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Easy Explanations or Elaborate Elucidations?:

Explanatory Preferences for Complexity Matching

A dissertation submitted in partial satisfaction of the

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by

Jonathan Billy Lim

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ABSTRACT OF THE DISSERTATION

Easy Explanations or Elaborate Elucidations?:

Explanatory Preferences for Complexity Matching

by

Jonathan Billy Lim

Doctor of Philosophy in Management

University of California, Los Angeles, 2018

Professor Daniel Oppenheimer, Chair

In everyday life, people are adept at generating and evaluating explanations for events around them. But what makes for a satisfying explanation? While some scholars argue that individuals find simple explanations to be more satisfying (Lombrozo, 2007), others argue that complex explanations are preferred (Zemla, et al. 2017). Uniting these perspectives, we posit that people believe a satisfying explanation should be as complex as the event being explained – what we term "the complexity matching hypothesis." Thus, individuals will prefer simple explanations for simple events, and complex explanations for complex events. Five studies provide robust evidence for the complexity-matching hypothesis. In Study 1, we re-examined existing data from previous work in the literature. Studies 2-4 provided novel experimental evidence in which participants were asked to predict the complexity of a satisfying explanation (Study 2), generate an explanation themselves (Study 3), and evaluate explanations (Study 4). Study 5 explored a

different manipulation of complexity to demonstrate robustness across paradigms. Lastly, Study 6 used real-world data from Amazon.com to show the generalizability of our hypothesis.

Keywords: Explanations, Matching, Complexity

The dissertation of Jonathan Billy Lim is approved.

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University of California, Los Angeles

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To my family, friends,

and most importantly,

God

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- Judgment and Decision Making
- Causal Reasoning

Introduction

People regularly seek explanations for their experiences. A family may wonder why they didn't enjoy their dinner at the local restaurant, a moviegoer may ask why she didn't like the new hit movie, and a student may consider why his expensive SAT prep class didn't raise his SAT score. While there are dozens, even hundreds, of possible explanations for these events, they will not all be equally satisfying. As a result, individuals must sift through all of these potential explanations to arrive at a suitable answer: the waiter was extremely rude, the movie's plot was boring, and the prep class went over basic techniques the student already knew. However, this raises the question: how were these conclusions reached, and why were they judged as being more acceptable than other possible explanations? More broadly, the question becomes: what makes an explanation satisfying?

In this work, we propose that one important cue that individuals use in identifying a satisfying explanation is its complexity. Specifically, the current work advances the complexity-matching hypothesis: people will find an explanation satisfying when it matches its precipitating event in terms of complexity. Therefore, we posit that individuals will prefer a simple explanation for a simple event, and a complex explanation for a complex event. We next review the relevant literature on explanation.

Theoretical Development

Philosophical Views on Explanation

Some of the earliest work on explanation was traditionally attributed to philosophers (e.g., Hempel & Oppenheim 1948, Friedman 1974, Kitcher 1989, Salmon 1984). These early theorists were concerned with what exactly comprised an explanation, and their work provided normative views on what the *structure* of a good explanation should look like. As a result, any explanation could be judged on whether it contained this desired structure, thus leaving us with the earliest standards on which to judge the satisfactoriness of an explanation. In turn, I briefly discuss the two most famous of these theories, the deductive-nomological framework and the unificationist account.

Deductive-Nomological Framework

Hempel and Oppenheim (1948) provided the beginning foundations for the study of explanation with the introduction of the deductive-nomological (DN) framework, which posited that any successful explanation for a given event must meet certain conditions. More specifically, the event must be able to be logically deduced from the premises of the explanation (*deductive*); given the explanation, an individual must be able to naturally conclude the event is true. Furthermore, the explanation's premises must contain initial conditions and at least one "law of nature"; without the latter, the whole explanation would fall apart (*nomological*). As an example, in order to account for why a child has Down's Syndrome, an explanation must have the following premises (Mayes 1995):

Initial condition: The child's cells have three copies of chromosome 21.

Law: Any child whose cells have three copies of chromosome 21 has Down's Syndrome.

Knowing the initial condition about the child, coupled with the universal law of nature, should naturally lead individuals to the conclusion that the child has Down's Syndrome. Events thus logically flow from explanations, and without the law of nature, the whole stream is disrupted. Thus, according to the DN framework, explanations should be evaluated on whether they are structured to contain the necessary conditions and laws needed to infer the event.

Unificationist Account

In addition to the DN framework, the unificationist account has proven to be very influential in early thought on explanation. Friedman (1974) was the first to propose the idea of unificationism, in which a good explanation is assessed on the extent to which it can unify various causes of an event. This notion was subsequently refined by Kitcher (1989) into its more current form. Unificationists argue that the world is comprised of systems of beliefs ("argument patterns") regarding a wide array of topics such as Newtonian physics, international politics, and sports. Thus, an argument pattern for sports may entail "why people think football is unsafe." Within this particular argument pattern are statements of belief ("schematic sentences"), such as

1. Players are crashing into each other at high speeds
2. Players are being tackled multiple times each game
3. The equipment is technologically outdated
4. The equipment is too flimsy to protect players

Schematic sentences can then be grouped to form higher-level "schematic arguments," with (1) and (2) perhaps forming an argument around "extreme physical contact leads to injuries" and (3) and (4) creating an argument regarding "poor equipment is not helping to prevent injuries." There could be dozens of schematic sentences in a schematic argument, and unificationists consider any combination of these sentences to be an explanation. Thus, a satisfying explanation would be judged on how many such schematic sentences it can subsume, with better explanations accounting for more sentences.

Recently, the idea of unificationism has caught the attention of psychologists, who have proposed similar theories of explanatory "subsumption" (Lombrozo & Carey 2006, Wellman & Liu 2007, Williams & Lombrozo 2010). Along the lines of unificationism, psychologists argue that a key characteristic of a good explanation is its ability to subsume the data being explained under more general patterns or regularities. Thus, a football player's concussion would be incorporated under the more general rule that extreme physical contact results in injuries. However, while the unificationist and subsumption accounts may appear similar, the former holds that in addition to explaining this specific concussion, a general rule should be able to also explain other disparate data as well. Thus, not only does extreme physical contact account for the player's concussion, it can also explain broken bones, torn ligaments, etc. Thus, the unificationist account may best be viewed as an extension of the more general subsumption theories.

