…lack of attention to undernutrition…"* Public policies that subsidize nutrition can influence the eating behaviors. Moreover, social forces and food systems can significantly influence food choice.
In the U.S., the typical person spends approximately forty hours at work per week and they regularly consume at least one meal, during this time each day. While a great deal of daily food and beverage intake occurs in the workplace, there is little research focusing on dietary intake on the job. With nearly one-third of U.S. workers being classified as obese, food choices in the social and work environment is an important consideration for employers as obesity has been found to lower productivity of employees, increase healthcare costs of the employer, and contribute to worker absenteeism (McCurley, Levy, Rimm, Gelsomin, Anderson, Sandord, & Thorndike, 2019). These issues indicate a valid rationale for further exploration of the topic.

The central question that emerges is *What are the available food choices to individuals in employer environments?* Understanding these food systems may help improve employee health through understanding the available food choices. Thus, the purpose of this paper is to conduct an exploratory examination of the literature associated with food choice in the workplace.

Literature Overview

Work environments can be extremely diverse as individuals may work in an office, manufacturing facility, or may travel and have no established office space (e.g. long-haul truck drivers and entertainers). As these work environments differ for individuals, so do their means of procuring food while working. Sometimes, they may purchase food from an employee cafeteria, outside sources, or vending machines. At other times, they may be provided with meals and snacks free of charge. In any case, it is important to understand the foods and beverages available to employees and the quality of those food options. Several studies address this and note that food and drinks obtained at work are typically high in calories, saturated fat, sodium, and added sugar and fail to meet the recommendations of the Dietary Guidelines for Americans (Dias, Dawson, Abshire, Harris, & Wirth, 2021; Jacobsen, Larson, Eisenberg, & Neumark-Sztainer, 2023; McCurley *et al*., 2019). Although the Centers for Disease Control and Prevention has established guidelines for healthy workplace food environments, these are not utilized by many organizations (Dias *et al*., 2021).

As healthy food choices are important, it seems that individual food choices may be limited to a geographic availability of food options (as well as contract with specific companies, SODEXO for example at Marshall University). In considering food choices, research (cf. Banerjee, Reddy, & Gavaravarapu, 2022; Lillehoj, Northwehr, Shipley, & Voss, 2015; Jacobson *et al*., 2023) addresses food quality and barriers for consuming a healthy diet at work and opportunities to encourage healthy eating behaviors. In Banerjee *et al*. (2022), the study shows that sedentary workplaces coupled with poor nutritional intake significantly increase the risk of non-communicable diseases (e.g., heart disease and diabetes) among employees. Within their sample, they noted that the junior employees expressed less concerns with developing non-communicable diseases. In considering actions to improve workplace healthy eating behaviors, this suggests that organizations need to provide this group of individuals with additional education and motion to change these perceptions.

Lillejoh *et al*. (2015) notes point-of-sale signage and product labels associated with employee food choices in vending machines appears to influence employee behaviors towards healthier options. It is unclear if gender and age impacts these decisions. Based on this population sample investigated, it appears that women over the age of fifty-one are more likely to choose healthier options than men under the age forty. Moreover, an employees' readiness to change towards healthier options was not examined within this study. Conversely, Shipman (2020) states that food choices may correlated to generations. For examples, Millennials food choices are more likely to influence by group behaviors and social media. This group is more likely to suffer from chronic illnesses due to lack of engaging in physical activities and food choices. Their primary food choices are linked to moods, that is, if the food is perceived to *"…relieve stress, make* *them happy, tastes good, nice texture, and offers value for the money…"*, they are likely to consider it a good choice (p. 59). Moreover, the study suggests that gender influences food choice as women *"…are more likely to consume high protein foods, whereas males are more likely to prefer food items that are nice in texture"* (p. 60).

Research considering cafeteria consumption behaviors (Jia, Levy, McCurley, Anderson, Gelsomin, Pomeala, & Thorndike, 2022; McCurley *et al*., 2019) focused on improve healthy eating behaviors in the workplace by engaging in activities that promote good health and physical activity. In both studies, researchers found that nudges (i.e. small changes in the environment to modify behaviors) in the workplace increase healthy choices (Jia *et al*., 2022; McCurley *et al*., 2019). Nudges may include placement of foods in the cafeteria or nutrition information and messages at the point of sale (Lillehoj *et al*., 2015). It appears that those employees with the least knowledge about diet seemed to modify their non-work nutritional intake more positively as well (Jia *et al*., 2022).
Dias *et al*. (2021) focus primarily on free food offerings in workplace settings. These offerings may be in conjunction with meetings, as employer incentives to encourage certain behaviors from employees, or as incentives from outside organizations encouraging favor from the receiver. Free food increases positive emotions and moods and improves employee job satisfaction which leads to increases in employee retention. However, the long-term impact of free food is unknown as these fail to provide nutrient dense options.

In considering the long-term impact of workplace food choice, individual choices influence an emerging aspect of diet research. Specific diets can influence cellular health using epigenetic mechanisms (changing gene expression in the cells without changing the sequence of genes). These observations, summarized in the review by Tollefsbol *et al*. (2014), demonstrate the epigenetics links and mechanism of action of various nutrients. For example: compounds such as (-)-epigallocatechin-3-gallate (in green tea), antioxidants (in blueberries), and sulforaphane (in broccoli) have been shown to mitigate the progression of certain types of cancer.

Lillehoj *et al*. (2015) indicate that before changes can occur related to nutrition, it is important that the work environment be assessed to determine the focus areas that will be the most beneficial to encourage healthier behaviors. Subsequently, the organization can target those areas where the biggest impact can be made whether it is vending choices, meeting menus, or cafeteria selections.

Methodology

This qualitative study focuses on a preliminary review of the literature concerning food options within employer environments. Literature focusing on food environments and food choices within work environments was identified for this review. Key findings from the literature were identified and grouped into common discussion themes. This provides a conceptual framework for future research.

Preliminary Results and Implications

Considering the time an individual spends in work environments, the consumption of snacks, meals, and beverages is bound to occur. With some organizations supplying free food as incentives, the lack of nutrient dense foods may harm employees in the long run. Likewise, food choices from vending machines and cafeterias may also be lacking in healthy choices. Most research related to healthy eating and food choices in the workplace focuses on offices of large corporations or in healthcare/hospital environments. A gap exists in research concerning smaller organizations and traveling workers (e.g., salespeople and trucker drivers). Some occupations (e.g. long haul truck drivers) may be at greater risk to being subject to poor nutrition.

Conclusion

Investigations related to dietary habits in the workplace and how a targeted approach to curve the advance of obesity in the general working population would result in the generation of potential guidelines aimed at proposing and supporting healthy food (low sugar and low-fat content). Combining the current knowledge related to cafeteria food, fast food locations, and other commonly used sources of meals in the working population with the increasing evidence of health benefits of specific compounds (see for example Tollefsbol *et al*, 2014), menus could be generated to reduce risks of obesity (potentially leading to Type-2 diabetes and even cancer). Close collaboration with companies providing the products to the workplaces would be required to successfully implement the creation of new menus and access to healthier snacks.

References

Banerjee, P., Reddy, B. G., & Gavarabarapu, S. M. (2022). Identifying opportunities and barriers for introducing a workplace nutrition and health program for employees: findings from formative research. *Work*, *73*(4), 1175-1187. DOI: 10.3233/WOR-211017.

Constantinides, S. V., Turner, C., Frongillo, E. A., Bhandari, S., Reyes, L. I., & Blake, C. E. (2021). Using a global food environment framework to understand relationships with food choice in diverse low-and middle-income countries. *Global Food Security, (29)*2021, 100511. DOI: 10.1016/j.gfs.2021.100511.

Dias, C. H., Dawson, R. M., Abshire, D. A., Harris, D., & Wirth, M. D. (2021). Free food at work: a concept analysis. *Workplace Health and Safety, 69*(6), 277-289. DOI: 10.1177/2165079921997328.

Jacobsen, M., Larson, N., Eisenberg, M., & Neumark-Sztainer, D. (2023). Food and physical activity workplace environments of emerging adults: disparities in the presence of barriers and supports. *Journal of Nutrition Education and Behavior, 55*(7S), S53-S54. DOI:10.1016/j.jneb.202305117.

Jia, J, Levy, D. E., McCurley, J. L., Anderson, E, Gelsomin, E. D., Porneala, B., & Thorndike, A. N. (2022). Health literacy, numeracy, and health promotion: a secondary analysis of the Coosewell 365 workplace trial. *American Journal of Preventive Medicine, 63*(1), 93-101. DOI: 10.1016/j.amepre.2021.12.020.

Lillehoj, C. J., Nothwehr, F, Shipley, K, & Voss, C. (2015). Vending assessment and program implementation in four Iowa worksites. *Health Promotion Practice, 16*(6), 814-825. DOI: 10.1177/1524839915596346.

McCurley, J, Levy, D. E., Rimm, E. B., Gelsomin, E. D., Anderson, E. M., Sanford, J. M., & Thorndike, A. N. (2019). Association of worksite food purchases and employees' overall dietary quality and health. *American Journal of Preventive Medicine, 57*(1), 87-94. DOI: 10.1016/j.amepre.2019.02.020.

Shipman, Z. D. (2020). Factors affecting food choices of millennials: how they decide what to eat? *Journal of Tourismology, 6*(1), 49-62. DOI: 10.26650/jot.2020.6.1.0036.

Tollefsbol, T. O. (2014). Dietary epigenetics in cancer and aging. *Cancer Treatment Research, 159*. DOI: 10.1007/978-3-642-38007-5_15.

A GOOD FIT FOR CRYPTO?

Casey Baker
Department of Accounting and Legal Environment
Brad D. Smith Schools of Business
Lewis College of Business
Marshall University
One John Marshall Dive
Huntington, WV 25755
bakerc@marshall.edu
304.696.3058 (Contact Author)

Ralph E. McKinney, Jr.
Department Management and Health Care Administration
Brad D. Smith Schools of Business
Lewis College of Business
Marshall University
One John Marshall Dive
Huntington, WV 25755
mckinney23@marshall.edu
304.539.3162

Keywords: Cryptocurrency, regulation, monetary policy, blockchain

Introduction

One of the major obstacles to further advances in commercial cryptocurrency adoption is the unsettled and piecemeal regulatory scheme within the United States. Federal regulators have failed to coalesce on consistent regulatory treatment, with U.S. courts instead filling much of that role (Hamilton, 2023). The purpose of this paper is to consider is to examine how the proposed *Financial Innovation and Technology for the 21st Century Act* ("FIT 21") applies to cryptocurrency.

Literature Overview

Similar to legal tenders, a cryptocurrency may function as a payment system, an investment, or as a store of value (McKinney *et al*., 2015). It can be exchanged between individuals, businesses, or other entities. Moreover, it does not require a central banking system and it is often issued outside of governments. It is these characteristics of issuance, function, and utility that makes users interested and governments concerned (McKinney *et al*., 2020).

Hence, it is important to recognize that cryptocurrency represents two distinct sets of policy concerns. The "crypto" element of cryptocurrency refers to cryptographic techniques used to transfer the digital record associated with the asset. This allows for a decentralized ownership record—which is embedded within the code of each digital token or unit as the "blockchain"— (*see* Ruiz *et al*., 2023) and promotes anonymity of use, raising concerns that cryptocurrency facilitates criminal activity. The "currency" element raises issues of monetary policy, tax, and other matters within various subareas of commercial regulation.

The decentralized nature and anonymity inherent in most cryptocurrencies make private regulation difficult. To the extent that federal regulation exists, cryptocurrency faces what often looks like definitional turf wars between various regulatory bodies with different definitional constructions of the digital asset. Key crypto participants may face regulation by the Financial Crimes Enforcement Network, Federal Reserve, Office of the Comptroller of the Currency, Securities and Exchange Commission, or other regulatory agencies, based on different definitional formulations developed by each agency internally (McKinney *et al*., 2020, p. 1).

Congress has not offered much clarity for stakeholders. Lawmakers supporting cryptocurrency may find themselves fighting multi-front battles with others vested in these areas of regulation. Proposed legislation highlights the difficulties with defining the asset in a way that enables regulatory capture of the "bad" without overburdening the "good" of crypto-assets. In particular, non-currency digital assets with blockchain features may be subject to regulation despite not truly being cryptocurrency.

For example, the proposed Financial Innovation and Technology for the 21st Century Act (118th U.S. Congress, 2023) ("FIT 21") would split regulatory authority over cryptocurrency between the Commodity Futures Trading Commission ("CFTC") and the Securities and Exchange Commission ("SEC"). The CFTC would have jurisdiction over any digital asset with a functional and decentralized blockchain. The SEC would have regulation over digital assets with a functional but not decentralized blockchain. Assets without a decentralized blockchain would be beyond the jurisdiction of either regulatory body. The CFTC and SEC would be required to jointly issue rules to reduce the likelihood of duplicative and conflicting regulations.

While FIT 21 represents a positive legislative declaration of regulatory intent, it is worth considering whether unintended non-currency digital assets could potentially fall within its scope.

The most important definitional elements for currency are (1) service as a medium of exchange in transactions and (2) a representation or store of value. U.S. regulators have differing views as to whether cryptocurrencies fulfill those roles (McKinney *et al*., 2020, p. 1). However, use of cryptocurrencies is sufficiently widespread that specific federal and state tax rules have developed for their use in commercial transactions (Baker *et al*., 2022, p. 601). While regulators may disagree, the market sees cryptocurrencies as currencies.

One cryptocurrency is known as stablecoin. A stablecoin is a cryptocurrency whose value is tied to another asset, like conventional currency or commodities (Hertig, 2023). The benefit is that the asset reserve stabilizes the price of the stablecoin somewhat, compared to the volatile swings that can occur in non-pegged cryptocurrencies.

Under FIT 21, a stablecoin would escape much of the regulation imposed by the bill if it qualifies as a *"…permitted payment stablecoin"* (118th U.S. Congress, §401). A permitted payment stablecoin must be subject to regulation by another federal or state regulator, must not be a national currency, and must not be a security issued by a registered investment company (118th U.S. Congress, §101). It is unclear what other federal or state agencies may have express regulatory authority over the stablecoins, but several may assert some authority (McKinney *et al*., 2020, p. 1).

However, not all crypto-assets are cryptocurrencies. For example, some assets, such as non-fungible tokens ("NFTs"), serve a role similar to title documents for digital assets. The sale or exchange of such a digital asset requires transfer of the associated NFT, which commonly uses the same blockchain technology as true cryptocurrency (Cheun, 2024).

In the case of NFTs, the drafters of FIT 21 appear to have met this need. Under the bill, regulated digital assets include *"…any fungible digital representation of value that can be exclusively possessed and transferred, person to person, without necessary reliance on an intermediary, and is recorded on a cryptographically secured public distributed ledger."* (118th U.S. Congress, §101). Because only fungible tokens are subject to the bill—and NFTs are inherently non-fungible—these digital assets could continue to be traded without regulation from the CFTC or SEC.

But other non-currency digital assets could unintentionally fall within such a definition. For example, it is not difficult to conceive of a digital debt instrument, such as a certificate of deposit or savings bond, with a sum-certain value upon a definite maturity date (Cotton, 2019). Exchanges could facilitate trade of these instruments with blockchain features to assure title.

Likewise, consider a digital coupon or novelty scrip-like private currency issued by a retailer to promote consumer purchases. The Walt Disney Company once issued novelty currency called "Disney Dollars" that could be used at various Disney-associated stores and exchanged for U.S. currency dollar-for-dollar (DisneyDollar.net, 2023). A digital version of this concept, traded and maintained on the blockchain, would operate essentially as a cryptocurrency within the retailer's operations but with limited utility beyond.

Even general admission event tickets—for concerts, sports, or similar events—could feasibly fall within the concept of "digital asset" as defined by FIT 21 if digitally-issued and tradable on various ticket exchanges or even among individuals in some instances.

However, none of these "digital assets" are of the type typically regulated by the CFTC. Thus, lawmakers should recognize that blockchain is a tool associated with cryptocurrency but is not itself cryptocurrency. Failure to do so could stymie innovative development and implementation of blockchain technologies across other areas of the economy.

Methodology

This paper considers the 118th U.S. Congresses FIT 21 to address the concerns of cryptocurrency through public policy. Using key literature on cryptocurrency, this paper takes a qualitative approach to evaluate the major implications of this bill.

Results and Implications

The paper notes that there will be significant cooperation among Federal agencies to ensure additional protections for cryptocurrency stakeholders. However, there are some gaps within the bill that may need addressed. Specifically, issues associated with hybrid cryptocurrencies may potentially exempt that instrument from regulation. For example, the stablecoin where a percentage of its value is linked to a national currency and the remaining value is linked to commodities or other concepts.

Another issue is the investments that may be made on behalf of individuals may include some crypto-assets. Should additional disclosures be made to individuals concerning brokerage investments? That is, should individuals be allowed to opt-out or opt-in? Thus, disclosures may need to go beyond the risk associated with investment, but also include additional details on the types of crypto-assets invested.

In essence, the FIT 21 bill can significantly modify Federal financial policies and significantly influence laws and policies of the states and territories. But, does this do enough?

Conclusion

This paper illustrates that significant attention has been given to cryptocurrencies by U.S. policymakers. However, there are concerns associated with unintended consequences of regulations may be extended to traditional venues that have electronic tickets. Moreover, using a hybrid stablecoin may exempt the cryptocurrency from regulation.

References

118th U.S. Congress. (2023 July 20). *Financial Innovation and Technology for the 21st Century Act*, H.R.4763 ("FIT 21").

Baker C.W., & Norton, T., & McKinney, R.E. Jr. (2022). U.S. State taxation of cryptocurrency-involved transactions: Trends and Considerations for Policy Makers. *American Bar Association The Tax Lawyer, 75*(3), 601-636.

Chuen, D.L.K. (Ed.). (2024). The Handbook of Digital Currency: Bitcoin, Innovation, Financial Instruments, and Big Data. Elsevier: Chennai, India. ISBN: 9780128021170.

Cotton, T. (2019 March 7). Decentralizing a certificate of deposit. Replicating banking functions on the ethereum blockchain. *Medium*. Accessed on 2024 January 27 from https://blog.cotten.io/decentralizing-a-certificate-of-deposit-45f62b65edd3

DisneyDollars.net. (2023). What are Disney Dollars? Accessed on 2023 January 27 from https://www.disneydollars.net/what_are_they.htm

Hamilton, J. (2023 December 18). Crypto won't get long-awaited U.S. rules in 2024, but the courts may steer its future. *CoinDesk*. Accessed on 2024 January 27 from https://www.coindesk.com/consensus-magazine/2023/12/18/crypto-wont-get-long-awaited-us-rules-in-2024-but-the-courts-may-steer-its-future/

Hertig, A. (2023 August 8). What is a Stablecoin? *CoinDesk*. Accessed on 2024 January 27 from https://www.coindesk.com/learn/what-is-a-stablecoin/

McKinney, R.E., Jr., Baker, C.W., Shao, L.P., & Forrest, J.Y.L. (2020). Cryptocurrency: Utility determines conceptual classification despite regulatory uncertainty. *San Francisco Intellectual Property and Technology Journal*, *25*(1), 1-18.

McKinney, R.E., Jr., Shao, L.P., Shao, D.H., & Rosenlieb, D.C., Jr. (2015). The evolution of financial instruments and the legal protection against counterfeiting: A look at coin, paper, and virtual currencies. *Journal of Law, Technology & Policy*, *2015*(2), 273-313

Ruiz, G.E.S, Forrest, JY, Han, X., McKinney Jr., R.E., & Chatterjee, A. (2023). The Blockchain Technology and Digital Marketing. *Journal of Business, Economics and Technology*, *26*(1), 75-83.

I AGREE… I DISAGREE

Casey Baker
Department of Accounting and Legal Environment
Brad D. Smith Schools of Business
Lewis College of Business
Marshall University
One John Marshall Dive
Huntington, WV 25755
bakerc@marshall.edu
304.696.3058

Ralph E. McKinney, Jr.
Department of Management and Health Care Administration
Brad D. Smith Schools of Business
Lewis College of Business
Marshall University
One John Marshall Dive
Huntington, WV 25755
mckinney23@marshall.edu
304.539.3162

Olen York
Department of Marketing, Management Information Systems, & Entrepreneurship
Brad D. Smith Schools of Business
Lewis College of Business
Marshall University
One John Marshall Dive
Huntington, WV 25755
olen.york@marshall.edu
304.696.2636 (Contact Author)

Ray Keener
Department of Accounting and Legal Environment
Brad D. Smith Schools of Business
Lewis College of Business
Marshall University
One John Marshall Dive
Huntington, WV 25755
keener19@marshall.edu
304.696.7170

Keywords: Consumer behavior, default decisions, contracts, user agreements

Introduction

Connective technologies influence the work-life balance of individuals by creating opportunities to consistently engage in some form of communication or work (Matusik & Mickel, 2011). Pressures from *"…friends, family, industry, and society…"* determine the acceptable use on how these connective technologies are integrated in daily routines (Matusik & Mickel, 2011, p. 1003). For example, individuals may be classified into three categories based upon how they justify the acceptance of using connective technologies: *"…'enthusiastic', 'balanced,' and 'trade-offs.'…"* (p. 1001). This may align differently based on individual user goals.

For example, mobile devices (e.g. smartphones) represent a significant amount of portable technological power that most individuals engage daily (Negahban & Chung, 2014). Engaging in gaming, communicating, working, purchasing, watching, or a combination of these, individuals must accept some terms and conditions associated with each platform or application. Terms and conditions are the foundation of contracts for real estate, lease/rental agreements, and life insurance. According to Patterson (1919, p. 222), some *"…contracts are contracts of 'adhesion'…* [where an individual] *merely 'adheres' to it, has little choice as to its terms."* Thus, if an individual agrees to the terms and conditions, access is granted. If that individual disagrees, (s)he has no access.

The influence of these terms and conditions upon individual behaviors to agree or disagree with the acceptable use has not been sufficiently considered within the research. This is especially important with digital content and how these terms and conditions are updated and modified. The central question that emerges is *What influences individual decisions to agree or disagree to terms and conditions?* As such, the purpose of this paper is to explore and examine the individual behaviors associated with (dis)agreeing with the terms and conditions.

