ANALYZING THE BOUNDARIES OF BALANCE THEORY IN EVALUATING CAUSE-RELATED MARKETING COMPATIBILITY

BY

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DISSERTATION

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ABSTRACT

The phenomenon of brands partnering with causes is referred to as cause-related marketing (CRM). This dissertation provides numerous steps forward within the realm of CRM research, as well as balance theory research. Some CRM partnerships may seem less compatible than others, but the level of perceived compatibility (also referred to as "fit") differs from consumer to consumer. I analyzed CRM compatibility through the lens of balance theory both via a survey-based approach, as well as a social media analytics approach. My contributions to CRM and balance theory are as follows: I found that a consumer's attitude towards a brand, along with their attitude towards a cause, predicts their perceptions of CRM compatibility. I also show that adding continuous measures of attitude and attitude strength enabled the prediction of balanced and unbalanced consumer evaluations of perceived CRM compatibility. This is the first time that attitude strength has been incorporated into balance theory. I found evidence that a consumer's attitude towards a brand (or towards a cause), and the strength of that attitude, can spill from one organization to another when brands and causes enter into CRM partnerships. Methodologically, I present a novel way to indirectly measure the strength of attitudes towards brands and towards causes through analyzing perceived conversation topic similarity via a self-reported survey measure, but I was not able to provide evidence that attitude strength could be measured via a social media analytics approach to conversation topic similarity. To dig deeper into this lack of social media analytics results, I provide some considerations with regards to research conducted using a hybridization of a survey-based approach tied to a social media analytics approach. Practically, I share recommendations as to how to choose CRM partners for future CRM partnerships, which should prove beneficial to CRM researchers, practitioners, and advertisers.

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LIST OF IMPORTANT TERMS & PHRASES

Brand   A shortened name for a for-profit company.

Cause   A shortened name for a not-for-profit company.

CRM   An acronym for cause-related marketing. In this dissertation, I define
                   CRM as a business strategy in which a brand partners with a cause
                   through various types of engagements, to address both organizations'
                   objectives.

CRM Triad   A triangular structure of three entities: a consumer, a brand, and a
                   cause. In this triad, the consumer evaluates their attitude towards the
                   brand, their attitude towards the cause, and their perception of
                   compatibility between the brand and the cause in the CRM partnership.
                   See Figure 1.1.

CSR   An acronym for corporate social responsibility. CSR refers to
                   corporate social actions that address social needs, while CRM is CSR
                   in which a brand partners with a cause to address social needs. Thus,
                   CRM is a subset of CSR.

LIST OF VARIABLES

AS_{BRAND}	An individual's self-reported strength of their attitude towards the brand within a CRM partnership.
AS_{CAUSE}	An individual's self-reported strength of their attitude towards the cause within a CRM partnership.
$AS_{DIFFERENCE}$	The mathematical difference between AS_{BRAND} and AS_{CAUSE} (the absolute value) for an individual.
AT_{BRAND}	An individual's self-reported attitude towards the brand within a CRM partnership.
AT_{CAUSE}	An individual's self-reported attitude towards the cause within a CRM partnership.
$AT_{DIFFERENCE}$	The mathematical difference between the absolute values of AT_{BRAND} and AT_{CAUSE} (The lesser subtracted from the greater) for an individual.
$ATAS_{DIFFERENCE}$	The mathematical difference between the absolute values of (AT_{BRAND} x AS_{BRAND}) and (AT_{CAUSE} x AS_{CAUSE}) (The lesser subtracted from the greater) for an individual.
$BALANCE_{CRM}$	A binary variable (0 or 1) that denotes whether a CRM triad is balanced or not. I accept weak balance as a condition of balance throughout this dissertation.
$COMP_{PERCEIVED}$	An individual's self-reported perceived CRM compatibility between a brand and a cause within a CRM partnership.
$SURVEYSIM_{BRAND}$	An individual's self-reported perceived amount of conversation topics that an individual believes to be similar to a brand (how similar are the topics that I speak about to the topics that I believe a brand would speak about).
$SURVEYSIM_{CAUSE}$	An individual's self-reported perceived amount of conversation topics that an individual believes to be similar to a cause (how similar are the topics that I speak about to the topics that I believe a cause would speak about).
$CODERSIM_{BRAND}$	Human coded similarity assessment between the dissertation participants' self-reported $SURVEYSIM_{BRAND}$ and their Text Razor $TWEETDIV_{BRAND}$.
$CODERSIM_{CAUSE}$	Human coded similarity assessment between the dissertation participants' self-reported $SURVEYSIM_{CAUSE}$ and Text Razor $TWEETDIV_{CAUSE}$.
$RAWDIV_{BRAND}$	The divergence (opposite of similarity) between computational raw word analysis of an individual's Twitter feed and a brand's Twitter feed.
$RAWDIV_{CAUSE}$	The divergence (opposite of similarity) between computational raw word analysis of an individual's Twitter feed and a cause's Twitter feed.
$TWEETDIV_{BRAND}$	The divergence (opposite of similarity) between computational conversation topic analysis of an individual's Twitter feed and a brand's Twitter feed.
$TWEETDIV_{CAUSE}$	The divergence (opposite of similarity) between computational conversation topic analysis of an individual's Twitter feed and a cause's Twitter feed.

CHAPTER 1: GENERAL INTRODUCTION AND DISSERTATION OUTLINE

CAUSE-RELATED MARKETING

In 1983, American Express launched an initiative to restore the Statue of Liberty and

Ellis Island ("American Express - Corporate Social Responsibility - Initiatives," n.d.). They did

this in partnership with two causes: The World Monuments Fund and the National Trust for

Historic Preservation. This effort was widely considered a success, as they raised $1.7 million

through this partnership. American Express widely promoted this effort and trademarked it as,

"cause-related marketing" (CRM) (Welsh, 1999). Some years later, Varadarajan and Menon

(1988) provided a definition of CRM as follows:

> Cause-related marketing is the process of formulating and implementing activities that
> are characterized by an offer from the firm to contribute a specified amount to a
> designated cause when customers engage in revenue-providing exchanges that satisfy
> organizational and individual objectives. (p. 60)

In the American Express partnership with the World Monuments Fund and the National

Trust for Historical Preservation, American Express contributed one cent for every credit card

charge, and a dollar per each new cardholder in the final quarter of 1983. This resulted in a 17%

increase in the number of credit cards and 28% more usage on American Express cards during

that period. This proved to American Express that CRM was a beneficial financial strategy, and

they were also able to promote their company as being socially responsible. In fact, this seems to

be the angle that they were most focused on, as they accentuate this point quite clearly:

> These initiatives aim to increase public awareness of the importance of historic and
> environmental conservation, preserve global historic and cultural landmarks, educate
> visitors on sustainable tourism and strengthen local communities through preservation
> efforts ("American Express - Corporate Social Responsibility - Initiatives," n.d.).

Barone, Miyazaki, and Taylor (2000) suggested that CRM has not just been limited to donations that are dependent on revenue-providing exchanges, but can apply to other types of cause-related partnerships, such as lump sum donations by brands to causes, or brands offering discounts for members of causes. For example, Royal Caribbean pledged to donate $5 million as a lump sum donation to the World Wildlife Fund in efforts to preserve the ocean environment (Hancock, 2016). Whereas an example of a CRM partnership involving a discount between a brand and a partnership is Wyndham Hotel's ten percent discount given to National Rifle Association members (Fairchild, 2013).

Cause-related marketing is sometimes used interchangeably with corporate social responsibility (CSR), but they are separate, albeit related, concepts. Brønn and Vrioni (2001) discussed the differences between the two, and suggested that CSR refers to corporate social actions that address social needs, while CRM is CSR in which a brand partners with a cause to address social needs. Thus, CRM is a subset of CSR. An example of CSR that is not CRM would be a company deciding to use 100% recyclable materials in its products. They are not partnering with a cause to do this (as in CRM), but it is an activity that a brand is conducting alone to provide societal benefit.

Although research has shown that there are definitely skeptics that do not trust the motivations behind CRM (Webb & Mohr, 1998), the phenomenon of CRM has substantially grown in popularity. Engage for Good, an organization that helps educate individuals and organizations about CRM, states that CRM spending has grown from $120 million in 1990 to $2.05 billion in 2017 ("ESP's Growth of Cause Marketing - Engage for Good," 2017). The growth and success of CRM has also been shown in newer advertising channels, such as in the realm of social media. Adweek, an American advertising trade publication, recently analyzed

what topics companies promote via social media (Vijay, 2017). They found that the topics that received the most engagement were the topics related to CRM. CRM researchers and practitioners would be wise to dig deeper into researching CRM on social media, as a recent Pew Research Center survey showed that up to 75% of adults in the United States use social media (A. Smith & Anderson, 2018). They also show that this percentage grows to 94% within the age range of 18 to 24 year olds with regards to social media use. Thus, these future consumers will most likely be interfacing with brands and causes on social media platforms.

Some more recent CRM examples are Starbucks with (RED) to fight AIDS, Warby Parker with Vision Spring to provide glasses for those in need, Fitbit with the American Heart Association to promote heart health, and Coca-Cola with the World Wildlife Fund to preserve polar bear habitats in the arctic. As another example of CRM effectiveness from these more recent partnerships, the World Wildlife Fund heralded the success of their partnership with Coca-Cola, as they were able to raise $2 million dollars for arctic conservation ("'Arctic Home' Generates over $2 Million in Donations for Polar Bear Conservation | Press Releases | WWF," 2012).

Cause-Related Marketing Compatibility/Fit

Although the World Wildlife Fund advertised the success of their partnership with Coca-Cola widely, it was not without controversy. Coca-Cola has been accused in the past to actually be destroying the environment (e.g., "In hot water," 2005), therefore there could be a perception that a partnership between Coca-Cola and the World Wildlife Fund does not seem to be a natural fit. This concept of assessing the compatibility of a brand and a cause within a CRM partnership is commonly called CRM fit (e.g., Lafferty, Goldsmith, & Hult, 2004) or CRM compatibility (e.g., Trimble & Rifon, 2006). CRM compatibility is an important concept within CRM

literature; in fact, a recent text-mining-based review of CRM literature found that brand-cause fit (compatibility) was the most frequently occurring topic across CRM literature from 1988 to 2013 (Guerreiro, Rita, & Trigueiros, 2016). Practically speaking, CRM compatibility is important as perceived compatibility has been shown to predict acceptance of CRM partnerships (Lafferty et al., 2004). One could imagine that both Coca-Cola and the World Wildlife Fund would have benefitted from understanding how consumers might accept or reject their partnership before they entered into it and/or widely advertised it. Previous studies have looked at how compatibility affects downstream variables such as attitudes towards partnerships and consumer behavior (e.g., Basil & Herr, 2006; Gupta & Pirsch, 2006; Pracejus & Olsen, 2004; Simmons & Becker-Olsen, 2006; Trimble & Rifon, 2006), but as far as I know, no studies have focused on how to predict a consumer's perception of compatibility in the first place. If we could understand how to predict a consumer's perceived CRM compatibility, then joining this together with previous research that shows that perceptions of CRM compatibility predicts acceptance of partnerships (e.g., Lafferty et al., 2004), there would be a possibility that we could predict this acceptance prior to brands and causes entering into partnerships.

The realm of social media is a place where brands and causes have feeds that are managed by individuals or groups working for those organizations. These social media managers normally attempt to discuss topics that a brand or cause would care about, as these discussions are also usually tied to their business mission and/or advertising strategies. As social media usage continues to grow (A. Smith & Anderson, 2018), finding ways to use social media analytics to predict aspects of CRM compatibility should provide great value to CRM researchers and practitioners. This may help us to understand when social media backlash could occur towards a CRM partnership. A recent example of CRM backlash is the case of the

#BoycottNRA social media campaign. After a series of recent mass shootings, consumers'

acceptance of CRM relationships between the National Rifle Association (NRA) and various

brands has substantially soured (Edevane, 2018). If I consider Lafferty et al.'s (2004) findings

that perceptions of CRM compatibility predicts CRM acceptance, then it may be helpful for the

partnering brands to understand how consumers construct their perception of CRM

compatibility. Additionally, as social media is increasingly becoming a platform for CRM

communication and advertising (Vijay, 2017), predicting aspects of CRM compatibility from

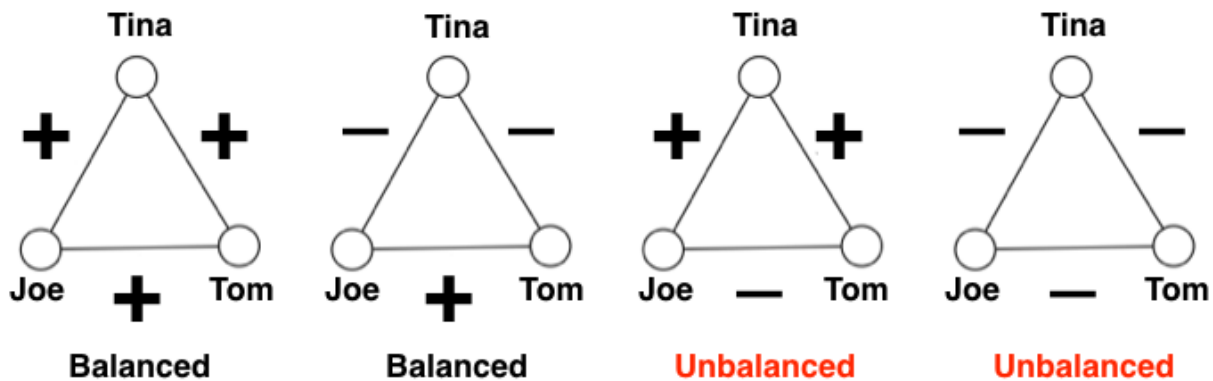social media is an important area of investigation as well.

Therefore, to address this gap of understanding how to predict consumers' perceived

CRM compatibility ratings, in this dissertation I will look into how consumers build their

perceptions of compatibility towards CRM partnerships (COMP$_{PERCEIVED}$), namely by looking at

their pre-existing attitudes towards the brands (AT$_{BRAND}$), and their pre-existing attitudes towards

the causes (AT$_{CAUSE}$), that are participating in the partnership. I will also investigate how I can

understand CRM compatibility both from a survey approach, as well as a social media analytics

approach. One theory that might help in predicting this compatibility is balance theory. Basil and

Herr (2006) were the first (and quite probably, the only) researchers to investigate whether using

a balance theory framework could help us gain insight into CRM partnerships. Thus, I will

briefly explain balance theory next.

Balance Theory

Balance theory was conceptualized by Fritz Heider, in which he wrote, "Attitudes

towards persons and causal unit formations influence each other" (Heider, 1946, p. 107).

Through this statement, Heider was suggesting that when attitudinal relationships occur between

people, objects (unit formations), or some combination of people and objects, these attitudes

affect each other. To clarify what is an attitude, Eagly and Chaiken (1993) defined attitude as, "a psychological tendency that is expressed by evaluating a particular entity with some degree of favor or disfavor" (p. 1). Heider (1946) suggested that attitudinal relationships move towards a state of balance. He defined balance as, "a harmonious state, one in which the entities comprising the situation and the feelings about them fit together without stress" (Heider, 1946, p. 180). One of the most well-known relationship structures of balance is the concept of triadic balance, where three people are represented as having attitudinal relationships towards one another (see Figure 1.1).

Figure 1.1: Example of Heider's (1946) Theory of Triadic Balance

Tina   Tina   Tina   Tina

| +   + | −   − | +   + | −   − |

Joe + Tom   Joe + Tom   Joe − Tom   Joe − Tom

Balanced   **Balanced**   **Unbalanced**   **Unbalanced**

In this example, Tina, Joe, and Tom all have relationships with each other. Positive signs denote a positive attitude, whereas negative signs denote a negative attitude. In Heider's original conceptualization, directionality of attitudes was not considered, as it was assumed that if Joe likes Tina, then Tina likes Joe. Although this is not always the case, this is in line with explaining Heider's original framework; this is also in line with evaluating CRM partnerships (organizations versus people), which will be explained later in this dissertation. In Heider's framework, these triads are supposed to move towards attitudinal balance or harmony. In the first triad (moving from left to right in Figure 1.1), Tina, Joe, and Tom all like each other, and

therefore there is a state of harmony or balance. In the second triad, Joe doesn't like Tina, and

Tina doesn't like Tom, so it is not a problem that Joe likes Tom. There is no inherent relational

stress in the second triad. In the third triad, Joe likes Tina, Tina likes Tom, but Joe does not like

Tom. This is a stressful relational situation. Maybe Tina would try to avoid Tom when Joe is

around, because Tina knows that Joe does not like Tom. Heider suggested that this is an

unbalanced triad, and therefore the system needs to change for balance to be restored. There are

numerous options as to how the system could change to bring it back into balance, but one of the

easiest conceptualizations of change for balance would be for Joe to reconcile with Tom and

enter into a positive relationship with each other. The fourth triad is an interesting one, as Heider

suggested that this was an unbalanced triad, but later research conceptualized this triad as

potentially balanced as well. Heider called three negative attitudes in a triad an unbalanced triad,

but Davis (1967) suggested that three negative attitudes in a triad were weakly balanced. In fact,

Davis (1967) pointed to the fact that even Heider suggested, "If two negative relations are given,

balance can be obtained either when the third relationship is positive or when it is negative,

though there appears to be a preference for the positive alternative" (Heider, 1958, p. 206). Thus,

although there is a strong tendency towards three negative relationships being imbalanced,

Heider (1958) and Davis (1967) acknowledged that there was the possibility of a weaker

tendency towards three negative relationships being balanced as well. Davis categorized this as a

condition of weak balance. I could conceptualize this when I consider the cliché, "an enemy of

my enemy is my friend." This is essentially the second triad in Figure 1.1., where Joe doesn't

like Tina, and Tina doesn't like Tom, so Joe likes Tom. I can consider though that Joe does not

necessarily have to like Tom, and that would not necessarily cause relational stress on the

system. Therefore, an enemy of my enemy can also be my enemy. I accepted the condition of

weak balance throughout this dissertation, as weak triadic balance has been proven to hold in real social data (Leskovec, Huttenlocher, & Kleinberg, 2010b). I will discuss Basil and Herr's (2006) connecting of triadic balance theory with CRM partnerships next. After this, I will move into discussing dyadic balance theory, and its potential connection with CRM partnerships and social media data.

Balance Theory and Cause-Related Marketing

Basil and Herr (2006) suggested that CRM partnerships could be considered as psychological triads, in which a consumer evaluates a brand, a cause, and their perceived compatibility between the brand and cause. Heider (1958) stated that triads could include both persons as well as entities, and that these entities could have also have some form of unit relationship to each other that was different than an attitudinal relationship (e.g., a person owning an object, thus having an assumed positive attitude towards that object). Basil and Herr's (2006) conceptualized triad is shown in Figure 1.1.

Figure 1.2: Cause-Related Marketing Triad
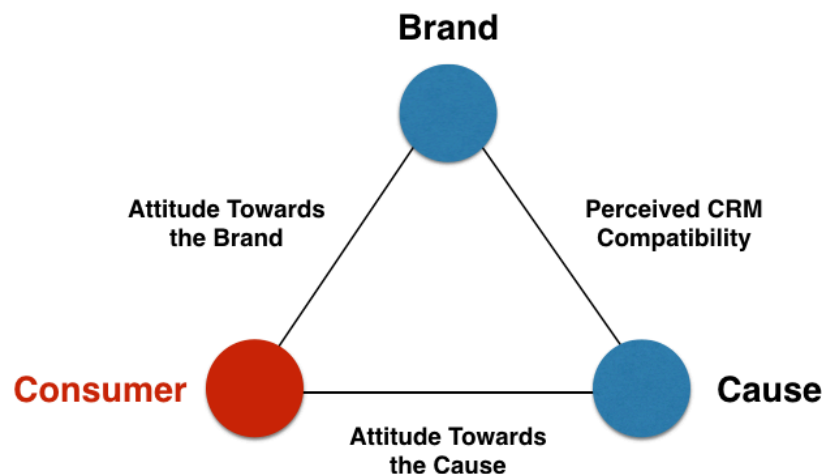
I use their conceptualized CRM triad for the first major chapter of this dissertation (Chapter 2), where I go into more detail about what Basil and Herr focused on in their study. From a high-level perspective, they set a foundation for my study in which they showed that a

balance theory framework could help us understand various aspects of CRM compatibility and attitudes towards CRM; with this said, they did not fully investigate how CRM compatibility could be comprehensively predicted by using this balance theory framework. I took this next step within this dissertation and found that perceived CRM compatibility ($COMP_{PERCEIVED}$) could be predicted through a consumer's attitude towards a brand (AT_{BRAND}), along with their attitude towards a cause (AT_{CAUSE}). I also question and dissect balance theory along the way.

One of the open questions within balance theory is the question of how continuous attitude measures would affect balance (e.g., Antal, Krapivsky, & Redner, 2006). Heider's (1946) original conceptualization only dealt with a dichotomous handling of attitude (either positive or negative, with no neutral), but attitudes have been shown to be continuous in nature (Eagly & Chaiken, 1993). Recent studies in balance have shown evidence that balance holds when attitudes are measured as continuous variables (e.g., Leskovec et al., 2010b), but less is known about how continuous attitude measurement affects balance within CRM triads. An open question therefore is whether using continuous attitude measures for AT_{BRAND} and AT_{CAUSE} (e.g., +2, -1, +3) versus dichotomous measures (e.g., +1, -1) will change whether or not $COMP_{PERCEIVED}$ will have a valence that follows balance theory. Through measuring participants' AT_{BRAND}, AT_{CAUSE}, and $COMP_{PERCEIVED}$, I assessed whether all three sides of the CRM triad followed balance or not ($BALANCE_{CRM}$). I found that balance within a CRM triad ($BALANCE_{CRM}$) could be predicted by looking at the degree of attitude valence differences between a consumer's attitude towards a brand and their attitude towards a cause ($AT_{DIFFERENCE}$), when participants had opposing valences of attitude towards a brand (AT_{BRAND}) and their attitude towards a cause (AT_{CAUSE}; e.g., a consumer likes the brand but dislikes the cause). Specifically, as the difference between a consumer's attitude towards a brand and attitude towards a cause

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($AT_{DIFFERENCE}$) grew larger, the probability that balance theory held grew smaller. This conceptually makes sense, as this is basically suggesting that the further I get away from Heider's original conceptualization of the dichotomous attitude structure of balance theory, there is more chance that CRM triads will be in states of imbalance ($BALANCE_{CRM} = 0$) versus being balanced ($BALANCE_{CRM} = 1$).

The final aspect of triadic balance and CRM partnerships that I cover within this dissertation is the question of whether adding attitude strength will benefit predictive models of balance within CRM partnerships. Research has shown that attitude strength is a separate construct than attitude, and that when attempting to predict behavioral change, attitude strength is what moderates the predictive nature of attitude on behavior (Petty & Krosnick, 1995). To clarify the difference between attitude and attitude strength, consider for example my attitudes towards Mondays and my attitudes towards bigotry. If I was to rate my attitudes on a scale from -5 to +5 (-5 being extremely negative, and +5 being extremely positive), my attitudes towards Mondays and bigotry would both rate at -5. Now I know that there is something different about those attitudes, but that difference does not show up in a simple valenced measurement of attitude alone. The measurement that picks up on the difference in those two attitudinal arenas is the measure of attitude strength. The strength of my attitude towards Mondays is fairly weak, meaning that it could be easily moved. If my workplace provided free lunches on every Monday, my attitude towards Mondays would quickly change to a +5. Since the strength of my attitude towards Mondays is weak, it is easy to change my attitude. Now with the example of my -5 attitudes towards bigotry, free lunches would not change my attitude, because the strength of my attitude towards that topic is very strong. In fact, there is potentially not much that I believe

someone could do to change my attitude on that topic. This example helps us to see the difference between attitude and attitude strength as psychological constructs.