Moving Beyond Traditional Philosophical Views

While the DN framework and the unificationist account remain influential, even to the present day (e.g., Woodward 2003, Strevens 2004), theorists have increasingly moved away from these models, instead placing emphasis on descriptions of what individuals *actually* look for in a good explanation, foreshadowing later psychological research. Work by a host of philosophers (Achinstein 1983, Salmon 1984, Woodward 2003) has called into question the true value of theories that do little to describe how individuals really behave. Most notably, Achinstein (1983) instead believed that explanation can be characterized as the product of an interaction between two individuals, one who asks a question (asker) and the other who tries to answer this question (explainer). The goal of the explainer is to produce understanding for the asker through how s/he answers the question of interest. However, the explainer must do so in a way that not only answers the question, but also fulfills the implicit "instructions" given by the asker. As a result, Achinstein believed that explanations were not bound in the rules of logic, but in the semantics of everyday conversation. A romantic inquiring into why he is falling in love is not looking for a detailed biochemical explanation of how synapses fire whenever he sees the object of his affection, but instead, for a rundown of the reasons why he enjoys being in the other person's presence. It is thus the explainer's job to understand this distinction, in order to successfully address his question, given the instructions he is providing.

Explanatory Virtues

However, in addition to these early theories on the structure of explanation, other work began to emerge within philosophy and psychology examining the ideal *qualities* of explanation. These characteristics were first introduced by philosophers (Kuhn 1977, Thagard 1978), and have commonly been termed "explanatory virtues" to reflect their standing as the traits inherent in a proper explanation. While a variety of different qualities have been considered, three in particular -simplicity, breadth, and coherence- traditionally stand out as being the most examined attributes (e.g., Lombrozo 2007; Chater & Vitanyi 2003; Bovens & Hartmann 2003; Read & Marcus-Newhall 1993; Preston & Epley 2005; Chinn & Brewer 1992; Schank & Ranney 1991; Gentner & Toupin 1986; Koslowski et al. 2008; Pennington & Hastie 1992; Khemlani, Sussman, & Oppenheimer 2011; Williams & Lombrozo 2010, 2013).

Simplicity

From the beginning, simplicity has traditionally been the virtue given the most thought by scholars and intellectuals. Aristotle proposed that "we may assume the superiority *ceteris paribus* of the demonstration which results from fewer postulates or hypotheses" (Baker 2016), while William of Occam famously postulated that "entities are not to be multiplied beyond necessity," forming the basis for his famous razor (Fitzpatrick 1995). More recently, Albert Einstein once surmised that "if you can't explain it simply, you don't understand it well enough," and the *FBI Law Enforcement Bulletin*, in providing guidance on judging criminal acts, advised that "the least complicated explanation of an event is usually the correct one" (Rothwell 2006).

Though simplicity has been much discussed, it is ironically, a complex, multifaceted construct that has eluded a standard definition by scholars. However, there are two characteristics that appear to define most conceptualizations of simplicity: parsimony (the number of elements described) and uniformity (the consistency of relationships among these elements), with simpler explanations featuring fewer elements and more consistent relationships among them (Baker 2016; Fitzpatrick 1995).

Despite disagreement on the meaning of simplicity, there has nonetheless traditionally been widespread empirical agreement that simpler explanations are more satisfying than complex explanations (e.g., Lagnado 1994; Chater & Vitanyi 2003; Bonawitz & Lombrozo 2012; Read & Marcus-Newhall 1993; Lombrozo 2007; Lu et al. 2008; Powell et al. 2016; Walker, Bonawitz, & Lombrozo 2017; Forster 2000; Kelly 2004). For example, Lombrozo (2007) demonstrated this preference for simplicity using a paradigm representing much of the work on this topic. Participants were given several pieces of data to evaluate (e.g., an alien has sore minttels and purple spots) and were provided information regarding these data (Tritchet's syndrome causes sore minttels and purple spots; Morad's disease causes sore minttels; Humel infection causes purple spots). They were then asked to consider different explanations accounting for the data, such as a simple explanation that was more parsimonious (e.g., the alien has Tritchet's syndrome) and a complex explanation that was less parsimonious (e.g., the alien has Morad's disease and a Humel infection). Overall, participants consistently favored simpler explanations, and this finding held true even when the complex explanations featured a higher probability of occurrence. In fact, Lombrozo found that participants only changed their preferences when the complex explanations were at least ten times more probable than the simpler alternatives.

This preference for simplicity has thus been shown to be quite robust, and children as young as four years old appear to demonstrate this inclination, as well (Bonawitz & Lombrozo 2012). Children observed a toy machine whose light and fan were both activated, and were asked to consider explanations that were either simple (a blue chip that turns both features on) or complex (a green chip that turns the fan on and a red chip that turns the light on). As with adults, children exhibited a preference for simple explanations of the toy's behavior, and once again, as with their older counterparts, children demonstrated this preference even when the complex explanations were more likely. Additionally, this preference for simplicity was also replicated when children were asked to actually explain an observed phenomenon (Walker, Bonawitz, & Lombrozo 2017).

Breadth

Over the years, a growing amount of research has focused on breadth (e.g., Preston & Epley 2005; Walker et al. 2016; Johnson et al. 2014; Williams & Lombrozo 2010, 2013; Williams, Lombrozo, Rehder 2013; Kim & Keil 2003; Rebitschek, Krems, & Jahn 2016; Samarapungavan 1992). While scholars have not agreed upon a universal definition of the virtue, Thagard's thoughts (1992) may come closest: "Other things being equal, we should prefer a hypothesis that explains more than alternative hypotheses. If hypothesis H1 explains two pieces of evidence while H2 explains only one, then H1 should be preferred to H2."