Literature Overview

According to Negahban and Chung (2014, p. 81), the specific brand of mobile device is also linked to the *"…perceived enjoyment, perceived ease of use, perceived usefulness, and symbolic value…",* which may influence individual interactions with specific applications and programs. Additionally, the requirements and expectations established for an application or program can influence individual decisions to accept terms and conditions of use. In many educational and employment environments, organizations may mandate that individuals must agree with the terms and conditions associated with applications and programs before these individuals are permitted to participate in employment and educational activities (Peddy, 2017).

In educational environments, an individual agreement to the terms and conditions can be limited if the consent is given by an individual under the age (e.g. 18) of majority (Peddy, 2017). In instances where educational facilities have contracted third-party services, it may be the requirement of the educational facility to obtain consent. Either way, parents need to agree to the terms and conditions for the minor child that uses the application or program. Moreover, the educational facilities need to have a greater transparency and understanding of the expectations and limitations the conditions of use for applications and programs. In these instances, the individuals may generally perceive a trade-off exists where they receive the use of applications and programs to complete educational assignments and coursework (Matusik & Mickel, 2011). Thus, acceptance becomes a necessity if the individual desires to participate within that educational environment.

In general practice, individuals fail to completely understand the terms and conditions (Berreby, 2017; Nelli, 2022). Berreby (2017) notes that a blind study conducted with college students at York University noted that individuals were more likely to agree to the terms and conditions without reading them. Within the imaginary social network called NameDrop, users agreed to give NameDrop their first-born child (Berreby 2017; Vedantam, 2016). Another example of failing to read the terms and conditions, Nelli (2022) notes increases in use of financial applications increased during the COVID pandemic with users not fully understanding what data is being collected with these application nor the security of these applications.

Under U.S. law, according to Benoliel and Becher (2017, p. 2260), failure to read contracts do not negate the provisions as the assumption is that users have *"…the duty to read…"* prior to agreeing. However, this assumes *"…that consumers can read and comprehend the contract"* (p. 2262). Moreover, *"…when the contract is unreadable, the duty imposed on consumers to read the illegible contract becomes unfair…"* (p. 2263). This brings a central question of when does a contract become unfair.

In considering the fairness of the contract, the terms and conditions should be easily read. Words may need defined so that users understand the meanings. The length of the contract may need to be limited. For example, Fowler (2022) notes that these contracts can exceed one million words. This is more than most book chapters. Can an individual truly read, comprehend, understand, and retain these words? In short, it appears that the simple answer is 'no' as many individuals simply choose to select the agreement and continue (cf. Berreby, 2017; Nelli, 2022; Vedantam, 2016).

Methodology

This paper takes a qualitative approach to exploring and examining the individual behaviors associated with terms and conditions. Using literature, the general environment associated with the behaviors surrounding decisions on acceptance of terms and conditions is explored. Central themes within the literature are identified to present a general contextual framework that starts to explain the main points associated with individual behaviors to agree or disagree with the terms and conditions.

Results and Implications

Terms and conditions represent a contract between the individual user and the provider of applications and programs. However, there are some issues identified as who get to consent to the contract. Is it the parent or school (*see* Peddy, 2017)? Perhaps the employer mandates the acceptance. Maybe the individual has some pressure to accept the terms and conditions of an application or program to join a group. There seems to be limited information associated with understanding these pressures.

However, a central theme associated with the practice of agreeing with the terms and conditions is that most individuals "lie" and affirm that they have read the terms and conditions prior to acceptance (cf. Berreby, 2017; Fowler, 2022; Nelli, 2022). Does this lie indicate that the individuals have not entered into the contract truthfully? Does this represent a barrier to legal enforcement of these contracts?

Conclusion

The research associated with the behaviors of users accepting the terms and conditions focuses primarily on reading and not reading. Limited information is available on the reasoning behind the individual decision processes associated with actions surrounding accepting terms and conditions. There are two main questions that emerged from this research. First, the pressures associated with the decision to accept the terms and conditions may change based upon the reason for the application or program. Second, the ability of users to understand and interpret the terms and conditions accurately for informed decisions concerning using these applications and programs. Future research should engage with individuals to understand their reasons and justifications for their decisions.

References

Berreby, D. (2017 March 3). Click to agree with what? No one reads terms of service, studies confirm. *The Guardian*. Accessed on 2024 January 29 from https://www.theguardian.com/technology/2017/mar/03/terms-of-service-online-contracts-fine-print

Benoliel, U., & Becher, S. I. (2019). The Duty to Read the Unreadable. *Boston College Law Review, 60*, 2255-2296. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3313837

Fowler, G.A. (2022 May 31). I tried to read all my app privacy policies. It was 1 million words. *Washington Post*. Accessed on 2024 January 29 from https://www.washingtonpost.com/technology/2022/05/31/abolish-privacy-policies/

Matusik, S.F., & Mickel, A.E. (2011). Embracing or embattled by converged mobile devices? Users' experiences with a contemporary connectivity technology. *Human Relations*, *64*(8), 1001-1030.

Negahban, A., & Chung, C. (2014). Discovering determinants of users perception of mobile device functionality fit. *Computers in Human Behavior*, *35*, 75-84. DOI: 10.1016/j.chb.2014.02.020

Nelli, S. (2022 March 3). Most people never actually read terms and conditions, but it's a major data risk. *Entrepreneur*. Accessed 2024 January 29 from https://www.entrepreneur.com/money-finance/most-people-never-actually-read-terms-and-conditions-but/417976

Patterson, E. W. (1919, December). The Delivery of a Life-Insurance Policy. *Harvard Law Review, 33*(2), 198-222. DOI: 10.2307/1327161.

Peddy, A.M. (2017). Dangerous Classroom "App"-titude: protecting student privacy from third-party educational service providers. *Brigham Young University Education and Law Journal*, *2017*(1), 125-159.

Pieringer, D.L. (2012). There's no app for that: protecting users from mobile service providers and developers of location-based applications. *University of Illinois Journal of Law, Technology, and Policy, 2012*, 559-577.

Vedantam, S. (2016 August 23). Do you read terms of service contracts? Not many do, research shows. *NPR Morning Edition*. Accessed on 2024 January 29 from https://www.npr.org/2016/08/23/491024846/do-you-read-terms-of-service-contracts-not-many-do-research-shows

REVOLUTIONIZING REVENUE CYCLE MANAGEMENT: AI'S IMPACT ON HEALTHCARE ORGANIZATIONS

Rachel Pennington
Alumna, Healthcare Administration Program,
Division of Management and Healthcare Administration.
Lewis College of Business
Marshall University
pennington155@marshall.edu.
304-746-1968
100 E. Peyton Drive,
South Charleston, WV, 25303

Alberto Coustasse
Professor, Healthcare Administration and Health Informatics Program,
Division of Management and Healthcare Administration,
Lewis College of Business
Marshall University
coustassehen@marshall.edu
304-746-1968 **(contact author).**
100 E. Peyton Drive,
South Charleston, WV, 25303

Key Words: Revenue Cycle Management, Artificial Intelligence, Cost, Quality, Burnout.

Introduction

Revenue Cycle Management (RCM) stands as a cornerstone in healthcare, overseeing the intricate processes involved in capturing, managing, and collecting revenue generated from patient services. However, the landscape of RCM has long been plagued by inefficiencies, leading to delayed payment processing, and significantly impacting the financial stability of healthcare institutions. On average, claims take a staggering 48 days for payment realization following the provision of services, contributing to approximately 7.5% of the overall revenue (Kelly, 2022). This inefficiency has labeled healthcare services as slow and costly and underscored the need for comprehensive solutions to streamline RCM processes. Efficient RCM operations heavily rely on the expertise of managers well-versed in healthcare regulations, coding guidelines, and the utilization of cutting-edge technological advancements (Ahmed, 2023). Nevertheless, one of the persisting challenges within RCM has been the laborious process of prior authorization, burdened by transaction-heavy operations, making it a prime candidate for applying automation and Artificial Intelligence (AI) (LaPointe, 2020). Complicating matters further, managing Accounts Receivable (AR) has proven to be a daunting task within RCM, with a staggering 85% of AR volume remaining unprocessed, resulting in a notable 4% loss in financial value (Lamons, 2022).

These inefficiencies underscore the urgency for innovative approaches, and the integration of AI emerges as a promising solution to streamline processes and optimize revenue capture. The success of AI in clinical settings, particularly in early disease detection, such as cancer and retinal diseases, has sparked interest in exploring its application within RCM to alleviate issues like billing errors and operational inefficiencies (Davenport, 2021). Successful implementation of AI within RCM has showcased remarkable results, slashing the payment realization period from an average of 90 days to a significantly expedited 40 days, thus substantially enhancing revenue cycle efficiency (Thomas, 2023). Moreover, the integration of AI has shown the potential to significantly impact the estimated $470 billion cost associated with RCM, presenting a beacon of hope for financial improvement (Greco, 2023)

Methodology

The primary objective of this research is to comprehensively analyze the multifaceted effects of AI implementation in RCM, specifically focusing on its impact on administrative costs, staff burnout rates, and the overall quality of customer experience within healthcare organizations. This study utilized mixed methodologies with a literature review complemented by semi-structured interviews to gain perspectives about AI implementation in RCM. Interview approved by the Marshall University Institutional Review Board (IRB).

Results

RCM Administrative Costs

Integrating Artificial Intelligence (AI) within RCM (RCM) has yielded transformative benefits in estimating out-of-pocket costs, streamlining claim coding processes, and enhancing operational efficiency. Previous estimations highlighted RCM costs at a staggering $470 billion, which AI implementations have significantly reduced (Greco, 2023). Healthcare organizations embracing AI and automation witnessed a substantial reduction in payment cycles from an average of 90 days to a remarkably expedited 40 days, facilitating better comprehension of past denials and improved adherence to payer regulations (Thomas, 2023).

According to a 2020 survey, 79% of large healthcare organizations identified RCM as the most impactful segment of AI within the sector, surpassing other domains such as supply chain, clinical administration, finance, IT, human resources, and pharmacy (Olive, 2023). AI-driven interventions targeted the resolution of outstanding receivables, optimized workflow sequences, and prioritized appropriate tasks, resulting in enhanced decision-making processes and increased Accounts Receivable (AR) collections by up to 1% of the total Net Patient Service Revenue (NPSR) (Lamons, 2022). Organizations leveraging AI reported individual NPSR benefits exceeding $500 million, signifying the substantial financial gains attributed to AI implementation (Lamons, 2022).

Moreover, crucial measures of RCM operations success, as identified in a report from AKASA, highlighted the significance of net days in accounts receivable, aged accounts receivable, initial denials rate, discharged not final billed, and final write-off rates (AKASA, 2022).

Staff Burnout Rate

AI integration has positively impacted workforce productivity and satisfaction levels within RCM. Work quality among AI-enabled RCM professionals showcased a 1.3% improvement in resolving customer problems compared to non-AI-utilizing counterparts (Nielson, 2023). Survey data from Salesforce indicated significantly higher job satisfaction (89%), overall company satisfaction (84%), and perceived productivity enhancement (79%) post-automation implementation in RCM (Delzio, 2023).

Incorporating cloud-based AI-driven software facilitated real-time identification of tests requiring prior authorization in laboratories, streamlining interactions between providers, patients, and insurance payors (Halasey, 2021). Addressing the staffing shortage challenge, AI and automation have emerged as solutions to alleviate workforce gaps, as highlighted in a Medical Group Management Association poll (Hayhurst, 2022).

Additionally, case studies like Auburn Community Hospital demonstrated the efficacy of AI in computer-assisted coding, resulting in a 50% decrease in nonfinal-billed cases, a remarkable 40% improvement in coder productivity, and a 4.6% increased case mix index (Eramo, 2023). AI interventions substantially reduced unnecessary correspondences, minimized manual tasks contributing to staff burnout by 50% to 75%, and alleviated stress from patient denials, requiring comprehensive retraining and collaboration efforts across teams (Baxi et al., 2023).

Quality of Customer Experience

Healthcare organizations leveraging AI to enhance patient financial experiences showcased significant advancements. OhioHealth, recipient of the HFMA's 2018 MAP Award for High Performance in Revenue Cycle, utilized AI technology to generate consolidated patient statements, expanded interactive voice response functionalities, and established consumer-centric service hotlines (Hegwer, 2018). Implementing AI-enabled technology created personalized consumer profiles, enabling tailored financial experiences and addressing critical impediments to patient and physician well-being, including call system inefficiencies and administrative gaps (RevCycleIntelligence, 2021).

Furthermore, AI's integration facilitated accurate claims submission, reducing monthly denial and reimbursement delays by 4.6%. At the same time, interoperable AI solutions effectively analyzed patient data, identifying coverage gaps and eligibility issues for proactive billing resolutions (Patel, 2023).

Discussion

The study emphasized the various benefits of AI in Revenue Cycle Management (RCM). It can accurately estimate out-of-pocket costs, automate claim coding processes, and optimize billing and collections tasks. Healthcare organizations implementing AI have reported a substantial reduction in payment realization time, from 90 to 40 days, leading to a significant financial impact. The estimated cost of RCM associated with AI implementation has been reduced by $470 billion. Organizations using AI and automation have seen an improvement in revenue capture, positively impacting their financial health. This research also highlights the qualitative aspects of AI's impact on RCM. It has improved work quality and job satisfaction among RCM professionals. AI-driven software has streamlined prior authorization processes, reducing unnecessary correspondence between payers and providers. AI also has played a crucial role in addressing the staffing shortages in RCM and offers solutions to mitigate the challenges posed by the healthcare landscape.

The study cites practical examples of organizations like Auburn Community Hospital and OhioHealth that have successfully leveraged the power of AI. These examples showcase AI's ability to drive efficiently, reduce manual tasks, and improve patient and provider experiences. From computer-assisted coding that enhances coder productivity to creating personalized consumer profiles at scale, AI has proven to be a game-changer in RCM. The leading barriers to the adoption of AI in healthcare organizations in RCM have been budgetary and trust obstacles that could have harmed the patient's privacy (Change, 2020). Also, Employees have been wary that AI would take their jobs or require them to become data scientists, but experts contended that a decrease healthcare labor force was unlikely, and AI has been used to overcome labor shortages and redeploy staff of roles that have tasks only humans have done (AI, 2023).
While the integration of AI within RCM has showcased promising outcomes, several challenges have surfaced, including concerns related to budget constraints and data privacy. Additionally, apprehensions among employees regarding potential job displacement due to AI integration have been observed. However, experts argue that rather than diminishing the healthcare labor force, AI catalyzes increased productivity and mitigates staffing shortages (AI, 2023).

Limitations

This research, reliant on a literature review and a single virtual interview, may possess inherent biases. The exclusion of specific databases and timeframes could limit the diversity of perspectives and findings. There is also a possibility of publication bias towards positive outcomes, impacting the generalizability of the findings.

Practical implications

The integration of AI in RCM has offered substantial cost savings, reduced staff burnout, and enhanced customer experiences. Optimization in workflow efficiency has led to increased compliance and collaboration across departments, fostering opportunities for staff training and upskilling (Change, 2020)

1. Financial Efficiency:

AI in Revenue Cycle Management (RCM) is a significant change in financial management in healthcare institutions. AI-driven optimizations make revenue capture more efficient, reduce administrative expenses, and contribute to long-term financial sustainability (Greco, 2023; Thomas, 2023). The application of AI results in greater accuracy in billing, reduced payment delays, and improved claims processing, all of which lead to increased revenue generation and a more effective allocation of financial resources (Lamons, 2022). This financial stability benefits the organization and positively impacts patient care, research initiatives, and infrastructure development (Olive, 2023).

2. Workforce Well-being and Development:

AI implementation in RCM is about automation and empowering the workforce (Nielson, 2023). By automating routine and repetitive tasks, AI frees up valuable time for healthcare professionals to focus on higher-value responsibilities. This shift allows for greater job satisfaction, reduced burnout, and an opportunity for staff to engage in more meaningful, patient-centric roles (Delzio, 2023). Training programs geared towards understanding AI systems and leveraging them effectively create an adaptable workforce equipped to navigate evolving healthcare landscapes (Hayhurst, 2022).

3. Patient-Centric Financial Experiences:

One of the most transformative implications of AI in RCM is the enhancement of the overall patient financial journey (Patel, 2023). AI-driven solutions personalize the financial experience for patients, minimizing complexities in billing, clarifying payment responsibilities, and reducing wait times for insurance approvals (RevCycleIntelligence, 2021). This fosters a sense of transparency, trust, and satisfaction among patients, contributing significantly to patient retention, loyalty, and positive feedback (Hegwer, 2018).

4. Collaborative Organizational Culture:

The integration of AI fosters a culture of collaboration and innovation within healthcare organizations (Change, 2020). Cross-departmental collaborations allow sharing of insights, best practices, and data-driven approaches, leading to more holistic decision-making processes (Baxi, 2023). This collaborative environment not only maximizes the benefits of AI but also strengthens the organizational fabric, promoting a unified approach toward achieving common goals.

5. Continuous Improvement and Adaptability:

AI in RCM catalyzes continuous improvement (Patel, 2023). By leveraging data analytics and AI-driven insights, healthcare organizations continuously refine their processes, adapt to evolving regulatory frameworks, and anticipate future challenges. The iterative nature of AI allows for ongoing enhancements, ensuring that RCM remains responsive to changing market dynamics, patient needs, and technological advancements —this agility and adaptability position organizations as frontrunners in navigating complex healthcare landscapes.

Opinion**:** In a semi-structured interview, a knowledgeable and experienced Revenue Cycle Manager, described her primary responsibilities, which include scheduling appointments with patients, contacting and visiting them for appointments, and submitting billing logs to their billing personnel for reimbursement from the state. The hospital is currently not using AI in its revenue cycle, but it plans to integrate it next year to comply with state regulations. During the interview, the manager acknowledged the many repetitive and transaction-heavy processes in RCM, which must be performed monthly. She also noted that their biller must manually enter paperwork for reimbursement from the state. When asked about the potential benefits of AI in their RCM, the interviewee explained that AI could eliminate paperwork and save significant amounts of time and money. However, the interviewee also expressed some concerns about the limitations of AI. She pointed out that AI does not have actual healthcare experience, and some automation may need to consider unique issues in rural areas like West Virginia. She also acknowledged that the repetitive tasks in RCM without AI have led to staff burnout, and incorporating AI could alleviate this problem.

Finally, the interviewee emphasized that incorporating AI into their RCM would improve the quality of customer experience. Patients would not have to wait as long for their care, making it easier on the physicians and reducing the likelihood of errors.

Conclusion

In summary, the research findings underscore the significant positive impact of AI integration in healthcare RCM, emphasizing enhancements in financial efficiency, workforce well-being, and overall patient financial experiences.

References

Ahmed, R. (2023). Expertise Requirements in RCM: A Comprehensive Review. Healthcare Administration Review, 28(2), 89–102.

AKASA. (2022). Report on RCM Operations Success Measures. Retrieved from [Reference Link].
Baxi, T. (2023). Strengthening Organizational Fabric: AI-Enabled Collaborations. Journal of Healthcare Collaboration, 19(1), 34–47.

Change, J. (2020). Fostering Collaborative Culture Through AI Implementation. Healthcare Organizational Development Journal, 9(3), 145–158.

Davenport, T. (2021). AI Applications in Clinical Settings. Healthcare Technology Advances, 10(2), 78–89

Delzio, M. (2023). AI Implementation and Job Satisfaction: Survey Insights. Healthcare Workforce Journal, 12(1), 56–67.

Eramo, J. (2023). AI in RCM: Impact Assessment. Journal of Healthcare Finance, 15(2), 123–135.
Greco, A. (2023). AI Integration for Streamlining RCM. Healthcare Innovation Report, 12(1), 56–67.

Greco, A. (2023). AI-Driven Optimization in RCM: Streamlining Revenue Capture. Healthcare Finance Management Association.

Halasey, P. (2021). Cloud-Based AI Solutions in Healthcare: Enhancing Workflow. Journal of Healthcare Technology, 8(4), 209–222.

Hayhurst, M. (2022). Adapting to AI: Upskilling Strategies for Healthcare Professionals. Journal of Continuous Learning in Healthcare, 17(4), 209–222.

Hegwer, L. (2018). OhioHealth's AI Integration: Enhancing Patient Financial Experience. Healthcare Experience Today, 35(2), 75–88.

Kelly, J. (2022). The Impact of Inefficiencies in RCM in Healthcare. Journal of Healthcare Finance, 19(3), 145–158.

LaPointe, J. (2020). Prior Authorization Challenges in RCM. Journal of Healthcare Compliance, 15(4), 201–215.

Lamons, S. (2022). Accounts Receivable Management in Healthcare: Challenges and Solutions. Healthcare Financial Management, 17(1), 45–58.

Nielson, A. (2023). Empowering Workforce Through AI Automation. Healthcare Staff Development Quarterly, 15(3), 87–98.

Olive, K. (2023). AI in Healthcare Finance: Paving the Way for Financial Sustainability. Healthcare Administration Review, 28(4), 321–335.

Patel, S. (2023). Personalized Financial Experience: AI's Impact on Patient Satisfaction. Patient-Centric Healthcare Quarterly, 25(1), 78–89.

RevCycleIntelligence. (2021). Transforming Patient Financial Journey Through AI-Driven Solutions. Revenue Cycle Innovation Magazine, 7(4), 45–58.

Thomas, R. (2023). Enhancing Revenue Generation Through AI-Enabled Claims Processing. Healthcare Organization Efficiency Journal, 20(3), 45–59.

ADVANCING THE RISK EVALUATION MODEL IN SPORT: A PROPOSAL (PART I)

Kadie Otto
School of Marketing, Entrepreneurship,
Hospitality & Tourism, and Sport Management
College of Business
Western Carolina University
1 University Way
Cullowhee, NC 28723
kotto@wcu.edu
828.227.3548

Keywords: Risk, evaluation, sport, psychosocial impact, reputation

Introduction

Managing risk is paramount to maintaining the integrity of sport and the sport industry. Up to this point, risk managers have been concerned with identifying, evaluating, and controlling physical and financial risks to limit injury/harm, protect reputation, and avoid liability. In evaluating identified risks, scholars have focused on rating the probability, likelihood, or frequency of injury/harm, the severity of the injury/harm, and the magnitude (number of people injured/harmed) to inform the mechanism of control or treatment (Clement, 1988; van der Smissen, 1990; Spengler, Connaughton, & Pittman, 2006; Fried, 2015).