Balance theory suggests that attitudes may change to achieve states of balance (see previous discussion on Figure 1.1). If balance theory considers systems in which attitudes are potentially changed, and attitude strength is a construct that shows us how resistant attitudes are to change, then it seems reasonable that considering attitude strength within balance theory would be fruitful. The combination of attitude strength and balance theory has not been previously researched within the realm of CRM partnerships. Therefore, I collected participants' strength of their attitudes towards a brand (AS_{BRAND}), and the strength of their attitudes towards a cause (AS_{CAUSE}) and found that attitude strength does improve my models in predicting balanced CRM triads. I assessed balance within CRM triads by assessing the valences of participants' AT_{BRAND}, AT_{CAUSE}, and $COMP_{PERCEIVED}$. This could be potentially considered as the first step towards a larger contribution to balance theory as a whole, but at the very least it is a furthering of our understanding of CRM partnership evaluations.

Finally, I looked at analyzing CRM partnership attitude strengths via dyadic balance theory and testing that relationship through survey measures as well as through social media analytics. I explain this next, and finish with a high-level view of the overall dissertation outline.

Balance Theory, Cause-Related Marketing, and Social Media

When considering dyadic balance theory (balance theory within two person/entity systems), Heider (1958) stated, "p similar to o induces p likes o, or p tends to like a similar o" (p. 184). Heider was suggesting that attitudes and unit formations influence each other even in two-person situations. In this case, similarity produces some form of relational unit between two people, and this affects their attitudes towards one another in a positive manner. Therefore,

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Heider is suggesting that similarity influences attitude. In network analysis, a close phenomenon to this is called homophily. McPherson et al. (2001) defines homophily as, "the principle that contact between similar people occurs at a higher rate than among dissimilar people." (p. 416). This does not necessarily assume positive attitudinal contact, but it draws a connection between similarity and behavior. Multiple studies have been conducted looking at homophily on social networks (e.g., Choudhury, 2011; Weng & Lento, 2014; Youyou, Schwartz, Stillwell, & Kosinski, 2017). Choudhury (2011) looked at homophily on Twitter by testing to see if there were any factors of similarity that influenced behavior, namely behavior in how people followed others on Twitter. The factors of similarity that she looked at were demographic attributes (location, gender, ethnicity), political orientation, activity-specific attributes (activity pattern, broadcasting behavior, interactiveness), and content-based attributes (topical interest, sentiment expression). She found that people seemed to follow others on Twitter that engaged in similar topical conversation as their own selves. Therefore, she found evidence that similarity of topic conversation influenced behavioral movement on Twitter.

Thus, I have the case that Heider (1958) suggested that similarity influences attitude, homophily suggests that similarity influences behavior, and Choudhury's (2011) research suggests that topic conversation similarity influences Twitter following. Heider did not consider attitude strength in his original conceptualization of balance theory, but research has shown that attitude strength moderates the ability to predict attitude change (Howe & Krosnick, 2017; Petty & Krosnick, 1995), and balance theory involves the possibility of attitudes changing. Additionally, previous research has shown evidence that one way to measure an individual's attitude strength towards a topic is if they talk about that topic, and how much they talk about it (Krosnick, Boninger, Chuang, Berent, & Carnot, 1993).

Putting all of these pieces together, if a person talks about the same topics as a brand (or cause), this suggests that they are similar (according to topics of conversation) with that brand (or cause). According to Choudhury's (2011) research, this similarity of topical conversation has be found to correlate with Twitter following behavior, of which behavior is influenced by attitude strength. Thus, I hypothesized that similarity of topics of conversations between a person and a brand (or cause) could be a way to measure the strength of their attitude towards that brand (or cause). As a clarifying note, attitude strength does not include valence (positive or negative), therefore a person may have a strong attitude towards a cause because they talk about the same topics (e.g., a person and the National Rifle Association both discussing guns), but the person may be speaking of guns negatively, and the NRA may be speaking of the guns positively.

When considering brands and causes within CRM partnerships, they are both entities with communications staff that promote certain topics according to their business mission or their advertising strategies. Thus, in the second main study of my dissertation (Chapter 3), I investigated the relationship between a consumer's perceived similarity of topical conversation with a brand ($SURVEYSIM_{BRAND}$), and the strength of that consumer's attitude towards the brand (AS_{BRAND}). I also investigated the relationship between a consumer's perceived similarity of topical conversation with a cause ($SURVEYSIM_{CAUSE}$), and the strength of that consumer's attitude towards the cause (AS_{CAUSE}). I found that a consumer's perceived topic similarity with a brand ($SURVEYSIM_{BRAND}$) predicted the strength of their attitude towards that brand (AS_{BRAND}), and their perceived topic similarity with a cause ($SURVEYSIM_{CAUSE}$) predicted the strength of their attitude towards that cause (AS_{CAUSE}). This new survey measure of the strength of attitudes towards brands and towards causes in CRM partnerships is a contribution to the realm of CRM, as it provides an indirect method of measuring attitude strength.

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In the second portion of Chapter 3, I investigated if a social media analysis of the topics that a consumer talks about could help me predict their attitude strength towards a brand or a cause. I did this by comparing the divergence (the opposite of similarity) between a consumer's topics of conversation in their Twitter feed compared to the topics of conversation of a brand's or cause's Twitter feed (TWEETDIV$_{BRAND}$ and TWEETDIV$_{CAUSE}$ respectively). If I can predict the strength of consumers' attitudes towards brands and causes via social media analytics, I will be closer to creating a prediction model for CRM compatibility using solely social media analytics. I did not find this social media analytics divergence method to be a way to measure the strength of consumers' attitudes towards a brand or a cause, but I did find that using a hybrid survey-based and social media analytics approach may have issues that have not been previously considered in social science research. Although there is no research using a hybrid survey-based and social media analytics approach within the realm of CRM, there are many examples of this type of method within social science research (e.g., J. Chen, Hsieh, Mahmud, & Nichols, 2014; Golbeck, Robles, Edmondson, & Turner, 2011; Youyou et al., 2017). I provide an explanation of some considerations when using this sort of hybrid method, as well as next steps in using this sort of approach in future CRM research.

DISSERTATION OUTLINE

My aim within this dissertation is to understand how balance theory can help to give us deeper insight into CRM compatibility, as well as how analyzing CRM compatibility could also further our understanding of balance theory.

This dissertation contains a general introduction (Chapter 1), followed by two chapters that are meant to be in publishable format as individual research journal papers. A summary of these two research papers (Chapter 2 and 3) is presented below. I then conclude with a general

discussion on the overall findings of this dissertation (Chapter 4). Within the final chapter, I will also discuss general limitations, future research thoughts, and indicate ways in which this dissertation has evolved since the proposal stage.

Chapter 2 describes a study in which I was able to predict participants' ratings of CRM partnership compatibility ($COMP_{PERCEIVED}$) via their self-reported attitude towards the brand (AT_{BRAND}), along with their self-reported attitude towards the cause (AT_{CAUSE}). I was also able to predict states of CRM triad balance/imbalance ($BALANCE_{CRM}$) within CRM partnership evaluations through incorporating the consideration of continuous attitude and attitude strength measures within balance theory. This allowed me to provide evidence that attitudes towards brands and towards causes were spilling over into one another. I will give further detail on spillover within Chapter 2. This study consisted of an online ($N = 993$) survey collection using Amazon Mechanical Turk.

Chapter 3 describes a study in which I investigated various ways to measure attitude strength within the realm of CRM and discussed the difficulties in comparing a survey approach with a social media analytics approach. I asked participants how similar they believed the topics that they talk about were with the topics that certain brands and causes talk about (the brands and causes from my first study in Chapter 2). I found that I was able to predict participants' assessments of the strength of their attitudes towards those brands and causes (AS_{BRAND} and AS_{CAUSE}) from their perception of topic discussion similarity with those brands and causes ($SURVEYSIM_{BRAND}$ and $SURVEYSIM_{CAUSE}$ respectively). This is a contribution to the realm of CRM, as this is a novel way to measure strength of attitudes towards brands and towards causes that may not suffer from social desirability bias as would a direct questioning of attitude strength. I was not able to predict the strength of their attitudes towards brands and causes (AS_{BRAND} and

AS$_\text{CAUSE}$) through a computational analysis of participants' Twitter feeds when compared to topic discussion divergence (opposite of similarity) of brand's or cause's Twitter feeds (TWEETDIV$_\text{BRAND}$ and TWEETDIV$_\text{CAUSE}$ respectively). I did find that my computational method to assess the topics that brands (or causes) were talking about on Twitter produced topics that were in line with what participants believed these brands (or causes) would be talking about. I also share considerations and issues with using a social media analytics approach within social science research. This study consisted of an online ($N = 170$) survey collection using Amazon Mechanical Turk (a subset of the $N = 993$ from Chapter 2), and a data collection of Twitter social media feed data from the participants in this study, as well as Twitter data from the brands and causes in this study.

CHAPTER 2: CAN WE FIND THE RIGHT BALANCE IN CAUSE-RELATED MARKETING? ANALYZING THE BOUNDARIES OF BALANCE THEORY IN EVALUATING BRAND-CAUSE PARTNERSHIPS

The phenomenon of brands partnering with causes is referred to as cause-related marketing (CRM). Some CRM partnerships may seem less compatible than others, but the level of perceived compatibility (also referred to as "fit") differs from consumer to consumer. We know a great deal about how perceptions of compatibility affect attitude and behavior towards CRM partnerships, but we know less about how to predict a consumer's perception of compatibility. Therefore, my purpose was to investigate the boundaries in which balance theory could be used to analyze CRM partnerships, particularly in the context of attitude strength. This is the first study to consider the construct of attitude strength (versus attitude alone) when considering balance theory. I found that a consumer's attitude towards a brand, along with their attitude towards a cause, predicts their perceptions of CRM compatibility. I also found that CRM triadic balance could be predicted when attitude strength was included in the models, and that balance theory allowed me to observe preliminary evidence of attitude and attitude strength spillover effects when predicting the valence of CRM compatibility ratings. This could be useful for advertising practitioners, as I explain how they can use these insights to determine which organizations to partner with in the future, as well as how advertising these partnerships may affect consumers.

"Unfortunately, it seems that a number of large environmental groups will not be challenging the corporate world anytime soon. Amazingly, several have "sold out" to the very companies that are destroying the environment. Some even have partnerships with the planet's most unethical corporations" (Filmore, 2013).

Fillmore's (2013) negative remarks are in response to various environmental non-profits, such as The World Wildlife Fund (WWF), forming business relationships with major corporations like Coca-Cola in 2007 ("Coca-Cola | Partnerships | WWF," 2017), or WWF partnering recently with Royal Caribbean in 2016 (Hancock, 2016). This phenomenon of for-profit businesses (brands) partnering with not-for-profit organizations (causes) is commonly referred to as cause-related marketing (Varadarajan & Menon, 1988). As noted by Fillmore (2013), some cause-related marketing (CRM) partnerships may seem more unusual or incompatible than others, but the level of perceived compatibility (also referred to as "fit") has been shown to differ from consumer to consumer (Basil & Herr, 2006). Several studies have explored how consumer perceptions of compatibility affect attitudes towards partnerships and consumer behavior (Basil & Herr, 2006; Gupta & Pirsch, 2006; Pracejus & Olsen, 2004; Simmons & Becker-Olsen, 2006; Trimble & Rifon, 2006), but no one has shown how we can predict a consumer's potential perception of compatibility prior to entering into a CRM partnership by looking solely at their attitude towards a brand, and their attitude towards a cause. This is important because perceived compatibility has been shown to predict acceptance of CRM partnerships (Lafferty et al., 2004). Thus, if I could predict consumers' potential perceived compatibilities through their attitudes towards a brand, and their attitudes towards a cause, before the organizations enter into a partnership, this could provide much practical value to CRM practitioners and advertisers. Therefore, in line with this gap in understanding, my purpose was to investigate the boundaries in which balance theory (Heider, 1946) can be used to analyze CRM partnerships and predict consumer perceptions of CRM partnership compatibility.

I summarize my contributions and findings as follows: I provide a theoretical contribution to the arena of CRM, as I found that a consumer's current attitude towards a brand, along with their current attitude towards a cause, predicts their perceptions of CRM compatibility; I present a methodological contribution by contributing a means to predict psychological balance towards CRM partnerships by incorporating both continuous attitude and attitude strength measures into the prediction model; finally, I provide a practical contribution, as I found preliminary evidence that spillover effects may be occurring from brands to causes (and potentially vice versa) to affect perceived ratings of CRM compatibility. Simonin and Ruth (1998) provided evidence that consumers' attitudes towards brand partnerships have been found to influence each other after they enter into a partnership (denoted by Simonin and Ruth as a spillover effect), but this phenomenon has not been studied within CRM partnerships. The ability to predict potential CRM compatibility perceptions, and to understand how consumers' attitudes and attitude strengths towards brands and causes are affected through CRM partnerships has practical value for both brands as well as causes. As in Filmore's (2013) previous example, WWF and Royal Caribbean could have benefitted in understanding how people may perceive the compatibility of their partnership prior to engaging in it. Additionally, advertisers of CRM partnerships need to be able to understand how consumers will perceive partnerships before they are entered into, or widely communicated.

Guiding Research Question: *What are the boundaries of using balance theory to evaluate cause-related marketing compatibility?*

LITERATURE REVIEW

Cause-Related Marketing

Varadarajan and Menon (1988) defined CRM as follows:

Cause-related marketing is the process of formulating and implementing activities
that are characterized by an offer from the firm to contribute a specified amount to
a designated cause when customers engage in revenue-providing exchanges that
satisfy organizational and individual objectives. (p. 60)

Thus, in their definition, CRM is specifically limited to partnerships where a brand ties a

donation to a cause for every transaction that a consumer engages in with the brand. Barone,

Miyazaki, and Taylor (2000) suggest that CRM partnerships can have a broader definition, as

some CRM partnerships may not involve a direct donation to a cause per every brand purchase.

A brand could just make a large donation to a charity without any sales ties. A very recent

example of this was Royal Caribbean's pledge to donate $5 million to the World Wildlife Fund

to support ocean conservation (Hancock, 2016). Thus, I define CRM as a business strategy in

which a brand partners with a cause through various types of engagements, to address both

organization's objectives.

Varadarajan and Menon (1988) suggested that one of the driving factors in brands

partnering with causes is to boost sales through the association with causes that could help

brands tap into markets that were previously untapped. Brands may be attempting to associate

themselves with certain social positions to convince various segments of consumers to purchase

their products/services, such as in the case of Royal Caribbean and the WWF. This is in line

conceptually with Henderson et al.'s (1998) work in applying associative network analysis to

brands, as they found that certain concepts are associated with brands (e.g., the concept of

"value" associated with McDonald's), and these concepts form networks with other brands and

concepts within the human mind. Thus, McDonald's might be associated with Burger King in a

consumer's mind, linked by the concept of "value". One of the goals of CRM could be to take the concept of "environmentally green" that is associated with the WWF and build an association between "environmentally green" with Royal Caribbean by positioning a partnership between WWF and Royal Caribbean.

However, the brands and causes entering into CRM partnerships may not have entirely compatible associations. For example, while intentions of ocean conservation might seem enticing, we have evidence that cruises themselves are contributing to the decline in ocean health due to water and air pollution (Moodie, 2016). Therefore, there is the possibility that consumers might reject the association between Royal Caribbean and WWF. Much research has been conducted to analyze the effects of how CRM "fit" or "compatibility" influences consumer behavior in response to CRM partnerships, but there is a gap in understanding what psychological constructs contribute to the formation of this compatibility perception in each consumer.

Cause-Related Marketing Compatibility/Fit

Assessing the fit between partnering companies has been studied not just in CRM partnership research, but brand partnership research in general. Simonin and Ruth (1998) looked at the phenomenon of brand partnerships (corporations partnering with corporations), and analyzed the effects that these partnerships had on consumer attitudes towards those partnerships. One of the factors found to affect consumer attitudes was the level of fit between the two companies that formed a partnership together. They described fit to be the level of cohesiveness and/or consistency that partnering brands possessed. Fit has also been found to be important in CRM partnerships, and has been found to affect cause-brand partnership attitude (Basil & Herr, 2006; Lafferty et al., 2004; Trimble & Rifon, 2006), brand equity (Simmons &

Becker-Olsen, 2006), consumer choice (Pracejus & Olsen, 2004), and purchase intentions (Gupta & Pirsch, 2006). Guerreiro et al. (2016) recently conducted a text-mining analysis of journal articles on the subject of CRM between 1988 and 2013, and found that brand-cause fit was the most frequently used topic across the articles. Thus, it seems that the concept of fit is an important topic within CRM research. Trimble and Rifon (2006) suggested that the term "compatibility" is a more comprehensive term from all the terms that have previously been used. Since compatibility is a term that conveys the meaning of these terms more naturally, I use the term compatibility throughout this study.

In previous studies, researchers directly measured how participants rated compatibility between brands and causes through self-reported survey measures (Gupta & Pirsch, 2006; Lafferty et al., 2004; Myers & Kwon, 2013), asking questions such as how congruent, compatible, or consistent were the CRM partnerships between the brands and causes. This is the first study that attempts to dissect how participants construct that rating psychologically. For example, this rating might be based on objective comparisons of the stated missions of the brand and the cause, or it might be based more on subjective attitudes. Basil and Herr (2006) provided a balance theory approach to investigate how attitudes towards a brand and a cause affect attitudes towards CRM partnerships. Although it was not the focus on their study, they found some interesting connections between balance theory and components of CRM compatibility. I will review balance theory and Basil and Herr's (2006) work next.

Balance Theory and CRM Triads

Heider (1946) wrote, "Attitudes towards persons and causal unit formations influence each other" (p. 107). Thus, in this statement, Heider was acknowledging that people can have attitudes towards other individuals as well as entities, and these attitudes influence each other.

Eagly and Chaiken (1993) defined attitude as, "a psychological tendency that is expressed by evaluating a particular entity with some degree of favor or disfavor" (p. 1). Heider suggested that attitudinal relationships move towards balanced states. A balanced state is explained as, "a harmonious state, one in which the entities comprising the situation and the feelings about them fit together without stress" (Heider, 1958, p. 180). Historically, work on balance has focused on Heider's triadic relationship work (three person or entity relationships). In a three-person triad (with the three people being denoted as "A, B, and C", "+" denotes mutual liking, and "-" denotes mutual dislike), Heider hypothesized that balance (triadic balance) would be found in the case where A+B, B+C, and A+C (all positive attitudinal sentiments in this triangle of relationships). Balance can also occur when two relationships in the triad are negative and one is positive. So, if I think of A-B, B-C, and A+C, this would also be balanced; in this case, A and C, who are friends, have a mutual enemy of B. Heider added that individuals can have relationships with entities as well, such as an individual owning a piece of property; this type of relationship was not denoted as an attitudinal relationship, but rather just a positive association with an object, and these unit formations fell under the umbrella of triadic balance theory as well.

As a slight departure from Heider's original balance theory, Davis (1967) suggested that an all negative relationship is a balanced state as well (e.g., an enemy of my enemy can still be my enemy without apparent tension in the system). Including this additional state of balance is considered assessing balance via weak balance (Easley & Kleinberg, 2010), and I incorporated weak balance into this study.

Balance theory has been incorporated into consumer psychology research (Woodside & Chebat, 2001), and more specifically, Basil and Herr (2006) took this triadic balance theory framework and applied it to the realm of CRM partnerships. They pointed to the fact that Heider

(1958) specifically indicated that entities could have relationships to each other, and these relationships were called unit relationships. Basil and Herr (2006) conceptualized CRM partnerships as being a consumer, brand, and cause triad as shown in Figure 2.1. Instead of conceptualizing the relationship between the brand and the cause as attitudes between the two organizations, they suggested that we could view this triad as a one-way psychological evaluation of a CRM partnership from the perspective of a consumer. Thus, they conceptualized the relationship between the brand and the cause as a consumer's assessment of the compatibility between the brand and the cause.

Figure 2.1: Cause-Related Marketing Triad
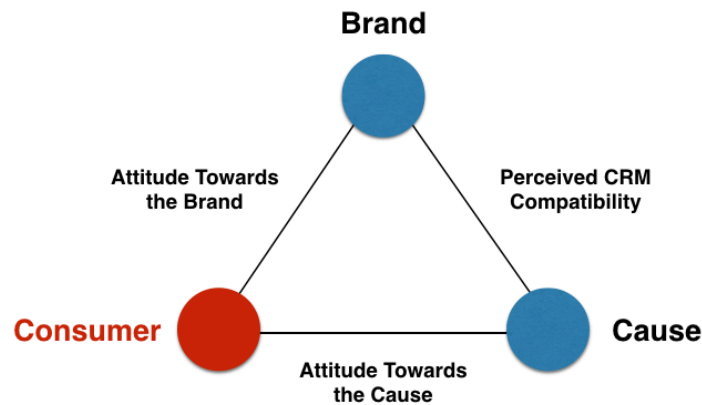
Their focus was taking this CRM triad and using the balance theory framework to predict aspects of participants' attitudes towards CRM partnerships. They found that when consumers' attitudes towards brands and their attitudes towards causes were both negative (consumer-brand and consumer-cause), participants rated the partnerships to be appropriate, but not necessarily appealing. This is important because they showed that there was a predictive relationship between an attitude combination and ratings of appropriateness for the CRM partnerships. With this said, they did not provide a comprehensive predictive model for taking separate attitudes towards a brand and a cause and predicting CRM compatibility. Thus, I hypothesize that a consumer's attitude towards a brand (AT_{BRAND}), along with their attitude towards a cause

(AT$_{\text{CAUSE}}$), should positively predict a consumer's perception of CRM compatibility

(COMP$_{\text{PERCEIVED}}$) in CRM triads.

H1: *Consumers' attitudes towards a brand (AT$_{\text{BRAND}}$), along with their attitudes towards a cause (AT$_{\text{CAUSE}}$), will positively predict their perceptions of CRM compatibility (COMP$_{\text{PERCEIVED}}$) in CRM triads.*

Being able to predict CRM compatibility is important because we have evidence that CRM compatibility predicts acceptance of CRM partnerships (Lafferty et al., 2004). Now this hypothesis does not necessarily assume that all CRM triads will be balanced, but rather that consumers' attitudes towards brands and their attitudes towards causes can predict perceptions of CRM compatibility.