Empirically, Preston and Epley (2005) found that people held their beliefs to be more valuable when these beliefs were able to explain, as opposed to being explained by, a vast array of other phenomena. The authors asked participants to consider a diverse assortment of beliefs, ranging from scientific to historical to religious, and to think about how many observations each of these beliefs could either explain or be explained by. Across domains, the finding was robust –

participants viewed beliefs accounting for a wide variety of information as being more valuable than those that were explained by the same information. The authors reasoned that as beliefs account for an increasing number of phenomena, their relevance only increases, making them more important to the user.

Williams and Lombrozo (2010) further delved into why people seek out breadth in explanations. Per the subsumption theories previously discussed (Lombrozo & Carey 2006, Wellman & Liu 2007), they predicted that when people explain, their natural tendency is to "subsume" observations under general patterns or regularities. As a result, explanations that are broader in scope will intuitively be favored over those that are narrower. In their studies, the authors gave participants a set of fictitious observations regarding a class of robots and asked them to specify the underlying pattern defining category membership. Participants who were prompted to explain were more likely to discover the categorization rule that united 100% of the robots, when compared with those who were asked to perform other tasks (either thinking aloud, description, or free study). Those in the non-explaining conditions were more likely to instead settle on an imperfect rule that could only categorize 75% of the observations. Thus, the act of explaining led people to favor accounts broader in scope, a finding that has been extended to children as well (Walker et al. 2016). Taking it one step further, Lombrozo and Carey (2006) argue that the reason why individuals seek to subsume data under general patterns is because it allows for greater prediction and control, one of the main functions of explanation (e.g., Gopnik 2000, Craik 1943, Heider 1958). By understanding the patterns and regularities of their environment, individuals are in a better position to use past events to predict future occurrences, and to better control the outcomes of these occurrences.

Coherence

While much attention has been paid to simplicity and breadth, a large body of work has also examined coherence as well (e.g., Bovens & Hartmann 2003, Koslowski et al. 2008, Thagard 1989, Amini 2003, Gentner & Toupin 1986, Pennington & Hastie 1993). Thagard (1989) defined several different variations of coherence, such as deductive (logical consistency among propositions), probabilistic (consistency with the rules of probability), and semantic (similar meanings among propositions), and explanatory (consistency among explanatory relations), but once again, a standard definition has failed to emerge on the topic (Bovens & Hartmann 2003).

Despite these definitional ambiguities, research has repeatedly demonstrated people's preference for coherence. Koslowski and colleagues (2008) showed that individuals considered information to be relevant to understanding an event if they had an explanation available to them that could combine both the information and the event into a unified causal framework. Participants were asked to consider potential questions of interest (e.g., Why many large mammals became extinct in North America after humans migrated there), and were provided with two potential explanations, along with some background information. While both explanations could account for the event, only one of them (termed the target alternative explanation) could also incorporate the background information as well, while the other could not (the control alternative explanation). The authors found that people rated the background information as being relevant when they read the target alternative explanation as opposed to the control alternative explanation, and the former was thought to be more convincing, as a result.

Implications for Evaluation

As is evident, a wide body of literature shows that people often use explanatory virtues when thinking about and assessing explanations. Furthermore, these virtues are not just useful in and of themselves; they often do have demonstrable utility in helping individuals optimally evaluate explanations. Forster and Sober (1994), for instance, determined that in the domain of curve-fitting, simpler curves have less of a tendency to over-fit the data (i.e., to track both underlying stable patterns *and* noise) than do more complex curves, given that the propensity to over-fit is linear in the degrees of freedom of the family of functions chosen. Given this, curves from families of functions with fewer degrees of freedom will tend to be better fits to the data than those from families with higher degrees of freedom. Additionally, Kelly (2004) argued that simplicity was a critical attribute in hypothesis generation, as simpler hypotheses often need to be modified less by users in order to fit various situations. Thus, simplicity can often help guide students' learning of new material, helping them to formulate theories that are useful in a wide variety of contexts. As a result, it is little wonder that individuals adopt a preference for simplicity from a young age (Bonawitz & Lombrozo 2012; Walker, Bonawitz, & Lombrozo 2017). Along with this work on simplicity, Chinn and Brewer (1993) reasoned that when learners are presented with new theories that contradict their current beliefs, they may often resist modifying their prior views. However, if these new potential beliefs are broad and coherent, then they are more likely to be integrated into individuals' current network of knowledge.

Boundary Conditions on Explanatory Virtues

Despite the robust body of research demonstrating the efficacy of explanatory virtues, some have called into question how useful these virtues truly are. Previous work has already catalogued how the act of explaining can harbor negative effects on memory (Legare & Lombrozo 2014, Walker et al. 2014, Mishra & Brewer 2003) and causal inference (Kuhn & Katz 2009), and emerging research on explanatory virtues has shown that they can similarly lead users astray (e.g., Williams, Lombrozo, & Rehder 2013; Pennington & Hastie 1992; Lombrozo 2007; Zemla et al. 2017).

Breadth

Recent work by Williams and colleagues (2013) demonstrated that when individuals focused on generating high-breadth explanations for a set of data, they often glossed over unique exceptions. In one study, participants were asked to either explain or simply think about why hypothetical individuals donated to charity, based on select demographic information about each person (age, personality type, major, geographic location). Participants asked to explain these individuals' behavior were better at finding underlying patterns for why they donated (e.g., "Older people frequently donate," "Extraverted people rarely donate"), in line with work by Williams and Lombrozo (2010). However, they overgeneralized these patterns, missing out on key exceptions in the data (e.g., Older people who rarely donated, Extraverted people who frequently donated). As a result, while breadth was important in finding a pattern that could explain the data, the upshot was that participants tended to overlook cases where the pattern was not warranted.

Coherence

Additionally, our penchant for seeking out coherent explanations may at times work against us, a point echoed in classic work by Pennington and Hastie (1992). Participants were given court cases to read, with the goal of evaluating whether the defendant was guilty. The authors found that participants were more likely to assign guilt when the evidence in the cases was arranged in narrative form (as opposed to being sorted by topic), as this allowed them to construct a clear story of what happened. Thus, participants relied on the coherence of the case in order to help them judge the guiltiness of defendant, even when this cue should not have been relevant to their decision-making.