With social media firmly embedded in our lives and culture, this researcher proposes an upgrade to the Risk Evaluation Model is needed by setting forth the framework and criteria for the inclusion of a new category of evaluation—Psychosocial Impact. This category of evaluation is novel in that it seeks to predict the second-hand impact (ripple effect) that a first-hand injury/harm will have on people/groups via social media reactions. This paper is Part I of a two-part study and includes a combination of qualitative and quantitative considerations in the establishment of the framework and criteria for Psychosocial Impact. A case study serves as the instrument to demonstrate the proposal. Part II, then, will operationalize Psychosocial Impact by way of a case study to include data collection and analysis to test the efficacy of the proposed category toward the goal of more completely evaluating the full extent of risk that exists.

Literature Review

The risk management is the systematic process of identifying, evaluating, and controlling various risks in sport with the aim of reducing or eliminating injury or death and potential liability (Clement, 1988; Spengler, Connaughton, & Pittman, 2006). The purpose of managing risk in sport is to maintain a safe environment for all involved, thereby reducing potential exposure to loss (physical and/or financial) and legal liability (Clement, 2004; Cotton & Wolohan, 2010). Thus, the primary focus of a risk manager in sport has been to create a safe environment to reduce the number of injuries or accidents that may result in harm to attendees, game participants, and employees pre-event, event, and post-event (i.e., inspection/preparation of fields/stadia, fan safety, securing security/ushers/concessioners, establishing safe crowd/parking flow routes, compliance with OSHA, etc.) (Fried, 2015).

Existing risk evaluation models in sport focus on physical and financial risks. Clement's (2004) risk continuum evaluates physical risks from low to high by assessing the probability (of injury/harm), severity (seriousness of injury), and magnitude (number of people injured). Once evaluated, a control mechanism is chosen: "1) accept the risk and assume responsibility; 2) retain the activity and transfer the risk through insurance or contract; 3) alter the activity to reduce the risk; 4) eliminate the activity" (p. 225-226). Similarly, Cotton and Wolohan's (2010) "D.I.M. Process" calls for the development, implementation, and management of a risk management plan (p. 283). Similar to Clement's continuum, risks are identified, classified (evaluated) in terms of frequency (how often) and severity (degree of injury/harm), and a method for treating (controlling) the risk is selected.

In terms of identifying the risks, van der Smissen's (1990) seminal work is instructive as she called for the identification of public liability risks (i.e., malpractice, defamation, sex/race discrimination, constitutional rights violations, etc.). Her insight highlighted the need for sporting entities to be aware of potential liability in the form of civil rights litigation, which has the likelihood of negatively affecting the responsible entity. Applying van der Smissen's insight to today's social media environment, the notion of reputational risk likely precedes any potential litigation. Given this, predicting the Psychosocial Impact, and controlling it, will protect sports entities from unnecessary reputational damage (i.e., a flood of fierce social media pressure can instantly "cancel" a company, athlete, coach, etc.).

Methodology

The method is the establishment of the framework and criteria to evaluate Psychosocial Impact which incorporates a combination of qualitative and quantitative considerations. The case study below is used to demonstrate the proposal.

Case Study: The Risk of Injury/Harm to Players Due to Court Storming

There's an inherent danger to players, coaches, referees, and fans during a court storming incident. A basketball court is a relatively small space, 94L x 50W, especially when hundreds, sometimes thousands, of fans rush the court in rapid fashion. On January 21, 2024, hundreds of Ohio State fans rushed their home court when the Ohio State women's basketball team upset second ranked Iowa. While storming the court, "an Ohio State fan inadvertently collided" with national player of the year Caitlin Clark from Iowa (Philippou, 2024, para 1). Numerous bystanders caught the incident on video and posted to various social media outlets. As a result of the collision, Clark fell and was quickly surrounded by event management staff. While she did not sustain significant injury, Clark told reporters it was a "kind of scary" situation that could have been worse" (Philippou, 2024, para 3).

Following the incident, both head coaches Lisa Bluder (Iowa) and Kevin McGuff (Ohio State) conveyed that this sort of thing shouldn't happen. Indeed, Ohio State had security and event management staff on the court, but students managed to rush the court anyway. This incident took place before the largest crowd in Ohio State women's basketball regular-season history (18,660 attended the game). Highly regarded ESPN college basketball analyst Jay Bilas weighed in on the incident calling court storming "a player safety issue" noting that there has been a multitude of court storming incidents and it's only time until a player gets seriously hurt; college basketball needs to do a better job protecting its players (Schutte, 2024, para 8).

The Proposal

The Framework

The framework encompasses the meaning of Psychosocial Impact and is primarily qualitative in nature. Psychosocial Impact centers on the influence of social factors on a person's mind/behavior and how people's behavior is influenced by the presence/behavior of others (Finsterbusch, 1982). Given the powerful and pervasive role that social media plays in society and in sport, Psychosocial Impact is a measure of the psychological, social, and interplay effects on people who witness the harm/injury first-hand and on people/groups who are secondarily impacted by the incident through social media. Thus, the primary source for data collection is social media (Facebook, X [formerly "Twitter"], Instagram, Blogs, Snapchat, YouTube, etc.); the secondary source is mainstream media outlets (ESPN, Sports Radio Talk Shows, Sports Illustrated, The Athletic, etc.).

Phase 1: Establishing the Criteria

The establishment of criteria was conducted in phases, reflecting the need for refinement. To measure Psychosocial Impact data analysis of social media collected begins with a focus on the following criteria: type, intensity, and duration. "Type", defined as a negative, category (sub-type), or neutral/positive response, is gleaned from social media posts, videos, comments, emojis, etc. "Intensity", which probes the disapproval or shock/trauma of the response, should be assessed using a thematic analysis to determine common emotions, comments, and patterns resulting from the incident. "Intensity" should also take into weighted consideration responses, comments, and potential themes coming from public figures (e.g., Jay Bilas, in this case study) because of their degree of influence. "Duration" accounts for the length of time the impact may last (i.e., a few minutes, hours, days, weeks [noting that "time" in the world of social media is considerably shorter in "Duration" because reactions happen so quickly/are immediate; also, an initial assessment may require a prediction (a projection of time) which would need to be revisited at a later point to determine actual time]).

The Psychosocial Impact Matrix is comprised of three rows, from the top down and on a high to low scale (1-0 rating). The top row (darkest shading) equates to a high rating (.7-1), the middle row equates to a moderate rating (.6-.3), and the bottom row equates to a low rating (.3-0) (Table 1).

TYPE		INTENSITY		DURATION	
Negative		Disapproval		Days to Weeks +	
Category (sub-type)		Shock/Trauma		Hours to Day	
Neutral or Positive		Neutral or Positive		Minutes to Hours	

Table 1. Psychosocial Impact Matrix

Phase 2: Refining the Criteria

The initial construction of the criteria for Psychosocial Impact Matrix identified necessary categories of analysis (*see* Table 1). Phase 2, refines the Matrix to include an additional consideration which sharpens and deepens the understanding of the effect of Psychosocial Impact—"Volume". "Volume" is defined as the amount/number of reactions by *different* people or groups and is to be considered in a two-fold fashion: over-arching the three-criterion compared to similar situations and assessed in a stepwise fashion. "Volume" "type" (Vt) informs "Volume" "intensity" (Vi), which, in turn, informs "Volume" "duration" (Vd) (Table 2).

"Volume" of Similar Situations

Vt → Vi → Vd

Table 2. Two-Fold Assessment of "Volume"

Phase 3: Applying the Criteria

Using the case study provided in the Methods section, *The Risk of Injury/Harm to Players Due to Court Storming*, we begin the demonstration utilizing hypothetical data. In applying "Volume" to "Type", let's say an examination of "Type" reveals 100 reactions to Caitlin Clark (hereinafter, "(CC)") getting knocked down by a fan rushing the court which is first measured against the "Volume" of reactions of similar court storming situations (i.e., if similar court storming incidents resulted in, on average, 5,000 reactions/incident, then 100 reactions may not be of great concern). However, let's say of the 100 reactions, 70 are classified as "negative" (e.g., "Terrible security!", "(CC) could have been seriously injured!"). Given that the "Volume" of "negative" comments is high (70%), the resulting rating for "Type" would also be high (~.7), while at the same time keeping in mind the low total "Volume" of reactions (100) compared to similar court storming situations (5,000).

Since the "Volume" of "negative" reactions is high, the next step is to conduct a deep dive to determine the "Intensity" of the "negative" reactions. Let's say, of the 70 "negative" reactions, 50 are classified as "disapproval" (e.g., "Absolutely Unacceptable!", "Ohio State should be ashamed of itself!"). Here, is where "Volume" is applied again. Fifty of 70 (nearly 72%) of reactions equate to a high "Volume" of "disapproval", thus the "Intensity" rating would also be high but would be curtailed a bit by the fact that there are only a total of 100 reactions (compared to 5,000 in similar incidents) and that of the total of 100 reactions, half (50) "negatively" ("Type") "disapproved" ("Intensity") (~.6).

Last, "Duration". Say the 100 reactions last 10 minutes, but of the 100, the 50 "negative" "disapproval" reactions carry on for three days, over which time 125 new "negative" "disapproval" reactions surface, including comments by a highly regarded sports commentator (i.e., Jay Bilas), thereby increasing the "Intensity" because it is weighted, and "Volume". Here, "Duration" affects "Intensity" and "Volume", creating a ripple effect—If the "negative" "disapproval" reactions stopped after 30 minutes, it may have been the case that the additional 125 "negative" "disapproval" reactions wouldn't have entered the fray (one, of which, was Jay Bilas). Also, an examination of "Duration" and "Volume" in similar court storming situations informs this "Duration" rating. If, for example, reactions to other court storming situations came and went in a few minutes, then the fact that, while small in total reaction "Volume" (100), "disapproval" spilled over such that 125 different people/groups (including Bilas) reacted over the span of three days is something to pay attention to, thus resulting in a moderate to high "Duration" rating of (~-.6).

Conclusion

This study set forth the framework and criteria for a new category of risk evaluation in sport—Psychosocial Impact. Part II of this study will operationalize Psychosocial Impact by way of a case study trial (to include data collection and analysis of social media). The limitation of this proposal centers on ensuring that the social media data collected is authentic/credible (not AI generated, compromised, or otherwise false/fake), since social media reactions can result in the immediate "cancellation" of a product, League, or athlete. Future studies should trial the Psychosocial Impact category using different risks, at different levels, and across different sporting environments toward a more comprehensive understanding of the full extent of reputational risk that exists.

References

Clement, A. (2004). *Law in sport and physical activity* (3rd ed.). Dania, FL: Sport and Law Press.

Cotton, D.J. & Wolohan, J.T. (2010). Law for recreation and sport managers (5th ed.). Dubuque, IA: Kendall Hunt.

Finsterbusch, K. (1982). Psychological impact theory and social impacts. *Impact Assessment, 1*(4), 71-79.

Fried, G. (2015). *Managing sport facilities* (3rd ed). Champaign, IL: Human Kinetics.

Philippou, A. (21, Jan. 2024). Iowa's Caitlin Clark: Colliding with Buckeyes fan 'kind of scary'. ESPN.com. https://www.espn.com/womens-college-basketball/story/_/id/39356881/iowa-caitlin-clark-colliding-buckeyes-fan-kind-scary

Schutte, D. (28, Jan. 2024). ESPN's Jay Bilas wants court-storming to end in college basketball. SI.com. https://www.si.com/college/indiana/big-ten/espn-analyst-jay-bilas-wants-court-storming-ended-college-basketball-college-gameday

Spengler, J.O., Connaughton, D.P., & Pittman, A.T. (2006). Risk management in sport and recreation. Champaign, IL: Human Kinetics.

van der Smissen, B. (1990). Legal liability and risk management for public and private entities. Cincinnati, OH: Anderson.

THE IMPACT OF MACHINE LEARNING ON BIAS IN BUSINESS SETTINGS

Riley Hayden
BlueSky Tennessee Institute
College of Business and Technology
East Tennessee State University
1 Cameron Hill Circle
haydenr@etsu.edu

Brian T. Bennett
Department of Computing
College of Business and Technology
East Tennessee State University
464 Nicks Hall | PO Box 70711
Johnson City, TN 37614
bennetbt@etsu.edu

Mathew Desjardins
Department of Computing
College of Business and Technology
East Tennessee State University
464 Nicks Hall | PO Box 70711
Johnson City, TN 37614
desjardinsm@etsu.edu

Keywords: Artificial Intelligence, Machine Learning, Bias, Bias Detection

Introduction

Machine Learning (ML) has become an influential part of technology within these past years—primarily due to its application in so many areas such as the medical, entertainment, and business fields. Whether detecting a tumor, recommending shows, or making a more streamlined hiring process, the growth in the popularity of ML language models, known as generative Artificial Intelligence (AI), indicates its vast potential. ML can predict and generate text in a way that provides recommendations and steers perception of the current reality. Thus, ML recommender systems could create bias either toward or against a product, service, or idea. Through the development of new machine learning capabilities, it should be possible to detect unknown biases and gain an understanding of the impacts on the everyday work environment. This paper surveys current research in ML bias detection and describes a new unified framework for detecting biases in communication.

Literature Overview

Machine Learning

ML is a subfield of Artificial Intelligence (AI) that uses data sets to train algorithms to create models that classify information, predict outcomes, and generate text. Louridas & Ebert (2016) state that machine learning allows the computer to learn a task by reviewing a training set. Then, it can perform the same task with new data it has not previously seen. ML models are developed through various learning techniques: Supervised, Unsupervised, Semi-supervised, and Reinforcement Learning. Supervised Learning requires the ML algorithm to have the training data with a labeled input that corresponds to a known output, thus informing the model where each input maps. Trained ML models can then perform their task (e.g., classification or prediction) repeatedly with new sets of previously unseen data. On the other hand, Unsupervised Learning requires no labels, as they are primarily used to show natural relationships within sets of data. Semi-supervised learning uses all accessible data most of the time with a small amount of labeled input and a large amount of unlabeled input. Reinforcement Learning is a trial and error-based model where the focus is not on the inputs and outputs, but instead on what helps better achieve the goal given to the model (Moshawrab et al., 2023). For example, in a chess match trying to determine which moves will lead to a specific player winning.

One major component of Machine Learning is its ability to perform predictive analytics. Predictive analytics takes a data set and forecasts an outcome or output based on previous inputs and outputs. For example, some systems attempt to predict a person's level of pain based on facial expressions (De Sario et al., 2023). Predictive analytics can also be used to reveal how effective a social media campaign was (Kennedy et al., 2021).

More recently, ML is used increasingly to generate text based on large language models (LLMs). The ML algorithm creates a language model based on existing text to generate new text. An example implementation of an LLM is ChatGPT, which generates text in response to a user's questions.

Combining the ideas of predictive analytics and LLMs, ML can provide recommendations based on the context provided by users. ML recommendations are provided by utilizing users' previous patterns along with other factors such as popularity, rating, etc. These recommendations are used to recommend webpages to visit, products to buy, shows to watch, and friends to add (Parveen, & Varma, 2021). Businesses and other organizations are beginning to incorporate LLM implementations in their day-to-date processes (such as recommendations, reviews, email responses, and others), which introduces the possibility of bias based on the models' training.

<u>Bias in Machine Learning</u>

Bias is a judgment of or inclination towards or against a specific person, group, idea, or entity based on previous experiences or stereotypes. Biases are negative when they lead to or perpetuate unfair or inaccurate assumptions. Thus, ML algorithms could create biased models if training data is slanted toward or against a particular thing.

Biases present within ML algorithms are called algorithmic bias—evident when an algorithm provides an output that shows bias. Algorithmic bias does not determine what or who the bias is towards, which would require a more in-depth look into the outputs and the algorithm itself. Literature suggests that a less diverse workplace could lead to unconscious biases being implemented and could surface later, but also noted that there was no defined correlation with that possibility (Nicol, 2018). Therefore, it is reasonable that a less diverse training set would contain bias that the ML algorithm could acquire and perpetuate.

Not only can ML algorithms contain biases, ML-generated recommendations can alter a person's perception of reality. Parveen & Varma (2021) describe how recommendations are sometimes based on popularity, content, or ratings. Recommendation systems can be particularly effective for altering a person's perceptions, due, for example, to a post or news article going "viral." When such a viral post or article contains misinformation, those reading it may adopt the misinformation as reality. Understanding this phenomenon is very important when businesses use generated marketing materials.

Methodology

The remainder of this paper presents a survey of recent ML bias detection research. The purpose of this survey is (1) to develop a unified framework that could be used for bias detection, and (2) to integrate techniques in a way that could improve a bias detection model. Because widely available LLMs are relatively new, this review was limited to papers written in 2022 or later.

Bias Detection Research

While current research indicates it may not be possible to determine if a statement is biased or not, it has shown that there are methods to detect or mitigate bias generated by ML algorithms. Donald et al. (2023) document the types of bias in ML processes (Figure 1), resulting from user interactions, data, or algorithmic bias. From this, the authors detail bias detection techniques such as comparisons (using sentiment analysis or association tests) and performance metrics, noting that not all techniques are applicable for every use case.

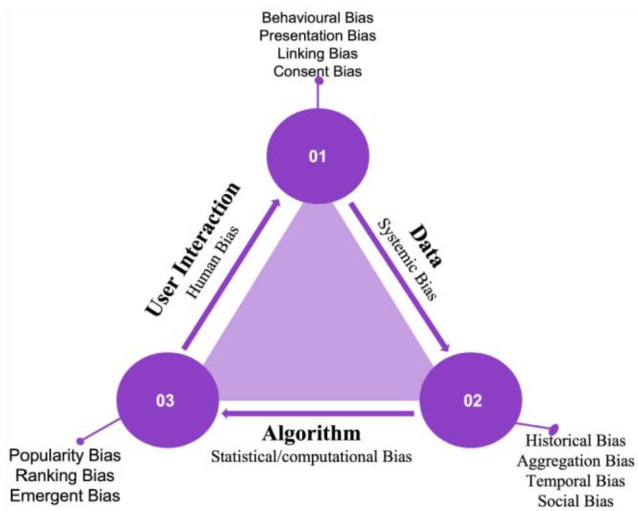


Figure 1. An Overview of Bias in the ML process. (Donald et al., 2023, p. 53704)

Other studies use techniques to detect existing bias instead of preventing it. Orphanou et al. (2022) explain a three-step approach called Auditing and Discrimination Discovery. The study notes that several human stakeholders—developers, end-users, and third parties—should be involved in auditing potential bias. Next, through discrimination discovery, the authors suggest using metrics to find discriminations against specific groups. An example of this method is finding a recommendation system that has a trend in displaying specific ads towards a specific group. The paper shows how important considering stakeholder perspectives may be in bias detection. Figure 2 displays the methods used in this framework to capture who would conduct each method and what biases are discovered. (Orphanou et al., 2022)

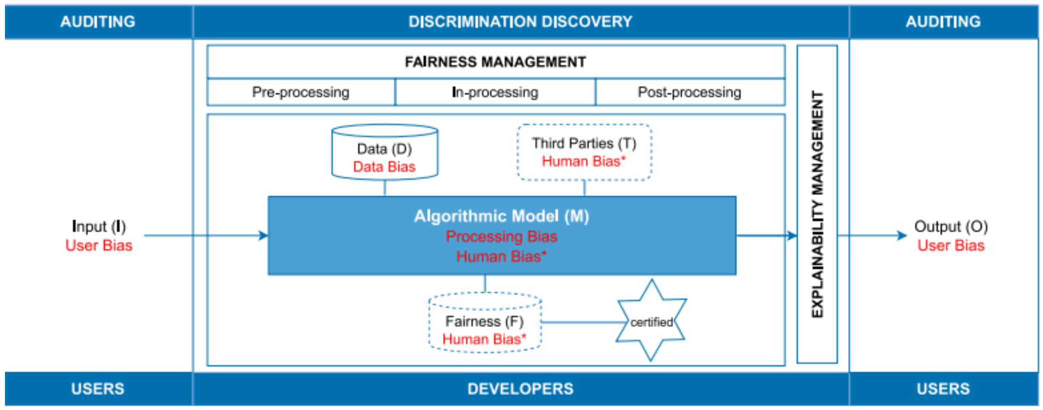


Figure 2. Auditing and Discrimination Discovery by Orphanou et al. (2022, p. 87:25)

Raza et al. (2024) breaks bias detection into four layers: Data collection, corpus construction, model development, and evaluation. First, the data collection layer's main purpose is to collect, preprocess, and consolidate data from social media and other portals to increase efficiency. Second, the corpus construction layer detects and labels any bias within a dataset both manually and semi-autonomously. Third, the model development layer goes into the specific languages used to detect bias within text. The authors adapted BERT language model to classify tokens and adapt them for named entity recognition. Lastly, the evaluation layer helps create the full circular workflow of ML algorithms by assessing the quantitative and qualitative data to verify the overall model performance. (Raza et al., 2024)

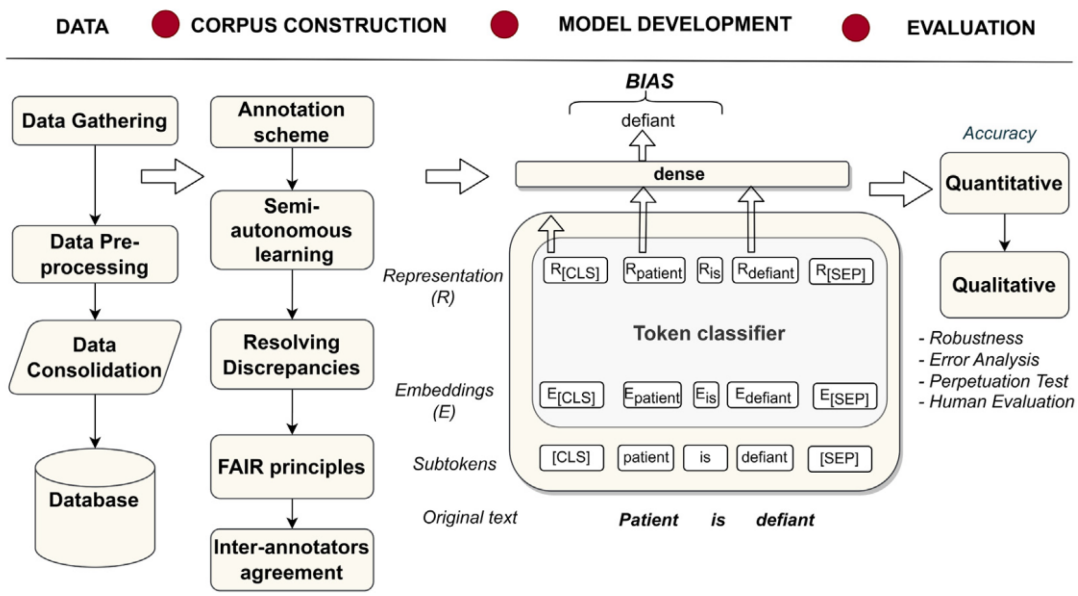


Figure 3. Raza et al. (2024, p. 121542) Bias Detection Framework

Low et al. (2023) conduct a study that looks specifically for bias detection in diversity, equity, and inclusion (DEI). Their framework collected data using an online survey that gathered words associated with gender, race, and income. Next, they used Word2Vec (a Python library) alongside k-Means clustering to analyze survey responses. The study found shifts in word associations across generations: A shift in gender stereotypes and increased awareness of social issues in Gen-Z respondents. Low et al. (2023) suggested this research could be expanded to other age groups and to other issues that are subject to bias.