The Boundaries of Predicting CRM Triadic Balance

In the original conceptualization of balance theory, all attitude relations were equal in extremities (e.g., 1, 1, 1), but with potentially opposing valences (e.g., +1, -1, -1). In fact, even a recent analysis of balance theory in online social networks only used two categorical conditions, either positive or negative, in testing balance theory (Leskovec et al., 2010b), but attitudinal evaluations have been shown to be continuous in nature (Eagly & Chaiken, 1993). How does considering continuous attitudinal evaluations affect how we think about balance theory (e.g., instead of -1, +1, -1, we consider +5, -2, +3)? Previous research has entertained this exact question, as Antal et al. (2006) concluded their research within social networks with the open question of how continuous edge values affect balance theory (attitudes in triads can also be called edges). Kułakowski et al. (2005) entertained the effect of continuous edge values on mathematical models that simulated balance theory effects, and found that over time, continuous edge values appear to also move towards balanced states. Marvel et al. (2011) also found this to be the case with network graphs that were much larger than just an individual triad, but the

process of getting to a balanced state occurs over a period of time (all the triads within a larger system end up balanced). When considering these continuous edge values and the transition period from unbalanced to balance states, there is even the possibility that triads can end up in a "jammed" state of imbalance (Antal, Krapivsky, & Redner, 2005), meaning that triads got stuck in states of imbalance (e.g., a triad sits stuck at an imbalanced state of A+B, B-C, A+C, even though this triad should move to a balanced state). Thus, I suggest that the expectation of CRM triads being balanced is dependent on looking at the differences between separate continuous attitudes towards brands and causes in which the valences are opposing each other. Let us consider a clarifying example through Figure 2.2.

Figure 2.2: Separate Attitudes Difference to Predict Balance Example

Consumer Name	AT_{CAUSE} (WWF)	AT_{BRAND} (Royal Caribbean)	$COMP_{PERCEIVED}$	$AT_{DIFFERENCE}$	$BALANCE_{CRM}$
John	+5	-5	Negative	0	1 (Yes)
Mary	+5	-1	Positive	4	0 (No)

Spillover (Osgood and Tannenbaum, 1955; Simonin & Ruth, 1998)

John has a very negative attitude regarding Royal Caribbean (AT_{BRAND}), and a very positive attitude regarding WWF (AT_{CAUSE}). John's attitude towards Royal Caribbean and his attitude towards WWF are identical in their extremities ($AT_{DIFFERENCE} = 0$), but their valences are opposing one another. This is a situation similar to which triadic balance theory was originally

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conceptualized (Heider, 1958), and thus I predict that this triad would be balanced ($BALANCE_{CRM}$ = 1) when looking at the valences of AT_{BRAND}, AT_{CAUSE}, and $COMP_{PERCEIVED}$.

Conversely, let us consider a consumer named Mary. She has a slightly negative attitude regarding Royal Caribbean (AT_{BRAND}), and a very positive attitude regarding WWF (AT_{CAUSE}). Mary's attitude towards Royal Caribbean and attitude towards WWF are different in their extremities ($AT_{DIFFERENCE}$ = 4, when taking the absolute values of AT_{BRAND} and AT_{CAUSE}), and their valences are also opposing one another. Although Mary's attitude towards Royal Caribbean is negative, it is only slightly negative. This is now a situation that is not similar to which balance theory was originally conceptualized, as the attitudes are continuous, and the extremity difference between the separate attitudes ($AT_{DIFFERENCE}$) is large.

As a clarification to my method in calculating $AT_{DIFFERENCE}$, the reason I am using the absolute values of AT_{BRAND} and AT_{CAUSE} is because I am focusing on the magnitude differences between each attitude. In the example of John and Mary from Figure 2.2, John's attitudes were closer to the originally conceptualized balance theory by Heider (1946) as their magnitudes were equal (AT_{BRAND} = -5 and AT_{CAUSE} = +5) even though their valences were different. Therefore, in an attitude scale ranging from -5 to +5, one example of a combination of attitudes that are furthest away from Heider's (1946) originally conceptualized dichotomous structure of equal magnitude valences (+1 and -1) would be Mary's example from Figure 2.2 (AT_{BRAND} = -1 and AT_{CAUSE} = +5, which leads to $AT_{DIFFERENCE}$ = 4 when taking the absolute values first of AT_{BRAND} and AT_{CAUSE}). If I did not take the absolute values of AT_{BRAND} and AT_{CAUSE} first, but rather just subtracted the values and then taken the absolute value of the result, this would not be in line with comparing how far continuous attitudes take me from original balance theory (or keeps me close to original balance theory). Looking at John's example (AT_{BRAND} = -5 and AT_{CAUSE} = +5),

if I did not take the absolute values first of AT_{BRAND} and AT_{CAUSE}, $AT_{DIFFERENCE}$ would either equal +10 or -10, depending on how you ordered the subtraction. This is against the goal of my analysis, which is to create a variable that represents how close I am to original balance theory. By taking the absolute values of AT_{BRAND} and AT_{CAUSE} for John first and subtracting the lesser from the greater, I obtain an $AT_{DIFFERENCE} = 0$, which is exactly the value I am looking for. This also allows me to analyze attitudes with the same valence, but that have large differences in magnitude (e.g., $AT_{BRAND} = +5$ and $AT_{CAUSE} = +1$, which still leads to $AT_{DIFFERENCE} = 4$ when taking the absolute values first of AT_{BRAND} and AT_{CAUSE}).

Simonin and Ruth (1998) found that when brands enter into partnerships with other brands, their post-partnership attitudes changed the separate attitudes towards each of the brands (which they called a "spillover effect"). More specifically, they found that in these brand alliances (a brand partnering with another brand), consumers' pre-existing attitudes towards each brand affect their attitudes towards the partnership as a whole, and these attitudes towards the partnership then change their post-partnership attitudes towards each brand. Thus, we have evidence that attitudes towards entities in a partnership are spilling into (or influencing) one another. As a clarification of this spilling or influencing effect, Osgood and Tannenbaum (1955) found that more extreme attitudes tended to hold greater influence on end states of psychological congruity when paired with less extreme attitudes. This is a concept very similar to balance theory, as Osgood and Tannenbaum (1955) suggested that when previously independent attitudes are paired together in some form of relationship (e.g., I do not like ice cream, but I do like the flavor of chocolate, and now I am being presented with chocolate ice cream), this relationship would change an individual's attitudes (e.g., I might decide that I like ice cream a bit more, maybe chocolate a bit less, or some combination of both). Thus, putting together insights from

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Heider (1946), Simonin and Ruth (1998), and Osgood and Tannenbaum (1955), I should find

evidence that Mary's attitude towards Royal Caribbean and her attitude towards the WWF will

spill into one another.

Thus, Mary may evaluate the CRM partnership to be positively compatible even though it

does not create a balanced CRM triad (AT_{BRAND} is negative, AT_{CAUSE} is positive, and

$COMP_{PERCEIVED}$ is positive, which is not a balanced triad). Therefore, the key to predicting

whether or not balance will hold in this CRM triad depends on the difference between the

extremities ($AT_{DIFFERENCE}$) of Mary's attitude towards the brand (AT_{BRAND}), and her attitude

towards the cause (AT_{CAUSE}). The larger that the difference ($AT_{DIFFERENCE}$) grows, the further I

am getting away from Heider's (1946) original balance theory. Therefore, in Mary's case, a

CRM triad may not be balanced, but it may still result in a compatible partnership

($COMP_{PERCEIVED}$ is positive, but $BALANCE_{CRM} = 0$). Thus, I am hypothesizing that as the

difference between consumers' separate attitudes ($AT_{DIFFERENCE}$) increases, the probability that

CRM triads will be balanced ($BALANCE_{CRM}$) will decrease.

H2: *As the difference between the absolute values of consumers' attitudes towards the brand and their attitudes towards the cause ($AT_{DIFFERENCE}$) increases, the probability that CRM triads are balanced ($BALANCE_{CRM}$) will decrease.*

Brands and causes have much to gain from understanding when unbalanced evaluations

occur in consumers. In Heider's (1958) discussion on balance, unbalanced states were considered

as suboptimal, but unbalanced states may actually be positive situations for CRM partnerships. If

I revisit Mary's situation, this is a case where the slightly disliked Royal Caribbean has the

potential to gain from a CRM partnership with the extremely liked WWF.

Now that I have looked at predicting balance through differences in attitudes

($AT_{DIFFERENCE}$), I would like to discuss a way to improve my predictive model by adding the

additional factor of attitude strength. Attitude strength has been shown to predict psychological movement better than measures of attitude alone (Petty & Krosnick, 1995), therefore attitude alone may not be able to give me a full picture of how balance theory may be affected by continuous attitudinal values. Thus, I will discuss the difference between attitude and attitude strength next.

Attitude and Attitude Strength within CRM triads

Attitudes are often measured with scales ranging from negative to positive extremities (e.g., -5 to +5, Eagly & Chaiken, 1993), but one of the issues with this scale is that it does not consider attitude strength. Petty and Krosnick (1995) defined attitude strength as the degree to which attitudes possess the features of persistence, resistance to change, impact on information processing and judgments, and guiding behavior. Attitude strength is a construct distinct from attitude, and often measured with a positive scale (e.g., +1 to +11, Bassili, 1996). Since there is evidence that attitude strength moderates the relationship between attitudes and behaviors (Petty & Krosnick, 1995), adding attitude strength to my evaluation should improve my prediction of balance. Since I am using logistic regression (as detailed in the methods section), I will look at the change in Akaike information criterion (ΔAIC) to assess whether the predictive model was improved by the addition of attitude strength.

H3: *Adding the measurement of attitude strength (AS_{BRAND} and AS_{CAUSE}) will improve the models (ΔAIC) for predicting CRM triadic balance ($BALANCE_{CRM}$).*

Let us go back to my example with John and Mary, but with the addition of attitude strength to my model (See Figure 2.3).

Figure 2.3: Attitude X Attitude Strength Difference to
Predict Balance Example

Consumer Name	AT_{CAUSE} X AS_{CAUSE} (WWF)	AT_{BRAND} X AS_{BRAND} (Royal Caribbean)	$COMP_{PERCEIVED}$	$ATAS_{DIFFERENCE}$	$BALANCE_{CRM}$
John	+5 X 11 = +55	-5 X 11 = -55	Negative	0	1 (Yes)
Mary	+5 X 11 = +55	-1 X 3 = -3	Positive	52	0 (No)

Spillover (Osgood and Tannenbaum, 1955;
Simonin & Ruth, 1998)

Let us say that John has a very negative attitude (AT_{BRAND}) and very strong attitude

(AS_{BRAND}) regarding Royal Caribbean, and a very positive (AT_{CAUSE}) and very strong attitude

(AS_{CAUSE}) regarding WWF. Although original balance theory did not consider attitude strength,

this is still a situation in which equal extremities of attitude and attitude strength

($ATAS_{DIFFERENCE} = 0$) are close to the conceptualization of original balance theory, and thus I

predict that there is a greater probability that the CRM triad will be balanced ($BALANCE_{CRM} =$

1).

The major difference in my example comes into play if I consider Mary once again. Let

us consider that she has a slightly negative attitude (AT_{BRAND}) regarding Royal Caribbean, but

that attitude is very weak in strength (AS_{BRAND}); conversely, she has a very positive attitude

(AT_{CAUSE}) regarding WWF, and that attitude is very strong in strength (AS_{CAUSE}). Compared to

my previous consideration of Mary, since I have additional information as to the strength of

Mary's attitudes towards WWF, my ability to predict balance should be improved with the

addition of attitude strength to my model. In my previous prediction model (hypothesis 2),

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attitude alone was considered first, as original balance theory was only based on attitudes. With

this said, since psychological movement is better predicted by attitude strength (Petty &

Krosnick, 1995), this model should provide more predictive insight.

H4: *As the difference between the absolute values of consumers' attitudes x attitude strengths towards the brand and their attitudes x attitude strengths towards the cause ($ATAS_{DIFFERENCE}$) increases, the probability that CRM triads are balanced ($BALANCE_{CRM}$) will decrease.*

METHODS

Pre-Test

My first task was to identify CRM partnerships to analyze for this study, as I wanted to

see how my predictions differed across a wide range of levels of average compatibility. Thus, I

tested to find three real CRM partnerships that were, on average, perceived as having high

compatibility, average compatibility, and low compatibility. The four CRM partnerships that I

pre-tested were Fitbit and American Heart Association (FitbitAHA), Royal Caribbean and the

World Wildlife Fund (RoyalWWF), Grey Goose and the National Gay and Lesbian Task Force

(GreyGooseNGLTF), and Wyndham Hotels and the National Rifle Association

(WyndhamNRA). I recruited thirty-seven staff members from a Midwest university to participate

in my pre-test. I chose university staff members due to their range of ages being closer to my

intended main study participants (rather than being limited to the ages of a college student

sample). This was important since my main study was going to use Amazon MTurk as its

sample, and Amazon MTurk has workers from 18 years old to 60+ years old (J. Ross, Zaldivar,

Irani, & Tomlinson, 2010). They were asked to evaluate how compatible each of the partnerships

were ($COMP_{PERCEIVED}$) on an 11-point scale from -5 (Not compatible at all) to +5 (Extremely

compatible). For example, to assess a participant's perception of CRM compatibility towards the

partnership between Royal Caribbean and the WWF, I asked, "How compatible do you think this

partnership is between Royal Caribbean and the World Wildlife Fund for Nature?" This compatibility measure was adapted from Basil and Herr (2006), as they asked how strong participants perceived CRM alliances to be on a -5 to +5 scale. The results were recoded to a positive 11-point scale (one through eleven) for statistical analyses.

Due to violations of normality in the data when conducting Shapiro-Wilks normality tests, I used nonparametric measures to compare means. Using a Kruskal Wallis test, I found that on average, FitbitAHA was rated as having high compatibility ($M_{COMP\_PERCEIVED}$=10.11, SD=1.95), RoyalWWF as having average compatibility ($M_{COMP\_PERCEIVED}$ =6.23, SD=2.68), GreyGooseNGLTF as having average compatibility ($M_{COMP\_PERCEIVED}$ =5.46, SD=2.89), and WyndhamNRA as having low compatibility ($M_{COMP\_PERCEIVED}$ =3.59, SD=2.31); the differences overall were significant (H(3)=73.28, p=.00) when compared against each other. With this said, when conducting Mann-Whitney pairwise comparisons, I found that all comparisons were significant (p<.01) except that GreyGooseNGLTF ($M_{COMP\_PERCEIVED}$ =5.46, SD=2.89) was not significantly different from RoyalWWF (U=9.97, p=1.00), and GreyGooseNGLTF was not significantly different from WyndhamNRA (U=22.51, p=.14). Therefore, I excluded GreyGooseNGLTF and kept RoyalWWF as my average compatibility partnership.

Participants

For the main study, I collected survey responses from participants through Amazon Mechanical Turk (MTurk) from September 6, 2017 to September 20, 2017. MTurk has been found to be at least as reliable as data obtained by traditional methods (Buhrmester, Kwang, & Gosling, 2011), and although there has been some controversy with regards to its validity when being used for research studies, various studies have given insights into how to best manage studies utilizing MTurk for use in research (Chandler & Shapiro, 2016; Mason & Suri, 2012).

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They suggested things such as disguising the purpose of the study until the task was accepted, monitoring evidence of cross-talk, and paying a fair wage. I followed these principles as I made sure that the MTurk advertisement did not divulge the purpose of the study until workers accepted, I made sure that finalization codes were randomized at the end of the survey to make sure that workers were not sending codes to each other, and I calculated a fair wage. I used Qualtrics to estimate the survey time length (eight to twelve minutes), multiplied that time to a percentage of United States minimum wage, and compensated each participant accordingly ($1.45 each). Also, recently Kees et al. (2017) provided evidence that MTurk is a very good platform for collection data for advertising research, and they also focused on the issue of paying a fair wage to increase participant engagement.

I collected N=997 responses, but four participants were removed after reviewing the data. One participant came very close to explaining what they thought the purpose of this study was, one participant stated that they were confused as to what they were supposed to be doing, and two participants expressed anger and annoyance at filling out the survey. Therefore, N=993 responses were analyzed for this study.

Measures

I collected attitude measures towards the brands (AT_{BRAND}), and attitude measures towards the causes (AT_{CAUSE}) on 11-point scales from -5 (Extremely negative) to +5 (Extremely positive), drawn from Basil and Herr (2006). For example, to assess a participant's attitude towards Royal Caribbean, I asked, "How would you rate your attitude towards Royal Caribbean International?" I also collected attitude strength measures towards the brands (AS_{BRAND}), and attitude strength measures towards the causes (AS_{CAUSE}), measured on 11-point scales from +1 (Not strong at all) to +11 (Extremely strong), which was adapted from Bassili (1996). As an

example, to assess a participant's attitude strength towards Royal Caribbean, I asked, "How strong is your attitude toward Royal Caribbean International?" I also asked a question assessing the participant's perception of CRM compatibility ($COMP_{PERCEIVED}$) on an 11-point scale from -5 (Not compatible at all) to +5 (Extremely compatible), which was adapted from Basil and Herr (2006). For example, to assess a participant's perception of CRM compatibility towards the partnership between Royal Caribbean and the WWF, I asked, "How compatible do you think this partnership is between Royal Caribbean and the World Wildlife Fund for Nature?" Each participant was presented with all three partnerships, but the order of partnerships was presented randomly. Additionally, for each partnership that was presented to the participants, the presentation order of the brand and cause was also randomized. See Appendix 1 for the survey instrument.

Analyses

To test the robustness of my results, I separated my analyses by each partnership to see if my hypotheses were supported across a wide range of average perceived compatibilities. Additionally, $COMP_{PERCEIVED}$ was recoded to a positive 11-point scale to better interpret the statistical results.

For hypothesis 1, I used multi-regression analysis with the participant's AT_{BRAND} and AT_{CAUSE} as the predictor variables, and $COMP_{PERCEIVED}$ as the outcome variable. To test hypotheses 2-4, I calculated four derived variables from this subset of data. I computed the first variable, $BALANCE_{CRM}$, by categorizing each participant's results, either balanced or not balanced, by looking at the valences of AT_{BRAND} and AT_{CAUSE}, and the valence of their $COMP_{PERCEIVED}$. As a note, if an attitude value was zero, I removed these participants from the testing of hypotheses 2-4. Heider's (1958) balance theory does not consider neutral (a value of

zero) attitudes, and even recent balance theory work in real world social networks does not include the analysis of neutral edges (Antal et al., 2006; Leskovec, Huttenlocher, & Kleinberg, 2010a). I discuss this further in the limitations and future research section.

I then computed the second variable, $AT_{DIFFERENCE}$, by taking the absolute value of a participant's AT_{BRAND} and AT_{CAUSE} and subtracting the greater attitude value from the lesser attitude value (e.g., the absolute value of -1 subtracted from the absolute value of +5 equals 4, see Figure 2.2 for this example). Once $AT_{DIFFERENCE}$ was constructed, I ran a logistic regression to see if an increasing $AT_{DIFFERENCE}$ would decrease the probability of $BALANCE_{CRM}$ to test hypothesis 2.

For hypotheses 3 and 4, I created the third variable, $AS_{DIFFERENCE}$, by taking a participant's AS_{BRAND} and their AS_{CAUSE} and subtracting the lesser value from the greater value. Finally, I computed the fourth variable, the $ATAS_{DIFFERENCE}$. I did this by first multiplying a participant's AT_{BRAND} by their AS_{BRAND}. Then I multiplied a participant's AT_{CAUSE} by their AS_{CAUSE}. Finally, I took the absolute values of both these results (for the same reason I took absolute values as previously explained for $AT_{DIFFERENCE}$), and subtracted the greater from the lesser (e.g., -1 x +3 subtracted from +5 x +11 equals 52; see Figure 2.3 for this example); this fourth variable functioned as the interaction variable in my analyses. Then I ran a logistic regression to see if an increasing $AT_{DIFFERENCE}$, $AS_{DIFFERENCE}$, and $ATAS_{DIFFERENCE}$ increases the probability of $BALANCE_{CRM}$ and strengthens my model.

RESULTS

By conducting manipulation checks using an one-way ANOVA test, I found that on average, FitbitAHA was rated as having high compatibility ($M_{COMP\_PERCEIVED}$ =9.86, SD=1.57), RoyalWWF as having average compatibility ($M_{COMP\_PERCEIVED}$ =7.57, SD=2.64), and

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WyndhamNRA as having low compatibility ($M_{COMP\_PERCEIVED}$ =5.72, SD=3.41), and all three were significantly different from one another (F(2,2976)=868.10, p=.00).

Hypothesis 1 stated that AT_{BRAND} and AT_{CAUSE} should predict $COMP_{PERCEIVED}$ in CRM triads. Multiple regression analyses showed that hypothesis 1 was fully supported (see Table 2.1).

Table 2.1: Predicting CRM Compatibility with Attitude

Partnership	Variables	B	SE B	ß	t	p	R^2
Fitbit & American Heart Association (N = 993)	Constant	6.08	.26	-	23.73	.00	
	AT_{BRAND}	.26	.02	.33	10.95	.00	.20
	AT_{CAUSE}	.18	.03	.21	6.86	.00	
Royal Caribbean & World Wildlife Fund (N = 993)	Constant	2.38	.44	-	5.40	.00	
	AT_{BRAND}	.44	.04	.32	10.60	.00	.15
	AT_{CAUSE}	.23	.04	.16	5.20	.00	
Wyndham Hotels & National Rifle Association (N = 993)	Constant	1.22	.36	-	3.38	.00	
	AT_{BRAND}	.21	.05	.12	4.09	.00	.28
	AT_{CAUSE}	.43	.03	.48	17.16	.00	

DV – $COMP_{PERCEIVED}$

Hypothesis 2 stated that as $AT_{DIFFERENCE}$ increases, the probability that $BALANCE_{CRM}$ is balanced will decrease. Logistic regression analyses showed that $AT_{DIFFERENCE}$ significantly predicted $BALANCE_{CRM}$, for RoyalWWF and WyndhamNRA, but not for FitbitAHA (see Table 2.2). For logistic regression, the odds ratio is the change in odds; when the odds ratio is under 1,

this tells me that as the predictor increases ($AT_{DIFFERENCE}$), the odds of the outcome occurring decreases ($BALANCE_{CRM}$). For WyndhamNRA, I found the odds ratio to be .82. Thus, in the case of RoyalWWF and WyndhamNRA, hypothesis 2 was supported, but when I considered each of the three partnerships, hypothesis 2 was only partially supported. Sample sizes for the analyses were less than the sample sizes in hypothesis 1 because neutral attitudes were removed from the analysis of hypotheses 2-4. This is discussed further in my limitations and future research section.

Table 2.2: Predicting Balance with Attitude Differences

Partnership	Variables	B	95% CI for Odds Ratio			*p*	AIC
			Lower	Odds	Upper		
Fitbit & American Heart Association (N = 758)	Constant	2.44	7.87	11.45	17.23	.00	423.47
	$AT_{DIFFERENCE}$	.01	.81	1.01	1.29	.92	
Royal Caribbean & World Wildlife Fund (N = 584)	Constant	1.98	4.95	7.15	10.58	.00	537.32
	$AT_{DIFFERENCE}$	-.26	.64	.77	.93	.01	
Wyndham Hotels & National Rifle Association (N = 452)	Constant	1.54	3.29	4.67	6.76	.00	475.35
	$AT_{DIFFERENCE}$	-.20	.67	.82	1.00	.05	

DV – $BALANCE_{CRM}$

Hypothesis 3 stated that adding the measurement of attitude strength will strengthen the models for predicting $BALANCE_{CRM}$. My prediction models were strengthened by the addition of AS_{BRAND} and AS_{CAUSE} for FitbitAHA (ΔAIC=-49.57), RoyalWWF (ΔAIC=-9.99), and WyndhamNRA (ΔAIC=+2.84) (see Table 2.3). The Akaike Information Criterion (AIC) estimates the quality of a model, relative to another model. When the change in AIC is negative,

that means the model was improved. Thus, in the case of FitbitAHA and RoyalWWF, hypothesis 3 was supported, but when I considered each of the three partnerships, hypothesis 3 was only partially supported.