Simplicity

In addition, recent work has begun to shed light on whether simpler explanations are always better fits for the types of real-world events that people often experience (Zemla, Sloman, Bechlivanidis, & Lagnado 2017). Zemla and colleagues have argued that when participants are given a contrived scenario, such as the alien example from Lombrozo (2007), a simple explanation may be most satisfying. However, such artificial scenarios often do not approximate the types of situations individuals usually come across in real life, or recruit from semantic memory. The penchant for simplicity may thus be an artifact of the experimental paradigm used by previous researchers, and it may not accurately reflect individuals' explanatory preferences for more typical everyday situations.

To investigate this possibility, Zemla and colleagues (2017) gave participants a set of real-world questions (e.g., "Why isn't China's population decreasing if they had a one-child policy for 35 years?"), along with explanations that were either simple, featuring only one or two causes (more parsimonious):

> A: "Ethnic minorities and rural populations are exempt from the rule" or
>
> B: "Chinese are living longer on average, and wealthier couples can pay the fine associated with rule violation"

or complex, featuring three causes (less parsimonious):

> AB: "Ethnic minorities and rural populations are exempt from the rule. Also, Chinese are living longer on average, and wealthier couples can pay the fine associated with rule violation"

In contrast with previous research, they found that participants preferred complex explanations featuring more reasons and detail. As a result, an overreliance on simple explanations may be a suboptimal strategy in dealing with the kinds of events most individuals encounter on a regular basis. Even in her own work, Lombrozo (2007) showed one downside of a dependence on simplicity – participants often misremembered the probability of simple explanations, judging them to be higher than they actually were.

Going even further, research by Siegler (1995) demonstrated that the use of complex explanations may at times be *beneficial* in children's reasoning. Young participants were trained to learn number conservation (i.e., the number of items in a row does not change just because the row is shortened or elongated). After being tested on the concept, those who were asked to explain the experimenters' reasoning for the correct answer actually learned more than those explaining their own thought processes for the answer they chose. Even though the act of explaining was important, Siegler argued that one reason why children did better in the former condition was because explaining an adult experimenter's rationale may lead to them coming up with a complex explanation that more closely aligns with an understanding of the nuance of number conservation. Thus, it seems that there are situations when a reliance on complexity may actually be helpful in guiding individuals' thinking and understanding.

Re-defining what an Explanatory Virtue is

While researchers are beginning to increasingly question the value of explanatory virtues in reasoning and thought, an emerging body of literature is bringing into focus the more fundamental question of what *actually* constitutes an explanatory virtue. While previous work has pointed to simplicity, breadth, and coherence as being qualities people look for in satisfying explanations, there has been growing evidence to demonstrate that this may not always be the case. Instead, it appears that at times, people may be seeking out the exact *opposite* qualities in explanations.

Breadth

For example, work by Khemlani, Sussman, and Oppenheimer (2011) has examined the notion of whether individuals singularly value greater breadth in explanations. More specifically, the authors show that when people consider the breadth (referred to as scope in this case) of possible events that an explanation *could* account for (latent scope), they prefer explanations with narrower latent scope – contrary to what previous work on breadth would have predicted. As a result, when asked why George dyed his hair black and then shaved it, they preferred to rationalize it as being due to George discovering lice (narrow latent scope), as opposed to George going through a midlife crisis (broad latent scope). Whether for real life events such as this or more fictitious ones, people continued to favor narrow latent scope, a preference that has continued to receive support (Johnson, Rajeev-Kumar, & Keil 2016) and which has been found to hold for children as well (Johnston et al. 2017). Khemlani and colleagues argued that this surprising outcome is a function of individuals seeking explanations that explain the most observed effects (consistent with previous work on breadth) while also accounting for the least unobserved effects (consistent with the findings on latent scope). As a result, it appears that people do not always favor greater breadth in explanation; instead, their preferences will depend on the nature of the data to be explained.

Coherence

While people may prefer explanations whose components cohere (e.g., Pennington & Hastie 1993), there is some debate over the extent of this preference. Work by both Gregg and colleagues (2001) and Chinn and Brewer (1993) have shown that people often harbor incorrect beliefs and struggle to incorporate the correct beliefs into a coherent framework, instead choosing to reject these new viewpoints. Even when provided with proper training, individuals often remain resistant to change, with any gains made usually only being temporary (Gregg et al. 2001). It seems likely then that people may be fine with holding beliefs that are incongruent with what they know to be correct, suggesting that perhaps other goals besides a need for coherence might be at play. In addition, some have even argued that far from being coherent, individuals' knowledge may actually be fragmentary, divided up into rudimentary pieces called *phenomenological primitives* (di Sessa 1993; di Sessa et al. 2004). Di Sessa and colleagues argue that these pieces often do not fit well with one another, making coherence a lofty, perhaps unattainable, virtue for the human mind.

Furthermore, Fodor (1998) argued that the notion of coherence eventually runs into the problem of "holism," the issue that at some level, everything is connected to everything else. Thus, romantic attraction is usually described as the emotions that one experiences in the presence of another, but it could also be categorized in terms of the biochemical reactions going on inside the person's brain, or in terms of the situational factors that brought the individuals together in the first place. Because there are multiple layers to any single event, determining the proper level of explanation can be challenging, a difficulty noted by the philosopher Charles Sanders Peirce (1997/1903), who contended that there are potentially an infinite number of explanations that could account for any given question or event. While some have proposed a solution to this problem (Johnson & Keil 2014), it still remains an issue in need of further exploration.

Simplicity

Previous work by Zemla and colleagues (2017) has already demonstrated that individuals harbor at times a preference for complexity, and research by O'Keefe (1997, 1998, 1999) has advanced this notion that a unanimous preference for simplicity may not exist. Through a series of meta-analyses, O'Keefe (1999) examined individuals' views on one-sided versus two-sided arguments. While some would reason that presenting both sides of an argument might allow for greater scrutiny and debate over its premises, potentially weakening its credibility and persuasive appeal, the author still found a stronger preference for these more in-depth appeals. Going even further, when participants were given different types of two-sided arguments, they exhibited a preference for more complex arguments in which opposing views were refuted, as opposed to arguments in which such views were merely acknowledged. Additionally, participants exhibited a strong preference for well-developed arguments –those in which the sources were identified and cited, ideas were fully fleshed out and viewpoints made explicit, and quantitative support was provided– even if such arguments were longer and more complex (O'Keefe 1997, 1998). Such findings from O'Keefe corroborate research showing that in certain situations, people prefer explanations that are longer in length (Weisberg, Taylor, & Hopkins 2015; Kikas 2003) and that use more complex language (Lawson 2014).