Results and Implications

The various techniques in the existing research show that a more unified approach is necessary. Such an approach should detect and mitigate both explicit and implicit bias and incorporate both automatic and human elements to identify hard-to-detect bias. We propose a new unified framework that can be used to detect bias in business applications with five steps:

1. **Data Collection.** This step will gather varied datasets from sources that may contain bias and then attempt to identify explicit bias with preprocessing.
2. **Bias Detection with NLP.** This step uses advanced NLP techniques (such as clustering analysis) to identify explicit and implicit bias.
3. **Human Analysis.** Using human evaluators to check automatic techniques will minimize errors and provide indicators that the algorithm needs adjustment.
4. **Bias Mitigation.** Depending on the differences detected with human analysis, mitigation techniques like reweighting training data or updating the model building algorithm could be necessary to ensure a better result.
5. **Evaluation and Adaptation.** Over time, new data and social changes could lead to model degradation. Continuous monitoring and adaptation would ensure the model continues to be fair and effective alongside the real-world changes.

Donald et al. (2023) noted that many biases are created by data, human interactions, and algorithms. The proposed framework attempts to address each of these three areas. First, the preprocessing that occurs in the Data Collection step can address bias created from the data itself. Second, Human Analysis can help mitigate biases created by humans that were implicitly added to the data. The Mitigation and Evaluation steps can adjust the algorithm as necessary to deal with and prevent algorithmic bias.

Conclusion

Existing research shows the need for good bias detection and mitigation in ML, especially in the world of generative AI. This can be imperative for businesses who use generative AI to conduct day-to-day tasks. Bias detection techniques are typically multifaceted, some using natural language processing and human-based strategies to improve bias detection techniques. This paper presents a new unified framework that identifies explicit and implicit bias, incorporates human feedback, mitigation strategies, and the ability to adapt over time. This framework can assist with addressing bias created by the data, by human interactions, and by algorithmic learning. Future research will implement this framework using real data sets for further validation and adjustment.

References

De Sario, G. D., Haider, C. R., Maita, K. C., Torres-Guzman, R., Emam, O. S., Avila, F. R., Garcia, J. P., Borna, S., McLeod, C. J., Bruce, C. J., Carter, R. E., & Forte, A. J. (2023). Using AI to Detect Pain through Facial Expressions: A Review. *Bioengineering*, *10*(5), 548. https://doi.org/10.3390/bioengineering10050548

Donald, A., Galanopoulos, A., Curry, E., Muñoz, E., Ullah, I., Waskow, M. A., Dabrowski, M., & Kalra, M. (2023). Bias Detection for Customer Interaction Data: A Survey on Datasets, Methods, and Tools. IEEE Access, 11, 53703–53715. https://doi.org/10.1109/ACCESS.2023.3276757

Kennedy, H., Kunkel, T., & Funk, D. C. (2021). Using Predictive Analytics to Measure Effectiveness of Social Media Engagement: A Digital Measurement Perspective. *Sport Marketing Quarterly*, *30*(4), 265–278. https://doi.org/10.32731/SMQ.304.1221.02

Nicol, T. L. (2018). Detecting racial bias in algorithms and machine learning. *Journal of Information, Communication & Ethics in Society*, *16*(3), 252-260. https://doi.org/10.1108/JICES-06-2018-0056

Louridas, P., & Ebert, C. (2016). Machine Learning. *IEEE Software, 33*(05), 110–115. https://doi.org/10.1109/MS.2016.114

Low, B., Lavin, D., Du, C.R., & Fang, C. (2023). "Risk-Informed and AI-Based Bias Detection on Gender, Race, and Income Using Gen-Z Survey Data" *IEEE Access*, 11, 88317-88328. https://doi.org/10.1109/ACCESS.2023.3305636

Moshawrab, M., Adda, M., Bouzouane, A., Ibrahim, H., & Raad, A. (2023). Reviewing Federated Learning Aggregation Algorithms; Strategies, Contributions, Limitations and Future Perspectives. *Electronics 2023*, *12*(10), 2287. https://doi.org/10.3390/electronics12102287

Parveen, R., & Varma, N. S. (2021). Friend's recommendation on social media using different algorithms of machine learning. Global Transitions Proceedings, 2(2), 273–281. https://doi.org/10.1016/j.gltp.2021.08.012

Orphanou, K., Otterbacher, J., Kleanthous, S., Batsuren, K., Giunchiglia, F., Bogina, V., Tal, A. S., Hartman, A., & Kuflik, T. (2022). Mitigating Bias in Algorithmic Systems—A Fish-eye View. *ACM Computing Surveys, 55*(5), 87:1-87:37. https://doi.org/10.1145/3527152

Raza, S., Garg, M., Reji, D. J., Bashir, S. R., & Ding, C. (2024). Nbias: A natural language processing framework for BIAS identification in text. *Expert Systems with Applications*, 237, 121542. https://doi.org/10.1016/j.eswa.2023.121542

NFL PLAYOFFS PREDICTION: A MACHINE LEARNING APPROACH LEVERAGING DEFENSIVE STATISTICS

Ahmad Al Doulat
Department of Computing
College of Business and Technology
East Tennessee State University
1276 Gilbreath Dr
Johnson City, TN 37614
aldoulat@etsu.edu

Anna White
Department of Mathematics & Statistics
College of Arts and Sciences
East Tennessee State University
1276 Gilbreath Dr
Johnson City, TN 37614
whiteab@etsu.edu

Keywords: Machine Learning Classifiers, NFL Playoffs Prediction, Defensive Performance Analytics, Run Defense, Offense-Defense Mismatch

Introduction

The National Football League (NFL) is a multi-billion dollar sports business that captivates audiences across the United States. With only 14 out of 32 teams advancing to the playoffs each year, competition is fierce to secure one of those coveted playoff spots. This has led teams to heavily invest in analytics and data science to gain a competitive edge. An area of increasing interest has been using machine learning models to try to predict which teams will make the playoffs based on their regular season performance. Past studies have focused on using both offensive and defensive statistics as predictors. However, isolating team defense allows for a unique analysis on that unit's contribution to overall team success.

This paper analyzes the efficacy of different machine learning techniques at predicting NFL playoff teams using only defensive performance metrics. Models considered include K-Nearest Neighbors, Random Forest, Support Vector Machine, and Neural Networks. Metrics used span defensive performance against opposing quarterbacks, running backs, wide receivers, and tight ends. By training models on 9 seasons of data (2013-2021) and testing on the 2022 season, playoff predictions are generated and evaluated. Beyond overall model accuracy, further analysis identifies which defensive attributes prove most critical to playoff qualification. Teams that outperform or underperform their projected playoffs odds are also examined to reveal mismatches between offense and defensive production. This allows new insights into the factors driving team success in the NFL. The paper concludes by discussing implications for teams and future research directions building on this analysis.

Literature Overview

Predicting outcomes in the NFL using analytics and machine learning approaches has become an increasingly popular research area. Past studies have developed models using both offensive and defensive performance data to forecast team success. Predicting winner margins in NFL games was explored by Warner (2010), training a Gaussian process model on offensive, defensive and situational statistics from over 2000 games. The model achieved 64% accuracy in picking game winners, though still below the success of the Vegas betting lines. Other works have focused more specifically on individual plays - Hsu et al. (2019) used logistic regression with NFL field goal data to model late-game pressure kick situations. Outside of the NFL, predictive models utilizing machine learning have been built across various sports including baseball (Tolbert, 2016), basketball (Cao, 2012), and soccer (Raju, 2020).

Beyond predicting game outcomes, machine learning has been leveraged for other facets of football analysis. Hill (2022) developed in-game win probability models for the Canadian Football League, taking into account factors like score differential and field position over time. In the context of fantasy sports, neural networks and Markov models have been employed to optimize weekly lineups and roster decisions (Becker et al., 2016).

In summary, past literature has shown promise in leveraging machine learning techniques to forecast NFL team performance and outcomes. However, most analyses have incorporated both offensive and defensive metrics as joint predictors. By isolating defensive productivity alone, this paper provides uniquely precise insights into that unit's contribution towards overall team success. The presented methodology expands on past works by testing additional models like Neural Networks while focusing the feature space specifically on defensive statistics.

Methodology

The methodology followed to develop the machine learning model for predicting NFL playoff qualifications based on defensive performance metrics encompassed a structured, phased approach. Comprehensively compiling a dataset of key defensive indicators across 9 seasons enabled thorough investigation of the impact of defensive proficiency on postseason advancement. Though defense may not garner headlines, strong defensive play suppresses opponent scoring and tilts the probability of winning games. Careful data preprocessing, methodical training and evaluation of four sophisticated machine learning classification algorithms, along with rigorous model selection aimed to uncover signal amidst noise in the dataset - quantitatively assessing if defensive metrics contain predictive power. The entire model development process, outlined in Figure 1, entailed critical analysis of defensive production against opposing positions, mapping metrics to playoff results. Tuning model hyperparameters and focusing on generalization performance sought to avoid overfitting to past seasons. The final model was tested on fresh 2022 data, definitively determining predictive accuracy. If successful in accurately classifying playoff and non-playoff teams this season based solely on input defensive metrics, the credibility and viability of this machine learning approach for informing NFL analytics would be demonstrated. The following subsections detail the phases taken in this research to construct, refine, and validate this defensive data-driven model.

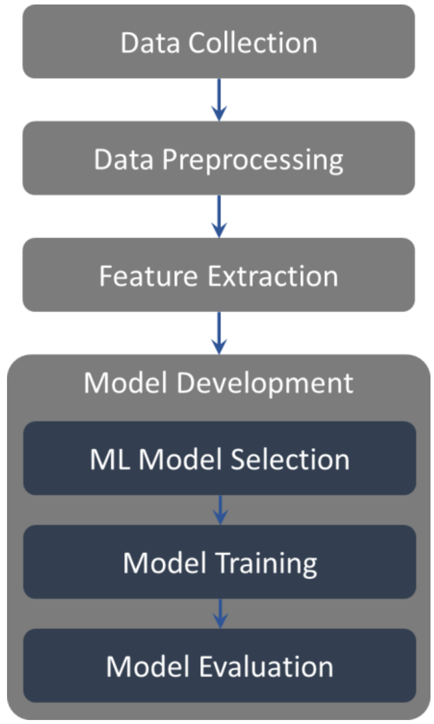


Figure 5. The proposed Machine Learning Model

Data Collection: Defensive performance data was collected from Pro Football Reference for all 32 NFL teams across 9 regular seasons from 2013-2021. Specific metrics gathered reflect those used in fantasy football platforms, quantifying defense against opposing quarterback, running back, and receiver positions. In total 15 metrics were compiled per team per season, including fantasy football scoring, yielding a training dataset of 2,592 team-season observations.

Data Preprocessing: Several preprocessing steps were taken, including: calculating per-game averages to account for varying games played each season; consolidating teams that changed names across years; conducting correlation analysis to identify collinear variables to potentially exclude; normalizing the data using scikit-learn's StandardScaler; and splitting the data 70/30 into train and test sets.

Feature Extraction: The key inputs to the model are the 15 defensive performance metrics gathered per team per season. These reflect success against passing, rushing and receiving plays. Fantasy football scoring synthesizes the metrics into an overall defensive performance measure.

Model Development: With the target variable defined as a binary classification of whether each team qualified for the playoffs (1) or not (0) each season, four machine learning algorithms were selected, implemented, and evaluated: K-Nearest Neighbor (KNN), Random Forest, Support Vector Machine (SVM), and Neural Network. The hyperparameters for each model were tuned using grid search cross-validation to optimize predictive performance. The models were then trained on 70% of the preprocessed dataset. Evaluation on the remaining 30% test set leveraged metrics including Receiver Operating Characteristic Area Under Curve (ROC AUC), accuracy, precision, recall and F1-score to quantify model fit. Through comparing evaluation metrics across the models, the best performing algorithm was selected as the final model for testing on the 2022 season data. Rigorously training multiple classification models with optimized hyperparameters, systematically evaluating on a holdout dataset, and selecting the top model aimed to increase robustness and generalizability for accurate predictions on new defensive data.

Results and Implications

The Random Forest classifier emerged as the top performing model from the training process with a cross-validation ROC AUC of 0.89 and accuracy of 83%. This significantly exceeded the other models tested. On the held-out 2022 season data, the Random Forest achieved a predictive accuracy of 80% in correctly projecting playoffs teams. Confusion matrix analysis showed a higher tendency towards false negatives than false positives, indicating the model was generally more conservative about predicting playoff qualification.

Of key interest, 7 teams were misclassified as falsely predicted to make the playoffs and 3 teams were falsely predicted to miss the playoffs. Examining these 10 teams revealed several notable mismatches between offensive and defensive strength. Teams like the Broncos, Commanders and Steelers had defensive metrics that indicated a solid playoff squad. Yet their anemic offensive production failed to deliver commensurate wins. Oppositely, teams like the Chargers, Giants and Seahawks overcame defensive deficiencies through offensive firepower to sneak into playoffs that models projected they would miss.

Feature analysis illuminated average running back rushing attempts against (18% importance) followed by average running back rushing yards gained against (15%) as the most influential metrics. As seen in Figure 2, teams who made the playoffs had allowed a lower average running back rushing attempts and average rushing yards gained than teams who did not make the playoffs for that season.

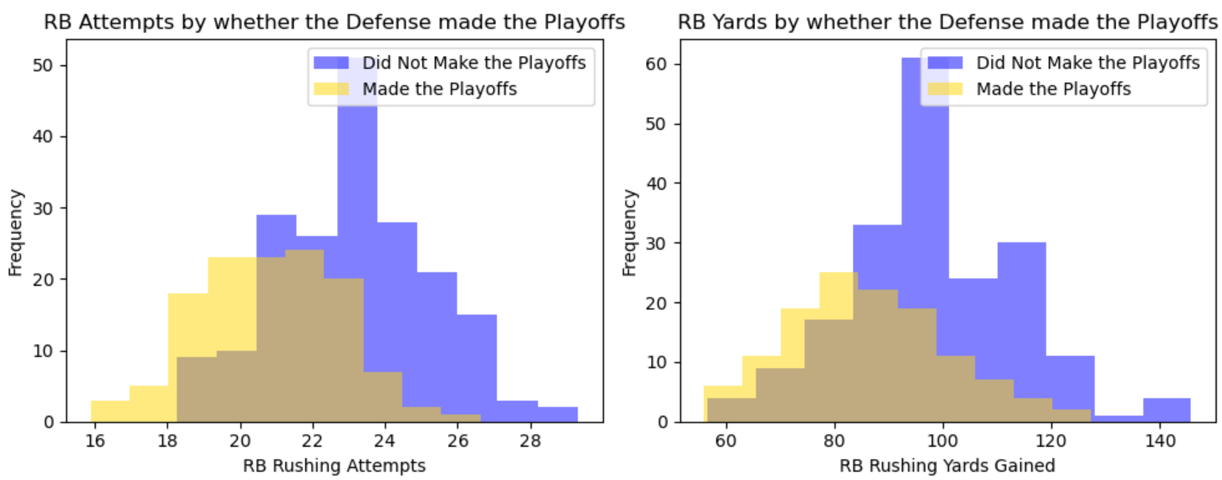


Figure 2. Average running back rushing attempts and yards gained allowed by playoff teams from 2013 - 2022.

This emphasizes a key insight - stopping the opponent's ground game proves pivotal for a defense to enable playoff qualification. Total fantasy points against also featured strongly (14%), synthesizing across metrics into a singular performance score.

The analysis provides several key implications for NFL teams:

- Rushing defense anchors overall defensive success and translates strongly into team victories. Priority should be placed on run stuffing.
- Offense / defense mismatches are what commonly trip up playoff aspirants. Seeking roster balance should be an off-season priority.
- Machine learning models can supply reliable, nuanced projections to inform team decisions.

By isolating defensive performance, new perspectives have been gained. Future analysis can now focus exclusively on offensive metrics for an even more complete picture of the ingredients yielding NFL glory.

Conclusion

This paper presented a machine learning approach to predict NFL playoff teams relying solely on defensive performance metrics. By training models on 9 seasons of data and testing on the 2022 season, predictive accuracy reached 80% for the best performing Random Forest model. This demonstrates defensive productivity alone contains strong signals on a team's playoff viability. The analysis enabled direct comparisons of projected versus actual playoffs teams to reveal offense and defense mismatches across the NFL.

Of notable importance, stopping the run proved the most critical indicator of defensive success, with rushing attempts against and rushing yards against the most influential features. This reinforces fundamental football wisdom – while the passing game captures headlines, championships are still won in the trenches. Teams must prioritize run defense accordingly.

Stepping back, the machine learning techniques demonstrated here provide new tools for teams to gain actionable insights. Models can forecast scenarios – for example, quantifying the defensive improvement needed to lift a squad into playoff contention. They further supply nuanced player evaluations – isolating which defenders yield the most impact. As coverage becomes more advanced, models may eventually prescribe tailored personnel decisions and schemes modifications to best counter opponents.

Multiple promising directions exist to build on this analysis. Firstly, complimentary models could focus solely on offensive metrics to provide a complete breakdown of a team's strengths and weaknesses. Comparing the outputs would enable precise targeting of roster weak spots. Secondly, temporal models like RNNs could encode season evolution rather than just end totals. This may improve predictions and refine in-season recommendations.

Expanding the inputs could also prove beneficial - defensive injury history, draft investments, and team budgets could all influence performance. Extending to other sports would demonstrate the generalizability of the techniques as well. And practically speaking, all models should be refreshed and retrained as new seasons conclude for sustained accuracy. Here the 2022 NFL season serves only as an initial proof-of-concept. Ongoing application is where machine learning will yield greatest returns for franchises in any sport.

References

Warner, J. (2010). *Predicting margin of victory in NFL games: Machine learning vs. the Las Vegas line.* Carnegie Mellon University Research.

Hsu, Nai-Wei, Kai-Shuo Liu, and Shun-Chuan Chang. "*Choking under the pressure of competition: A complete statistical investigation of pressure kicks in the NFL, 2000–2017.*" PloS one 14.4 (2019): e0214096.

Tolbert, Brandon, and Theodore Trafalis. "*Predicting major league baseball championship winners through data mining*." Athens Journal of Sports 3.4 (2016): 239-252.

Cao C. Master's Thesis. Technological University Dublin; Dublin, Ireland: 2012. *Sports Data Mining Technology Used in Basketball Outcome Prediction*.

Raju, Muntaqim Ahmed, et al. "*Predicting the outcome of english premier league matches using machine learning*." 2020 2nd International Conference on Sustainable Technologies for Industry 4.0 (STI). IEEE, 2020.

Hill, S. E. "*In-game win probability models for Canadian football*." Journal of Business Analytics 5.2 (2022): 164-178.

Becker, Adrian, and Xu Andy Sun. "*An analytical approach for fantasy football draft and lineup management.*" Journal of Quantitative Analysis in Sports 12.1 (2016): 17-30.

A SKEPTIC'S APPROACH TO TEACHING PRESONALITY THEORY IN MARKETING AND PERSONAL SELLING CLASSES

Donald Shemwell
Department of Management & Marketing
College of Business and Technology
East Tennessee State University
204 Sam Wilson Hall PO Box70625
Johnson City, Tn
shemweld@etsu.edu
423.439.6987

Keywords: Teaching marketing, teaching sales, myers-briggs, myers-briggs type indicator, personality theory, adaptive selling.

Introduction

Personality theory has a long well-researched history. A search for "Myers Briggs," short for the official name "The Myers-Briggs Type Indicator" (hereafter MTBI) in the Ex Libris Discovery's database brings up more than 5000 matches, more than 2000 of them refereed publications (and at least for the university where the author works, this resource access rarely goes back more than 25 years.

Fellow skeptic Emre (2018) notes that elite businesses like Standard Oil and General Electric have used the Myers-Briggs Type Indicator (hereafter MBTI) to hire, fire and promote people. Elite colleges like Swarthmore and Bryn Mawr have used it in their admission process. It has been used by churches to figure out which ministers to ordain and how to assignment them, by government to hire and appoint civil servants, by the navy to figure out who could and could not withstand submarine duty and by the CIA.

The MTBI's basic operationalization uses forced choice semantic differential choices between apparently opposite preferences on four dimensions (percentages of the U.S. population given by Personality Max 2024):

Table 1

Personality Type Primary	% of U.S. Population	Opposite Pole Personality Type	% of U.S. Population
Extroverted (E)	49.3%	Introverted (I)	50.7%
Sensing (S)	73.3%	Intuition (N)	26.7%
Thinking	40.2%	Feeling	59.8%
Judging	54.1%	Perceiving	45.9%

The four dimensions of personality in the MBTI do not correspond to the normal meaning. For many years, for example, it was common to follow the Jungian spelling: "Extraversion," and it is still considered okay grammatically to use either spelling (Barnett 2024). In the received view, each dimension, itself, is multi-faceted (Quenk 2009, p9). The dichotomy Extroversion-Introversion, for example, is not limited to how much people enjoy mingling at parties, but covers activity level, expressiveness, and other similar areas (Quenk 2009, p. 5; Kroeger, Thuesen and Rutledge 2002, Ch. 3 p2).

These four dimensions lead to 16 personality types (percentages of the U.S. population given by Personality Max 2024).