Table 2.3: Predicting Balance with Attitude X Attitude Strength Differences

| Partnership | Variables | B | 95% CI for Odds Ratio | | | p | ΔAIC |
			Lower	Odds	Upper		
	Constant	2.96	12.47	19.22	30.82	.00	
Fitbit & American Heart Association (N = 758)	$AT_{DIFFERENCE}$	-.43	.42	.65	.99	.04	-49.57
	$AS_{DIFFERENCE}$	-.80	.36	.45	.56	.00	
	$ATAS_{DIFFERENCE}$	.12	1.08	1.13	1.19	.00	
	Constant	2.12	5.63	8.29	12.52	.00	
Royal Caribbean & World Wildlife Fund (N = 584)	$AT_{DIFFERENCE}$	-.39	.48	.67	.93	.02	-9.99
	$AS_{DIFFERENCE}$	-.27	.66	.76	.88	.00	
	$ATAS_{DIFFERENCE}$	.04	1.01	1.04	1.08	.02	
	Constant	1.50	3.09	4.48	6.63	.00	
Wyndham Hotels & National Rifle Association (N = 452)	$AT_{DIFFERENCE}$	-.33	.52	.72	.99	.04	+2.84
	$AS_{DIFFERENCE}$	-.00	.86	1.00	1.15	.98	
	$ATAS_{DIFFERENCE}$	.01	.98	1.01	1.05	.38	

DV – $BALANCE_{CRM}$

Hypothesis 4 stated that as $ATAS_{DIFFERENCE}$ increases, the probability that $BALANCE_{CRM}$ is balanced will decrease. When I added attitude strength into the model, logistic

regression analyses showed that when $AT_{DIFFERENCE}$ increased, the probability that $BALANCE_{CRM}$ was balanced significantly decreased across all three partnerships, in line with my hypothesis 4. Logistic regression also showed that when $AS_{DIFFERENCE}$ increased, the probability that $BALANCE_{CRM}$ was balanced significantly decreased in FitbitAHA and RoyalWWF, but not for WyndhamNRA, which was partially in line with my hypothesis 4. With this said, when $ATAS_{DIFFERENCE}$ increased, the probability that $BALANCE_{CRM}$ was balanced significantly increased for FitbitAHA and RoyalWWF, which was against the direction of my hypothesis 4. Thus overall, hypothesis 4 was only partially supported (see Table 2.3).

GENERAL DISCUSSION

My objective was to analyze CRM partnerships using a balance theory framework. Basil and Herr (2006) took this triadic balance theory framework and applied it to the realm of CRM partnerships, but they did not attempt to predict CRM compatibility from consumers' separate attitudinal ties to the brand and the cause. This is important because we have evidence that CRM compatibility predicts acceptance of CRM partnerships (Lafferty et al., 2004). I found that consumers' attitudes towards a brand (AT_{BRAND}), along with their attitudes towards a cause (AT_{CAUSE}), did in fact positively predict their perceptions of CRM compatibility ($COMP_{PERCEIVED}$) in CRM triads (see Table 2.1). One might think that a consumer would evaluate the compatibility of a CRM partnership through an objective evaluation (without attitudinal bias) of the compatible missions and attributes of the brand and cause, but I found evidence that CRM partnership compatibility is strongly influenced by pre-existing attitudes. This has important managerial relevance, as brands and causes cannot just rely on logically compatible partnerships leading to consumers positively accepting CRM partnerships. This also opens the door for partnerships that may not make the most logical sense when objectively

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comparing the missions and attributes of the brand and cause. If the general public, on average, has positive attitudes towards the brand, and positive attitudes towards the cause, this partnership might end up being positively accepted, even if the objective missions of the brand and the cause are at odds with each other. This also gives more evidence that advertisers of brands and causes may want to make sure they do their due diligence to raise the publics' attitudes towards a brand and attitudes towards a cause, so that they are both positive (on average), before they enter into a partnership, rather than relying on the partnership itself to raise attitudes towards the brand and/or the cause. In 2010, KFC partnered with the breast cancer advocacy group Susan G. Komen for the Cure to donate money to breast cancer research when people bought fried chicken at KFC. This partnership was ridiculed as an incompatible partnership due to the illogical pairing of unhealthy fried chicken with a health cause, with news headlines strongly challenging the CRM partnership by stating, "What the cluck?" (Hutchinson, 2010). However, KFC has also been rated as one of America's most hated fast-food restaurants (Picchi, 2015), thus this partnership may have gone wrong due to general attitudes towards KFC rather than the objective incompatibility of the missions of the two entities.

I also looked at the issue of balance within CRM triads. The original conceptualization of balance theory did not consider continuous attitude measures, and therefore I predicted that incorporating the continuous nature of attitudes into my analyses would help me predict when CRM triads would become unbalanced. I predicted that as the difference ($AT_{DIFFERENCE}$) between the absolute values of the consumers' attitudes towards the brand (AT_{BRAND}) and their attitudes towards the cause (AT_{CAUSE}) increases, the probability that CRM triads are balanced ($BALANCE_{CRM}$) will decrease. I found that this was only supported in the two cases of FitbitAHA and RoyalWWF (see Table 2.2). The likely reason that my hypothesis 2 was only

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partially supported could be due to previous research suggesting that attitude strength must be incorporated into my models when attempting to predict psychological movement (Petty & Krosnick, 1995). Therefore, my third hypothesis looked at whether or not adding attitude strength would strengthen my model for predicting balance, as attitude strength was not previously considered when evaluating CRM triads. As far as I know, attitude strength has also not been previously incorporated into balance theory. I hypothesized that adding attitude strength into my model would strengthen the prediction of balance, and this held true for FitbitAHA and RoyalWWF, but not for WyndhamNRA. The predictive model for balance in the case of WyndhamNRA was basically unchanged with the addition of attitude strength (ΔAIC=+2.84), whereas the other two models were improved. Although this was only partial support for hypothesis 3, when I added attitude strength, I was able to predict balance for all three partnerships in line with hypothesis 4 (see Table 2.4). In all three cases, when attitude strength was included in the models, as the difference between consumers' attitudes towards the brand and their attitudes towards the cause ($AT_{DIFFERENCE}$) increased, the probability that CRM triads were balanced ($BALANCE_{CRM}$) decreased, which followed the direction of hypothesis 4. This provided evidence that more extreme attitudes are spilling into less extreme attitudes (and possibly vice versa, which again will be discussed in my limitations section) and affecting the valence of participants' perceived compatibility ratings. I was only able to see this effect across all three partnerships when I included attitude strength into the predictive models. Thus, measuring attitude strength proved to be important when predicting balance in CRM partnerships.

With regards to the main effect of $AS_{DIFFERENCE}$, in the cases of FitbitAHA and RoyalWWF, as the difference between the strength of consumers' attitudes towards the brand

and the strength of their attitudes towards the cause ($AS_{DIFFERENCE}$) increased, the probability that CRM triads were balanced ($BALANCE_{CRM}$) decreased, which followed the direction of hypothesis 4. This also provided evidence that for FitbitAHA and RoyalWWF, stronger attitudes were spilling into weaker attitudes (and possibly vice versa, which again will be discussed in my limitations section) and affecting the valence of participants' perceived compatibility ratings. This was not true though for WyndhamNRA.

Unexpectedly though, as the difference between consumers' attitudes x attitude strengths towards the brand and their attitudes x attitude strengths towards the cause ($ATAS_{DIFFERENCE}$) increased, the probability that CRM triads are balanced ($BALANCE_{CRM} = 1$) slightly increased for FitbitAHA and RoyalWWF, but not for WyndhamNRA. This was against the direction of hypothesis 4, as this suggests that balance is more stable when $ATAS_{DIFFERENCE}$ is greater between consumers' attitudes x attitude strengths towards the brand and their attitudes x attitude strengths towards the cause. With this said, I believe that it is a strong possibility that this is an artifact of manually multiplying the attitude and attitude strength measures for both the brand and the cause before taking the extremity differences. As an example, there may be a different coefficient needed in the multiplication of attitude and attitude strength measures for brands versus causes. Understanding this dynamic of how a better interaction formula could be built for adding attitude strength into balance theory would require a study testing different combination of coefficients (and possibly additional mathematical models) with a large group of partnerships, thus it was beyond the scope of my study. I provide a starting point for future research into the deeper investigation this interaction. Attitude strength has not previously been considered in balance theory, therefore I had to start from what I knew about general interaction effects.

Therefore, when looking at the results for hypotheses 3-4, WyndhamNRA seems to be the outlier, as the addition of attitude strength does not seem to improve the model for predicting balance in its CRM triads ($BALANCE_{CRM}$). My initial thought as to why this partnership was different was that maybe the differences in attitudes ($AT_{DIFFERENCE}$) towards Wyndham and the NRA were on average much larger with greater separation across participants than with the other two partnerships, but this was not true. The average difference of attitudes towards the brand and attitudes towards the cause were very close to one another: FitAHA ($M_{AT\_DIFFERENCE}=1.25$, SD=1.13), RoyalWWF ($M_{AT\_DIFFERENCE}=1.47$, SD=1.14), and WyndhamNRA ($M_{AT\_DIFFERENCE}=1.31$, SD=1.12), although a one-way ANOVA showed there were significant differences ($F(2,1791)=6.48$, $p=.00$). After running a Tukey post-hoc pairwise test, it was only the average difference of attitudes for FitbitAHA that was significantly different than RoyalWWF ($p=.00$).

The only major difference I found was that NRA was the only organization where the average of participants' attitudes towards the NRA was close to neutral, but there was a much wider variance to participants' attitudes as shown by the difference in standard deviation as compared to the other brands/causes (see Table 2.4). Additionally, after running a Tukey post-hoc pairwise test, I confirmed that it was only the NRA that was different in attitude as compared to AHA and WWF ($p=.00$ in both pairwise cases).

Table 2.4: One-Way ANOVA for AT$_{BRAND}$ and AT$_{CAUSE}$

Brand/Cause	*M*	*SD*	F(2,1791)	*p*
Fitbit (N = 758)	8.73	1.78		
Royal Caribbean (N = 584)	7.99	2.10	25.89	.00
Wyndham Hotels (N = 452)	8.29	1.83		
American Heart Association (N = 758)	9.65	1.60		
World Wildlife Fund (N = 584)	9.49	1.63	308.60	.00
National Rifle Association (N = 452)	6.55	3.52		

Even when looking at attitude strength across all the brands and causes, there was not a large difference across the organizations (see Table 2.5).

Table 2.5: One-Way ANOVA for AS$_{BRAND}$ and AS$_{CAUSE}$

Brand/Cause	*M*	*SD*	F(2,1791)	*p*
Fitbit (N = 758)	7.59	2.46		
Royal Caribbean (N = 584)	6.94	2.60	11.06	.00
Wyndham Hotels (N = 452)	7.22	2.53		
American Heart Association (N = 758)	8.61	2.20		
World Wildlife Fund (N = 584)	8.58	2.29	8.11	.00
National Rifle Association (N = 452)	8.08	2.67		

Thus, it seems that the major difference was that attitudes towards the NRA were the only attitudes that were both close to neutral on average, and also quite divided across the participants in my sample. Since the mean of attitudes towards the NRA were so close to the midpoint of the scale ($M_{ATCAUSE}$=6.55, on a scale from 1 to 11), and the standard deviation was much larger than the rest of the brands and causes, I decided to look at how results for H4 would look if I split the analyses by the midpoint, by separating participants with positive attitudes towards the NRA ($M_{ATCAUSE} > 6$) from those with negative attitudes towards the NRA ($M_{ATCAUSE} < 6$). The results can be found in Table 2.6.

Table 2.6: Predicting Balance with Attitude X Attitude Strength Differences for NRA Split by Positive and Negative Attitudes

Partnership	Variables	B	95% CI for Odds Ratio			p
			Lower	Odds	Upper	
	Constant	1.65	2.56	5.19	11.28	.00
Wyndham Hotels & National Rifle Association, with Negative Attitudes Towards the NRA (N = 183)	AT$_{DIFFERENCE}$	-.22	.53	.80	1.22	.30
	AS$_{DIFFERENCE}$	.06	.87	1.06	1.32	.57
	ATAS$_{DIFFERENCE}$	.00	.95	1.00	1.03	.83
	Constant	1.54	2.99	4.70	7.62	.00
Wyndham Hotels & National Rifle Association, with Positive Attitudes Towards the NRA (N = 269)	AT$_{DIFFERENCE}$	-.81	.24	.45	.81	.01
	AS$_{DIFFERENCE}$	-.25	.60	.78	1.01	.06
	ATAS$_{DIFFERENCE}$	.07	1.01	1.08	1.15	.02

DV – BALANCE$_{CRM}$

As seen in Table 2.6, I gain much deeper insight into the prediction of BALANCE$_{CRM}$ for the NRA. By looking at AT$_{DIFFERENCE}$ for both the positive group and the negative group, I see

that H4 is partially supported only in the positive group. Thus, I only have evidence that attitudes are spilling over when attitudes are positive towards the NRA. Moreover, I can see a significant interaction effect between attitude and attitude strength ($ATAS_{DIFFERENCE}$) for the NRA in the positive group when I split the groups by valence towards the NRA. Since I know that attitudes towards Wyndham were on average positive (see Table 2.4), I have evidence that when a brand that is generally viewed positively partners with a cause that is viewed positively (the split group of participants that view the NRA positively), spillover is occurring across the brand and the cause ($AT_{DIFFERENCE}$ predicts $BALANCE_{CRM}$) to influence changes in perceived compatibility of the CRM partnership. What about when a brand such as Wyndham partners with a cause that is viewed negatively? When looking at only the participants that had negative attitudes towards the NRA, I find no evidence of spillover ($AT_{DIFFERENCE}$ does not predict $BALANCE_{CRM}$), and thus no influence on changing perceived compatibility towards the CRM partnership. Judging from these results, this study further confirms intuition that there does not seem to be any benefit from partnering with a cause in which people generally hold negative attitudes towards.

Key Takeaways and Recommendations

I would like to conclude this discussion with a summarized list of key takeaways and recommendations for CRM practitioners, advertisers, and researchers.

- I found that perceived compatibility of CRM partnerships is strongly formulated by consumers attitudes towards the brand and the cause in the partnership (subjective attitudes), therefore practitioners and advertisers should not rely on a CRM partnership to raise attitudes towards a brand or a cause, but rather should consider efforts to raise attitudes towards a brand and a cause prior to the partnership being widely advertised.

- When measuring attitudes towards brands and causes in CRM partnerships to predict balance, I found that including the measurement of the strength of attitudes towards those brands and causes was important, as attitude strength improved my models of predicting changes to peoples' perceptions of CRM compatibility. Therefore, practitioners, advertisers, and researchers should consider the inclusion of attitude strength into their models of analyzing CRM partnerships' effects on consumer behavior.

- When brands and causes, in which people hold generally positive attitudes towards, partner with one another, I found evidence that attitudes towards the brand and towards the cause were spilling over into one another to change perceptions of compatibility. This could be considered a positive outcome, as it suggests that people are blending their views towards a brand and a cause together, which could be one of the aims of CRM.

- When brands, in which people hold generally positive attitudes towards, partner with causes, in which people hold generally negative attitude towards, I found no evidence that attitudes towards the brand and towards the cause were spilling over into one another to change perceptions of compatibility. Thus, there seems to be no benefits that I could find within this study for this type of partnership. The negatively viewed cause may be expecting that positive attitudes towards a well-liked brand could "rub-off" on the cause, but this does not seem to be the case.

LIMITATIONS AND FUTURE RESEARCH

Direction of Spillover Effects

Simonin and Ruth's (1998) research into spillover effects within brand alliances used structural equation modeling with the assessment of attitudes towards brands before and after presentation of the alliance. Although finding the end state of attitudes towards brands and causes, and the strength of those attitudes, was not the initial focus of this study, surveying these downstream measures could have given me more insight into understanding if there is a consistent direction with regards to the spillover effect that I found preliminary evidence for within CRM triads. With my current analysis, a limitation was that I could not be for sure which direction attitude, and the strength of those attitudes, are spilling over into/from. Future research into CRM partnerships could benefit from combining my study's methods with the Simonin and Ruth's (1998) to provide more insight into the effects of CRM partnerships (as they focused solely on brand-brand alliances, and not brand-cause alliances). They used a structural equation modeling approach that assessed participants' attitudes pre-partnership and post-partnership (as well as the strength of those attitudes), thus giving them insight into which direction the spill-over effects were occurring.

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Spillover Effects Analyses Over Time

Marvel et al. (2011) provided theoretical proof that triads (and larger systems that include triads) become balanced over time, but this study focused only on a snapshot of time. In the future, by collecting attitude, attitude strength, and perceived compatibility measures over time, I could also see whether or not more CRM triads eventually end up in states of balance as was proved by Marvel et al. (2011). Their findings were based on simulation data, but looking at how continuous attitude, attitude strength, and perceived compatibility measures move with regards to balance in CRM triads over time could provide empirical evidence to their findings.

Neutral Attitudes and Balance Theory

Another limitation was the prevalence of neutral separate attitudes towards brands and causes in my sample. There was a total of 2,979 total responses across three partnerships (N=993 per partnership). The number of responses in which one of more of the separate attitudes towards the brands and causes were neutral (AT_{BRAND}=0 and/or AT_{CAUSE}=0) was 1,185. This was a large number of responses that were excluded from my analyses for hypotheses 2-4, as previous studies on balance theory have not considered what to do with neutral attitudes. Future research should work to understand how to handle neutral attitudinal edges within questions of balance; additionally, researchers could consider expanding the initial sample size of data collection to make sure that all partnerships have an appropriate number of data points even if neutral edges need to be removed.

Single-Item vs. Multiple-Item Measures

This study used single-item measures for the measurement of attitude, attitude strength, and perceived compatibility, which could be initially considered a limitation. With this said, Bergkvist et al. (2007) compared the predictive validity of single-item measures and multiple-

item measures for attitudes towards advertising, and found that there was no difference in predictive validity between single-item versus multiple-item. Future research could consider incorporating multiple-item measures to see if there are any predictive differences in outcomes.

Interaction Variable for Attitude and Attitude Strength

Another limitation, as mentioned previously, was that my calculation of attitude x attitude strength was an informed, but preliminary approach that may have contributed to my mixed findings. This study seems to be the first to consider attitude strength in CRM partnership research, and thus it is only a starting point. Thus, future CRM studies may find that taking a more nuanced approach, looking at different statistical models to assess direction of spillover, seeing how balance changes over time, researching how to handle neutral attitudes, testing multiple-item measures, and considering coefficient differences for organizations, could prove fruitful.

Attitude Strength and its Relationship with Arousal and Involvement

Petty and Krosnick (1995) suggested that measuring attitude strength alongside attitude would enable us to better measure impact on information processing and judgments, as well as help us predict behavior. Although I only measured attitude strength in this study with regards to a construct that modifies the effect of attitude on processing and behavior, there have been other psychological constructs that have shown to be moderators of information processing and behavior.

For example, we have evidence that measuring arousal alongside with attitudes also enables us to better measure impact on information processing, specifically helping to predict how people process advertisements (Shapiro, MacInnis, & Park, 2002). Arousal has also been measured alongside emotions within excitation transfer theory, in which emotion-arousing

situations affect behavior due to portions of "excitation" that transfer from previously related or unrelated emotionally arousing situations (Zillmann, 2007). As implied from excitation transfer theory, arousal is thus related to interest, and interest is another way to measure attitude strength (Petty & Krosnick, 1995). Additionally, involvement has been suggested as a highly related construct to attitude strength (Petty & Krosnick, 1995), and Kokkinaki and Lunt (1997) found that involvement and attitude accessibility (attitude accessibility is yet another way to measure attitude strength; Petty & Krosnick, 1995) predicted attitude-behavior consistency in how participants chose consumer products. Kokkinaki and Lunt (1997) also found that involvement and attitude accessibility were indeed separate, albeit related, constructs within their study.

Thus, as examples of additional psychological constructs that moderate behavior and processing, there seems to be connections between attitude strength, arousal, and involvement. Future research may benefit from looking at how either one of these constructs (or various combinations of them) may affect behavior within CRM partnerships. One example could be measuring attitude strength alongside a measure of involvement, such as the personal involvement inventory (Zaichkowsky, 1994), which could provide a well-tested multiple-item measure to pair alongside the measurement of attitude strength. I could look to see both the correlations between the measurements of the different constructs, as well as see how a construct such as involvement changes my results with regards to CRM partnerships and compatibility.

Alternate Ways to Predict Consumers' Acceptance or Rejection of Partnerships

This study built upon Lafferty et al.'s (2004) findings that perceived compatibility predicted CRM partnership acceptance, but what about the cases in which I found that perceived compatibility was positive, but the CRM triad was not balanced ($BALANCE_{CRM}=0$)? A positive perceived compatibility should predict positive acceptance of a CRM partnership according to

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previous research (Lafferty et al., 2004), but if the CRM triad is not balanced, then Heider's (1946) balance theory suggests that the CRM triad may bring psychological pressure to change. Future studies should look to study this apparent contradiction. Interestingly, when looking at the distribution of balanced to unbalanced triads in this study's data, the percentages of triads that were balanced for each partnership were as follows: FitbitAHA (91.74%), RoyalWWF (80.06%), and WyndhamNRA (69.99%). As of late February 2018 (after this study was conducted), Wyndham Hotels ended their partnership with the National Rifle Association in the wake of the Marjory Stoneman Douglas High School shooting in Parkland, Florida (Edevane, 2018). Future research should look at if there is a potential connection between WyndhamNRA having the lowest number of balanced CRM triads, and public backlash against the partnership.

CRM Research and Social Media Data

One final promising area of future research could be within the realm of social media data, as researchers could potentially use social media data to assess attitudes towards brands and towards causes (as well as the strength of those attitudes). This could provide a means for brands, causes, and advertising practitioners to make even more informed decisions regarding the realm of CRM. After the previous mentioned Florida school shooting, Wyndham Hotel's Twitter account was filled with tweets condemning their partnership with the NRA, thus providing even more evidence that social media is an important arena for CRM partnership research.

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CONCLUSION

</div>

The purpose of this study was to investigate the boundaries in which balance theory (Heider, 1946) can be used to analyze CRM partnerships and predict consumer perceptions of CRM partnership compatibility. Within this investigation, I brought together theoretical understandings of balance theory and the difference between attitude and attitude strength to

predict balance in CRM triads. My findings benefit researchers, as they advance theory both for balance theory as well as for CRM research, but they also bring value to CRM and advertising practitioners. Having the understanding of how to predict potential CRM compatibility perceptions is important, especially if it can be used prior to entering into a partnership. Additionally, by providing insight into how to predict balance in CRM triads, this gives CRM and advertising practitioners deeper understanding into how to choose future CRM partners, as well as considering campaigns to advertise brands and causes individually to raise attitudes towards them before entering into a partnership.