Even young children may at times demonstrate a preference for complexity (Bartsch & Wellman 1989, Hickling & Wellman 2001, Callanan & Oakes 1992). Bartsch and Wellman (1989) asked kids to think about the reasons for the actions of hypothetical individuals (e.g., "Jane is looking for her kitten under the piano. Why is Jane doing that?"). Participants overwhelmingly favored psychological reasons ("She is trying to find her kitten") over behavioral ("Jane always looks there") or physical ones ("The wind blew her there"). Previous research (Strickland, Silver, & Keil 2016) has shown that explanations invoking social systems tend to be more complex than those regarding physical systems; thus, the children in Bartsch and Wellman's studies appealed to more complex explanations in order to account for the hypothetical actions. Interestingly, this finding extends beyond these simple actions into explanations of others' emotions (Wellman & Banerjee 1991) or past experiences as well (Lagattuta, Wellman, & Flavell 1997).

Explanatory Virtues or Vices?

It thus appears to be the case that what should be considered an explanatory virtue may not be quite as set in stone as previously theorized. In fact, if an explanatory virtue is by definition the qualities individuals look for in a good explanation, then it stands to reason that what we classify as being a virtue may depend on the context at hand. As a result, it appears that people do not carry around a set of defined explanatory preferences that they inflexibly look for when evaluating explanations. Instead, they base their explanatory preferences on the particulars of the situation, creating a set of explanatory criteria that is suited to these contextual nuances. For example, when all the effects for a given cause are observable, people tend to prefer causes with greater breadth (e.g., Preston & Epley 2005). However, when these effects may not be observable, individuals are willing to trade some of this breadth for greater certainty, leading them to select causes with lower scope (Khemlani, Sussman, & Oppenheimer 2011). People thus respond to environmental uncertainty by selecting explanations that best adapt to this key situational feature. It is thus likely that people are similarly adaptive in their preferences for other explanatory virtues, as well.

Complexity-Matching

One other key environmental variable that individuals may take into account is the complexity of the event at hand. A large body of work by Lombrozo (2007) and others has demonstrated that people exhibit a preference for simplicity in explanation, while emerging research, as exemplified by Zemla and colleagues (2017), is beginning to show that individuals may actually prefer explanatory complexity instead. It could be the case that both sides are partially correct, and what people are really responding to is complexity in the environment. Notably, the events to be explained in Zemla et al. (2017) were in and of themselves more complex than the simpler lab stimuli used by Lombrozo (2007). Thus, it could be the case that people's preference for simplicity or complexity in explanations is actually moderated by the simplicity or complexity of the event needing to be explained. For simple events (as in the work of Lombrozo (2007)), individuals may favor simple explanations, whereas for complex events (as in the work of Zemla et al. (2017)), they may prefer complex explanations. We term this the complexity-matching hypothesis—people prefer for an explanation to match its precipitating event in complexity.

The concept of matching does have precedent in the causal reasoning literature. Previous research has shown that individuals prefer causes and effects that match in terms of magnitude (e.g., a plane crash being the result of a terrorist attack, as opposed to a minor malfunction; Ebel-Lam et al. 2010; Spina et al. 2010) and physical appearance (e.g., an illness that is treated by a remedy physically resembling it; Einhorn & Hogarth 1986; Gilovich & Savitsky 2002). This preference for matching holds true even when the cause has no diagnostic value in predicting the effect (LeBoeuf & Norton 2012). We extend the matching principle beyond these physical dimensions and into the domain of complexity, and we examine explanations, which often invoke causal accounts of effects (i.e., the precipitating events).

Overview of Studies

The following package of studies examines the descriptive validity of the complexity-matching hypothesis. In Study 1, we re-analyzed data from Zemla et al. (2017) for evidence of complexity matching. Studies 2-4 provided participants with a set of scenarios manipulated to differ in complexity, based on the number of details provided (parsimony criterion). Participants were asked to assess the satisfactoriness of an explanation in three different ways: predicting the complexity of a satisfying explanation (Study 2), generating a satisfying explanation themselves (Study 3), and evaluating how satisfying a potential explanation was (Study 4). Study 5 then examined potential accounts of why people engage in complexity matching. Finally, in Study 6, we used a second operationalization of scenario complexity, in which the valence of scenario details varied (uniformity criterion).

Study #1

Zemla et al. (2017) featured two studies examining people's explanatory preferences. In the second study, Zemla and colleagues explicitly tested preferences for explanatory complexity by providing participants with a set of real-world questions and asking them to predict how complex an ideal explanation for each question would be. We sought to capitalize on naturalistic variations in complexity within Zemla et al.'s set of questions to see if their participants rated more complex questions (relative to simple questions) as requiring more complex explanations, per our hypothesis.

Method

Stimuli norming

A sample of participants (n = 30) was recruited from Amazon's Mechanical Turk platform. They were shown all six questions (e.g., "Why are cancer rates increasing?", "How did the Black Death in the 14th century come to an end?") from Zemla et al.'s (2017) second study.

After viewing each question, they were asked to rate: "How complex of a question is this? (i.e., how complex is the subject matter of this question?)" on a 1-9 Likert scale, anchored by 1 = Extremely Simple and 9 = Extremely Complex.

There were differences in complexity among the scenario questions (see Figure 1), $F(5, 174) = 2.98$, $p = .01$. Specific contrasts showed that the question regarding cancer was viewed as being more complex than the average of the other five questions, $F(1, 174) = 10.51$, $p < .01$.