Table 2

Personality Type	Percentage of U.S. Pop.
ESTJ	8.7%
ESTP	4.3%
ESFJ	12%
ESFP	8.5%
ENTJ	1.8%
ENTP	3.2%
ENFJ	2.5%
ENFP	8.1%
ISTJ	11.6%
ISTP	5.4%
ISFJ	13.8%
ISFP	8.8%
INTJ	2.1%
INTP	3.3%
INFJ	1.5%
INFP	4.4%

Why Would a Skeptic Teach Personality Theory In Sales Classes and Use the MBTI for Instrumentation?

Emre (2018) immersed herself into the belly of the MTBI beast, to the point of paying several thousand dollars for certification, and was struck, and constantly amazed at the extent of belief. She used the term true believer to describe the people she met there and to separate those and others who like herself remained forever skeptical. Some of the true-believers she met felt that learning to "talk type" and getting certified changed their lives. She gives several examples of people who felt they were "saved" by their conversion. Yet, while she herself remained a skeptic and was troublesome enough in the training sessions to be denied access to Isabel Briggs Myers personal papers, her ulterior (or prime) motive for putting herself through the training process even though she was never going to use the certification, she resists the temptation to be dismissive of the concept and is never condescending towards the true believers.

Besides being the most popular (and widely studied) personality typing schema (Emre 2018, p 245; Miller (2018), it has also been widely used in teaching personal selling, sales management and other business disciplines (Reagan, Capella and Miles 1995; Borg and Shapiro 1996; Gardner and Martinko 1996; Amato and Amato 2005). Early in the senior author's career, he regularly went to the National Conference in Sales Management. Attending primarily teaching-oriented conference sessions, personality theory generated the most robust discussions (and not unrelatedly, the most disagreement). Publishing/presenting at this conference first as a PhD student and then as a very junior associate professor, the senior author was lucky enough to go to be at presentations about the teaching of personality theory in personal selling and sales management by established researchers who taught in programs with sales programs (as opposed to a course or two in a marketing degree). In particular Ramon Avila and Dick Planck generously gave of their time to talk to the then very green author of this manuscript in various group and one on one settings about the merits of teaching personality theory. Dr. Avila was more of a MBTI believer and Dr. Planck was more of a skeptic, though his skepticism was more about the MBTI than about the merits of teaching personality theory.

In these discussions, both Ramon and Dick emphasized one key principle, though they came about it in different ways and used different points of reference, and that is to teach sales students that other people are different from them, *and* it is up to her/him as the salesperson to *adapt* to differences in communications styles or attitudes between her/him and the purchasing agent or client, and *not the other way around*.

The term "adaptive selling" was then currently in vogue from Reagan, Capella and Miles (1995). To become an adaptive seller, students need some framework for recognizing that other people are different. They need to be trained to deal with the differences and learn to be adaptable and flexible in their dealings with each individual customers. Despite its imperfections, it was and is the most widely used schema for that purpose (Emre, 245).

Teaching Method

Students were given a version of the MTBI early in the semester, usually the first class of the second week. The first instructions were, in full professorial voice, "do not put your name on this." Instead, students were instructed to put the last four digits of their grandmother's phone number. This instruction did not always work. Some students did not have their grandmother's number. There were also several instances where a student responded sadly that her or his "grandmothers had passed away." We then told students to use the last four digits of his or her mother's phone number. Another full professorial admonition was not to use 1-2-3-4 or any similarly ridiculous code. Even then, four digits is not fool proof. In a 25-person class there's about a 3% chance of duplication. The two times it happened over 19 years, though, the students instantly recognized either their personality or their handwriting. Finally, a high-involvement scenario was created. Again, in a loud, imperative tone, the professor told the students that it was. "Important to answer honestly. Understanding your own personality profile would make it easier to get a good grade on the personality theory exam and it would help them in their role play assignments which had adaptive selling and adjusting to purchasing agents or clients with different personality types built-in."

Once the scores on a spreadsheet designed to adjust for reverse-worded items were posted on each survey, the professor returned them to the students in a later class by spreading them out on a couple of long tables and asking students to come in one at a time and pick up their profile. Each student recorded her/his score and was told to use it as a reference as the professor gave the personality theory lectures.

How Skepticism was Injected into the Process

The author of this manuscript does not believe there is a perfect type or superior personality and even more importantly there are not any imperfect or inferior personality types. The author also believes that it is wrong to use the MTBI for hiring, promotions or other important evaluations, something that was once common (see Coe 1992 for a discussion of abuses). Kroeger, Thuesen and Rutledge (2002) give just one of the sixteen types, ENFJ, as the personality that makes the best salesperson. And they did this without any empirical validation, just from their true believer's understanding of personality archetypes.

As a skeptic, the professor was very careful not to attach negative value statements about any of the personality archetypes or the four dimensions. A generation ago Introversion, for example, was treated almost as a personality flaw with expressions describing extroverts like "outgoing" treated as synonyms for happy, well-adjusted, and successful, *and* three quarters of the population in the U.S. were extroverts (Kroeger, Thuesen and Rutledge 2002). Now, as noted in Table 1 above, almost half the population prefers Introversion. Is it that society has changed that much in a generation or is it possible that society sees more value in what introverts are good at, like being a good listener and the ability to concentrate when working alone? The professor is thus very careful to emphasize the positive aspects of each side of all four dimensions.

The greatest emphasis in the lecture, exam and cases was on how to adjust to people who are different. Different ways of overcoming objections, different ways to close and different ways to build good, long-lasting relationships with clients were the primary focus. Perceivers, for example, are much harder to sell to because they tend to want to gather more data rather than decide quickly. An approach that uses a series of trial closes, known colloquially as the Summary and Agreement Technique, would tend to work better. Perceivers also experience cognitive dissonance much more quickly and intensely, so it is much more important to follow-up with good after-sales service and maintain more regular contact through the delivery cycle. Thinkers need to understand that not everyone wants to make *the* logical, rational decision. Their counterparts often rely on emotional cues and think about how a decision affects the people involved, and Feelers are *comfortable making decisions that way*. Extroverts need to be very careful not to run over an introverted purchasing agent/client and dominate the conversation because, generally, the more the client is talking and asking questions in any dyadic interaction, the better salesperson will do (Amato and Amato 2005; Reagan, Capella and Miles 1995).

Conclusion and Limitations

Teaching personality theory in personal selling and sales courses benefits students by getting them to be other directed (Reagan, Cappella and Miles 1995). Discrimination by personality type, though, is not justified (Coe 1992). Every person can be a good sales representative no matter which of the sixteen profiles they prefer. It is the ability to make adjustments and be adaptable that counts, and that is a lot easier to do if you have some framework of reference to understand those differences and make those adjustments.

The author teaches personal selling and sales management using a business-to-business, relationship-oriented contextual framework. It is easy to see that introverts might not make it selling Amway, life insurance or real estate because they do not want to use every human contact as someone to sell their products to. Extending concepts meant to be used in a professional, relational exchange approach where being honest and keeping promises weight heavily to sales oriented to accomplishing a single transaction, things often akin to hustling and scamming, would not be appropriate.

References

Amato, C. H. & L. H. Amato (2005), Enhancing Student Team Effectiveness: Application of Myers-Briggs Personality Assessment in Business Courses. Journal of Marketing Education. 27 (1), 41-51.

Baker, D.S. and D. Delpechitre (2016), “An Innovative Approach to Teaching Cultural Intelligence in Personal Selling.” *Journal for Advancement of Marketing Education*, 24 (1) 78-87.

Baker, D. S., & Delpechitre, D. (2013). Collectivistic and Individualistic Performance Expectancy in the Utilization of Sales Automation Technology in an International Field Sales Setting. *Journal of Personal Selling & Sales Management*, 33(3),

Barnett G. (2024). “Is it Extraversion or Extroversion?” *The Predictive Index*. Retrieved from https://www.predictiveindex.com/blog/is-it-extraversion-or-extroversion/

Borg, M. O., and S. L. Shapiro. 1996. Personality Type and Student Performance in Pprinciples of Economic Education. *Journal of Economic Education* 27 (1) 3-25.

Coe, C.K. (1992), "The MBTI: Potential Uses and Misuses in Personnel Administration," *Public Personnel Management*, 21 (4) 511-22.

Delpechitre, D., & Baker, D. S. (2017). Cross-Cultural Selling: Examining the Importance of Cultural Intelligence in Sales Education. *Journal of Marketing Education*, 39 (2), 94-108.

Gardner, W.L. and M.J. Martinko (1996), "Using the Myers-Briggs Type Indicator to Study Managers: A Literature Review and Research Agenda," *Journal of Management*, 22 (1), 5-83.

Hart Research Associates. (2010). Raising the bar: Employers' views on college learning in the wake of the economic downturn. Retrieved from https://hilo.hawaii.edu/academics/gened/documents/AACU_Report_Employers_on_College_Learning_2010.pdf

Kroeger, O, J. M. Thuesen & H. Rutledge (2002). *Type Talk at Work* (2nd ed.). Delta.

Personality Max (2024) retrieved at: https://personalitymax.com/personality-types/population-gender/

Quenk, N. L. (2009) *Essentials of Myers-Briggs Type Indicator Assessment* (2nd ed.). Wiley.

Reagan, C.C., L.M. Capella, and M.P. Miles (1995), "Adaptive Selling to the Professional Service Market: Utilizing the Myers-Briggs Type Indicator to Direct Style Flexing," *Journal of Professional Service Marketing*, 11 (2), 23-44.

ASSET RETURN DISTRIBUTIONS USING QUANTILE FUNCTIONS AND DISTRIBUTIONAL LEAST SQUARES

Zekeriya Eser
College of Business
Eastern Kentucky University
521 Lancaster Avenue
Richmond, KY 40475
Zekeriya.Eser@eku.edu
859.622.6156

Keywords: Asset returns, quantile functions, fat tails, distributional least squares

Introduction

It is well known that asset returns, especially stock returns, decidedly do not have normal distributions. Most asset returns are not symmetrically distributed, typically skewed to left, and tails are much fatter than commonly used probability distributions such as the normal distribution and the logistic distribution. In addition to the generic skewed shape of the return distributions, left tails tend to be much fatter than the right tails. Proper risk modeling requires probability models that capture the salient features of asset returns.

Using the standard logistic distribution as a starting point we derive a five-parameter family of probability distributions represented by a quantile function that has a computationally convenient functional form. These five parameters control the location, scale, general skew, and thickness of left and right tails of the distribution. Parameters of the distribution can easily be estimated without a need to calculate the likelihood function. Given a functional form for the quantile function, parameters of the model can be easily estimated using so-called Distributional Least Square (DLS) which involves comparison of the actual data values to the fitted values obtained by calculating the quantile function for the empirical CDF from the data.

We applied the method developed in this short paper to an ETF for Large-Cap Growth stocks and observe that the 5-parameter family of distributions performs remarkably well and shows considerable improvement over the standard location-scale or location-scale-skew family o distributions. We plan to extend the method of general regression type models for the location and scale parameters such as the GARCH type models where conditional location and volatility are modeled.

Literature Overview

Literature on the non-normality of asset returns is rather extensive and fat tails and skew of individual as well as market level asset returns are well documented. There are many papers modeling nor-normality but to our best knowledge there is no paper that employs quantile functions and uses DLS as an estimation method.

As noted by Leland (1999) non-normality of asset returns also affects how we should measure performance of asset portfolios. Modeling non-normality is also critical for calculation of value-at-risk. An extensive review of this issue can be found in Sollis (2009). The effect of non-normality of stock returns on expected returns from option strategies is studied in Figelman (2009). Our derivations on quantile functions are based on Gilchrist (2000) which is a go to source for quantile modeling and estimation.

Methodology

Let X be a continuous random variable defined uniquely by its CDF

$$F(x|\theta) = p[x \leq x|\theta]\ ;\ -\infty < x < \infty \tag{1}$$

where θ is a vector of unknown parameters that affect location, scale, and shape of the probability distribution. Inverting the CDF yields the QF which is defined implicity:

$$[Q(p|\theta)] = p\ ; 0 \leq p \leq 1 \tag{2}$$

In many cases this inversion needs to be obtained by numerical methods as the equation that implicitly defined the QF often has no analytical solution. A probability distribution can also be characterized by the quantile density function (QDF) which is obtained by differentiating the QF:

$$q(p|\theta) = \frac{\partial}{\partial p}[Q(p|\theta)]\ ; 0 \leq p \leq 1 \tag{3}$$

Parametric families of QFs are often much easier to obtain, hence creating a family of parametric probability distributions are easier when the QF is specified first, and if necessary, calculate the CDF by inverting the QF.

In addition to immediate use of QFs to generate random samples for simulations, the QFs can be used to fit a parametric distribution to a given sample without any need to obtain the CDF first. This is the method of Distributional Least Squares (DLS). Let X be a vector of values for a sample of size n. First define the Empirical CDF as:

$$p_i = \left(\frac{1}{n+1}\right)\sum_{j=1}^{n} 1\left(x_j \leq x_i\right); 1 \leq \mathrm{i} \leq n \tag{4}$$

where 1(.) is an indicator function that takes on a value of 1 if the argument is true, and zero otherwise. Let $Q(p|\theta)$ be a QF that depends on a vector of unkown parameters θ. Then, an estimator for θ can be obtained by minimizing the squared difference between the actual sample vakues and fitted values obtained by evauatiing the QF at the empirical CDF points:

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}} \frac{1}{n}\sum_{i=1}^{n}[x_i - Q(p_i|\theta)]^2 \tag{5}$$

In order to derive the family of QFs, let F(x) denote the CDF of the standard logistic distrbution:

$$F(x) = \frac{1}{1+\mathrm{e}^{-x}} \tag{6}$$

Now, define Y $\equiv |X|$. It can easily be verified that

$$G(y) \equiv P(Y \leq y) = \frac{\mathrm{e}^{-y}}{(1+\mathrm{e}^{-y})^2}\ ; y \geq 0 \tag{7}$$

With its associaed QF:

$$Q(p) = \ln[(1+p)/(1-p)] \tag{8}$$

As noted in Gilchrist (2000), any monotone transfrormation of a QF is also a QF. Define a 3-parameter family of QFs using

$$R(p) = (1+\delta)\left(\frac{\beta}{\alpha}\right)[Q(p)]^{\alpha} - (1-\delta)\left(\frac{\alpha}{\beta}\right)[Q(1-p)]^{\beta}, -1 < \delta < 1, \alpha > 0, \beta > 0 \qquad (9)$$

Noe that letting $\alpha = \beta = 1, \delta = 0$ yields a distrubution that looks a lot like the logistic distribution. Parameter α controls thickness of the right-tail and β controls the left tail, and if $\alpha = \beta$ the parameter δ controls the symmetry: negative values imply a left skew and a positive values imply a positive skew.
In order to obtain a five=parameter family, we add location and scale to the QF in (9):

$$T(p) = \lambda + \eta\, R(p) \qquad (10)$$

To ilustrate the method decsribed above, we downloaded weekly returns (adjusting for splits and dividends) for VUG which is a Large-Cap Growth Index administered by Vanguard and invests in mainly large cap tech stocks yielding a sample of 1,044 observations.

We fit three nested models: a three-parameter model that assumes $\alpha = \beta = 1$, yielding essentially a skewed logistic distribution. Next model assumes that $\alpha = \beta$ hence requires that left and right tails are essentially similar. Finally, we also estimated the five-parameter model given in (10). Since the purpose of this short paper is to ilustrate the method, we will show only pictures to discuss the results.

Results and Implications

The results section should provide a brief statement of the major findings of the study. This section should also describe the research and/or practical implications of the study. Figure one below charts the estimated CDFs for these three models and compares it to the empirical CDF. In order to view the differences between models and he empirical CDF the vertical scale is logarithmic, and we chart square root of $F(x|\theta)\,[1 - F(x|\theta)]$, hence the quadratic shape.

Clearly, the three-parameter model that does nothing about the tail thickness is woefully inadequate. Four parameter model overfits the left tail and underfits the right tail. The five-parameter model fits the right tail almost perfectly and overshoots the left tail a little bit. Given that estimates of the empirical CDF are rather crude and we have not otherwise modeled the location and scale of the distribution, as we would in regression type settings, getting such a nice fit using only five parameters is encouraging.

We also calculated the histogram of the actual returns, a simple one generated by Data Analysis ass-in of Excel. Given the estimated QF, we also inverted to obtain the CDF and differentiated this CDF to obtain the implied probability density function and charted them together. Since we found that 3-paameter and four parameter models are not up to the task, we are using only the PDF for the five-parameter model. These are shown in Figure 2. It looks like the fit of the left and right tails are very good while there is room for improvement in the center of the distribution. We suspect that underperformance in the center of the distribution can be improved by modeling the location and scale of the distribution as well as getting a better estimate of the histogram as Excel's version is known to be rather crude.

Given our encouraging results, future research will incorporate models for the location and scale parameters, as in GARCH type models that also allow for common factors such as market portfolios and returns to risk-free assets such as short-term Treasury bills and bonds.

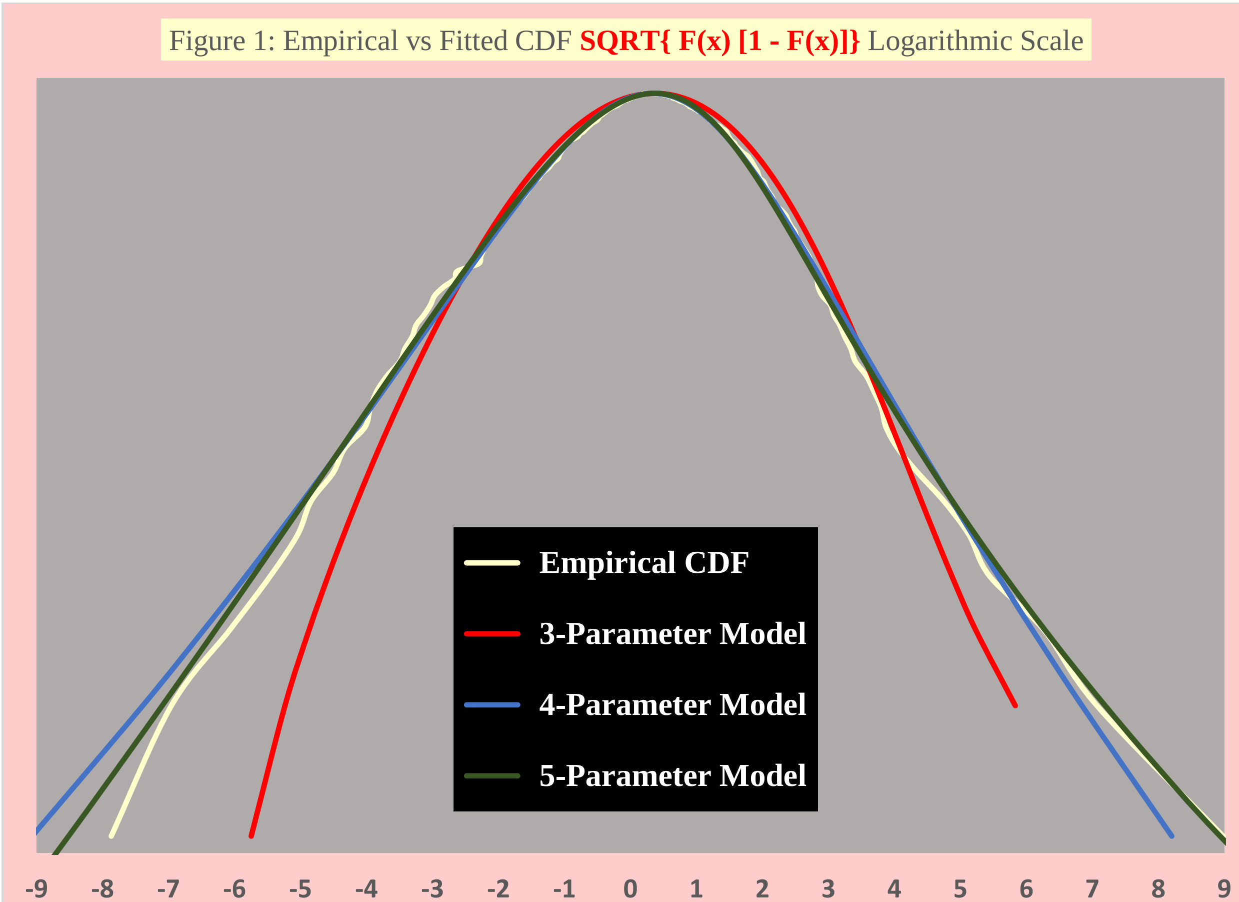
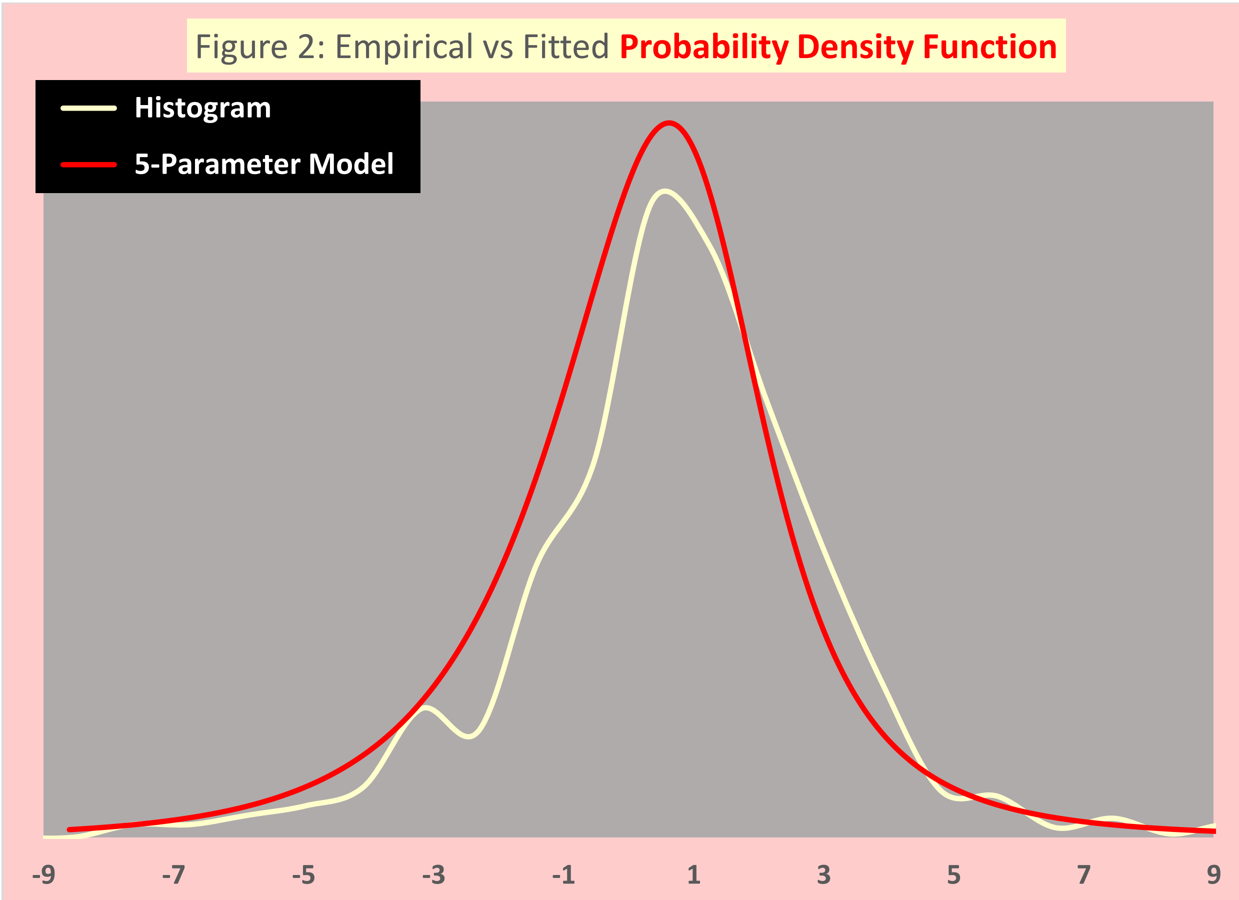


Figure 1: Empirical vs Fitted CDF SQRT{ F(x) [1 - F(x)]} Logarithmic Scale
Empirical CDF
3-Parameter Model
4-Parameter Model
5-Parameter Model
-9 -8 -7 -6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6 7 8 9



Conclusion

This short study demonstrated that Parametric Functions are promising to model skew and tail-thickness of asset returns. Yet, this is only a demonstration on a single stock and should be extended to multiple asset classes. It would also be interesting to model co-dependencies between different asset classes by incorporating quantile function methods into copula approaches. Further study is needed on how to use quantile functions in risk measurement and management of asset returns.