CHAPTER 3: PERILS AND PITFALLS OF SOCIAL MEDIA ANALYTICS: A COMPARISON BETWEEN SURVEY AND SOCIAL MEDIA ANALYTICS APPROACHES WHEN USING BALANCE THEORY TO MEASURE ATTITUDE STRENGTH IN CAUSE-RELATED MARKETING PARTNERSHIPS

Social media has brought about many changes within the realm of cause-related marketing (CRM). As in the case of recent social media backlash towards causes like the National Rifle Association, it seems that consumers' attitudes towards brands, as well as their attitudes towards causes, can change in a very short period of time. Research has shown that the ease in which attitudes towards organizations can be changed is dependent on how strong peoples' attitudes are towards those organizations. Therefore, in light of the importance of attitude strength within CRM, my purpose was to compare different ways to measure the strength of consumers' attitudes towards brands, and towards causes, within the domain of CRM. I examined two novel ways of assessing consumers' attitude strengths towards brands and causes through balance theory: a survey measure assessing discussion topic similarity to indirectly measure attitude strength, and a social media analytics method of analyzing social media discussion similarity as another indirect measure of attitude strength. I found that by assessing the similarity of topic conversation between a consumer and a brand (or cause), I could predict the strength of a consumer's attitude towards that brand (or cause) using a survey measure, but not using social media analytics. I explain my thoughts on why one approach worked versus the other, as well as share some considerations when conducting psychological research using a hybridization of a survey approach and a social media analytics approach.

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In late February 2018, after the mass shooting at Marjory Stoneman Douglas High School in Parkland, Florida, ThinkProgress posted a list of all the companies that were engaged in a cause-related marketing partnership with the National Rifle Association (NRA) to offer discounts to NRA members (Lerner, 2018). Cause-related marketing (CRM) is a phenomenon of for-profit businesses (brands) partnering with not-for-profit organizations (causes) for reasons that are beneficial to both of the organizations' objectives (Barone, Norman, & Miyazaki, 2007; Varadarajan & Menon, 1988). ThinkProgress' posting, alongside growing use of #BoycottNRA and #NeverAgain on social media, started a domino-effect of companies ending their CRM partnerships with the NRA (Edevane, 2018). It seems that the benefits that existed for the companies partnering with the NRA were outweighed by the public anger towards the mass shooting and the topic of gun-ownership in America. Some CRM partnerships may seem more incompatible than others, and research has shown that perceived compatibility predicts acceptance (or rejection) of CRM partnerships (Lafferty et al., 2004), consumer choice (Pracejus & Olsen, 2004), and purchase intentions (Gupta & Pirsch, 2006). In Chapter 2 of this dissertation, I investigated a CRM partnership between Wyndham Hotels and the NRA, and found that this partnership was perceived, on average, as incompatible. Notably, Wyndham was also a company that ended their relationship with the NRA in light of the backlash in February 2018. I also found that measuring attitude strength enables the prediction of consumers' perceptions of CRM compatibility in ways that attitude alone cannot predict, therefore I believed that it would be important to investigate novel ways to measure the strength of attitudes towards brands, as well as the strength of attitudes towards causes, that participate (or will participate) in CRM partnerships.

Investigating new ways to measure the strength of attitudes towards brands, as well as the strength of attitudes towards causes, can provide an important step forward for the realm of CRM research and practice. Previously, the only way to measure the strength of attitudes towards people or objects was through self-reported survey measures and/or survey response latency measurement, but a way to measure attitude strength via social media analytics does not currently exist within research literature. Social media analytics is the process of using computational methods and tools to extract insights from social media data (Fan & Gordon, 2013), and it is being widely used by companies to analyze consumer behavior (Yun & Duff, 2017). A recent Pew Research Center survey showed that up to 75% of adults in the United States use social media (A. Smith & Anderson, 2018). They also show that this percentage grows to 94% within the age range of 18 to 24-year-olds with regards to social media use. In August of 2017, AdWeek analyzed how people reacted to various topics of postings by brands on Facebook, and they found that content that featured corporate social responsibility initiatives (cause-related marketing is a form of a corporate social responsibility) received by far the most engagement versus other topics of conversation (Vijay, 2017). If I could use social media analytics to detect the strength of attitudes towards brands, and the strength of attitudes towards causes, this would bring me one step closer to developing a social media analytics method to predict potential CRM compatibility prior to organizations entering into CRM partnerships. In this study, I experimented with a topic-based approach to measuring attitude strength (both via a survey and social media analytics), as this could be a more indirect way to measure how strong attitudes may be towards brands or towards causes. Since attitude strength is a measure of how easily attitudes can be changed, cause-related advertisers should also be interested in different ways to get at measuring attitude strengths towards brands and towards causes.

I only focused on the measurement of attitude strength within CRM partnerships for this study, rather than looking at both attitude and attitude strength for the following reasons.

First, I was interested in investigating how I could use a social media analytics approach to assessing attitude strength apart from assessing attitude, as the methodology and data needed to assess either in the realm of CRM have key differences. Measuring attitudes towards people or objects within social media has been previously researched (also referred to as opinion mining or sentiment analysis; e.g., Eirinaki, Pisal, & Singh, 2012), but attitude strength has not been previously measured through social media data as a separate psychological construct. Measuring attitude towards CRM brands and causes would require acquiring data of social media users talking directly about those brands and/or causes, and then I could use previously developed methods of detecting attitude towards objects in text (e.g., Eirinaki et al., 2012). In contrast, I hypothesized that CRM attitude strength could be detected in social media data that does not directly discuss CRM brands and causes, and therefore it offered a way for CRM practitioners to assess general strength of attitudes towards brands and causes across a broader set of data.

Secondly, this research considers Krosnick et al.'s (1993) study, in which they focused on investigating the various different ways to measure attitude strength (apart from the measurement of attitude). They found that each way to measure attitude strength (e.g., attitude certainty, attitude importance) were distinct yet correlated measures, and that any given measure may be more appropriate to ask for various circumstances or realms of assessment. I was interested in seeing if I could identify a novel indirect survey-based measure of attitude strength specifically within the realm of CRM, and that could potentially help avoid issues that come from directly asking for attitude strength (e.g., the issue of social desirability bias).

Thus, due to the previously researched importance of attitude strength within CRM partnerships (Chapter 2 of this dissertation), the lack of research within the computational realm of detecting attitude strength from social text, the possibility that attitude strength could be detected from social data that is more widely accessible, and the desire to find an alternative measure of attitude strength within the realm of CRM, I chose to focus specifically on attitude strength within this study.

By looking at measuring attitude strength both via a survey-based approach and a social media analytics approach, I compare and contrast these methods in efforts to bring additional insight into various considerations that researchers and practitioners should take when considering using either approach (or a hybridized approach). With regards to a theoretical framework, previous research has used Heider's (1946) balance theory in analyzing CRM partnerships (Basil & Herr, 2006; Chapter 2 of this dissertation). Thus, my purpose was to investigate how I could use balance theory (Heider, 1946) to discover novel ways (both via survey-based and social media analytics approaches) to measure the strength of attitudes towards brands, as well as the strength of attitudes towards causes, participating (or that will participate) in CRM partnerships.

Guiding Research Question: *How can I use balance theory to discover novel ways to measure the strength of attitudes towards brands, as well as the strength of attitudes towards causes, that participate (or will participate) in cause-related marketing partnerships via a survey approach as well as a social media analytics approach?*

LITERATURE REVIEW

Cause-Related Marketing Compatibility and Attitude Strength

As previously stated, cause-related marketing (CRM) is a phenomenon of for-profit businesses (brands) partnering with not-for-profit organizations (causes) for reasons that are beneficial to both of the organizations' objectives (Barone et al., 2007; Varadarajan & Menon, 1988). Some examples of CRM partnerships include Starbucks with (RED) to fight AIDS, or Coca-Cola with the World Wildlife Fund to preserve polar bear habitats in the arctic. CRM has grown in popularity over the years, as CRM spending has increased from $120 million in 1990 to $2.05 billion in 2017 ("ESP's Growth of Cause Marketing - Engage for Good," 2017).

According to a recent text-mining analysis of CRM research between 1988 and 2013, the concept of CRM fit (or CRM compatibility) was one of the most prominent topics discussed and researched within the CRM realm (Guerreiro et al., 2016). Some CRM partnerships are perceived as more compatible than others, as previous research has shown that the partnership between Fitbit and the American Heart Association has been perceived on average as more compatible versus the partnership between Wyndham Hotels and the NRA (Chapter 2 of this dissertation). We have evidence that perceived CRM compatibility predicts acceptance of CRM partnerships (Lafferty et al., 2004), consumer choice (Pracejus & Olsen, 2004), and purchase intentions (Gupta & Pirsch, 2006). Thus, understanding how consumers form their perceptions of CRM compatibility has practical importance for brand managers, public-relations professionals, and cause-related advertisers. In Chapter 2 of this dissertation, I found that incorporating attitude strength improved my models for predicting CRM compatibility across three CRM partnerships, compared to predicting via attitude measures alone.

In describing attitude strength, Howe and Krosnick (2017) suggested that some attitudes are strong versus weak, and it is strong attitudes that most affect our thoughts and behaviors. Petty and Krosnick (1995) stated that strong attitudes are resistant to change, they are stable over time, they influence our thoughts, and they are better predictors of behavior than weak attitudes. An individual may have the same extreme attitude towards two topics, such an extremely negative view towards pollution as well as an extremely negative view towards Mondays. With this said, attitude strength deals with how resistant that attitude is to change, and how easily that attitude can be influenced. That same individual's views towards pollution may be very strong, thus preventing any sort of change in attitudes.

With regards to how attitude strength specifically affected CRM compatibility, I found evidence that degree differences in the attitudes towards brands and attitudes towards causes ($AT_{DIFFERENCE}$) was related to changes in participants' perceptions of the compatibility of the CRM partnership when attitude strength was included in my predictive models (Chapter 2 of this dissertation). Thus, it is important to understand how to assess the strength of individuals' attitudes towards brands and towards causes before they enter into a CRM partnership or advertise the partnership widely.

Attitudes have historically been measured through a variety of measures and methods. Some of these methods include self-reported survey measures (e.g., the Likert scale assessment of attitudes, Likert, 1932), behavioral survey measures (e.g., the implicit association test, Greenwald, McGhee, & Schwartz, 1998), and physiological methods (e.g., facial electromyographic activity, Krosnick, Charles, & Wittenbrink, 2005). On the other hand, attitude strength has only been assessed through self-reported survey measures of attitude strength (Petty & Krosnick, 1995), or behaviorally measuring the response latency to survey questions (Bassili,

1993, 1996). Preceding the 1990 Ontario provincial election, Bassili (1993) asked participants which political party they were going to vote for in, how certain they were of their choice, and asked them which political party they actually voted for after the election. Assessing how certain someone is of their attitudes is one of the many ways to measure self-reported attitude strength (Petty & Krosnick, 1995). Bassili (1993) found that participants' response latency towards the question of which political party they were going to vote for was a stronger predictor of which political party they actually voted for as compared to how they answered with regards to the certainty of their choice. Attitude certainty was still a predictor of voting behavior, but response latency was a much stronger predictor. Thus, response latency has been considered a valid behavioral measure of attitude strength. Bassili (1996) later followed up with comparing the use of response latency as a behavioral measure of attitude strength to a larger number of self-reported measures of attitude strength (e.g., attitude certainty, attitude importance, attitude knowledge, attitude strength, etc.), and found response latency to be the most predictive of behavior.

Previous research has not measured strength of attitudes towards brands and towards causes within CRM partnerships outside of directly asking this via a self-report survey (Chapter 2 of this dissertation). Self-reported measures of attitude and attitude strength may suffer from both social desirability response bias as well as self-deception (Krosnick et al., 2005). Social desirability response bias is the tendency to self-report in ways that are driven by a desire to be viewed more favorably by others. As an example, an individual may actually like the National Rifle Association, but they may believe that there is such negative media attention on the association right now that they feel a bit embarrassed to report their attitude (and the strength of their attitude) towards the NRA on a survey. Therefore, they may change their response due to

social desirability response bias. Self-deception works in a similar way, except the motive of this bias is driven more from an individual's desire to view their own self favorably. Thus, if I could provide other indirect ways to predict consumers' separate attitude strengths towards brands and causes, this may provide strong value practically within the realm of CRM.

Using response latency could be an indirect way to measure attitude strength towards brands and causes, but there have not been any previous studies to show that web-based surveys via MTurk can provide enough time sensitivity (and consistency) required for detecting attitude strength. Lab based studies using software such as DirectRT (Jarvis, 2016) have the benefit of having controlled computational environments, but I focused on finding measures that would be accessible to a range of people (e.g., practitioners within non-profits that may be looking for low-cost methods to evaluate potential CRM partners), while still ensuring that there was the potential to overcome issues such as social desirability bias. Thus, one of the main contributions of this study is providing a new indirect survey measure of the strength of attitudes towards brands and towards causes within the realm of CRM. To explain this novel method, I turn to balance theory next.

Balance Theory and Attitude Strength

Heider's balance theory (1946) is probably most well-known as applied to triads of relationships, but he also spoke of the application of balance theory within two person/entity systems. I will refer to this as dyadic balance theory. Heider suggested that individuals can have attitudes towards other people and/or objects, and these attitudes influence each other. While speaking about dyadic systems, he stated, "p similar to o induces p likes o, or p tends to like a similar o" (Heider, 1958, p. 184). Therefore, he was stating that similarity affects attitudinal evaluation, although he did not clarify similarity on what grounds. The relationship between

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similarity and group formation has been studied in network analysis for quite some time as well. In network analysis, this phenomenon is usually referred to as homophily. McPherson et al. (2001) defines homophily as, "the principle that a contact between similar people occurs at a higher rate than among dissimilar people. The pervasive fact of homophily means that cultural, behavioral, genetic, or material information that flows through networks will tend to be localized" (p. 416). Thus, the effects of similarity within balance theory runs alongside the concept of homophily in network analysis.

Choudhury (2011) tested this concept of homophily on Twitter, as she looked at Twitter users and any new people that they would follow over a period of time, and compared the new people they followed with the original Twitter user to see if there was any correlation with the following attributes: location (Twitter profile location), gender (Twitter first names compared to US Census data on gender), ethnicity (Twitter last names compared with US Census data on ethnicity), political orientation (words denoting political orientation in Twitter profiles), activity-pattern (distribution of posting tweets over a 24 hour period), broadcasting behavior (fraction of retweets to total posts), interactiveness (fraction of @mentions to total posts), topical interest (topic codes derived from analyzing tweets via opencalais.com), and sentiment expression (sentiment analysis of tweets utilizing Linguistic Inquiry Word Count; Pennebaker, Boyd, Jordan, & Blackburn, 2015). Although she found mixed effects for most of the attributes, she found that Twitter users tended to follow other users that were discussing topics similar to what they were discussing.

One could imagine that people follow others on Twitter due to liking them or their content, but they could also follow someone due to the topic that they are discussing regardless of the valence of their attitude towards the Twitter account. For example, if someone was

interested in efforts to reduce carbon emissions worldwide, they might still follow Exxon

Mobil's Twitter feed even if they strongly disliked Exxon Mobil. They might follow Exxon

Mobil on Twitter due to their strong attitude strength towards the topic of climate change,

regardless of their negative attitudes towards the brand. In fact, there is even a suggested term for

this on Twitter: Tweetenfreude ("the hate-follow"; Weissman, 2014). Thus, my explanation of

Choudhury's (2011) findings is that there is a connection between similarity of topical discussion

and attitude strength. Interestingly, one of the ways that has been shown to measure the strength

of attitudes towards topics is by measuring what topics an individual talks about, and how often

they talk about those topics (Krosnick et al., 1993). Thus, by synthesizing insights together from

Choudhury (2011), Krosnick et al. (1993), and Heider (1958), I am proposing a new indirect

self-reported measure of the strength of attitudes towards brands and towards causes within the

realm of CRM. I hypothesize that a consumer's perceived similarity of topical conversation

between themselves and a brand ($SURVEYSIM_{BRAND}$) within CRM partnerships will predict the

strength of their attitude towards that brand (AS_{BRAND}). I also hypothesize that a consumer's

perceived similarity of topical conversation between themselves and a cause

($SURVEYSIM_{CAUSE}$) within CRM partnerships will predict the strength of their attitude towards

that cause (AS_{CAUSE}).

H1a: *As the perceived similarity of topics of discussion between a consumer and a brand ($SURVEYSIM_{BRAND}$) increases, the strength of the consumer's attitude towards that brand (AS_{BRAND}) will increase.*

H1b: *As the perceived similarity of topics of discussion between a consumer and a cause ($SURVEYSIM_{CAUSE}$) increases, the strength of the consumer's attitude towards that cause (AS_{CAUSE}) will increase.*

Social Media and Attitude Strength within Cause-Related Marketing

Social media has impacted the realm of CRM greatly. In August of 2017, AdWeek analyzed how people reacted to various topics of postings by brands on Facebook, and they found that content that featured corporate social responsibility initiatives (cause-related marketing is a form of corporate social responsibility, or CSR) received by far the most engagement versus other topics of conversation (Vijay, 2017). Bühler et al. (2016) looked at how Facebook and YouTube advertising of a CRM campaign affected intentions to purchase the CRM brand's products, and found that using these social media platforms rivaled print advertising and point of sale positioning. However, engagement with CRM does not uniformly benefit companies. Hashtag campaigns such as #NeverAgain and #BoycottNRA have caused some CRM partnerships to separate (Popken, 2018). Therefore, having a deeper understanding of how CRM practitioners and advertisers could use social media should be a very practical area of investigation.

We have evidence that Twitter is a platform in which similarity of topical discussion has been found to be correlated with users following other users with the same topical interest (Choudhury, 2011). Research has shown that one of the ways to measure the strength of attitude towards a topic is by measuring how much an individual talks about that topic (Krosnick et al., 1993). Sprout Social, a social media analytics company founded in 2010 that has customers such as Microsoft, Hyatt, and Titleist, found that successful organizations are consistent with their topics of conversation on social media (Jackson, 2017). They also suggest that most large organizations have Twitter accounts, as it is both an avenue for public messaging as well as a way for taking in customer services requests and responses. Thus, bringing together Choudhury's (2011) homophily findings on topical discussion, Heider's (1958) theoretical framework of

dyadic balance, and the consideration that Twitter is a platform in which large organizations are

discussing various topics of organizational interest, I hypothesize that computational similarity

between a Twitter user's discussion topics and a brand's discussion topics (TWEETDIV$_{BRAND}$)

within CRM partnerships should predict the strength of the user's attitude towards that brand

(AS$_{BRAND}$). I also hypothesize that computational similarity between a Twitter user's discussion

topics and a cause's discussion topics (TWEETDIV$_{CAUSE}$) within CRM partnerships should

predict the strength of the user's attitude towards that cause (AS$_{CAUSE}$). As a clarifying point to

the hypothesis, I actually used the measure of divergence (the opposite of similarity) due to the

sparse nature of computational topic analysis. This will be explained further in the methods

section.

       H2a*: As the divergence of topics discussed on Twitter between a consumer and a brand (TWEETDIV$_{BRAND}$) increases, the strength of the consumer's attitude towards that brand (AS$_{BRAND}$) will decrease.*

       H2b*: As the divergence of topics discussed on Twitter between a consumer and a cause (TWEETDIV$_{CAUSE}$) increases, the strength of the consumer's attitude towards that cause (AS$_{CAUSE}$) will decrease.*

METHODS

CRM Brands and Causes

I used the same brands and causes from my previous study (Chapter 2 of this

dissertation), as this current study was an extension of the survey instrument from Chapter 2 (see

Appendices 1 and 2). Therefore, the three partnerships that I included in this study were Fitbit

and American Heart Association (FitbitAHA), Royal Caribbean and the World Wildlife Fund

(RoyalWWF), and Wyndham Hotels and the National Rifle Association (WyndhamNRA). I

collected data from September 6, 2017 to September 20, 2017, which was five months before

Wyndham Hotels ended their partnership with the National Rifle Association.

Participants

For this study, I collected survey responses from participants through Amazon Mechanical Turk (MTurk). Although there has been some debate about MTurk and its viability for research studies, Kees et al. (2017) provided evidence that advertising research could reliably use Amazon MTurk. I collected N=997 responses, but four participants were removed after reviewing the data, due to concerns over their understanding of the purpose of the data, or whether they were fit to fill out the survey due to their post-survey comments. Therefore, N=993 responses were remaining. Towards the end of my survey, I asked participants to provide their Twitter usernames, so that I could compare analyses of their Twitter accounts to their surveyed responses. I made sure that participants were well informed as to what would be happening with their Twitter usernames if they provided it, and that they knew this step was optional (see Appendix 2 for the exact verbiage given to participants). N=337 participants responded with their Twitter usernames, but after checking to see if the usernames were actual Twitter accounts and checking that they actually had any tweets in their timelines, the number of responses were reduced to N=184. I also limited my scope to users with tweets within the year of 2017, so as to standardize for those that have more years of tweets than others historically. All analyses were thus conducted on these remaining N=170.

Measures

I collected additional survey questions that were not reported on the first study due to the scope of the study (Chapter 2 of this dissertation). Please refer to Appendix 1 for the first study's survey instrument. Due to the importance of attitude strength to this current study, I re-iterate that I collected strength of attitude towards the brands (AS_{BRAND}), and strength of attitude towards the causes (AS_{CAUSE}; See Appendix 1). The attitude strength measures were adapted

from Bassili (1996) and were measured on an 11-point scale from +1 (Not strong at all) to +11 (Extremely strong). To assess this, I asked, "How strong is your attitude toward [brand/cause]?" Each participant was presented with all three partnerships, but the order of partnerships (as well as the presentation order of the brand and the cause) was presented randomly.

With regards to measures of topics of discussion and topic similarity, I first collected participants' self-reported similarity of topical conversation with a brand (SURVEYSIM$_{BRAND}$) or a cause (SURVEYSIM$_{CAUSE}$) by asking, "The topics that [brand/cause] would talk about are consistent with the topics that I talk about." This was measured on an 11-point scale from -5 (Not consistent at all) to +5 (Extremely consistent). My measure of computational topics divergence between a participant and a brand (TWEETDIV$_{BRAND}$) or cause (TWEETDIV$_{CAUSE}$) was derived through running a divergence analysis between the topics discussed on a participant's Twitter feed and a brand/cause's Twitter feed. The reason why I used a divergence analysis instead of a similarity analysis was due to the issue of symmetric similarity comparisons producing a large number of zero overlapping topics of discussion. For example, if Joe talks about religion, nature, and basketball, and a brand talks about boxing, fishing, and rodeos, the similarity would be zero. With regards to running statistical analyses against attitude strength, this would pose a mathematical problem. Therefore, I used a divergence measure called Kullback-Leibler divergence (KL divergence). KL divergence is not a similarity measure, but rather an asymmetric comparison of probability distributions (Joyce, 2011). The formula for KL divergence is represented in Equation 3.1.

$$D_{KL}(p||q) = \sum_{i=1}^{N} p(x_i) \cdot log \frac{p(x_i)}{q(x_i)} \tag{3.1}$$

P(x) and *q(x)* are two probability distributions of a discrete random variable *x*. As a clarifying example, you may use KL divergence to assess how far a study's data frequency

distribution (*p(x)*) strays from a normal distribution (*q(x)*). In this case, a normal distribution is your reference point, and KL divergence looks at each frequency level, and calculates how all of them in aggregate stray from a normal distribution. Therefore, if the two distributions are exactly the same, the KL divergence value is zero (lower values = greater similarity in distributions). As the distribution under consideration grows further away from the prototype, the KL divergence grows in value. Thus, going back to my example of Joe and the brand, I have six total topics between Joe and the brand (religion, nature, basketball, boxing, fishing, and rodeos). If I were to consider this as a distribution of topic frequency, while keeping the order of the topics the same, a probability distribution vector that includes all the topics would look like [1, 1, 1, 1, 1, 1]. If I just consider the topics that the brand talks about, its probability distribution vector looks like [0, 0, 0, 1, 1, 1]. This is my prototype distribution if I am considering KL divergence. A smoothing constant must be added to the zero values within the distributions as zero values would create undefined KL divergence values, as dividing by a zero in Equation 3.1 would result in an undefined value (Han & Kamber, n.d.). With the addition of this smoothing constant (.001 in this case), Joe's original distribution vector for the topics he talks about would be represented as [1, 1, 1, .001, .001, .001]. Therefore, with regards to similarity analysis, [1, 1, 1, .001, .001, .001] compared against [.001, .001, .001, 1, 1, 1] would be zero, but with KL divergence it would be the non-zero number of D_{KL}(Joe||Brand) = 6.89. Having these non-zero KL divergence numbers are important if I am calculating statistical correlations between computational topics divergence ($TWEETDIV_{BRAND}$ or $TWEETDIV_{CAUSE}$) and attitude strength (AS_{BRAND} or AS_{CAUSE} respectively). I used the SciPy entropy function to calculate KL divergence (Jones, Oliphant, & Peterson, 2014), and added a smoothing constant of .001 to each value within the topic distribution vectors.