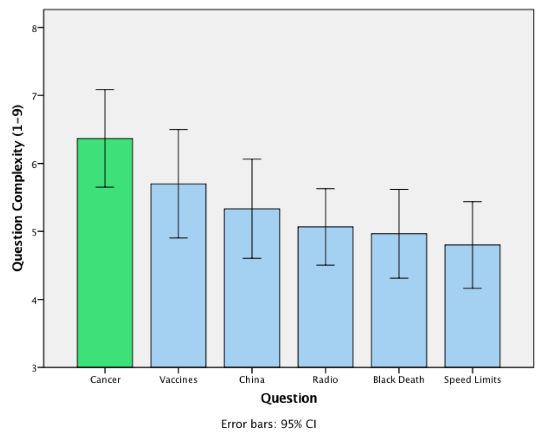

Figure 1. Differences in rated complexity among original stimulus questions. Error bars are 95% confidence intervals.

Re-analysis of Zemla et al. data

In Zemla et al.'s (2017) original work, participants viewed six stimulus questions, and for each question, answered: i) how detailed a good answer to the question should be, and ii) how many reasons a good answer should have. If the complexity-matching hypothesis is correct, then the participants should have rated a good answer as being more detailed and having more reasons when in response to a more complex question. We used data from the norming study along with the original data from Zemla et al (2017) to determine whether this prediction holds.

Results

Answer detail

There were differences in participants' predictions of how detailed a good answer to the various stimulus questions should be, $F(5, 534) = 7.46$, $p < .01$. Importantly, cancer, which was rated in the norming study as being the most complex subject matter, was predicted to require a more detailed answer than the other questions, $F(1, 534) = 24.28$, $p < .001$. Overall, the pattern of responses (see Figure 2) mirrored those from the norming study.

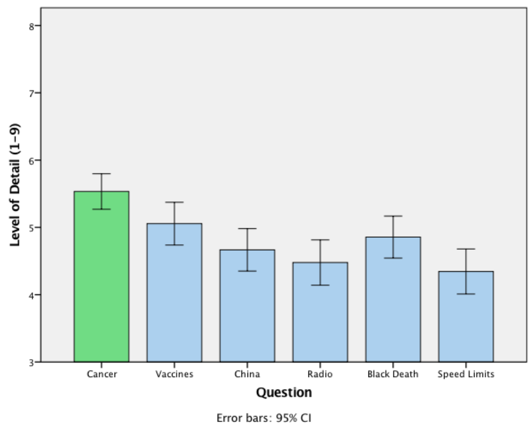

Figure 2. Differences in level of detail needed for answers to original stimulus questions. Error bars are 95% confidence intervals.

Number of reasons

Once again, there were differences in perceptions of how many reasons a good answer should have, $F(5, 534) = 12.54$, $p < .01$. Cancer was thought to need more reasons, as compared to the other questions, $F(1, 534) = 46.26$, $p < .01$. The pattern of responses (see Figure 3) again paralleled those from the norming study.

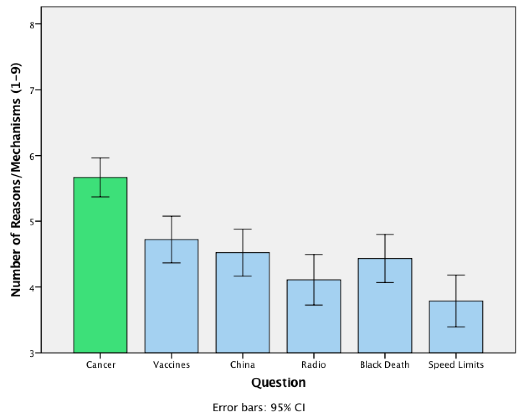

Figure 3. Differences in number of reasons/mechanisms needed for answers to original stimulus questions. Error bars are 95% confidence intervals.

Discussion

Re-analysis of Zemla et al.'s (2017) study provided preliminary evidence for the complexity-matching hypothesis. More complex stimulus questions were rated by Zemla et al.'s (2017) participants as requiring a more detailed answer featuring more reasons. While this finding is in line with our hypothesis, Zemla et al.'s (2017) work was not explicitly meant to test complexity matching. As a result, their work was not optimized for a rigorous analysis of complexity matching. The following studies provide a more thorough test of our hypothesis, wherein the complexity of the stimuli is carefully controlled and experimentally manipulated.

Study #2

Method

Participants

As in Study 1, participants (n = 286) were recruited through Amazon's Mechanical Turk platform. In order to be conservative, sample size was based on a power level of 0.8 and an estimated eta-squared effect size of 0.02. The sample was 39% male, 61% female, with an average age of 37 years.

Materials

A set of four scenarios was created: a company experiencing success, a university having a great academic year, a baseball team going through several rough seasons, and an employee failing at his job. As with Lombrozo (2007) and Zemla et al. (2017), we operationalized complexity in terms of parsimony. Thus, for each scenario, we varied the number of details that participants saw. In the complex version of each scenario, participants viewed three details pertinent to that scenario, whereas in the simple version, they saw a more parsimonious account featuring only one detail. For example, in the university scenario, the complex version read:

> "Friedman University has been having a great year. It was recently christened a top-twenty university by Canadian News & World Report, the first time the school had ever received such an honor. Additionally, upon graduation, 90% of Friedman's senior class this year will either be employed or attending graduate school. On top of this, the entering freshman class looks to be very strong, with an average high school GPA of 3.98 (out of 4.00)."

The simple version of the scenario only contained one of the three details from the complex version. Three simple scenario versions were thus created, one for each of the three details described in the complex version. For example:

> "Friedman University has been having a great year. It was recently christened a top-twenty university by Canadian News & World Report, the first time the school had ever received such an honor."

The other three scenarios (company, baseball team, and employee) were similarly constructed, with one complex version and three simple versions of each scenario. Participants saw all four scenarios, but only one version of each scenario.

For each scenario, participants answered the following question: "How complex do you think a satisfying explanation to this event will be?" (cf. Zemla et al. 2017). Explanation complexity was assessed on a 1-9 Likert scale, anchored by 1 = Extremely Simple, 9 = Extremely Complex. As a manipulation check, participants were also asked to evaluate the complexity of the scenario that they had read, assessed on the same 1-9 Likert scale.