References

Gilchrist, W.G. (2000) *Statistical modeling with quantile functions*. Chapman & Hall/CRC: London.

Leland, E.L. (1999). Beyond mean-variance: Performance measurement in a nonsymmetrical world. *Financial Analysts Journal*, *55*(1), 27-36.

Solis, R. (2009). Value at-risk: A critical review. *Journal of Financial Regulation and Compliance*, *17*(4), 398-414.

Figelman, I. (2009). Effect of non-normality dynamics on the expected return of options. *The Journal of Portfolio Management*, *35*(2), 110-117.

STOCK MARKET PREDICTION USING THE LONG-SHORT-TERM MODEL (LSTM) WITH VARYING HYPERPARAMETERS

Joseph Akumatey*
Department of Computing
College of Business and Technology
East Tennessee State University
1276 Gilbreath Dr
Johnson City, TN 37614
akumatey@etsu.edu

Kingsley Fasesin*
Department of Computing
College of Business and Technology
East Tennessee State University
1276 Gilbreath Dr
Johnson City, TN 37614
fasesin@etsu.edu

Ahmad Al Doulat
Department of Computing
College of Business and Technology
East Tennessee State University
1276 Gilbreath Dr
Johnson City, TN 37614
aldoulat@etsu.edu

Keywords: Machine Learning, Artificial Intelligence, Long-short-term model, Hyperparameters, Bollinger Bands, Exponential Moving Average, Unsupervised learning, Mean Squared Error, Root Mean Squared Error, Mean Absolute Error.

Introduction

The stock market is influenced by many factors such as company earnings, investor sentiment, political events, and economic indicators. This makes predicting stock prices very challenging. However, accurate predictions are essential for traders, investors and analysts to maximize returns, minimize risks and optimize investment strategies. The problem is compounded by the fact that stock prices tend to fluctuate wildly and unpredictably. In today's fast-changing financial markets, the ability to reliably forecast prices has become a crucial skill. Additionally, the extensive data available contains intricate patterns and dependencies that traditional predictive methods struggle to fully utilize. Developing robust prediction models using historical data remains an extremely difficult task.

Making reliable prediction models using historical stock price data to predict future movements accurately remains a major challenge. In response to these difficulties, sophisticated machine-learning methods have surfaced as potentially useful resources for more accurate stock price prediction. The objectives are to understand the difficulties in predicting stock prices and investigate the elements affecting the stock values of businesses engaged in various industries. By solving this issue, we hope to provide insightful information enabling market players to make more strategic and well-informed decisions in the face of a constantly changing financial environment. The Long Short-Term Memory (LSTM) model is being used to forecast the stock prices of three well-known companies — Amazon, Lucid, and IBM, in this final report. Long-term dependencies in sequential data can be captured by LSTMs, a form of recurrent neural network (RNN) that is widely recognized for its suitability for time-series forecasting tasks like stock price prediction.

In this study, we examined the accuracy of using Artificial Intelligence/Machine Learning (AI/ML) models, particularly when the dataset is supplemented with additional technical indicators during model training, as well as the importance of using LSTM models to examine historical stock price data to find patterns, trends, and possible indicators that could lead to more precise forecasts. A thorough assessment of the model's performance across several industries is made possible by selecting the following companies: Lucid, a cutting-edge participant in the electric vehicle market; Amazon, a major player in global e-commerce and cloud computing; and IBM, a mainstay in the computer industry. Understanding the inherent difficulties in stock price prediction, assessing how well LSTM models capture market dynamics, and offering insights into the aspects affecting the stock prices of Amazon, IBM, and Lucid are the main goals of this research. We hope to provide insightful analysis that will help financial analysts and investors make wise choices by contrasting the output of our prediction models with real market patterns. Focusing on minimizing overfitting and vanishing points, the major issues using the long short-term model in prediction. Acknowledging the dynamic nature of financial markets and the inherent limits of any prediction model is crucial as we commence this exploration. However, the potential to improve our comprehension of market behavior and increase prediction accuracy highlights the importance of looking into cutting-edge machine learning techniques in stock price forecasting.

This paper serves as a roadmap for readers, guiding them through the complexities of stock market prediction. We delve into the challenges, leverage AI/ML models, and emphasize the role of LSTM models in capturing historical data intricacies. By the conclusion, our aim is to furnish financial analysts and investors with insightful analyses, enabling more strategic decision-making in the ever-evolving financial environment. The subsequent sections will provide an in-depth exploration of our methodology, literature overview, results, and implications, culminating in a comprehensive understanding of the potential of LSTM models in stock market prediction.

Literature Overview

Making predictions about the stock market has proven complicated. However, new developments in machine learning have produced a variety of tools for trend analysis, forecasting, and developing the best trading methods. Machine learning models and algorithms have undergone considerable improvements, methodologies, and obstacles to anticipate the stock market successfully. Before using ML in stock price prediction, price-to-earnings ratios, moving averages, and emotive analysis of social media trends are just a few financial indicators researchers use on these projects (Tetlock et al., 2007).

Researchers have adopted ML approaches by introducing computational power and data availability early. Lo A.W. (2004) was one of the early researchers in this area, publishing a study on the Adaptive Market Hypothesis in 2004. This laid the groundwork for using ML to make stock market predictions. Since then, other scholars have published more papers that employed AI/ML models in stock prediction. Shen S. et.al., (2012) used global stock data and some other financial product data as inputs in a machine-learning model for price predictions. Correlation analysis in their results shows connections between the US stock index and global markets that close just before or at the start of US market operations; they also highlighted that numerical machine learning models suggest high accuracy.

According to Akhtar, M.M. et.al., (2022), ML was also applied to stock market prediction, and the SVM model was compared to a random forest classifier. Using performance metrics such as the Mean Square Error (MSE) and Root Mean Square Error (RMSE), SMV, with an accuracy score of 78.9%, performed lower compared to the Random Forest Classifier, with an accuracy score of 80.8%. Another type of AI/ML model that has been employed in predicting stock price includes Neural Networks; according to Fischer & Krauss, 2018, this model uses deep learning models such as Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs), which have shown promise in capturing challenging patterns in the stock price data. One that stands out among the RNN models used in stock price prediction is the Long Short-Term Memory (LSTM); Fischer & Krauss, 2018 defined this as an RNN model designed to model sequential data, making them appropriate for time series prediction in stock markets.

Nelson D.M. et al., (2017) used LSTM to predict price movements by non-text-based input as data. They opined that LSTM, as a type of recurrent network model, has proven successful, given its ability to distinguish between recent and early examples by assigning weights to each while losing memory of what it considers irrelevant. Their investigation included a statistical analysis of LSTM results derived and considered metrics like p-value (< 0.05) and an appreciable F1 score to ascertain its accuracy; they concluded that LSTM offers fewer risks. Although LSTM has proven useful for price prediction, particularly because it retains long and short-term memories, it has been reported to have problems with overfitting and vanishing gradient points. We'll use the LSTM model for stock market price predictions coupled with several technical indicators while addressing overfitting and the issue with vanishing gradient points.

Methodology

The section describes our approach to examining the accuracy of LSTM on the selected three stocks with varied hyperparameters. The datasets to be used for the training and validation of the model were acquired from the Yahoo Finance Database. The model is being trained and tested on three datasets, and the performances will be compared. The three datasets to test the effectiveness of the Long Short-Term Memory (LSTM) for predicting stock prices are the historical data of the Amazon, IBM, and Lucid group stocks. The Amazon and the IBM stocks data span 5 years, from September 2018 to September 2023, while the Lucid group historical stock spans September 2020 to September 2023. The datasets were acquired from the Yahoo Finance stock market database as CSV of seven attributes: date, opening price, high price, low price, closing price, adjusted closing price, and volume.

The choice of companies—Amazon, Lucid, and IBM—was driven by a deliberate strategy to represent diverse industries, offering a comprehensive evaluation of the LSTM model's applicability. Amazon, a global e-commerce, and cloud computing giant, Lucid, a pioneer in the electric vehicle market, and IBM, an industry stalwart in computer technology, collectively present varied market dynamics. This selection aims to test the robustness and versatility of the LSTM model across different sectors, providing insights applicable to a broad range of financial scenarios.

The preprocessing of the datasets was done with Excel, and with Jupyter Notebook using Python programming. The notebook scripts include lines that assessed the quality of the datasets in terms of missing values, variability, spread, completeness, and consistency, as well as distribution.

The overall structure of our approach to answering the research question involved training the LSTM model based on historical data and then predicting stock market prices. The model's architecture includes multiple LSTM layers with dropout rates to prevent overfitting and clip values to handle vanishing gradient point problems. The model’s design also captures the learning of patterns and trends from historical data to predict future stock prices.

Part of the data preprocessing necessary to be carried out before training the model includes calculating technical indicators, which have been found to improve LSTM’s accuracy in predicting stock market prices. The technical indicators being used in this project are.

- Technical indicators calculation
- Simple Moving Average (SMA – 10,15,20)
- Exponential Moving Average (EMA – 10,15,20)
- Bollinger Bands (upper, lower, and width)
- Commodity Channel Index (CCI)
- Average True Range (ATR)

As shown in Figure 1, the structure of the model being tested comprises 6 main parts. These steps include (1) Data Preprocessing, (2) Sequence Creation, (3) Random Splitting, (4) Model Architecture (5) Character Training, and (6) Prediction and Evaluation. The 6 parts are further discussed in the following section.

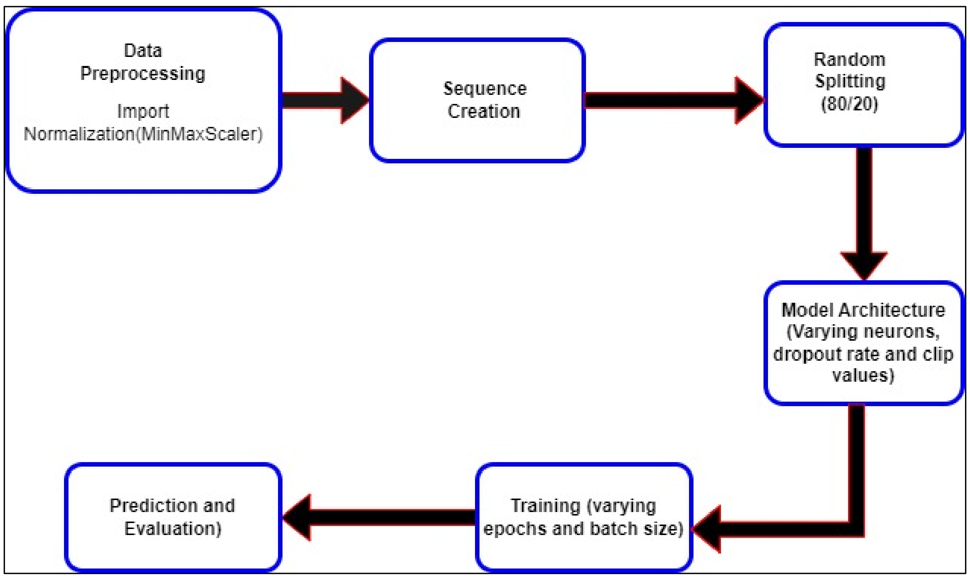


Figure 1: Flow of Project's Implementation

The implementation of the project begins with [1]***data preprocessing***, which includes data import and normalization using *MinMaxScaler* to bring all values into a common range useful for building the model. Following that is [2]***creating a sequence*** of historical data to be used, after which the data was [3]***split randomly*** into 80% training and 20% test data. The data is now ready to be re-shaped into an appropriate size for building LSTM models.

[4]***Building the LSTM models*** requires having hyperparameters that can be adjusted for different runs of the model being trained; these include the number of neurons (LSTM layers), dropout rates, and a clip value necessary during compilation. These hyperparameters are necessary to prevent overfitting of the model and to handle vanishing gradient problems (any values outside the range will clipped/neglected). The [5]***model training*** is then carried out using the *model.fit* function from Keras (a Python library useful in neural network models), and this required setting hyperparameters like epochs (the number of times the function runs through the entire dataset during training) and the batch size which is the samples in each iteration through the epochs and the weight of the model gets updated after every batch is done.

The model was then tested and validated using the test dataset, and [6]***predictions*** were made using the model. The prediction function was also from Keras. The image below is a graphical representation of the project's implementation in Jupyter Notebook. In testing the model's accuracy, we ran the model four times with Amazon, Lucid, and IBM datasets while varying the hyperparameters, and the table below shows the results for each time the model was tested. The model is being evaluated using performing metrics like,

- Mean Squared Error (MSE)
- Root Mean Squared Error (RMSE)
- Mean Absolute Error (MAE)

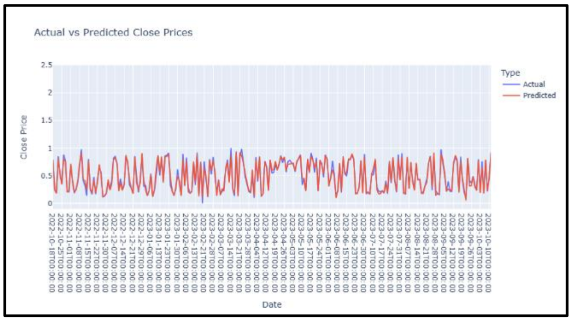
Results and Implications

The application of the Long Short-Term Memory (LSTM) model, incorporating varying hyperparameters, yielded compelling results across multiple runs on datasets representing Amazon, Lucid, and IBM. The table below encapsulates the key performance metrics, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). A lower value for these metrics signifies superior model performance.

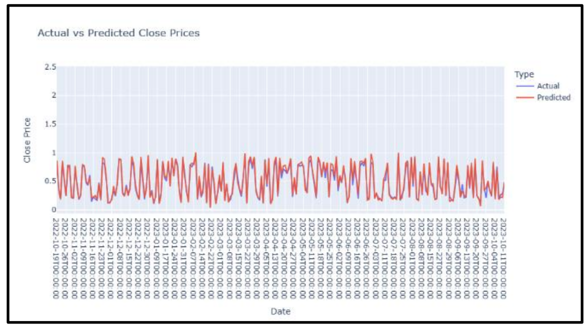
Table 1: Results of Running Different Models with Varying Hyperparameters

Model Run	Sequences	Neurons (# of Layers)	Dropout Rate	Clip Value	Epochs	Batch size	MSE	RMSE	MAE
AMZN_1	20	40	0.1	0.5	30	25	0.0022	0.047	0.034
AMZN_2	8	35	0.1	0.3	35	50	0.0024	0.049	0.036
AMZN_3	10	60	0.1	0.5	60	40	0.0015	0.039	0.029
AMZN_4	10	55	0.1	0.4	55	40	0.0018	0.042	0.032
LCD_1	20	40	0.1	0.5	30	25	0.0057	0.075	0.04
LCD_2	8	35	0.1	0.3	35	50	0.0090	0.095	0.049
LCD_3	10	60	0.1	0.5	60	40	0.0029	0.054	0.028
LCD_4	10	55	0.1	0.4	55	40	0.0012	0.035	0.024
IBM_1	20	40	0.1	0.5	30	25	0.0036	0.060	0.0043
IBM_2	8	35	0.1	0.3	35	50	0.0043	0.065	0.049
IBM_3	10	60	0.1	0.5	60	40	0.0026	0.051	0.037
IBM_4	10	55	0.1	0.4	55	40	0.0028	0.053	0.039

The next set of figures compares the actual model runs versus predicted values (the good and best model runs are displayed for each stock). The good model run is one with the highest performance metrics for each stock, and the best model run is one with the least performance metrics for each stock.

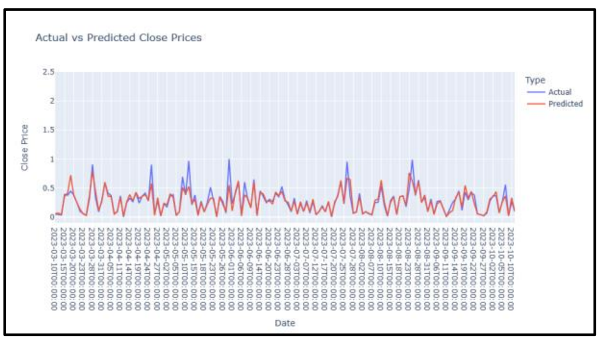


(a) The Good Model Run



(b) The Best Model Run.

Figure 2: **Amazon Stock Model Prediction Chart** – Actual vs Predicted Close Price

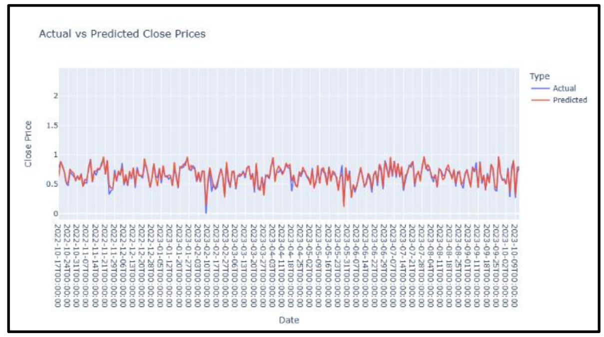


(a) The Good Model Run

(b) The Best Model Run

Figure 3: **Lucid Stock Model Prediction Chart** – Actual vs Predicted Close Price

(a) The Good Model Run



(b) The Best Model Run

Figure 4: **IBM Stock Model Prediction Chart** – Actual vs Predicted Close Price

In terms of the hyperparameters used to build the LSTM model, a lower sequence number which was between 8 and 10, 50 – 60 neurons (LSTM layers), dropout layer of 0.1, 50 – 60 epochs, and a batch size of 40 produced the best model runs of the performance metrics.

The results underscore the significance of hyperparameter choices in LSTM model training. Notably, model runs with lower sequence numbers, a moderate number of neurons, and specific dropout rates and clip values consistently outperformed others. This finding aligns with the broader literature on LSTM models, emphasizing the delicate balance required to prevent overfitting and vanishing gradient issues.

In the context of existing literature, our study contributes valuable insights into the nuanced impact of hyperparameters on LSTM model performance, particularly in the realm of stock market prediction. By visualizing predictive accuracy and summarizing key metrics, we offer practitioners and researchers a clear understanding of the implications of LSTM application in financial forecasting.

Conclusion

Based on the research question of whether stock market price predictions can be made almost accurately using the Artificial Intelligence/Machine Learning (AI/ML) model when the dataset is coupled with other technical indicators in model training, AI/ML models like the LSTM model runs generated provides an answer that supports stock market price prediction AI/ML models. Varying the hyperparameters helped distinguish the model runs based on the performance metrics used. More technical indicators in the datasets provide robustness regarding the number of attributes employed in the model training.

The LSTM model, as trained and tested on the three datasets, produced interesting results based on the performance metrics. More technical indicators in the datasets also aided the successful training of the model with robust datasets. Also, varying the hyperparameters helped distinguish the best among the model runs carried out. The model seems to perform reasonably well, given the performance metrics produced from all the model runs and the visualization of actual vs predicted closed prices charts.

Future work

In the future, we will be interested in testing this model on real-life situations while factoring the market dynamics, global events, and so on in a model like this. The parameters can also be fine-tuned to achieve better results that agree with other researchers' views.

References

Akhtar, M. M., Zamani, A. S., Khan, S., Shatat, A. S. A., Dilshad, S., & Samdani, F. (2022). Stock market prediction based on statistical data using machine learning algorithms. Journal of King Saud University-Science, 34(4), 101940.

Fischer, T., & Krauss, C. (2018). Deep learning with extended short-term memory networks for financial market predictions. European Journal of Operational Research, 270(2), 654-669.

Lo, A. W. (2004). The Adaptive Markets Hypothesis: Market Efficiency from an Evolutionary Perspective. Journal of Portfolio Management, 30(5), 15-29.

Nelson, D. M., Pereira, A. C., & De Oliveira, R. A. (2017, May). Stock market's price movement prediction with LSTM neural networks. In 2017 International joint conference on neural networks (IJCNN) (pp. 1419-1426). Ieee.

Shen, S., Jiang, H., & Zhang, T. (2012). Stock market forecasting using machine learning algorithms. Department of Electrical Engineering, Stanford University, Stanford, CA, 1-5.

Tetlock, P. C., Saar-Tsechansky, M., & Macskassy, S. (2007). More than Words: Quantifying Language to Measure Firms' Fundamentals. The Journal of Finance, 62(3), 1437-1467.