To actually compute the topics being discussed on the Twitter feeds of the participants and the brands and the causes, I used Text Razor's machine-learned topic tagging API ("TextRazor - The Natural Language Processing API," n.d.). Describing their tool, they write, "TextRazor's topic tagger uses millions of Wikipedia pages to help assign high level topics to your content with no additional training on your data, using our knowledgebase of entity and word category relationships." When I sent this tool a Twitter timeline, it sent me back a listing of predefined topic terms with their associated probabilities of occurring within the timeline. As an example, when I sent the National Rifle Association's Twitter timeline to Text Razor's Topic Tagging API, the first topic that it returned was "Handgun" with a 100% probability that it was being discussed in the timeline. After analyzing the frequencies of topics for each brand/cause and their associated probabilities, I set a cutoff probability of 80% for topic inclusion within my analyses. The 80% probability cutoff point was also the top 5% of topics for each brand/cause (See Appendix 3 for all of the 80% probability and above topics for each brand/cause).

Text Razor has been shown to be one of the most effective toolsets for named-entity recognition (computationally identifying entities such as persons or organizations within bodies of text) (Rizzo, van Erp, & Troncy, 2014). With this said, I do not believe their topic-tagging tool has been used previously in scholarly research. Additionally, since they are a for-profit company, details of the machine learned model training process for their topic-tagging is proprietary, and therefore the model is "black-box". Therefore, as a validation check to compare against this "black-box" topic-tagging, I also conducted a term-frequency (TF) matrix divergence analysis of words between a participant's Twitter feed and the words on a brand's (or cause's) Twitter feed. I will refer to this as a participant's raw word divergence with a brand (RAWDIV$_{BRAND}$) or with a cause (RAWDIV$_{CAUSE}$) throughout the rest of this study. As a computationally clarifying note,

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before I conducted the TF analysis, I tokenized (normalizing word-casing), removed stop words, stemmed, vectorized, and then converted each Twitter timeline into a TF matrix. Tokenization (in my context) is breaking down tweets into tokens, which could be words, hashtags, URLs, etc. I used the TweetTokenizer within the NLTK toolkit, which is a custom made tokenizer to recognize tokens appropriately within tweets (Loper & Bird, 2002). Stemming is the process of taking various forms of a word and reducing them to their most basic stem (e.g., running and runs both reduce to the stem "run"). This is important when frequency distributions of words are being created. I used the same NLTK toolkit for this stemming function as well. Vectorization and the subsequent conversion into TF matrices is the process of taking all the stemmed tokens and creating term frequency matrices (similar to the frequency vectors for topics previously mentioned), and then conducting a divergence analysis. I used the scikit vectorizer functions to vectorize (Pedregosa et al., 2012), and I conducted the KL divergence analysis using the SciPy entropy function (Jones et al., 2014). Just as with my KL divergence analysis of topics, I added a smoothing constant of .001 to each value within the raw word frequencies to prevent undefined values.

Finally, as a validation check between the measure of self-reported similarity of topical conversation (SURVEYSIM$_{BRAND}$ and SURVEYSIM$_{CAUSE}$) and the measure of computational topics divergence (TWEETDIV$_{BRAND}$ and TWEETDIV$_{CAUSE}$ respectively), I collected thought-listings of what topics participants believed each brand or cause would talk about. I provided twelve open-ended text boxes, with a minimum required topic listing of one, as this was in line with Cacioppo and Petty's (1981) paper on using a thought-listing technique. This was also similar to Ross et al.'s (2006) recent thought-listing procedure in collecting participant's brand associations towards sports teams. The question I asked was, "If [brand/cause] was a person,

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what topics do you think [brand/cause] would talk about? Please provide up to 12 topics, with a minimum of 1 topic."

Analyses

For all of my hypotheses, I separated my analyses by each brand and cause to see if my results could be validated six times with six different organizations. I also normalized SURVEYSIM$_{BRAND}$ and SURVEYSIM$_{CAUSE}$ from a -5 to +5 scale to a +1 to +11 scale, as this allowed for a more straightforward statistical analysis against AS$_{BRAND}$ and AS$_{CAUSE}$ respectively. For hypothesis 1a, I used linear regression analysis with SURVEYSIM$_{BRAND}$ as the predictor variable, and AS$_{BRAND}$ as the outcome variable. For hypothesis 1b, I used linear regression analysis with SURVEYSIM$_{CAUSE}$ as the predictor variable, and AS$_{CAUSE}$ as the outcome variable. To test hypothesis 2a, I used linear regression analysis with TWEETDIV$_{BRAND}$ as the predictor variable, and AS$_{BRAND}$ as the outcome variable. To test hypothesis 2b, I used linear regression analysis with TWEETDIV$_{CAUSE}$ as the predictor variable, and AS$_{CAUSE}$ as the outcome variable. To conduct a validation check on hypothesis 2a, I used linear regression analysis with RAWDIV$_{BRAND}$ as the predictor variable, and AS$_{BRAND}$ as the outcome variable. To conduct a validation check on hypothesis 2b, I used linear regression analysis with RAWDIV$_{CAUSE}$ as the predictor variable, and AS$_{CAUSE}$ as the outcome variable.

RESULTS

Descriptive Statistics

Descriptive statistics for AS$_{BRAND}$ and AS$_{CAUSE}$ are presented within Table 3.1. A one-way ANOVA test showed that the averages for both the brands and the causes were significantly different than one another.

Table 3.1: Descriptive Statistics for Attitude Strength

Brand/Cause (N = 170)	M	SD	F(2,507)	p
Fitbit	7.28	2.67		
Royal Caribbean	6.27	2.87	14.35	.00
Wyndham Hotels	5.66	2.90		
American Heart Association	8.58	2.00		
World Wildlife Fund	8.15	2.49	11.47	.00
National Rifle Association	7.26	3.11		

Descriptive statistics for SURVEYSIM$_{BRAND}$ and SURVEYSIM$_{CAUSE}$ are presented within Table 3.2. A one-way ANOVA test showed that the averages for both the brands and the causes were significantly different than one another.

Table 3.2: Descriptive Statistics for Self-Reported Similarity of Topical Conversation

Brand/Cause (N = 170)	M	SD	F(2,507)	p
Fitbit	8.14	2.05		
Royal Caribbean	6.87	2.55	24.46	.00
Wyndham Hotels	6.32	2.74		
American Heart Association	8.00	2.05		
World Wildlife Fund	7.99	2.08	62.42	.00
National Rifle Association	5.34	3.28		

Descriptive statistics for TWEETDIV$_{BRAND}$ and TWEETDIV$_{CAUSE}$ are presented within Table 3.3. A one-way ANOVA test showed that the averages for the brands were significantly different than one another, but not for the causes.

Table 3.3: Descriptive Statistics for Computational Topics Divergence

Brand/Cause (N = 170)	M	SD	F(2,507)	p
Fitbit	5.54	1.58		
Royal Caribbean	4.99	1.53	58.04	.00
Wyndham Hotels	3.79	1.49		
American Heart Association	6.23	1.71		
World Wildlife Fund	6.43	1.75	2.53	.08
National Rifle Association	6.02	1.68		

Descriptive statistics for $\text{RAWDIV}_{\text{BRAND}}$ and $\text{RAWDIV}_{\text{CAUSE}}$ are presented within Table 3.4. A one-way ANOVA test showed that the averages for both the brands and the causes were significantly different than one another.

Table 3.4: Descriptive Statistics for Raw Word Divergence

Brand/Cause (N = 170)	M	SD	F(2,507)	p
Fitbit	5.44	1.29		
Royal Caribbean	6.08	1.35	18.30	.00
Wyndham Hotels	6.23	1.19		
American Heart Association	5.30	1.41		
World Wildlife Fund	5.64	1.31	3.41	.04
National Rifle Association	5.30	1.46		

Hypotheses Results

My hypothesis 1a was that as $\text{SURVEYSIM}_{\text{BRAND}}$ increases, AS_{BRAND} will increase. Linear regression analyses showed that hypothesis 1a was fully supported (see Table 3.5). My hypothesis 1b was that as $\text{SURVEYSIM}_{\text{CAUSE}}$ increases, AS_{CAUSE} will increase. Linear

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regression analyses showed that hypothesis 1b was also fully supported (see Table 3.5). As a note, the R^2 values for WWF (R^2=.04) and NRA (R^2=.03) were concerningly low, and I address this in the general discussion section.

Table 3.5: Predicting Attitude Strength with Self-Report Topic Similarity

Brand/Cause	Variables	B	SE B	t	p	R^2
Fitbit (N=170)	Constant	3.51	.78	4.52	.00	.12
	SURVEYSIM$_{BRAND}$	.46	.09	5.01	.00	
Royal Caribbean (N=170)	Constant	1.43	.51	2.83	.01	.36
	SURVEYSIM$_{BRAND}$	.70	.07	10.23	.00	
Wyndham Hotels (N=170)	Constant	2.48	.49	5.10	.00	.21
	SURVEYSIM$_{BRAND}$	.50	.07	7.07	.00	
American Heart Association (N=170)	Constant	5.00	.56	8.98	.00	.19
	SURVEYSIM$_{CAUSE}$	.44	.07	6.59	.00	
World Wildlife Fund (N=170)	Constant	6.10	.73	8.31	.00	.04
	SURVEYSIM$_{CAUSE}$	.25	.09	2.84	.00	
National Rifle Association (N=170)	Constant	6.29	.44	14.36	.00	.03
	SURVEYSIM$_{CAUSE}$	.17	.07	2.52	.01	

DV – AS$_{BRAND}$ or AS$_{CAUSE}$

My hypothesis 2a was that as TWEETDIV$_{BRAND}$ increases, AS$_{BRAND}$ will decrease. Linear regression analyses showed that hypothesis 2a was not supported (see Table 3.6). My

hypothesis 2b was that as TWEETDIV$_{CAUSE}$ increases, AS$_{CAUSE}$ will decrease. Linear regression

analyses showed that hypothesis 2b was not supported (see Table 3.6).

Table 3.6: Predicting Attitude Strength with Computational Topic Divergence

Brand/ Cause	Variables	B	SE B	t	p	R^2
Fitbit (N=170)	Constant	7.71	.88	8.78	.00	.00
	TWEETDIV$_{BRAND}$	-.05	.15	-.35	.73	
Royal Caribbean (N=170)	Constant	6.71	.88	7.66	.00	.00
	TWEETDIV$_{BRAND}$	-.09	.17	-.53	.60	
Wyndham Hotels (N=170)	Constant	5.11	.61	8.34	.00	.01
	TWEETDIV$_{BRAND}$	.15	.15	.97	.34	
American Heart Association (N=170)	Constant	9.18	.61	15.00	.00	.00
	TWEETDIV$_{CAUSE}$	-.08	.09	-.83	.41	
World Wildlife Fund (N=170)	Constant	7.80	.79	9.85	.00	.01
	TWEETDIV$_{CAUSE}$	.11	.12	.91	.37	
National Rifle Association (N=170)	Constant	7.46	1.49	5.01	.00	.00
	TWEETDIV$_{CAUSE}$	-.03	.24	-.13	.90	

DV – AS$_{BRAND}$ or AS$_{CAUSE}$

Raw Tweet Divergence Validation Check

Since the Text Razor topic tagging tool is a proprietary "black box" machine-learned model, I also ran a raw term-frequency divergence analysis. When I conducted this analysis, I found that as $RAWDIV_{BRAND}$ increased, AS_{BRAND} significantly increased (see Table 3.7). Additionally, as $RAWDIV_{CAUSE}$ increased, AS_{CAUSE} significantly increased only for American Heart Association (see Table 3.7). For the four results that were significant, the effect size ranges were extremely low ($R^2 = .02–.07$). The low effect sizes suggest that these results are not of practical significance, and statistical significance was not found across all brands/causes. Thus, hypotheses 2a and 2b were not supported when conducting this raw word divergence validation check.

Table 3.7: Predicting Attitude Strength with Raw Word Divergence

Brand/Cause	Variables	B	SE B	t	p	R^2
Fitbit (N=170)	Constant	4.87	.87	5.60	.00	.04
	$RAWDIV_{BRAND}$	.44	.16	2.85	.00	
Royal Caribbean (N=170)	Constant	2.89	.98	2.94	.00	.06
	$RAWDIV_{BRAND}$	.56	.16	3.52	.00	
Wyndham Hotels (N=170)	Constant	1.56	1.15	1.36	.18	.07
	$RAWDIV_{BRAND}$	.66	.18	3.63	.00	
American Heart Association (N=170)	Constant	7.34	.60	12.37	.00	.02
	$RAWDIV_{CAUSE}$	.23	.11	2.15	.03	

Table 3.7 (cont.)

Brand/Cause	Variables	B	SE B	t	P	R^2
World Wildlife Fund (N=170)	Constant	6.80	.84	8.08	.00	.01
	RAWDIV$_{CAUSE}$	.24	.15	1.65	.10	
National Rifle Association (N=170)	Constant	7.17	.90	7.95	.00	-.01
	RAWDIV$_{CAUSE}$	.02	.16	.11	.92	

DV – AS$_{BRAND}$ or AS$_{CAUSE}$

GENERAL DISCUSSION AND CONSIDERATIONS FOR SOCIAL MEDIA ANALYTICS RESEARCH

My guiding research question for this study was figuring out how I could use balance theory to discover new ways to measure strength of attitudes towards brands and towards causes that participate (or will participate) in cause-related marketing partnerships. I was able to use principles of dyadic balance theory, homophily, and attitude strength measured via topics of discussion, to predict the strength of attitudes towards brands and causes within CRM partnerships using a survey-based approach. When I asked participants to report their perceived similarity of topical conversation with a brand (SURVEYSIM$_{BRAND}$), I found evidence that this predicted the strength of participant's self-reported attitude towards the brand (AS$_{BRAND}$) across all three brands (supporting hypothesis 1a). When I asked participants to report their perceived similarity of topical conversation with a cause (SURVEYSIM$_{CAUSE}$), I found evidence that this predicted the strength of participants' self-reported attitude towards the cause (AS$_{CAUSE}$) across all three causes (supporting hypothesis 1b). This is an important contribution to cause-related practitioners and advertisers, as this provides an indirect way to assess the strength of

consumers' attitudes towards brands and/or causes. Due to being an indirect survey measure, it has the potential to help in overcoming social desirability bias or self-deception bias than when just asking for attitude strength directly.

One issue with the results from hypotheses 1a and 1b was the low R^2 values for WWF ($R^2=.04$) and NRA ($R^2=.03$). A potential reason for such low fit for these two organizations is the possibility that these two organizations may have a stronger potential to suffer from social desirability bias compared to all the other organizations in my study. The issues of climate change and gun ownership have proven to be very divisive issues in America (Funk, 2016; Parker, 2017), and this could have affected some participants' responses to the attitude strength question of, "How strong is your attitude toward the World Wildlife Fund (or the National Rifle Association)?" This would then affect the linear fit (R^2) between attitude strength measured directly and attitude strength measured indirectly. If this was the case, future CRM studies that measure the strength of attitudes towards brands and towards causes could benefit from adopting this study's indirect measure of attitude strength for brands and for causes.

When I assessed the computational topical conversation divergence between participants' Twitter feeds and the Twitter feeds of brands (TWEETDIV$_{BRAND}$) and causes (TWEETDIV$_{CAUSE}$), this did not predict participants' self-reported attitude strengths (AS$_{BRAND}$ and AS$_{CAUSE}$ respectively; hypotheses 2a and 2b). I will now dig a bit deeper into the results of hypotheses 2a and 2b within the following sections, with an additional focus on outlining some considerations when comparing a social media analytics approach to a survey approach. More specifically, I present some of the issues that can arise from automated analysis of social media data when forecasting psychological constructs, such as attitude strength. I provide additional analyses from the data within this study to address some of the issues within this study, as well

as provide commentary on how to potentially address issues that could not be investigated further within this study's current dataset.

Consideration #1: Nuances of Survey Measure Wording Affecting Computational Analysis Comparisons

There could be many reasons why hypotheses 2a and 2b were not supported, but one reason could have been due to a discrepancy between what topics participants believed that a brand (or cause) talked about, versus what that brand (or cause) actually talks about on Twitter. For example, when a participant was asked, "The topics that Fitbit would talk about are consistent with the topics that I talk about," they could have assumed that Fitbit talks about vacations, and then assessed that they were very similar in conversational topics with Fitbit because they also talked a lot about vacations. This could have caused an issue with the computational analysis of topics, because Fitbit's Twitter does not mention the topic of vacations, and therefore a participants self-reported topic similarity with Fitbit would be fundamentally different than their Twitter topic similarity with Fitbit. Due to this potential discrepancy, I investigated this in greater detail with my validity checks on participants' thought listings of topics for each brand and cause. As shown in Appendix 2, I asked each participant to list what topics they believed each brand and cause would talk about (up to 12 topics, with 1 minimum topic listed). I then recruited three full-time employees from a large Midwestern university to help code my data. I presented each coder with what topics a participant thought a brand (or cause) would talk about, and what topics the Text Razor Topic Tagging engine produced for the Twitter timeline of the brand (or cause). An example can be found in Table 3.8.

Table 3.8: Thought-Listing Coding Example of Fitbit

Participant's Thought-Listing of What Topics Fitbit Discusses	Text Razor's Topic Tagging of Topics from Fitbit's Twitter Feed
Fitness, being healthy, exercise, sleep, workout routines, tracking your activities	Fitbit, Smartwatch, Motivation, Physical exercise, Physical fitness, Health, Weight loss, Dieting, Relaxation (psychology), Sleep, Personal trainer

I wanted to assess how similar participants' perceptions of what topics each brand and causes talks about is to what Text Razor's Topic Tagging model pulled out of each brand or cause's Twitter feed. I had each coder rate the self-report to Text Razor similarity ($CODERSIM_{BRAND}$ and $CODERSIM_{CAUSE}$) across the two cells (e.g., the two cells in Table 3.3) on a scale of -2, -1, +1, and +2. I met with all the coders to discuss each rating, and we came to a consensus that +2 would be when the stemmed form of a word (e.g., walking to walk) or more was in both cells, +1 would be that no words are shared between cells but the topics are very related to one another, -1 would be that the topics are very distantly related to one another, and -2 would be that there is absolutely no relationship between the two cells. After coding, inter-rater reliability was assessed using a two-way, absolute agreement, average-measures intra-class correlation (ICC) (McGraw & Wong, 1996) to assess the agreement between coders. The resulting ICCs were in the excellent range for Fitbit ($ICC_{CODERSIM\_BRAND}$=.93), American Heart Association ($ICC_{CODERSIM\_CAUSE}$=.84), World Wildlife Fund ($ICC_{CODERSIM\_CAUSE}$=.82), and the National Rifle Association ($ICC_{CODERSIM\_CAUSE}$=.78) according to Cicchetti (1994). Royal Caribbean ($ICC_{CODERSIM\_BRAND}$=.46) and Wyndham Hotels ($ICC_{CODERSIM\_BRAND}$=.57) were in the fair range according to Cicchetti (1994). When discussing with the coders as to what might have caused problems with Royal Caribbean, they indicated that the topic of "emergency evacuation" on Royal Caribbean's Twitter timeline caused some confusion (see Appendix 3). With regards to

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Wyndham Hotels, Wyndham's Twitter timeline only produced one topic via Text Razor's Topic Tagging tool: Tourism. Since coders only had one topic to compare against, they stated that it was much more of a subjective call when comparing this one topic against all the topics that the participants listed.

To gain more insights into the issues with Royal Caribbean and Wyndham's Twitter timelines, I conducted a term frequency analysis of their timelines. After Twitter tokenization with NLTK TweetTokenizer (Loper & Bird, 2002) and stop word removal, the top fifty term frequencies are represented in Table 3.9.

Table 3.9: Top Fifty Terms for Royal Caribbean and Wyndham Hotels

Brand	Top Fifty Terms
Royal Caribbean	('hi', 753), ("we're", 487), ('sorry', 423), ('please', 405), ('us', 403), ('sailing', 367), ('changes', 348), ('hey', 347), ("we'll", 343), ('info', 293), ('updates', 228), ('time', 222), ("i'm", 214), ('onboard', 206), ('dm', 196), ('welcome', 193), ('stay', 179), ('guests', 175), ('booking', 173), ('still', 171), ('made', 169), ('thanks', 159), ('tuned', 153), ('soon', 152), ('cruise', 146), ('make', 145), ('know', 139), ('update', 134), ('help', 131), ('zack', 128), ('hear', 124), ('visit', 123), (':)', 120), ('look', 118), ('see', 116), ('kiki', 116), ('monitoring', 112), ('nat', 110), ('keep', 107), ('check', 106), ('understand', 106), ('ana', 104), ('working', 104), ('storm', 104), ('itinerary', 103), ('sure', 102), ('sail', 100), ('like', 99), ('website', 97), ('let', 94)
Wyndham	('please', 131), ('sorry', 127), ('hear', 119), ('colleagues', 104), ('assist', 91), ('experience', 84), ('@whgsupport', 80), ('us', 71), ('may', 68), ('contact', 62), ('email', 60), ('whgcustomercare@wyn.com', 58), ('dm', 55), ('apologize', 48), ('assistance', 45), ('concerns', 43), ('matter', 41), ('whgsupport', 37), ('contacting', 36), ('concern', 24), ('issue', 23), ('situation', 21), ('wyndham', 14), ('friends', 13), ('aware', 12), ('troubling', 12), ('know', 12), ('taking', 12), ('seriously', 12), ('investigating', 12), ('owner', 12), ('@wyndhamchamp', 12), ('@wyndham', 12), ('would', 11), ('look', 11), ('#wyndhamchamp', 11), ('sure', 10), ('hotel', 9), ('love', 8), ("i'm", 8), ('able', 7), ('help', 6), ('community', 6), ('w', 6), ('@whg_news', 6), ('support', 5), ('happy', 5), ('local', 5), ('ceo', 5), ('hospitality', 5)

During the time period of my Twitter timeline collection, Hurricane Harvey forced Royal Caribbean and other cruise lines to cancel their cruises (Young, 2017). Thus, this is likely why the topic of "emergency evacuation" was found in the Text Razor topic list of Royal Caribbean

(see Appendix 3), and why many of the terms that are frequently appearing for Royal Caribbean in Table 3.9 have to do with an emergency (e.g., monitoring, changes, updates, sorry). With regards to Wyndham, there were many terms shown in Table 3.9 indicating that Wyndham is using their Twitter timeline primarily for customer service complaints (e.g., sorry, heart, assist, experience, aware, troubling, investigating, etc.). Upon deeper analysis of Wyndham's tweets from my collection period, one of the most prevalent tweets is the following tweet (although it is modified slightly for each response): "We apologize for your experience. Please contact our colleagues @WHGSupport so they may assist you with your concerns." Therefore, Text Razor's topic tagging engine most likely did not have enough unique tweets to work with, which probably contributed to Wyndham having only the one Text Razor topic tag of "tourism". Additionally, Text Razor has stated that their topic tagging is derived from data taken from Wikipedia, which poses an issue for a topic such as customer service. If Text Razor is using the descriptions of Wikipedia entries to predict the Wikipedia entry name via machine learning, topics such as customer service would not come up in a topic tagging assessment of a social media feed. This is due to the fact that the Wikipedia entry for customer service describes what customer service is, but it does not give examples of how organizations apply customer service conversationally on social media.