Results

The dependent measures were analyzed through linear mixed effects regression, with scenario complexity (simple, complex) entered as a fixed factor. We also included scenario (university, company, employee, baseball team) as an additional fixed effect, so that we could test the interaction between scenario complexity and scenario to see if any main effects of scenario complexity were qualified by the interaction. Participants were modeled as a random factor, to control for repeated measurements of each participant.

The manipulation check showed that our manipulation of complexity was successful—participants viewed the complex scenarios (M = 5.67, SD = .97) as being more complex than the simple scenarios (M = 4.88, SD = 2.21), $F(1, 1071.20) = 41.67$, $p < .001$.

As predicted by the complexity matching account, analysis revealed a main effect of scenario complexity, $F(1, 1082.95) = 28.83$, $p < .001$. Participants rated the complex versions of the scenarios (M = 5.59, SD = 2.04) as requiring more complex explanations than the simple versions of the scenarios (M = 4.95, SD = 2.15). There was also a main effect of scenario, $F(3, 907.35) = 20.25$, $p < .001$, but no interaction between scenario complexity and scenario, $F(3, 1071.98) = .52$, p = ns.

Discussion

This study provided experimental evidence for the complexity-matching hypothesis, showing that people expect complex events to have more complex explanations than simple events. However, in real life, individuals rarely *predict* the complexity of a satisfying explanation (even though that is a common dependent measure in the literature). More typically, people are tasked with coming up with explanations, either for themselves or for others. In these cases, do individuals *generate* explanations matching the complexity of the precipitating event?

Moreover, previous literature has demonstrated that people often have difficulty accurately predicting their preferences (Eastwick & Finkel 2008; Gilbert & Ebert 2002). Thus, it could be the case that even though people predict that they would prefer explanations matching the complexity of the precipitating events, their actual generated explanations may not follow suit. Study 3 thus examined whether people observe complexity matching when generating explanations for events.

Study #3

Method

Participants

Participants (n = 201) were recruited from Mechanical Turk. The sample was 40% male, 60% female, with an average age of 36 years. Sample size was based on same calculations as for Study 2.

Materials and Procedure

The same materials from Study 2 were used. After viewing each scenario, participants were asked to "write a compelling explanation for the [scenario] that would make sense to you or to the average person reading about the [scenario]." As in Study 2, participants were randomly assigned to see either simple or complex versions of each scenario.

Results

Coding

Two independent raters, who were blind to condition, read each explanation and assigned an intuitive complexity rating on a 1-10 scale (1 = Completely Simple, 10 = Completely Complex). The average of their ratings (r = .64) formed the "complexity rating" for each explanation. Two other independent raters, also blind to condition, counted the number of causes listed in each explanation, with the average of their scores (r = .88) defining the "number of causes" variable. Lastly, we acquired a word count and Flesch-Kincaid score for each explanation, both obtained from standard packages offered by Microsoft Word. The Flesch-Kincaid score is a measure of the level of education needed to understand any passage of text (e.g., a Flesch-Kincaid score of 6 means that an individual would need to have a sixth-grade level of education to comprehend the passage; Kincaid et al., 1975). If the complexity-matching hypothesis holds, then for complex scenarios, participants should write more complex explanations featuring i) a higher complexity rating, ii) more causes listed, iii) a higher word count, and iv) a higher Flesch-Kincaid score.

Linear mixed modeling was again used to analyze the four main dependent measures. For each dependent measure, scenario (university, company, employee, baseball team) and scenario complexity (simple, complex) were both entered as fixed factors, as was the interaction between them. Participants were included as a random factor.

Complexity rating

There was a significant main effect of scenario complexity, $F(1, 646.68) = 65.39$, $p <$ .001. Participants' explanations were rated as being more complex in response to a complex scenario (M = 4.53, SD = 1.48), than a simple scenario (M = 4.04, SD = 1.23). There was also a main effect of scenario, $F(3, 610.75) = 4.43$, p = .004, but no interaction between scenario and scenario complexity, $F(3, 645.78) = .80$, p = ns.

Number of causes

There was a trending, but non-significant, effect of scenario complexity, $F(1, 689.91)$ = 1.92, p = .17. Participants included slightly more causes when writing explanations for complex scenarios (M = 1.29, SD = .95) than for simple scenarios (M = 1.26, SD = .85). There was, a main effect of scenario, $F(3, 624.65) = 5.81$, $p = .001$. but the interaction between scenario and scenario complexity was once again not significant, $F(3, 688.20) = .45$, p = ns.

Word count

There was a significant main effect of scenario complexity, $F(1, 637.84) = 38.58$, $p < .001$. Participants wrote more for complex scenarios ($M = 30.90$, $SD = 20.58$) than they did for simple scenarios ($M = 26.37$, $SD = 16.70$). There was also a main effect for scenario, $F(3, 607.95) = 6.68$, $p < .001$, but no interaction between scenario and scenario complexity, $F(3, 637.11) = .41$, p = ns.

Flesch-Kincaid score

While Flesch-Kincaid scores fell in the predicted direction, the main effect for scenario complexity was not statistically significant $F(1, 714.91) = 1.31$, p = ns. The readability of participants' explanations did not reliably change from complex scenarios ($M = 8.57$, $SD = 3.08$) to simple scenarios ($M = 8.38$, $SD = 3.10$). There was a main effect of scenario, $F(3, 632.26) = 34.84$, $p < .001$, but no interaction between scenario and scenario complexity, $F(3, 712.67) = 1.04$, p = ns.

Discussion

Study 3 provided converging evidence for the complexity-matching hypothesis, demonstrating that individuals generate explanations matching with their precipitating events in complexity. Specifically, complex events elicited explanations with significantly higher complexity ratings and word counts than did simple events. Additionally, while only two of the four dependent measures reached conventional levels of statistical significance, all four measures trended in the predicted direction. Most importantly, raters strongly and reliably perceived the participants' explanations to be more complex for the complex scenarios and simpler for the simple scenarios, which suggests that complexity may come in forms that are hard to capture through simple numerical metrics such as Flesch-Kincaid scores.