HOW TO EFFECIENTLY SELL YOUR FIRM IN M&As: BASED ON CHINESE M&As

Lixun Su
Department of Marketing
College of Business
Eastern Kentucky University
512 Lancaster Ave.
Richmond, KY, 28608
Lixun.su@eku.edu
8596227019 (Contact Author)

Qian Xiao
Department of Management
College of Business
Eastern Kentucky University
512 Lancaster Ave.
Richmond, KY, 28608
qian.xiao@eku.edu

Keywords: acquisition, price premium, resource-based view, information asymmetry

Introduction

In mergers and acquisitions (M&As), target firms aim to secure the best possible selling price (Lee, 2018; Malhotra, Zhu, and Reus, 2022). Indeed, over the past few decades, target firms worldwide have consistently sold at prices exceeding their market value, known as a price premium (Laamanen, 2007; Li and Haleblian, 2022). However, it is important to note that a premium does not necessarily imply that acquirers overpay for M&As or that target firms exploit acquirers by extracting additional value from the transactions (Cheng, Li, and Tong, 2016).

Instead, acquirers base their valuation of target firms on the potential post-acquisition resource synergies, rather than solely relying on the market value or book assets of the target firms (Flanagan and O'Shaughnessy, 2003; Rahman, Lambkin, and Hussain, 2016). If the post-acquisition resource synergies between acquirers and target firms can compensate for the premiums paid, acquirers can actually benefit from the premiums, while target firms may be undersold (Fralich and Papadopoulos, 2018). In other words, target firms may receive less value than their true worth, despite gaining a premium from the M&A transaction. This underpricing phenomenon is observed in various firms due to different reasons (Kraakman, 1988).

The existing literature has predominantly focused on the buyer's perspective, overlooking how target firms can optimize their outcomes in M&As. Therefore, this study aims to investigate how target firms can achieve the best possible selling price by considering information asymmetry and the resource-based view (RBV). According to RBV, acquirers anticipate resource synergies from successful M&As, prompting them to scrutinize target firms' resources and assess the likelihood of achieving synergies before merging (Capron and Hulland, 1999; Popli, Ladkani, and Gaur, 2017). However, acquirers face challenges in fully understanding target firms' resources, such as technology and human capital, due to information asymmetry and resource complexity (Reuer, Tong, and Wu, 2012). Consequently, target firms' knowledge and information about their own resources, rather than the resources themselves, become crucial bargaining tools. Ideally, target firms can strategically decide what information to disclose or withhold to camouflage weaknesses, highlight strengths, and emphasize potential synergies (Cuypers, Cuypers, and Martin, 2017). However, acquirers may not trust all the information released by target firms.

From a selling or bargaining perspective, this study examines which information target firms should emphasize. Specifically, the present study focuses on four types of critical resources extensively investigated in the field of M&As, namely market, technology, product, and human resources (Bin, 2008; Capron and Shen, 2007; Krishnan, Hitt, and Park, 2007). Our findings indicate that marketing and technology resources have a positive impact on M&A premiums, while product and human resources do not significantly influence the premiums. These results offer valuable insights for target firms seeking to maximize their selling price when engaging in M&A transactions.

Literature Overview and hypothesis

M&A premium and RBV

M&A premium refers to "the percentage difference between the final per share price paid to the target firm and the target's prior share price" (Zhu, 2013, p. 800). Over the past decades, acquirers worldwide have consistently paid premiums ranging from 30-50% to over 100% above the target's stock price to close deals, depending on various factors such as location, industry, time, and environmental turbulence (Fralich and Papadopoulos, 2018; Laamanen, 2007). For example, in the United States, acquirers paid an average premium of 48% between 1980 and 2002 (Betton and Eckbo, 2000).

It's important to note that a premium does not necessarily indicate overpayment for target firms, as the value that acquirers gain from the M&A can sometimes compensate for the premium (Cheng, Li, and Tong, 2016). When acquirers anticipate potential post-acquisition synergies, they are willing to pay a premium that exceeds the target firms' market value. In this case, the premium can be seen as an investment to enhance future returns. Eccles, Lanes, and Wilson (1999) demonstrate that high-premium deals can lead to high returns, just as low-premium acquisitions can result in low performance. Hence, there is no universally correct price for an M&A (Eccles, Lanes, and Wilson, 1999). Acquirers' main objective is to enhance their value by acquiring another firm's resources rather than striking a favorable deal in the eyes of the stock market (Eccles et al., 1999). Furthermore, the perceived premium is often below the acquirers' reservation price (Borochin , Ghosh, and Huang, 2018). In this context, the premium is not considered overpayment for acquirers, but rather an indication of target firms being undervalued.

RBV can shed light on why acquirers are willing to pay premiums for M&As. RBV argues that firms should rely on rare, valuable, inimitable, and non-substitutable resources to establish sustainable competitive advantages (Barney, 1991). Developing some of these resources internally can be costly, requiring significant time and effort in a path-dependence manner (Barney, 1991; Su *et al.*, 2022). Additionally, due to the complexity and intricacy of certain resources, firms may be unable to develop them independently (Bahadir, Bharadwaj, and Srivastava, 2008; Yu, Umashankar, and Rao, 2016). Consequently, M&As often represent a cost-efficient way for firms to acquire the necessary resources (Capron and Hulland, 1999). In this context, the premiums paid by acquirers for M&As are, in fact, lower than the costs they would have incurred to obtain those resources independently. Therefore, acquirers are spending less money rather than overpaying for the acquired resources, despite seemingly paying premiums for M&As.

Indeed, not all acquired resources can be easily transferred and generate value for acquirers (Bauer, Matzler, and Wolf, 2016; Devers *et al.*, 2020). Therefore, our discussion will focus on identifying the resources that are more cost-efficient to acquire rather than develop internally, thus justifying acquirers' willingness to pay premiums to obtain such resources from the market.

Specifically, we propose that:

H1: Marketing resources of target firms can increase M&A premiums.

H2: Technological resources of target firms can increase M&A premiums.

H3: Product resources of target firms can increase M&A premiums.

H4: Human resources of target firms can decrease M&A premiums.

Methodology

Data collection

To test our hypotheses, we particularly focus on M&As that took place in the manufacturing industry in China between 2012 and 2021. Specifically, we included the top ten industries by the number of M&As in the database (See Appendix for the details), finally giving us 3,193 M&As.

Independent variables

Independent variables in this study focus on what resources (i.e., market, technology, product, and human resources) constitute the main reasons acquirers buy target firms. The present study used binary variables to measure if these are determinants of M&As. We manually coded the content of M&As announcements to obtain such data. Specifically, the variable of marketing resources was coded as 1 if an acquirer explicitly expressed that it would use marketing resources of a target firm to sell its products. Otherwise, it was coded as 0. The variable of technology resources was coded as 1 if an acquirer explicitly expressed that the target firm possesses advanced technologies that the acquirer needs. Otherwise, it was coded as 0. The variable of product resources was coded as 1 if an acquirer explicitly expressed that the target firm has particular products that they can take advantage of to achieve synergistic effects. Finally, the variable of human resources was coded as 1 if an acquires explicitly expressed that the targe firm has a team or person that it is particularly interested in obtaining. See table 1 for the examples for each variable. Each M&A announcement was coded by two researchers, and disagreements were resolved by discussions between coders.

Dependent variable

The premium rate is measured by the ratio of the difference between pay value and book value to the book value, which is equal to the product of equity of target firms and acquisition ratio.

Control variables

In this study, we added the *relative size* of acquirers to target firms as a control variable, which was measured by the ratio of acquirers' assets to target firm's assets and the ratio of acquirers' sales to target firms' sales in the previous year. The type of *integration* of resources was included as control variables (1=horizonal integration; 2=vertical integration; 3=mixed integration). We created dummy variables for this control variable. We also controlled acquirers' and target firms' *past firm performance* in the previous year by adding both sides' return on assets (ROAs) in the model. *The percentage of acquirers' shares* after M&As was included in the model. Finally, *physical proximity* between two firms influences the level of information asymmetry, so controlled proximity by measuring if acquirers and target firms are from the same city (0=No; 1=Yes).

Results and Implications

Before testing the hypotheses, we first used bootstrapping method to impute the missing values via "Amelia" package in R. The correlations between each two variables do not change significantly with imputed values. Next, we deleted cases with extreme premium rates, leaving 660 complete cases for further data analysis and the premium rate ranging between -2.69 and 4.24.

Finally, we used partial linear regression via Smart PLS 4.0 to test hypotheses. The results (See Table 3) show that market resources ($\beta = 0.09$, $t = 2.12$, $p < 0.05$) and technology resources ($\beta = 0.08$, $t = 1.97$, $p < 0.05$) increase premium rate, supporting H1 and H2. In contrast, product resources ($\beta = 0.04$, $t = 1.01$, $p > 0.10$) and human resources ($\beta = 0.02$, $t = 0.58$, $p > 0.10$) do not significantly influence premium rate, rejecting H3 and H4.

To test the robustness of the results, we removed cases with missing values on any of the variables included in the model, leaving 327 complete cases. The regression results remain consistent. Specifically, market resources ($\beta = 0.05$, $t = 1.98$, $p < 0.05$) and technology resources ($\beta = 0.09$, $t = 2.31$, $p < 0.05$) increase premium rate. On the contrary, product resources ($\beta = -0.02$, $t = -0.55$, $p > 0.10$) and human resources ($\beta = 0.05$, $t = 1.24$, $p > 0.10$) do not significantly influence premium rate, rejecting H3 and H4.

Conclusion

Given the significance of M&A premiums in conveying vital information about target firms and their influence on M&A activities (Eccles et al., 1999), top managers consider them a key aspect of their agendas. Building upon the perspective of information asymmetry and RBV, this study aims to investigate how important resources within target firms act as antecedents and impact M&A premiums. Moreover, it explores how target firms can optimize their M&A pricing strategies based on these important resources. Our findings indicate that market and technology resources have a positive effect on the premium rate, while product and human resources may not significantly contribute to obtaining higher premiums for target firms. These findings offer several contributions to the existing literature and provide valuable insights for managers.

Theoretical implications

First and foremost, this study presents an alternative perspective to understand M&A premiums from the seller's point of view. Existing literature has extensively examined the roles, consequences, and antecedents of premiums in M&As, primarily focusing on the perspective of the acquirer (e.g., Fieberg et al., 2021; Flanagan and O'Shaughnessy, 2003; Jackson and Gart, 1999; Varaiya, 1987). However, this study proposes that premiums do not necessarily have a negative impact on post-acquisition performance; rather, they can reflect the potential value that target firms offer to acquirers. In other words, acquirers would not pay a premium for a target firm if they did not see any value in it. Based on this reasoning, we argue that target firms must develop effective strategies to showcase their value and avoid being undervalued in M&A transactions.

Secondly, this research contributes to a deeper understanding of the antecedents of M&A premiums from the seller's perspective. Specifically, we provide an explanation for why acquirers pay different premiums based on the effects of different resources within target firms. Existing M&A literature explores various antecedents of premium changes from the perspective of acquiring firms, including manager-related factors such as decision-making processes, demographic characteristics, and social networks, as well as firm-level factors like networks and acquisition motives. However, an important question arises: How can target firms influence the premium and effectively sell themselves at the best possible price? This study addresses this question by empirically demonstrating how target firms' resources impact premiums. By doing so, we contribute to the literature by expanding our understanding of premiums through the lens of target firms' resources. Specifically, we find that market and technology resources have a positive association with premiums, while product and human resources do not significantly increase the premiums that acquirers are willing to pay. Consequently, our study highlights the critical role of target firms' resources in shaping premiums and positioning themselves for better negotiation outcomes.

Managerial implications

Our results provide valuable insights to managers on both sides of an M&A. Target firms always want to get the best price possible. However, without properly communicating the value of their resources, target firms usually undersell themselves even though they are the only ones with accurate information about their resources. Therefore, target firms must capitalize on their information edge by understanding what resources could boost acquisition premiums. Based on the data from 660 M&As in China, our results show that marketing and technology resources can increase premiums while product and human resources cannot help target firms get a good price. Therefore, when selling to an acquirer, a target firm should shed light on communicating marketing resources and technology resources with acquirers whenever possible. Notably, our results do not indicate that target firms should always direct all of acquirers' attention to marketing and technology resources. For instance, some acquirers may be only interested in target firms' human resources. Under this condition, our results suggest that bringing acquirers' attention to target firms' marketing and technology resources may somewhat help increase premiums since valuable marketing and technology resources can be a bonus when targeting human resources. However, target firms still need to spend the most time communicating human resources since they are the deal's focus.

Consistent with the implication above, our findings suggest that target firms may want to develop their marketing and technology resources before selling themselves. Admittedly, not many target firms have rich marketing and technology resources, and not all acquirers are interested in marketing or technology resources. However, if target firms can develop some marketing and technology resources in the short run, the resources may help them get a higher premium from M&A even though acquirers are interested in other resources. More importantly, some firms have plans to sell themselves since their inception, and these firms must build marketing and technology resources along the way.

For acquirers, our results suggest that acquirers should overcome their bias during the negotiation. Previous studies have shown that acquirers can be biased when determining a price for an M&A. In this study, our results show that acquirers tend to pay a premium for target firms with valuable marketing and technology resources. Therefore, acquirers must intentionally overcome this bias by scrutinizing target firms' marketing and technology resources to ensure they are not overestimated.

References

Barney, J. (1991). Firm resources and sustained competitive advantage, *Journal of Management, 17,* 99–120.

Capron, L., & Hulland, J. (1999). Redeployment of brands, sales forces, and general marketing management expertise following horizontal acquisitions: A resource-based view, *Journal of Marketing, 63*, 41–54.

Cheng, P., Li, L., & Tong, W. H. S. (2016). Target information asymmetry and acquisition price, *Journal of Business Finance & Accounting, 43*, 976–1016.

Cuypers, I. R. P., Cuypers， Y., & Martin，Y. (2017). When the target may know better: Effects of experience and information asymmetries on value from mergers and acquisitions, *Strategic Management Journal, 38,* 609–625.

Eccles, R. G., Lanes, K. L., & Wilson, T. C. (1999). Are you paying too much for that acquisition? *Harvard Business Review,* 77**,** pp. 136–136.

Flanagan, D. J., & O'Shaughnessy, K. C. (2003). Core-related acquisitions, multiple bidders and tender offer premiums, *Journal of Business Research, 56,* 573–585.

Fralich, R., & Papadopoulos, A. (2018). The financial crisis, acquisition premiums and the moderating effect of CEO power, *Long Range Planning, 51*, 204–218.

Laamanen, T. (2007). On the role of acquisition premium in acquisition research, *Southern Medical Journal*, *28*, 1359–1369.

Lee, K. H. (2018). Cross-border mergers and acquisitions amid political uncertainty: A bargaining perspective. *Strategic Management Journal*, *39*, 2992–3005.

Li, C., & Haleblian, J. (2021). The influence of nation-level institutions on acquisition premiums: A cross-country comparative study, *Journal of Management, 48*, 878–904.

Kraakman, R. (1988). Taking discounts seriously: The implications of "discounted" share prices as an acquisition motive, *Columbia Law Review, 88,* 891–941.

Malhotra, S., Zhu, P., & Reus, T. H. (2022). The diagnostic value and anchoring effect of references in acquisition premium decisions: The influence of overconfident and powerful CEOs, *British Journal of Management, 0,* 1–20.

Rahman, M., Lambkin, M., & Hussain, D. (2016). Value creation and appropriation following M&A: A data envelopment analysis, *Journal of Business Research*, *69*, 5628–5635.

ENTREPRENEUR CONNECTOME: UNLEASHING GENERATIVE ARTIFICIAL INTELLIGENCE FOR ENTREPRENEUR SOCIAL INFRASTRUCTURE IN DECENTRALIZED COMMUNITIES

Don Capener, PhD
Dean-Lewis College of Business
Brad D. Smith Schools of Business
Marshall University
Huntington, WV 25755
904 463-5188 cell or text
Capener@marshall.edu

Carlton L. Robinson
Jacksonville Regional Chamber of Commerce
3 Independent Drive
Jacksonville, FL 32002
carlton.robinson@jaxchamber.com
904-527-0290 cell or text

Keywords : Entrepreneur Social Infrastructure, Generative Artificial Intelligence, Pretrained Entrepreneur Support Model

Introduction

Aspiring entrepreneurs across the globe face a conundrum: a lack of readily accessible resources and support within decentralized communities. This "First Mile/Last Mile" problem hinders their connection to crucial entrepreneurial social infrastructure (ESI) – defined innovation ecosystems, resource availability, and social networks. Drawing on Flora and Flora's (1993) concept of ESI and Fortunato and McLaughlin's (2012) work on community interaction, this paper proposes Generative Artificial Intelligence (GAI) applications as a transformative tool to address how to better prepare entrepreneurs for the challenges of scaling their operations.

The versatility and creativity associated with Generative AI has captured the general population's attention while emerging utilities lie in domain specificity. Generative AI and Domain-Specific AI are two popular categorizations of artificial intelligence. And while Generative AI is designed to produce content, Domain-Specific AI is focused on analyzing, optimizing, and understanding domain-specific data. To advance ecosystem capacity, we sought to train GAI exclusively on an existing entrepreneur education model optimized to generate outputs relevant to that domain. Through new dimensions of interaction and purpose, this exploration uncovered an alternative engine to entrepreneur activities in the entrepreneur connectome. The connectome framework advances the concept of entrepreneur social infrastructure and ecosystems by categorizing new dimensions of interaction and purpose.

Entrepreneurial education has emerged as a critical tool for fostering the next generation of business founders. However, significant challenges persist in adequately preparing students for the demands of venturing into the unknown. Flora and Flora (1993) introduced the concept of Entrepreneurial Social Infrastructure (ESI), highlighting the importance of an individual's belief in their ability to successfully launch and manage a business. Cultivating strong ESI is essential for navigating the inherent uncertainties and challenges associated with entrepreneurship. Fortunato and McLaughlin (2012) further emphasize the significance of community interaction within entrepreneurial education. Their research suggests that fostering connections between aspiring entrepreneurs and established business owners within the local community can provide invaluable mentorship, access to resources, and a deeper understanding of the practical realities of running a business. By integrating these insights, entrepreneurial programs can move beyond traditional classroom instruction to create a more holistic learning experience that strengthens students' self-efficacy and fosters valuable community engagement.

While the concept of ESI has existed for decades, artificial intelligence has been obscured as an element of entrepreneur social infrastructure. The emergent utility of AI applications in learning environments has outpaced the rate of research on the impact of Generative Artificial Intelligence (GAI) applications in education and training (Hwand & Chen, 2023). However, it warrants broader interest as an element of interaction and purpose as it continues to push the boundaries of learning environments toward adaptive learning (Baidoo-Anu & Owusu Ansah, 2023).

Methodology

We present a case study of a Pretrained Entrepreneur Support Model (PESM) built from 10 years of successful administration, application, and assessment of an entrepreneurial education program in the Jacksonville, Florida ecosystem. To achieve PESM, a neural network of activities, feedback loops, and time durations was first developed as a dimension interaction and purpose. An additional entrepreneur dimension was constructed to delineate support strategies performed by educators and providers. The new dimensions of interaction and purpose provided an entrepreneurial connectome to map learning processes and dialogue for training. The pretrained model used GAI application to personalize learning, simulate scenarios, and facilitate connections within the entrepreneurial community from a resource provider perspective. The primary methods used for evaluating interaction and purpose represent activities, feedback loops, and innovation accounting administered in education settings. The evolution of these interactions took place over a five-year time series (2018-2023).

Activity	Feedback Loop	Rates of Support
In-Person Counseling Session	In-Person/Virtual Meetings	Weeks/Months
Online Forms	Online Workflows	Days/Weeks
Permissioned Blockchain	Online Workflows, P2P	Days/Hours
Prompt Engineering/Pretrained	Iterative Prompt-Response	Hours/Minutes of Adaptive Learning
Neural Network Mirroring	Interactive	Hours/Minutes of Spatial Learning

Table 1. Neural Network

Business Stage	ESI	Innovation Accounting	Paired AI
Conception	Task	Treatment vs Solution, Value Proposition	1:1 Prompt Engineering
Start-Up	Task, Workshop, Counseling	Minimum Viable Product, Minimum Viable Audience	1:1 Prompt Engineering and 1:M Pretrained Support
Growth	Workshop, Counseling, Training	Key Performance Indicators, Build-Measure-Learn Loops	1:1 Prompt Engineering, 1:M Pretrained Support,

			and Neural Network Mirroring.
Established	Workshop, Counseling, Training	Financial Projections and Valuations	1:1 Prompt Engineering, 1:M Pretrained Support, and Neural Network Mirroring.

Table 2. Entrepreneur Neural Network

Results and Findings

We evaluated the PESM's capacity through learning paths and innovation accounting within the Jacksonville (FL) entrepreneur social infrastructure. The results of our initial iterations suggest there are several applications for Generative AI in entrepreneur support. Each warrant more exploration towards measurable outcomes such as education emphasis, rates of efficiency, and support.

The first application involves exploring the utility of structured and unstructured AI solutions relative to the stage of business. An unstructured AI solution can be described as affording individual access to Generative AI and Pretrained Models, whereas structured AI solutions can be distinguished by an educational pairing of the Pretrained Model with a Pretrained Educator (Paired GAI) to a specific domain such as entrepreneurial education.

For example, in a controlled setting during model training, we conducted a workshop with nearly 100 participants ranging from new venture to established; each given the task of completing a one-page entrepreneurial canvas based on their venture problem and solution. Typically, a counseling session for one participant would occupy a timeframe of thirty minutes. A structured write-up of the encounter would add an additional fifteen minutes (4500 total minutes for the group). Using Paired AI with two controlled groups, we conducted a thirty-minute canvas completion workshop for each group with fifty participants (60 total minutes). Leveraging the pretrained model, we provided individualized algorithmic prescriptions to all participants within four hours (240 total minutes). The rate of support and efficiency of the feedback loop for this provider task improved from a 4500-minute task for providers to 240-minute task.

A further challenge in the realm of entrepreneur support has been the attempt to replicate successful ecosystems and programming. With Paired GAI, we experienced opportunities to mirror (replicate spatially) some of the complex variables within an entrepreneurial social infrastructure. Leading to a second application of dialogic design for Generative AI within learning paths. This technology has the potential to address the FM/LM problem of connectivity within social infrastructures through personal learning experiences and adaptive engagement. In several cases, the pretrained model enabled non-technical providers to provide technical solutions to an array of domains and industries increasing the individual capacity of each provider. In addition, the pretrained support provided consistency in the quality and speed of responses for participating providers.