The averages and standard deviations (in parentheses) of the coder ratings for the brands and the causes were $M_{CODERSIM\_BRAND}$=1.52 (1.17) for Fitbit, $M_{CODERSIM\_CAUSE}$=1.68 (0.95) for AHA, $M_{CODERSIM\_BRAND}$=0.24 (1.13) for Royal Caribbean, $M_{CODERSIM\_CAUSE}$=1.54 (0.94) for WWF, $M_{CODERSIM\_BRAND}$=-0.13 (1.13) for Wyndham Hotels, and $M_{CODERSIM\_CAUSE}$=1.48 (1.16) for the National Rifle Association. For all of the brands and causes that had excellent ICCs, they had averages that were $M_{CODERSIM}$=1.48 or higher, which means that what participants believed a

brand/cause would talk about were quite close to the topics that Text Razor's Topic Tagging model found on the brand/cause Twitter timelines. This functioned as an important validation step between participants' survey assessment of their topics of conversation as compared to a brand (or cause).

As one additional follow-up to the topic of emergency evaluation causing confusion with Royal Caribbean, I looked at what would happen to my attitude strength prediction results from hypothesis 2 if I removed the emergency evacuation topic from the Text Razor topic output. Even with the emergency evacuation topic removed, TWEETDIV$_{BRAND}$ still did not predict AS$_{BRAND}$ (see Table 3.10).

Table 3.10: Predicting Attitude Strength with Computational Topic Divergence

Brand/Cause	Variables	B	SE B	t	p	R^2
Royal Caribbean (N=170)	Constant	6.70	.85	7.90	.00	.00
	RAWDIV$_{CAUSE}$	-.09	.17	-.53	.60	

DV – AS$_{BRAND}$

Thus, in general, participants were assessing correctly as to what topics brands and causes were actually talking about. At the same time, I show that comparing and contrasting a survey approach against social media analytics approach should not be treated lightly. Additional validation steps should be taken to make sure that researchers are measuring appropriately across the two approaches. I share a few more insights on limitations of my comparison of attitude strength across the survey and social media results in the limitations section.

Consideration #2: Accuracy of Computational Topic Detection on Social Media Data

Another consideration that I entertained was whether or not computational topic tagging is accurate enough to conduct this study's analysis. Since there is an extensive body of knowledge that deals with a structured human assessment of content called content analysis (e.g., Harwood & Garry, 2003; Krippendorff, 2012; Skalski, Neuendorf, & Cajigas, 2017), I wanted to see how Text Razor's topic tagging analysis compared to the gold-standard of human content analysis. Thus, I conducted two phases of content analysis reviews of the social media data from this study.

First, I recruited two full-time employees from a large Midwestern university to conduct the content analyses, with myself functioning as the facilitator. The first content analysis phase was an effort to decide on which topics should be included in the set of topics that they would look for when reviewing the Twitter timelines for the brands and the causes. I adopted a provisional coding approach (Saldaña, 2009), which begins a coding process with a "start-list" of potential codes to start with prior to coding. My start-list was taken from the survey responses in which I asked each participant to list what topics they believed each brand and cause would talk about (up to 12 topics, with 1 minimum topic listed; see Appendix 2). After reviewing the suggested topics across all the brands and causes, I found enough consistency in responses between the following topics: Business Travel, Charitable Giving, Climate Change, Cruises, Customer Service, Diet, Environmentalism, Exercise, Fashion, Firearms, Gun Politics, Gun Violence, Health, Heart, Hotels, Hunting, Marketing, Medicine, Nature, Oceans, Religion, Sports, Technology, Vacations, Weather, and Wildlife. I then presented each coder with the Twitter timelines from the three brands (Fitbit, Royal Caribbean, and Wyndham Hotels) and the three causes (AHA, WWF, and NRA) separately as HTML web pages. Upon discussion, the

coders suggested that 100-150 tweets were as much as they could process visually and cognitively when attempting to look for topics being discussed, so I ran a random selection script to choose 150 tweets from each brand and each cause to be presented as separate HTML pages. The coders reviewed each Twitter timeline and indicated on a separate spreadsheet as to what topics they believed were being discussed from the previously constructed start-list of topics. They also were given the opportunity to write in suggestions of other topics being discussed that were not covered by the provided start-list of topics. Upon completion of this coding task, I ran a reliability analysis and found substantial agreement (κ=.70) between the two coders according to Viera and Garrett (2005). Additionally, after discussion of potential topics that were not part of the original start-list, the coders came to a joint conclusion that the start-list was comprehensive enough of a list without any necessary topics missing. They did indicate though that two topics from the start-list did not seem to be discussed across the three brands and the three causes, namely the topics of Business Travel and Religion. Thus, I removed those two topics from consideration for the next phase of coding.

When analyzing this first phase of coding, one of the most apparent discrepancies was between Text Razor's topic tagging of Wyndham's Twitter timeline and a human coded topic coding of Wyndham's Twitter timeline. Text Razor's topic tagging of Wyndham's timeline only produced the topic of "Tourism", whereas a human topic coding exercise of that same timeline produced the topics: Charitable Giving, Customer Service, Environmentalism, Health, Hotels, Marketing, Technology, and Vacations. Although Text Razor does not give details as to how their topic tagging was built, they do mention that they use "millions of Wikipedia pages" to assign "hundreds of thousands of different topics at different levels of abstraction" ("TextRazor - The Natural Language Processing API," n.d.). Judging from this description, they are using a

supervised machine-learned classification approach (Kotsiantis, 2007) in which they use

Wikipedia page titles as the name of the topic (e.g., Customer Service), and the page body as the

training data for that topic (e.g., for customer service,

https://en.wikipedia.org/wiki/Customer_service). One of the biggest indicators of this is the fact

that when Text Razor's topic tagging API reviewed the Twitter timeline for Wyndham, it only

returned the topic of "Tourism", but not the topic of "Customer Service". As seen in Table 3.9

though, Wyndham clearly uses much of their Twitter account for customer service. The reason

why Text Razor did not pick that topic up, and the reason why I suspect that they are using a

supervised machine-learned approach to classify topics through the content of Wikipedia pages,

is because Wikipedia's entry on "Customer Service" describes customer service only, rather than

also providing examples of people providing actual service to customers. This is clearly a major

pitfall to using social media analytics, especially with regards to black-box machine-learned

models, as this provides more evidence that it is very important to know how a machine-learned

model was trained and built. In this case, a human coded topic analysis was dramatically

different than the machine-learned model.

For the second phase of content analysis, I presented the same two coders from the first

phase with separate HTML pages for each of the 170 Twitter timelines from the participants

from this study. I ran a random selection script to choose 150 tweets from each timeline when

constructing the HTML pages, which was in line with what the coders had indicated that they

could handle visually and cognitively in the previous coding phase. The coders reviewed each

HTML page of participants' tweets and marked as many topics as they could determine were

being discussed from the topic list that was created from the previous coding phase. After

running reliability analysis, I found that their coding had moderate agreement (κ=.42) according

to Viera and Garrett (2005). This was not enough agreement to run additional analyses, but the disagreement brings about important insights. I went through extensive training with both coders in the first phase where we walked through how they would process what a topic is and what a topic isn't, and they achieved substantial agreement in phase one when analyzing brand and cause Twitter feeds. With this said, when they analyzed users' Twitter timelines, they found it much more difficult to code topics for these timelines. Interestingly, when I discussed with the coders as to which Twitter timelines were problematic, there was a mix of agreement and disagreement. They both agreed that timelines that were mostly in different languages should be removed from analysis, but they disagreed as to what level of photo to word ratio, English to other language ratio, or marketing to personal posts ratio was acceptable. This is yet another example of how "black-box" computational models really veil some complicated issues with the underlying data.

As a final point to this consideration, I wanted to address why I did not use traditional topic modeling (Blei, 2012; Blei et al., 2003) in this study. Topic modeling was originally developed to summarize a large corpus of documents, to provide a quick way to summarize what the documents were about (Blei et al., 2003). Thus, topic modeling assumed that there were many documents within a corpus, and each document had many words. The problem with applying topic modeling to Twitter is the question of what you consider a document. If you decide to consider each tweet a document, then there is not enough data within a tweet to adequately work to what topic modeling was originally conceptualized for. More recent topic modeling methods created specifically for Twitter have attempted to work around this limitation through various strategies, such as considering each conversation string between Twitter users as separate documents (Alvarez-Melis & Saveski, 2016), considering all the tweets that mention the

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same hashtag as a document (Mehrotra, Sanner, Buntine, & Xie, 2013), or considering all the tweets from the same author as a document (Hong & Davison, 2010).

Hong and Davison's (2010) strategy may seem like an appropriate method for this study, but the next issue is that traditional topic modeling does not actually output topics, but rather outputs words from the documents that are related to one another (e.g., instead of outputting a topic such as "environment", a topic modeling exercise would output a grouping of words such as: tree, climate change, oceans, green). A researcher must then code those topics, which is not a trivial task, and proper coding of topics should be based on theoretical knowledge and context-specific expertise (Humphreys & Wang, 2018; Saldaña, 2009). In some senses, this nullifies the allure of social media analytics, as part of the reason why a researcher may look to a social media analytics method is so that prior coding and training work from experts could be leveraged in a fully automatic way (without the need for intensive human coding). In fact, I would argue that running traditional topic modeling on social media data is actually not much different than running traditional content analysis of manually coding topics with human coders, with the additional help of grouping words that seem similar to one another. With this said, even the additional help of computationally grouping words together may also be erroneous in the case of this current study. This is due to the fact that the topics I am interested in would be the topics from my three brands and three causes, which using Hong and Davison's (2010) strategy would produce just six documents. Topic modeling was created based on the need to parse through thousands, if not millions, of documents rather than just six.

Thus, I chose to use a previously trained machine-learned model that has been trained on millions of topics and that can be used in a fully automatic fashion. Looking at my results from the human coding of topics, I can see that there is potential for danger with using these fully-

automated social media analytics models. The majority of these machine-learned topic discovery models do not have published articles explaining the inner-workings of the training of the models (e.g., "Classification by Taxonomy · Text Analysis API | Documentation," n.d.; "TextRazor - The Natural Language Processing API," n.d.; "Thomson Reuters | Open Calais," n.d.), but even the ones that do have articles associated with them do not actually publish the machine-learned model itself (which could be done as a Python pickle file) or any of the data used to train the model (e.g., Quercia, Askham, & Crowcroft, 2012).

Therefore, researchers and practitioners should be very cautious when running social media analytics methods such as topic discovery. It may still be the case that human coding is the best way to go about topic discovery in many cases. On the computational side, I have also shown evidence as to why we need more computational models where the details on the training of the model, as well as the model itself, is published. I would suggest that researchers should also consider publishing the data used to build the machine-learned models, but there are additional concerns with that practice, namely in the areas of privacy, data ethics, and social media platform terms of service. One example of a machine-learned model that has both sufficient published details of the training of the model, and the model itself is published, is IBM's Personality Insights model (Arnoux et al., 2017).

Consideration #3: Differences in Results Depending on Social Media Platform

There are clearly numerous other potential reasons why my social media analytics approach to predicting attitude strength did not work. One obvious reason is that maybe a social media analytics approach is not a viable way to measure attitude strength, but this conclusion seems a bit premature due to the vast landscape of additional social media platforms and topic tools that are available. In light of this, one of my limitations could have been that Twitter may

not be the optimal social media platform for this kind of analysis. Rosenstiel et al. (2015) surveyed 4,713 social media users, and found that 90% of Twitter users in the survey said that they used Twitter for reading and sharing news. Only 30% of those Twitter users stated that they used Twitter to tell others what they were doing and what they were thinking about. This could be a major reason why my social media analytics approach did not work, as only certain topics are being discussed in the news at any given time. Thus, a topic tagging tool running on Twitter timelines would pick up only a small set of topics being discussed in the news. Future research should consider using other social media platforms (e.g., Facebook, Reddit, Tumblr, etc.) in which people may talk about a wider range of topics.

In line with the consideration of differences across social media platforms, previous research has looked at how individuals interact with brands via various social media platforms. Smith, Fischer, and Yongjian (2012) analyzed brand-related user-generated posts (UGC) across Twitter, Facebook, and YouTube, and found that Twitter hosted the most percentage of posts in which brands were the focus of the UGC (76% of all brand-related UGC, as opposed to 66% for Facebook, and 42% for YouTube). Studies like this provide additional evidence that people operate differently depending on the social media platform that they are using, and thus one platform may be more appropriate for certain computational methods, whereas others may not. This is both an important consideration for researchers, as well as an open-area of research with regards to testing to see what methods are appropriate for which platforms.

Consideration #4: Lack of A-Priori Hypotheses in Previous Machine-Learned Social Media Studies

This potential inability to use Twitter for the analysis of individuals' full topics of conversation also brings about a deeper question for research using social media data. Social

science studies that deal with social media generally fall into three camps: studies that ask

participants to self-report about their behavior on social media platforms (e.g., Blackwell,

Leaman, Tramposch, Osborne, & Liss, 2017; Marshall, Lefringhausen, & Ferenczi, 2015;

Tandoc, Ferrucci, & Duffy, 2015), studies that analyze actual social media data directly (e.g., K.-

J. Chen, Lin, Choi, & Hahm, 2015; Leskovec et al., 2010b; Ranganath, Morstatter, Hu, Tang, &

Liu, 2015; Zhang, Bhattacharyya, & Ram, 2016), and studies that bridge between some form of

self-reported data and correlating this data with actual social media data (e.g., J. Chen et al.,

2014; Golbeck et al., 2011; Markovikj, Gievska, Kosinski, & Stillwell, 2013; Park et al., 2015;

Youyou, Kosinski, & Stillwell, 2015; Youyou et al., 2017). For the studies that ask participants

to self-report about their social media usage, a critique of this research is that self-reported social

media behavior and observed social media behavior could be different. The studies that directly

analyze social media data solely could be criticized for different reasons, such as not knowing if

accounts are bots, or not really understanding what deeper psychological markers could be

driving any observed effects. Therefore, it seems that a combined approach that has participants

both fill out a survey and give access to their social media data could be an ideal way to conduct

research within the realm of social media. Part of this assumption is that social psychological

measures that are self-reported should be detectable via online social media data. Previous

research seems to show that this is possible, as there has been much research conducted that

looks at correlating participants' self-reported personality tests with what words they use on

social media (e.g. Arnoux et al., 2017; Golbeck et al., 2011; Kern et al., 2014; Schwartz et al.,

2013). With this said, in all of these previous research studies, personality scores were first

calculated by self-reported personality tests, and then machine-learning was used to correlate

whatever words could be correlated to various personality score combinations to build a

predictive model. There was no prediction prior to building the machine-learned model as to which words would correlate with what personality dimensions; whereas in this study, I had a specific hypothesis that the divergence score of topics of conversation would predict one self-reported social psychological measure (attitude strength). Future research should look into this discrepancy, especially to see if there are certain ways or directions in which a survey-based approach does or does not work when correlated against social media data.

Consideration #5: Potential Differences in Self-Presentation on Social Media

Finally, one of the more fundamental questions when comparing social media data to self-reported psychological assessments is whether or not people present themselves on social media in the same way that they would present themselves in everyday offline settings. An assumption of my study, as well as previous studies correlating self-reported psychological measures and social media behavior (e.g. Arnoux et al., 2017; Golbeck et al., 2011; Kern et al., 2014; Schwartz et al., 2013), is that people present themselves on social media platforms in ways that are approximately close to who they really are in offline settings. Hogan (2010) refers to the interesting dilemma that social media brings when considering the platform in light of Goffman's (1959) dramaturgical approach in which Goffman suggests that an individual presents himself/herself in an idealized way when appearing "front stage" to certain audiences, and yet showing their true selves when appearing "back stage" to another subset of audiences (and/or to their own selves). The dilemma lies in how an individual now conceptualizes what is front stage and back stage within the realm of social media. Marwick and Boyd (2011) took this one step further and suggested that figuring out who is actually watching (the audience) becomes increasingly confusing on social media platforms. They directly surveyed 226 Twitter users by directly @mentioning them, asking them questions such as: Who do you imagine reading your

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tweets? Who do you tweet to? What they found was that peoples' perceptions as to who their actual audience was on Twitter varied widely even though all the individuals had fully public facing Twitter accounts. Thus, a platform like Twitter could be an environment where people may be presenting a different self than they would normally present, and this could present issues when correlating a private self-report measurement of psychological measures to a public-facing social media platform. Future research should consider the potential differences in how people present themselves online, and how that may affect the types of consumer research we could reliably conduct using social media analytics.

LIMITATIONS

Survey Measures for Topic Similarity and Attitude Strength

Although I found support for conversation topic similarities predicting attitude strengths via an indirect survey measure, there are limitations to this measurement for conversation topic similarity. The specific survey question regarding conversation topic similarity was as follows, "The topics that Royal Caribbean International would talk about are consistent with the topics that I talk about" (Royal Caribbean example). As far as I know, attitude strength with CRM has not previously been measured via similarity, thus I had to make a decision as to how to word this measure. I chose this "consistency" wording because I believed that it was a more natural way to ask this question, but research has shown that minor changes in how questions are worded can substantially affect results (Schwarz, 1999). Therefore, the word "similarity" could possibly have provided different results than the word "consistency". Additionally, I did not ask them to consider arenas of discussion, as people may talk about certain topics at work, but other topics at home. Future studies should consider how changing the wording of the measure affects outcomes.

Another potential limitation to my dissertation is the way that I measured attitude strength. I measure attitude strength by asking, "How strong is your attitude toward Royal Caribbean International?" (Royal Caribbean example; adapted from Bassili, 1996). Although this was not an incorrect way to measure attitude strength, research has shown that there are numerous different ways to measure attitude strength (e.g., attitude accessibility, attitude importance; Petty & Krosnick, 1995). While many measures of attitude strength correlate with one another, they each have been shown to represent different dimensions of attitude strength (Krosnick et al., 1993). Therefore, adding additional measures of attitude strength could have given me broader insight into its effects within CRM partnerships. We have evidence that another way to measure attitude strength is through response latency (Bassili, 1996), in which attitude strength has been reliably assessed by how quickly an individual responds to a question about their attitude towards a topic. For future research, attitude strength could be assessed by taking various self-reported survey measures of attitude strength, while also recording the response latency for each participant towards those questions. With this said, previous research has shown that the validity of response latency measurement for attitude strength measurement depends on how sensitive the mechanism is that picks up the time latencies (Bassili & Fletcher, 1991). This kind of response latency measurement would likely require surveys administered in a physical lab setting with computers that have very precise software installed for measuring response latency, such as DirectRT (Jarvis, 2016).

Frequency of Topics Beings Discussed

Another limitation of my study was that my method of computationally comparing topic similarity (divergence) to predict attitude strength was based simply on whether that topic was being discussed or not on a Twitter timeline. It did not account for the amount a topic was being

discussed on a Twitter timeline, which is a portion of Krosnick et al.'s (1993) findings on topic conversation predicting attitude strength. Machine-learned topic tagging does not currently count occurrences that a topic is being discussed in a body of text, but rather probabilities. With this said, future research could consider running topic tagging on smaller segments of social media feeds to get at an approximation of the frequency of the topics being discussed, but this would require filtering feeds that are much closer in number of posts to one another. Thus, this could have contributed to the lack of findings for hypotheses 2a and 2b.

Survey-Based Topic Similarity Measurement

Another consideration that was not brought up within Chapter 3 was the possibility that I was not comparing apples to apples when it came to comparing my indirect survey-based measure of attitude strength with a social media analytics approach. Maybe a more appropriate comparison would have been to ask each participant what topics they talk about as well as ask them what topics they believed a brand (or cause) talks about. Then I could have run a similar topic similarity (or divergence) comparison between the two to see if that correlates with the surveyed attitude strength as my base case. Another possibility would be to ask participants what topics of discussion would be in common with a brand (or cause), and what topics of discussion would be not in common with a brand (or cause). The ratio of common to not common could potentially be another way that is closer in comparison to the social media analytics approach. This is another avenue for future research in this area.

<div align="center">

CONCLUSION

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In this day and age where CRM partnerships are being actively discussed and debated on social media, cause-related advertisers and practitioners should benefit from understanding various ways in which attitude strength towards brands and causes can be measured. I provided

an indirect survey-based measure in which attitude strength could be measured towards brands and towards causes, but I was not able to prove out a social media analytics approach to detecting attitude strength towards brands and towards causes on social media. I also brought to light deeper considerations when conducting research across self-reported surveys and actual social media data. As social media environments become more and more segmented by various affiliations and beliefs, even beyond CRM debates, the search for how to detect attitude strength on social platforms becomes ever more important.

CHAPTER 4: GENERAL DISCUSSION AND CONCLUDING REMARKS

GENERAL DISCUSSION

CRM Compatibility Predictions by Attitudinal Bias

The focus of this dissertation was to understand how balance theory can help to give us deeper insight into CRM compatibility, as well as to analyze how CRM compatibility could also further our understanding of balance theory. One of my most important findings was that CRM compatibility can be predicted via consumers' attitudes towards brands, alongside their attitudes towards causes. Simmons and Becker-Olsen (2006) wrote that, "Compatibility between a firm and a sponsored cause is high when the two are perceived as congruent (i.e., as going together), whether that congruity is derived from mission, products, markets, technologies, attributes, brand concepts, or any other key association" (p. 155). With regards to the examples that they list, they are suggesting that consumers' assessments of congruence are based on some sort of logical comparison of metrics between the partnering organizations. What I found suggests that CRM compatibility is not just based on logical comparisons of key congruence metrics between a brand and a cause (if at all), but rather simply on separate subjective attitudes towards brands and towards causes. This is not that surprising, as previous research in human decision making has shown that people are prone to using biases in judgments rather than objective reasoning (Lord, Ross, & Lepper, 1979). Many times, we may be unaware that this is happening cognitively. In fact, Nisbett and Wilson (1977) showed that when people were asked to report on why we responded to things in a certain way, they were incredibly poor in accurately assessing what drove their responses. By understanding that we could assess consumers' perceptions of CRM compatibility by measuring their attitudes towards a brand, alongside their attitude towards a

cause, this opens up the possibility of predicting how consumers would perceive CRM compatibility between a brand and a cause before they actually enter into a CRM partnership. CRM practitioners and advertisers could measure attitudes towards brands and towards causes first, and then make a decision as to whether or not certain brands should partner with certain causes.