Overall, our initial findings show that PESM offers a promising solution to the First Mile/Last Mile problem. It democratizes access to ESI, enhances interaction within the community, and fosters innovative learning approaches. This case study contributes to the ongoing debate on effective ESI by demonstrating the potential of Generative AI in nurturing vibrant entrepreneurial ecosystems, even in resource-constrained contexts.

Conclusion

The long-held view of institutional resources with physical boundaries that represent an ecosystem warrants new archetypes to capture AI-generated interaction and purpose. Critical components of artificial intelligence like adaptive learning, algorithmic prescriptions, functional decomposition, recursive task decomposition, and neural networking have established new factors of production for entrepreneurial activity and education. This case demonstrates the need for a paradigm shift in the way we administer entrepreneur education. More broadly, the introduction of new dimensions of interaction and purpose in communities warrant a need to advance our descriptions of standard archetypes from entrepreneur social infrastructure and ecosystems to an entrepreneur connectome that communicate neural network activity.

Entrepreneur Connectome as a framework embodies entrepreneur connectivity, entrepreneur education, entrepreneur prescriptions, and temporal depth affected by the use of Generative AI. *Connections* represent elements of interaction, purpose, and dialogic innovation that connect entrepreneurs to resources within the social infrastructure of an ecosystem. *Education* represents the competence, demand, and supply models of learning pathways within the social infrastructure of an ecosystem. *Prescriptions* are treatments and solutions provided to entrepreneurs because of provider engagement. And *temporal depth* represents the amount of time that it takes for prescriptions to be generated and/or administered.

The integration of Generative AI into components of social infrastructure closes gaps in ecosystem capacity and the replication of successful programming. Exploring how these new entrepreneur neural networks can be mapped to support larger service areas with breadth and depth can be transformative for the entrepreneur education community. Future research should measure how these new archetypes, dimensions, and elements connect entrepreneurs and impact ecosystem capacity.

References

Baidoo-Anu, D., & Owusu Ansah, L. (2023). Education in the Era of Generative Artificial Intelligence (AI): Understanding the Potential Benefits of ChatGPT in Promoting Teaching and Learning. Journal of AI, 7(1), 52-62.

Flora, C. B., & Flora, J. L. (1993). Entrepreneurial social infrastructure: A necessary ingredient. Annals of the Academy of Social and Political Sciences 529:48-58.

Fortunato, M. & McLaughlin, D. (2012). Interaction and Purpose in Highly Entrepreneurial Communities. Entrepreneurship Research Journal, 2(1), 0000102202215756651049.

Gwo-Jen Hwang & Nian-Shing Chen (2023). Exploring the Potential of Generative Artificial Intelligence in Education: Applications, Challenges, and Future Research Directions. Educational Technology & Society. Apr, Vol. 26 Issue 2, p1-18.

NAVIGATING THE FUTURE OF HEALTHCARE: BIG DATA'S IMPETUS FOR INPATIENT QUALITY ENHANCEMET

Lakyn Hyre
Alumna, Healthcare Administration Program,
Division of Management and Healthcare Administration.
Lewis College of Business
Marshall University
304-746-1968
hare15@marshall.edu\
100 E. Peyton Drive,
South Charleston, WV, 25303

Brian Cox,
DBA student
cox403@marshall.edu
Lewis College of Business
Marshall University
304-746-1968
cox403@marshall.edu

Alberto Coustasse (corresponding Author)
Professor, Healthcare Administration and Health Informatics Program,
Division of Management and Healthcare Administration,
Lewis College of Business
Marshall University
coustassehen@marshall.edu
304-746-1968 (contact author).
100 E. Peyton Drive,
South Charleston, WV, 25303

Keywords: Big Data, Big Healthcare Data, Costs, Patient Outcomes, Quality Improvement

Introduction

In contemporary healthcare, quality improvement remains a critical concern globally, particularly in the United States (US), as evidenced by various scholarly reports (WHO, 2018; ARHQ, 2018). The ramifications of suboptimal quality encompass diverse challenges such as overuse, underuse, and misallocation of services, resulting in avoidable patient complications, increased healthcare costs, and even fatalities (ARQH, 2018). These issues significantly impact financial expenditures, with overtreatment alone accounting for 2%-2.7% of US healthcare spending in 2019, accumulating an estimated $76 billion in additional costs (Health Affairs Research Brief, 2022; Shrank et al., 2019). Concurrently, failures in care delivery and coordination contributed to an estimated $102-166 billion and $27-78 billion in costs, respectively, in the same year (Health Affairs Research Brief, 2022; Shrank et al., 2019).

Among these concerns, hospital readmission rates have become a pivotal indicator of healthcare quality, subsequently influencing healthcare policy, such as the Affordable Care Act's Hospital Readmissions Reduction Program (HRRP) (NEJM Catalyst, 2018b). In 2011, hospital readmissions accounted for 3.3

million cases, imposing $41.3 billion in associated costs (NEJM Catalyst, 2018b). The implementation of HRRP led to a decline in readmission rates from 21.5% in 2007 to 17.8% in 2015 (Zuckerman et al., 2016), reflecting positive strides in quality improvement.
The term "Big Data" has been widely used, but until recently, there was no universally accepted definition for it. According to McKinsey, Big Data refers to datasets too large for typical database software tools to handle effectively. Gartner proposed the "3V" definition: Big Data is characterized by volume, velocity, and variety and requires innovative forms of information processing to gain insights and make decisions. Some definitions also include a fourth dimension called "Veracity," which refers to the data's quality, authenticity, and trustworthiness.
Big Data in healthcare has been sourced from, but not limited to, medical imaging, Electronic Health Records (EHRs), payor records, genomic sequencing, pharmaceutical research, wearables, and medical devices (NEJM Catalyst, 2018a). Harnessing this data, alongside machine learning, holds promise in enhancing patient outcomes, curbing readmission rates, and potentially reducing costs (Kumar et al., 2018).

Methodology

This study aims to explore the impact of big data utilization on quality improvement in inpatient facilities, specifically assessing its influence on readmission rates, patient outcomes, and potential cost savings. This study utilized mixed methodologies with a literature review complemented by semi-structured interviews to gain perspectives about big data utilization on quality improvement in inpatient facilities. The Marshall University Institutional Review Board (IRB) approved the interview. This study's conceptual framework (Figure 1) was adapted from the research framework of Yao, Chu, and Li (Yao et al., 2010). The framework displays the reasoning of and approach to big data and machine learning for improving healthcare quality, specifically readmission rates and patient outcomes. The adoption of the use of big data begins with the need for tools and algorithms to support clinical and administrative functions due to big data's ability to support these improvements.

Results

Integrating big data analytics and machine learning has significantly transformed healthcare practices, offering predictive models that demonstrate substantial promise in improving patient outcomes and curbing hospital readmission rates.

In the Golas et al. (2018) study, developing a predictive model for 30-day heart failure readmissions utilizing Deep Unified Networks (DUNs) displayed promising accuracy. Trained on data from over 11,000 patients and 27,000 admissions, this model showcased an accuracy rate of 76.4%, highlighting its potential to identify candidates who would benefit from disease management programs, consequently reducing readmission rates and yielding cost savings of up to 3.403 ± 0.536. Rojas et al. (2018) delved into ICU readmission predictions using machine learning, demonstrating superior performance to existing algorithms such as SWIFT and MEWS. Achieving a specificity of 95% and a sensitivity rate of 28%, this model signaled enhanced capabilities in predicting ICU readmissions. Additionally, Stehlik et al. (2020) explored remote monitoring for heart failure using implantable cardiac sensors, which showcased notable sensitivity and specificity in predicting heart failure exacerbation. The platform detected precursors of hospitalization with a sensitivity range of 76% – 88% and a specificity of 85%, significantly aiding in timely interventions and reducing readmission occurrences.

Romero-Brufau et al. (2020) introduced a tool to assess readmission risks for general care unit patients, identifying high-risk hospitalizations. Their tool exhibited a 25% reduction in relative readmission rates, emphasizing its potential to stratify patients and intervene proactively. Furthermore, Moradi et al. (2023) leveraged machine learning on a massive National COVID Cohort Collaborative (N3C) dataset to predict outcomes for COVID-19 patients. With an accuracy rate of 81% in predicting patient mortality, their Gradient Boosted Decision Tree model presented promising results in forecasting patient outcomes.

Daghistani et al. (2020) explored appointment no-show predictions using machine learning techniques. Their Gradient Boosting model achieved an accuracy rate of 79%, assisting in establishing reliable appointment scheduling strategies and addressing concerns related to underutilized resources. Moreover, Taylor et al. (2015) designed a predictive model for sepsis mortality, with the random forest model exhibiting an 86% confidence level in predicting mortality among patients meeting sepsis criteria. Finally, Du et al. (2020) utilized machine learning to predict coronary heart disease onset among hypertensive patients. Their XGBoost model displayed a high % accuracy rate of 94% in predicting 3-year CHD onset based on electronic health record data.

Discussion

The review suggested that big data and machine learning applications have significant potential to achieve the study's objectives. Studies have demonstrated that predictive models accurately identify at-risk patients, enabling proactive interventions to lower readmission rates. The accuracy rates of these models, which range between 70% and 80%, highlight their potential to identify patients requiring additional care post-discharge. These studies illustrated the potential and effectiveness of leveraging big data and machine learning in healthcare. These models contributed to improved patient outcomes and offer promising strategies to mitigate readmission rates across various healthcare domains. However, the study faced limitations in directly confirming associated cost savings. The absence of concrete financial statistics hindered the ability to support the hypothesis regarding cost reductions unequivocally, thus presenting a deviation from the initial aim. While these findings present a promising outlook for integrating big data and machine learning in healthcare, several considerations warrant attention.

Practical Implications

The findings of this research present several practical implications that hold substantial importance for healthcare administrators, clinicians, and policymakers aiming to integrate big data and machine learning in inpatient facilities: Inpatient facilities require a structured strategy for incorporating predictive models into existing workflows. Collaboration among healthcare IT specialists, clinicians, and data scientists is crucial to embedding these models seamlessly into daily clinical practices. Healthcare professionals must receive adequate training to interpret and act upon predictions generated by these models. Targeted resource allocation and proactive patient management can optimize healthcare resources and reduce unnecessary costs. Continuous evaluation and refinement of predictive models is vital, with adherence to regulatory compliance and ensuring patient privacy central to deploying these models. Long-term studies and interdisciplinary collaborations foster innovation and drive the evolution of these models toward more excellent utility and reliability. Developing guidelines and incentives and encouraging research and funding initiatives could provide concrete evidence of the cost-saving potential of these models. In summary, these practical implications underscore the need for meticulous planning, effective integration strategies, continuous evaluation, ethical considerations, and collaborative efforts to harness the transformative potential of big data and machine learning in improving quality and optimizing healthcare outcomes in inpatient facilities.

Limitations

The need for comprehensive financial statistics limits the validation of the proclaimed cost-saving potential of these models. Moreover, challenges about data quality and the seamless integration of these predictive models into routine clinical practices necessitate further exploration.

Future Research Directions

More research is needed to validate the cost-saving benefits of these predictive models. Comprehensive evaluation is necessary for implementing these models in natural healthcare settings. Continued research and practical implementation strategies are crucial for realizing the potential of these innovative healthcare approaches.

Conclusion

In conclusion, while affirming the transformative potential of big data and machine learning in enhancing inpatient facility quality and patient outcomes, this study underscores the need for further research to validate cost-saving benefits and address implementation challenges.

References

Abouelmehdi, K., Beni-Hessane, A. & Khaloufi, H. (2018, January 9). *Big healthcare data: preserving security and privacy. Journal of Big Data* 5 (1). Retrieved on October 7, 2023 from https://doi.org/10.1186/s40537-017-0110-7.

Agency for Healthcare Research and Quality (AHRQ). (2018, June) *The challenge and potential for assuring quality health care for the 21st Century*. Retrieved August 29, 2023 from https://www.ahrq.gov/patient-safety/quality-measures/21st-century/index.html#:~:text=There%20are%20several%20areas%20where,higher%20costs%2C%20and%20premature%20deaths.

Bates, D. W., Saria, S., Ohno-Machado, L., Shah, A., & Escobar, G. (2014). Big data in health care: using analytics to identify and manage high-risk and high-cost patients. *Health Affairs*, *33*(7), 1123-31. DOI:10.1377/hlthaff.2014.0041 .

Centers for Medicare and Medicaid Services (CMS). (2021, December 1). *Quality Measurement and Quality Improvement*. Retrieved August 28, 2023 from https://www.cms.gov/medicare/quality-initiatives-patient-assessment-instruments/mms/quality-measure-and-quality-improvement-

Daghistani, T., AlGhamdi, H., Alshammari, R., Alhazme, RH. (2020, December 9).Predictors of outpatients' no-show: big data analytics using Apache spark. *Journal of Big Data* 7, 108. https://doi.org/10.1186/s40537-020-00384-9

Du, Z., Yang, Y., Zheng, J., Li, Q., Lin, D., Li, Y., Fan, J., Cheng, W., Chen, X.-H., & Cai, Y. (2020, July 6). Accurate prediction of coronary heart disease for patients with hypertension from electronic health records with Big Data and machine-learning methods: Model Development and Performance Evaluation. *JMIR medical informatics.8*(7), e17257. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7381262/

Findling, M., Blendon, R., Benson, J. (2020, December 14) Delayed Care with Harmful Consequences-Reported Experiences From National Surveys During Coronavirus Disease 2019. *JAMA Health Forum. 1*(12), e201463. doi:10.1001/jamahealthforum.2020.1463

Fischer, C., Lingsma, H. F., Marang-van de Mheen, P. J., Kringos, D. S., Klazinga, N. S., & Steyerberg, E. W. (2014). Is the readmission rate a valid quality indicator? A review of the evidence. *PloS one*, *9*(11), e112282. https://doi.org/10.1371/journal.pone.0112282

Golas, S.B., Shibahara, T., Agboola, S., Otaki, H., Sato, J., Nakae, T.,...Jethwani, K. (2018, June 22). A machine learning model to predict the risk of 30-day readmissions in patients with heart failure: a retrospective analysis of electronic medical records data. *BMC Medical Informatics and Decision Making. 18*(1),44 https://doi.org/10.1186/s12911-018-0620-z

Health Affairs Research Brief. (2022, June 9) *The Role Of Clinical Waste In Excess US Health Spending.* DOI: 10.1377/hpb20220506.432025

Henry, T. (2021, February 15) Why 41% of patients have skipped care during COVID-19 pandemic. *American Medical Association.* https://www.ama-assn.org/delivering-care/public-health/why-41-patients-have-skipped-care-during-covid-19-pandemic

Kumar S, Singh M. (2019, March) Big Data Analytics for Healthcare Industry: Impact, Applications, and Tools. *Big Data Mining and Analytics*, 2(1): 48-57. https://doi.org/10.26599/BDMA.2018.9020031

McQueenie, R., Ellis, D. A., McConnachie, A., Wilson, P., & Williamson, A. E. (2019). Morbidity, mortality and missed appointments in healthcare: a national retrospective data linkage study. *BMC Medicine, 17*(1), doi:10.1186/s12916-018-1234-0

Moradi, H., Bunnell, H. T., Price, B. S., Khodaverdi, M., Vest, M. T., Porterfield, J. Z., … Hodder, S. L. (2023, March 9). Assessing the effects of therapeutic combinations on SARS-COV-2 infected patient outcomes: A big data approach. *PLOS ONE*, *18*(3). doi:10.1371/journal.pone.0282587

NEJM Catalyst. (2018a, January 1). *Healthcare Big Data and the Promise of Value Based Care.* Retrieved on October 7, 2023 from https://catalyst.nejm.org/doi/full/10.1056/CAT.18.0290

NEJM Catalyst. (2018b, April). *Hospital Readmissions Reduction Program (HRRP).* Retrieved on October 7, 2023, from https://catalyst.nejm.org/doi/full/10.1056/CAT.18.0194

Rojas, J. C., Carey, K. A., Edelson, D. P., Venable, L. R., Howell, M. D., & Churpek, M. M. (2018, July). *Predicting Intensive Care Unit Readmission with Machine Learning Using Electronic Health Record Data. Annals of the American Thoracic Society, 15*(7), 846-853. https://doi.org/10.1513/AnnalsATS.201710-787OC

Romero-Brufau, S., Wyatt, K. D., Boyum, P., Mickelson, M., Moore, M., & Cognetta-Rieke, C. (2020, September 2). Implementation of Artificial Intelligence-Based Clinical Decision Support to Reduce Hospital Readmissions at a Regional Hospital. *Applied clinical informatics*, *11*(4), 570–577. https://doi.org/10.1055/s-0040-1715827

Shrank, W. H., Rogstad, T. L., & Parekh, N. (2019, October 7). *Waste in the US Health Care System*. JAMA. DOI:10.1001/jama.2019.13978

Stehlik, J., Schmalfuss, C., Bozkurt, B., Nativi-Nicolau, J., Wohlfahrt, P., Wegerich, S., . . . Pham, M. (2020, February 25). Continuous Wearable Monitoring Analytics Predict Heart Failure Hospitalization. *Circulation: Heart Failure, 13*(3), e006513. DOI:10.1161/CIRCHEARTFAILURE.119.006513

Subject Interview. Conducted by Lakyn Hare. (2023, November 16).

Taylor, AR., Pare, JR.,Venakatesh, AK., Mowafi, H., Melnick, ER., Fleischman, W., Hall, K. (2015, December 17) Prediction of in-hospital mortality in emergency department patients with sepsis: A local big data-driven, machine learning approach. *Academic Emergency Medicine*, *23*(3), 269-278. **https://doi.org/10.1111/acem.12876**

Tulane University. (2021, July 7). *Big data in health care and patient outcomes*. Retrieved August 28, 2023 from https://publichealth.tulane.edu/blog/big-data-in-healthcare/

World Health Organization (WHO). (2018, July 5) *Low Quality Healthcare is increasing the burden of illness and health costs globally*. Retrieved August 28, 2023 from https://www.who.int/news/item/05-07-2018-low-quality-healthcare-is-increasing-the-burden-of-illness-and-health-costs-globally

Yao, W., Chao-Hsien, C., Li, Z. (2010) The Use of RFID in Healthcare: Benefits and Barriers. Proceedings of the 2010 IEEE International Conference on RFID-Technology and Applications (RFID-TA), 128–34.

Zuckerman, R. B., Sheingold, S. H., Orav, E. J., Ruhter, J., & Epstein, A. M. (2016,). Readmissions, Observation, and the Hospital Readmissions Reduction Program. *The New England journal of medicine*, *374*(16), 1543–1551. https://doi.org/10.1056/NEJMsa1513024

Grande, D., Machado, J., Petzold, B., & Roth, M. (2020, December 16). How to reduce data costs while increasing speed and quality. *McKinsey & Company*. 1 retrieved on December 26, 2023 from Reducing data costs without sacrificing growth | McKinsey

Manyika J, Chui M, Brown B, et al. Big data: The next frontier for innovation, competition, and productivity. 2011. www.mckinsey.com/mgi (12 September 2019,

Beyer M, Laney D The Importance of 'Big Data': A Definition. Gartner report. 2012, 1–9.

Figures and tables

Figure 1: Conceptual Framework, adapted from (Yao, Chu, Li., 2010)

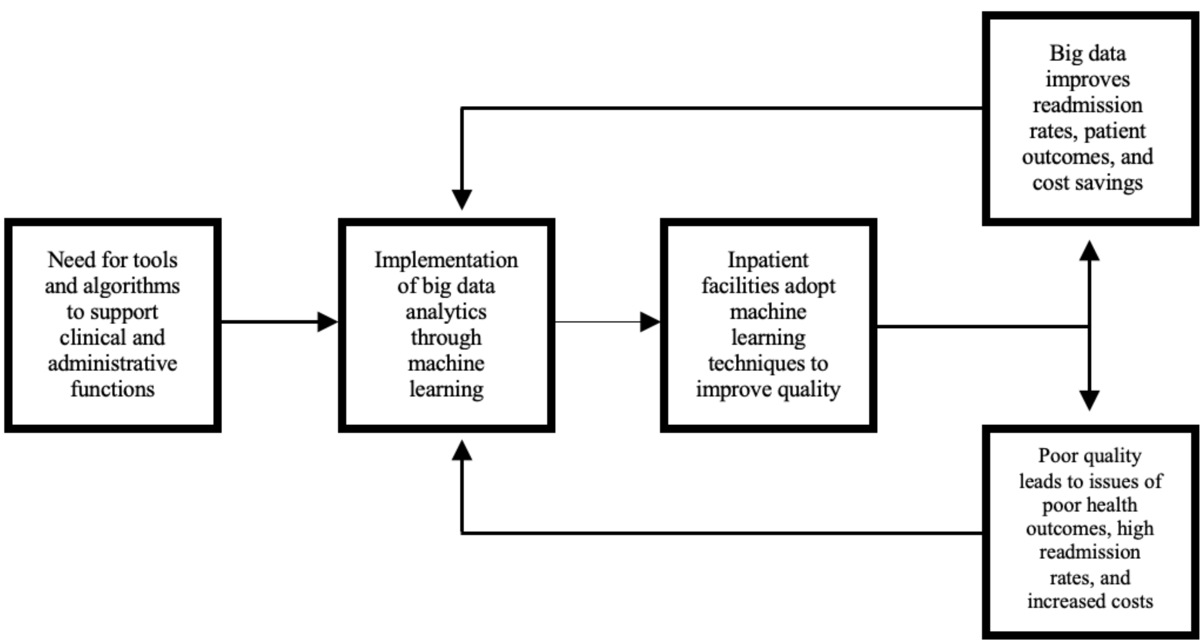


Table 1: Accuracy of different models on predicting outpatient no-show using different alidation methods. Data retrieved from (Daghistani et al., 2020).

Model	Accuracy (70/30 holdout method)	Accuracy (80/20 holdout method)	Accuracy (tenfold cross validation)
Random Forest	0.76	0.75	0.76
Gradient Boosting	0.79	0.79	0.79
Logistic Regression	0.75	0.75	0.75
SVM	0.73	0.54	0.73
Multilayer Perceptron	0.77	0.75	0.77