This gives further evidence then that CRM practitioners and advertisers should not rely largely on logical comparisons of brands and causes when considering future partnerships. Rather, they should be very concerned about general attitudes that people have towards brands and causes prior to entering into any form of CRM partnership. One consideration for CRM practitioners and advertisers could be that much work would still need to be done to increase consumers' attitudes towards a brand, as well as their attitudes towards a cause, prior to entering into a CRM partnership. In fact, it may be appropriate to include this stage as part of the overall timeline of the CRM partnership timeline and strategy. If consumers' attitudes cannot be changed positively prior to the partnership being publicly advertised, it may be wise to discontinue (or modify) the plans to partner.

Using Attitude Strength within Balance Theory

Attitude strength has not been considered previously within balance theory, and this is the first series of studies to consider attitude strength when predicting perceived CRM compatibility within CRM triads. Previous studies that found balance theory to hold in real world data (e.g., Leskovec et al., 2010a, 2010b) only looked at dichotomous attitude values (+1 or -1), but I focused on considering attitudes as continuous values within this dissertation. When only continuous measures of attitude towards the brand and towards the cause were considered, I was only able to predict whether or not CRM triads would be balanced in two out of the three CRM

partnerships within Chapter 2. Attitude strength has been shown to predict psychological movement better than measures of attitude alone (Petty & Krosnick, 1995), and balance theory is conceptually based on the prediction of psychological movement. Therefore, when I included continuous measures of attitude strength within the calculations of balance in CRM triads, I was able to predict balance for all three CRM partnerships. A consideration for future research could be that adding attitude strength to balance theory beyond CRM research may also show benefit to models of balance prediction. In fact, a recent review of attitude strength suggested that attitude strength may play a role in balance theory (Howe & Krosnick, 2017). With regards to the realm of CRM research, I have provided evidence that future studies should consider adding attitude strength when considering perceived CRM compatibility.

Spillover of Attitude within CRM Partnerships

Another major finding was the discovery that when attitude strength was included in my predictive model, I found evidence across all three partnerships that consumers' attitude towards brands and towards causes were spilling over into one another within CRM evaluations of compatibility. As mentioned earlier, Wyndham Hotels cut ties with the NRA in February 2018, due to consumers' responses to the recent mass shootings in the United States. In fact, one news report showed a Twitter snapshot to emphasize the work that Wyndham was doing to assuage consumers' concerns (Taylor, 2018, see Figure 4.1).

Figure 4.1: Twitter Snapshot from Business Insider Report (Names Blacked Out)
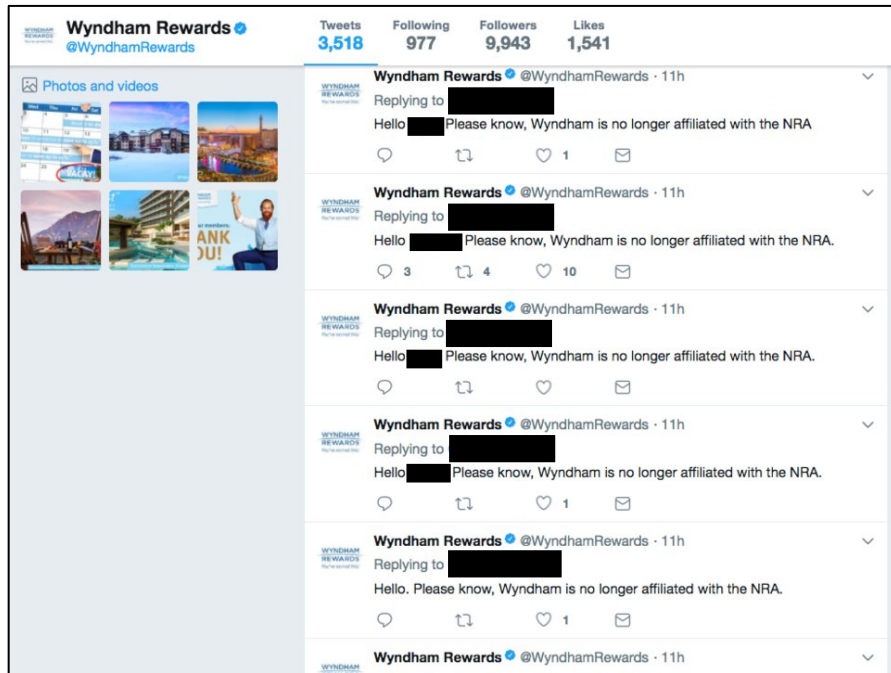
I assume that part of Wyndham's business reason for ending the partnership was that they believed that attitudes towards their brand was being negatively affected by the partnership with the NRA, especially due to all the activity they were receiving from social media users that I can assume have negative attitudes towards the NRA. Looking at the data from my dissertation though, it may not have been that case that attitudes towards Wyndham was being negatively affected by peoples' attitudes towards the NRA. In fact, when I looked at participants who had negative attitudes towards the NRA, I did not find any evidence that those negative attitudes were spilling into the attitudes towards Wyndham (or from Wyndham to the NRA). If I were to look only at the dataset within this dissertation, it seems that Wyndham's decision to end the partnership with the NRA might have been pre-mature. With that said, I considered analyzing the data for WyndhamNRA by looking at those who had positive attitudes towards Wyndham and negative attitudes towards NRA (N=158) and comparing it to those who had negative attitudes towards Wyndham and negative attitudes towards the NRA (N=25), but the sample size of the

latter was far too small to make any sort of statistical conclusions from. Lakens and Evers (2014) suggest that a minimum sample size of N=126 is needed before most statistical conclusions can be made for most social psychology studies. With this said, I already stated in Chapter 2 that I could find no benefit from a well-liked brand partnering with a disliked cause, and therefore it seems that the safest bet is for CRM practitioners and advertisers to stay away from a partnership such as the one between Wyndham and the NRA.

Topic Similarity Scope Changes Since the Dissertation Proposal

My findings on conversation topic similarity predicting attitude strength requires some further explanation as compared to the originally approved dissertation proposal. This dissertation has stayed largely on track with the committee approved dissertation proposal from the spring of 2017. The major change started theoretically within the first study (Chapter 2), as the original proposal suggested that I could also predict perceived compatibility from consumers' conversation topic similarities with a brand, alongside their conversation topic similarities with a cause. This hypothesis suggested that conversation topic similarity could predict both the measures of attitude and attitude strength together at the same time. Upon later consideration, and subsequent conversation with committee members, I realized that the measure of attitude (valence and degree of favor) could not be predicted from conversation topic similarity. I only have evidence that it is attitude strength (not attitude) that can be predicted by what topics an individual talks about, and how often they talk about those topics (Krosnick et al., 1993).

Thus, due to this change, the scope of the second study (Chapter 3) changed. One of the original intentions of the second study was to provide a comprehensive computational prediction model for CRM compatibility using social media data. To do this, I would also need to detect participants' attitudes towards brands and towards causes via a social media analytics approach.

Since one of the focuses of this dissertation was to compare participants' social media data with their surveyed responses, one way to measure participants' attitudes towards brands and towards causes would have been to run feature-based sentiment analysis on participants' social media data. Feature-based sentiment analysis is the measurement of attitude towards words (sometimes called tokens or features in the computational sciences) in a dataset (Eirinaki et al., 2012). The reason why this was not possible for the dataset in this dissertation was due to the fact that I was limited to the social media feeds of the Amazon Turk participants from my studies. To run feature-based sentiment analysis, the participants would have needed to be speaking about the specific brands (Fitbit, Royal Caribbean, and Wyndham Hotels) and the specific causes (American Heart Association, WWF, NRA) within their social media feeds. These brand (or cause) names would have been the features in which feature-based sentiment analysis could have been run on, but not enough participants had these features appearing within their social media feeds.

To illustrate this, I ran an analysis of all N=170 participants' Twitter feeds to see if there was enough mentions of the brands and/or causes to run feature-based sentiment analysis. For each brand and/or cause, I focused on looking for the following words/phrases: Royal Caribbean ('Royal Caribbean', 'RoyalCaribbean'); WWF ('WWF', 'World Wildlife Fund'); Fitbit ('Fitbit'); American Heart Assocation ('American Heart Association', 'AHA', 'AmericanHeart'); Wyndham Hotels ('Wyndham', 'Wyndham Hotels'); NRA ('NRA', 'National Rifle Association'). Across the N=170 participants, only one participant mentioned words related to Royal Caribbean, one participant mentioned words related to WWF, eight participants mentioned words related to Fitbit, seventeen participants mentioned words related to AHA, no participants mentioned words related to Wyndham Hotels, and seventeen participants mentioned

words related to NRA. Thus, even in the best case of having seventeen participants that spoke about the NRA on their Twitter feeds, this would not have been enough to run a regression analysis against self-reported attitudes towards the NRA.

Since I could not predict consumers' attitudes towards the brands and towards the causes within CRM partnerships, I focused on one piece of the predictive model, namely attitude strength. What I found was that although I could predict attitude strength from surveyed conversation topic similarities with brands (or causes), I could not predict attitude strength using a social media analytics approach. This brought about larger questions as to whether or not we can use a hybrid survey to social media analytics approach to answer specifically hypothesized social science questions with social media data. I have evidence that a hybrid approach works when there are no a priori hypotheses of what variables may correlate with a participants' survey responses and their social media data (e.g., Golbeck et al., 2011; Kern et al., 2014; Youyou et al., 2017), but I have less evidence that an a priori hypothesized correlation will work between participants' surveyed responses and their social media data. For this dissertation, I specifically hypothesized that topic similarity between a consumer and a brand (or cause) would predict their surveyed attitude strength. Although this was supported via an indirect survey measure, it was not supported via a social media analytics approach.

Prediction of Attitude Strengths via Topic Similarities

Part of the focus of this dissertation was to find new ways to measure attitude strength within CRM partnerships, and I found that participants' self-report of their perceived similarity of topical conversation with a brand (or a cause) was an indirect way to measure their self-reported attitude strength towards that brand (or that cause) when using a survey method. Conversation topic similarity may be a way for CRM practitioners to assess attitude strength more discretely towards brands and causes prior to entering into a CRM partnership, and this novel method could potentially suffer less from social desirability bias and self-deception bias concerns when using a survey to measure attitude strength.

Future Research on CRM Partnerships with Social Media Data

Moving forward, there is great potential for additional insights for CRM partnerships via social media data, including the following considerations.

Sentiment analysis for assessing separate attitudes towards brands and causes. In future studies, if a larger sample of participants that mention brands/causes directly on their social media feeds could be acquired, I could run sentiment analyses towards these brands and causes. Another strategy could be to find social media users that are talking about brands and causes within their feeds, and directly asking them if they would like to take a survey of their attitudes and attitude strengths towards those brands and causes. Drawing from my work on using perceived conversation topic similarity to predict attitude strength, there may be a possibility to detect attitudes towards brands and towards causes by assessing consumers' attitudes towards the topics that are most associated with a brand or a cause. For example, if I look at the topic tagging data from Fitbit's Twitter feed (see Appendix 3 from Chapter 3), I see that one of the topics that Fitbit discusses is physical fitness. If I was able to run sentiment

analysis towards the topic of physical fitness on consumers' Twitter feeds (for the consumers that discuss physical fitness), could this predict their attitude towards Fitbit? As mentioned in Chapter 3, Twitter may not be the best social media platform to assess this, as the breadth of topic discussion may be limited. However, pairing the computational assessment of separate attitudes towards brands and causes with the assessment of separate attitude strengths towards brands and causes could provide the pieces to create a computational predictive model for CRM compatibility using social data.

Computational topic similarity prediction of attitude strength via image analysis. Another consideration for future research would be attempting to predict attitude strength through entity recognition via social media images. Instagram is a social media platform in which each social media post requires the sharing of some sort of image or picture. Amongst 18-24 year old Americans, Instagram is one of the most popular social media platforms today (A. Smith & Anderson, 2018). As individuals share vast numbers of photos and images on Instagram, there is an interesting opportunity to analyze these photos to understand what the individuals are interested in. Advances in machine learning, and specifically deep learning, have produced tools that allow us to analyze image similarity (e.g., van der Walt et al., 2014) and recognize entities (e.g., bicycle, female, dog) within images (e.g., "Amazon Rekognition – Video and Image - AWS," n.d.). Entities that are detected within images could potentially be correlated with topics that the posting individual is interested in. Therefore, I could compare the similarity of entities within images that are shared on brand (or cause) Instagram accounts with the Instagram accounts of consumers to check for a correlation between this similarity and attitude strength. I could also consider a raw image similarity analysis (without the entity recognition) as a baseline analysis between Instagram accounts. This Instagram study could also give me more

insight as to whether correlating social media data with a specifically hypothesized social psychological measure could work.

LIMITATIONS

Neutral Attitudes and Balance Theory

Heider (1958) briefly discussed neutral edges within balance theory, but excluded their consideration in his final models of balance. More recently, Altafini (2012) studied how opinions are formed within structurally balanced networks, and he commented on neutral edges within structural balance by stating, "Also for this more general definition (the one adopted in this paper) structural balance implies a lack of ambiguity in the way each individual classifies each other individual as a friend or as an enemy" (p. 1). Other studies have pointed to the fact that there needs to be further research in considering neutral edges within balance theory (e.g., Antal et al., 2005, 2006), but I could not find any that actually included them in their studies. I did not realize this issue until I was in the data analysis stage of this dissertation, thus the only reasonable decision I could make was to exclude triads that included neutral attitudes from my analyses. At the very least, future studies should consider using an even-numbered scale, as that will obviously prevent anyone from denoting a neutral attitude.

Number of CRM Partnerships Pre-Tested

The four CRM partnerships that I pre-tested were Fitbit and American Heart Association, Royal Caribbean and the World Wildlife Fund, Grey Goose and the National Gay and Lesbian Task Force, and Wyndham Hotels and the National Rifle Association. My aim was to find three partnerships that exhibited, on average, high perceived compatibility, mid-level perceived compatibility, and low perceived compatibility. The three partnerships that I chose were FitbitAHA ($M_{COMP\_PERCEIVED}$=10.11, SD=1.95), RoyalWWF ($M_{COMP\_PERCEIVED}$=6.23, SD=2.68),

and WyndhamNRA ($M_{COMP\_PERCEIVED}$=3.59, SD=2.31). I had made the assumption that amongst the four partnerships being tested, I was going to find the three levels of perceived compatibility, and this was indeed the case. With this said, pre-testing more partnerships would have been the safer route, and would have potentially given me even greater separation between perceived compatibilities. There could have also been the possibility of including a range of perceived compatibilities that spanned across four or more partnerships, although I would have had to consider survey fatigue for the participants at a certain point.

CONCLUDING REMARKS

In this dissertation, I analyzed CRM compatibility through the lens of balance theory both via a survey-based approach, as well as a social media analytics approach. I found evidence that a consumer's attitudes towards a brand, along with their attitudes towards a cause can predict their perceived CRM compatibility, and that attitude and attitude strength can spill over within CRM partnerships. I also showed that attitude strength can be measured indirectly through analyzing perceived conversation topic similarity via a self-reported survey measure. Although this does not give me the final picture that I need to predict CRM compatibility both from a survey-based approach and a social media analytics approach, this dissertation provides numerous steps forward within the realm of CRM research, as well as balance theory research. As far as I know, this was the first series of studies that included attitude strength within balance theory. I also provided insight and subsequent questions into research conducted using a hybridization of a survey-based approach tied to a social media analytics approach. Building on this, I provided some considerations for future research building upon these methods, especially in the context of newer computational techniques to analyze social media data. Lastly, this dissertation provided insights that are beneficial to CRM researchers, practitioners, and

advertisers as we move forward in our efforts to acquire a greater understanding of CRM

partnerships as a whole.

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These questions pertain to Royal Caribbean International. Royal Caribbean International is a for-profit cruise line brand.

How would you rate your attitude towards Royal Caribbean International?

-5 (Extremely negative) -4 -3 -2 -1 0 (Neither negative nor positive) 1 2 3 4 5 (Extremely positive)

How strong is your attitude toward Royal Caribbean International?

1 (Not strong at all) 2 3 4 5 6 7 8 9 10 11 (Extremely strong)

-- page break --

These questions pertain to the World Wildlife Fund for Nature. The World Wildlife Fund for Nature (WWF) is a non-profit organization focused on nature conservation.

How would you rate your attitude towards the World Wildlife Fund for Nature?

-5 (Extremely negative) -4 -3 -2 -1 0 (Neither negative nor positive) 1 2 3 4 5 (Extremely positive)

How strong is your attitude toward World Wildlife Fund for Nature?

1 (Not strong at all) 2 3 4 5 6 7 8 9 10 11(Extremely strong)

-- page break –

In 2016, Royal Caribbean International and the World Wildlife Fund for Nature (WWF) announced a global partnership to support ocean conservation.

How compatible do you think this partnership is between Royal Caribbean and the World Wildlife Fund for Nature?

-5 (Not compatible at all) -4 -3 -2 -1 0 (Neither compatible nor incompatible) 1 2 3 4 5 (Extremely compatible)

-- End of Survey –

APPENDIX B: ADDITIONAL SURVEY QUESTIONS – RC EXAMPLE

Take a moment to think about Royal Caribbean International.

If Royal Caribbean International was a person, what topics do you think Royal Caribbean International would talk about? Please provide up to 12 topics, with a minimum of 1 topic.

Topic 1 _____
Topic 2 _____
Topic 3 _____
Topic 4 _____
Topic 5 _____
Topic 6 _____
Topic 7 _____
Topic 8 _____
Topic 9 _____
Topic 10 _____
Topic 11 _____
Topic 12 _____

Now think about how you see yourself. Once you've done this, indicate your agreement or disagreement with the following statement:

The topics that Royal Caribbean International would talk about are consistent with the topics that I talk about.

-5 (Not consistent at all) -4 -3 -2 -1 0 (Neither negative nor positive) 1 2 3 4 5 (Extremely consistent)

-- after all the CRM questions –

Lastly, please provide your Twitter username below. We will utilize a computational scan that analyzes your Twitter posts to look for things related to the brands mentioned in this survey. Only brand information will be stored, and it will be stored with an anonymous ID, which cannot be tracked back to your Twitter account. You may email Joseph Yun at jtyun@illinois.edu if you have any questions or concerns with this computational scan of your Twitter account. *This step is optional.*

Please enter you Twitter username:

_____

-- End of Survey –

APPENDIX C: TEXT RAZOR TOPICS OF EACH BRAND AND CAUSE

Brand/Cause	Text Razor Topics from Twitter Timeline
Fitbit	Fitbit, Smartwatch, Motivation, Physical exercise, Physical fitness, Health, Weight loss, Dieting, Relaxation (psychology), Sleep, Personal trainer
Royal Caribbean	MS Adventure of the Seas, Emergency evacuation, Royal Caribbean International, Water transport, Sailing
Wyndham Hotels	Tourism
American Heart Association	Stroke, Atrial fibrillation, Coronary artery disease, Myocardial infarction, Cardiopulmonary resuscitation, Heart, Health, Cardiovascular disease, Hypertension, Cardiac arrest, American Heart, Association, Hypercholesterolemia, Physical exercise, Cholesterol, Medicine, Medical specialties, Clinical medicine, Antiplatelet drug, Health sciences, Heart failure, Cardiovascular system, Disease, Adherence (medicine), Diseases and disorders, Venous thrombosis, Thrombosis, Healthy diet, Management of acute coronary syndrome, Peripheral artery disease, Surgery, Risk, Health care, Artery, Cardiovascular diseases
World Wildlife Fund	Council, Endangered species, Vaquita, World Wide Fund for Nature, Biodiversity, Rhinoceros, Coral bleaching, Orangutan, Elephant, World Heritage Site, Coral reef, World Oceans Day, Earth, Poaching, Coral, Conservation biology, Earth Overshoot Day, Natural environment, Climate change, Giraffe, Deforestation, Protected area, Wildlife, Snow leopard, Donana National Park, Ivory trade, Sea turtle, Shark Whale, Irrawaddy dolphin, Belize, Polar bear, Bear, Turtle, Leopard, Palm oil, Ecology, Facebook, Wetland, Paris Agreement, Great Barrier Reef, Conservation, Extinction, Coral Triangle
National Rifle Association	Handgun, National Rifle Association, Overview of gun laws by nation, Concealed carry in the United States, Gun politics in the United States, Concealed carry, Firearm, Shotgun, Assault weapon, Second Amendment to the United States Constitution, Revolver, Hunting, American Rifleman, Government, Firearms, Projectile weapons, Weapons, Law, Projectiles, Rifle, Shooting sport, Constitutional carry, Eddie Eagle, Suppressor, Neil Gorsuch, Winchester Repeating Arms Company, Security, Justice, Bolt action, United States, Sturm, Ruger & Co., Politics, Public sphere, United States Congress, Right to keep and bear arms, Gun, Remington Arms

APPENDIX D: IRB LETTER

UNIVERSITY OF ILLINOIS
AT URBANA-CHAMPAIGN

Office of the Vice Chancellor for Research

Office for the Protection of Research Subjects
805 West Pennsylvania Avenue
Urbana, IL 61801

June 13, 2017

Brittany Duff, PhD
University of Illinois at Urbana-Champaign
Advertising
322 Greg Hall
810 South Wright Street
Urbana, IL 61801

RE: *Cause-Related Marketing Analysis*
        IRB Protocol Number: 17827

Dear Dr. Duff:

Thank you for submitting the completed IRB application form for your project entitled *Cause-Related Marketing Analysis*. Your project was assigned Institutional Review Board (IRB) Protocol Number 17827 and reviewed. It has been determined that the research activities described in this application meet the criteria for exemption at 45CFR46.101(b)(2).

This determination of exemption only applies to the research study as submitted. Please note that additional modifications to your project need to be submitted to the IRB for review and exemption determination or approval before the modifications are initiated.

Copies of the attached, date-stamped consent form(s) are to be used when obtaining informed consent. If there is a need to revise or alter the consent form(s), please submit the revised form(s) for IRB review, approval, and date-stamping prior to use.

Exempt protocols will be closed and archived five years from the date of approval. Researchers will be required to contact our office if the study will continue beyond five years. If an amendment is submitted once the study has been archived, researchers will need to submit a new application and obtain approval prior to implementing the change.

We appreciate your conscientious adherence to the requirements of human subjects research. If you have any questions about the IRB process, or if you need assistance at any time, please feel free to contact me at OPRS, or visit our website at http://oprs.research.illinois.edu

Sincerely,

Jennifer Ford, MS
Human Subjects Research Specialist, Office for the Protection of Research Subjects

Attachments: 2 online consent documents, 1 waiver of documentation of informed consent, 1 research team attachment

c: Joseph Yun

U of Illinois at Urbana-Champaign • IORG0000014 • FWA #00008584
telephone (217) 333-2670 • fax (217) 333-0405 • email IRB@illinois.edu