The previous two studies have provided experimental evidence showing that people both predict and generate explanations matching in complexity with their precipitating events. However, generation remains an imperfect measure, as previous research has shown that individuals can have trouble identifying what others will find satisfying (Baskin et al. 2014). Thus, the next study relied on a third important dependent measure: evaluation. Participants were shown explanations varying in complexity and asked to assess how satisfying they found the explanations.

Study #4

Method

Participants

Participants (n = 523) were recruited from Mechanical Turk. The sample was 36% male and 64% female, with an average age of 36 years.

Materials and Procedure

The same scenarios from Studies 2 and 3 were used. To reduce logistical complexity, we only used two of the four possible scenarios (baseball team and university), and within each scenario, we used the complex version and one randomly selected simple version. This left us with four conditions.

To obtain explanations, we sampled from explanations generated by participants in Study 3. Within each condition (simple and complex), we examined the set of explanations that participants had generated, using the coders' average complexity rating (which was assessed on a 1-10 scale) to identify the lowest-rated explanation (simplest) and the highest-rated explanation (most complex), providing us with a complexity range (e.g., 4-9). Within this range, we randomly sampled an explanation from each half-point (e.g., 4, 4.5, 5, 5.5, 6, 6.5, 7, 7.5, 8, 8.5, 9), providing us with eight to thirteen randomly sampled explanations for each version of each scenario. Participants were then given one version of each scenario to view and one corresponding explanation to evaluate, meaning approximately 25 participants viewed each explanation.

After reading each scenario and its accompanying explanation, participants were asked: 1) How satisfied are you with the MTurker's explanation, and 2) How complex was the MTurker's explanation? Questions were counterbalanced and assessed on a 1-9 Likert scale (first question: 1 = Extremely Dissatisfied, 9 = Extremely Satisfied; second question: 1 = Extremely Simple, 9 = Extremely Complex).

Results

Correlations were used to assess the strength of the relationship between the two dependent measures. The complexity-matching hypothesis would predict that the correlation between explanatory satisfaction and explanatory complexity would be positive for complex scenarios, and negative for simple scenarios. In other words, participants should be increasingly satisfied as the explanations become more complex for the complex scenarios, and as the explanations become less complex for the simple scenarios.

As expected, for the complex versions, there was a moderately strong positive relationship between explanatory satisfaction and perceived explanatory complexity, $r(263) = .39$, $p < .01$. Unexpectedly, for the simple versions, there was also a positive relationship between explanatory satisfaction and explanatory complexity, $r(256) = .23$, $p < .01$. However, this relationship was significantly weaker than the relationship for the complex versions, $Z = 2.86$, $p < .01$.

Similarly, analysis of the correlation between explanatory satisfaction and the independent coders' complexity ratings from Study 3 showed a moderately strong positive relationship for the complex versions, $r(263) = .38$, $p < .01$. There was a positive relationship for the simple versions as well, $r(256) = .16$, $p < .01$. Once again however, this relationship was significantly weaker than the relationship for the complex versions, $Z = 3.85$, $p < .01$.

Discussion

Overall, participants tend to be more satisfied with an explanation as it increases in complexity (c.f. Zemla et al. 2017). However, this relationship is stronger for complex scenarios than for simple scenarios, providing modest support for the complexity-matching hypothesis. The data pattern suggests two additive forces working in conjunction: a general preference for more complexity (which leads to consistently positive correlations), along with a preference for complexity matching (which weakens those correlations when the events and explanations do not match in complexity).

The scenarios used here trend towards the realistic stimuli used by Zemla et al. (2017) rather than the simpler laboratory stimuli of Lombrozo (2007). While our scenarios did involve made-up events (e.g. a fictional baseball team), these are topics for which participants' existing semantic memory would be relevant in evaluating the quality of the explanations (as opposed to the blank predicate structure of diagnosing alien diseases, cf. Lombrozo 2007). In addition, the scenarios generally involved social events that may be seen as more complex in nature than the contrived stimuli of previous studies (Strickland, Silver, & Keil 2017). However, even under such conditions for which individuals may have a general bias towards complex explanations, it seems that they still moderate this preference based on the complexity of the event at hand.

Study #5

The previous studies all manipulated complexity in the same way: number of details (parsimony). However, as for all multifaceted constructs, any given operationalization of complexity will vary on multiple dimensions, leading to the possibility of confounds. For example, one could argue that differences in length underlie the results from previous studies, as longer scenarios may produce a demand effect, indirectly prompting people to expect and generate longer explanations. Alternatively, as more details are provided in a scenario, participants may believe that explanations would need to be longer in order to account for the extra information. Thus, to address these arguments and provide robust evidence for the complexity-matching hypothesis, the current study uses a fundamentally different operationalization of complexity— uniformity (the consistency of relationships among scenario details). In the following study, we hold the number of scenario details constant (thus holding length constant), and manipulate uniformity by providing either valence consistent (details were either all positive or all negative) or inconsistent (a mix of positive and negative details) information. Previous research has shown that people often have trouble with reasoning through events featuring both positive and negative elements, since positive and negative emotions represent the extremes of a bipolar dimension of affect (e.g., Green, Goldman, & Salovey 1993). Given this difficulty with mixed emotions, valence-inconsistent events should be perceived as more complex than valence-consistent events. As a result, the complexity-matching hypothesis would then predict that valence-inconsistent scenarios should merit more complex explanations than valence-consistent scenarios.

Method

Participants

A sample of MTurk participants (n = 253) was used, comprised of 45% males, 55% females, with a mean age of 33.3 years. Sample size was based on the same calculations as for Studies 2 and 3.

Materials

The four scenarios from Study 2 were used (store, baseball team, employee, university). Each scenario had two details, with the same two details appearing in all versions of the scenario. However, we manipulated each detail to be either positive (+) or negative (-) in valence. For example, the following detail regarding the university was (+):

> "It was recently christened a top-twenty university by Canadian News & World Report, the first time the school had ever received such an honor."

The (-) version of this detail then read:

> "It was recently dropped from the list of top-twenty universities by Canadian News & World Report, the first time the school had ever been absent from the list."

Because there were two details for each scenario, this resulted in a total of four possible versions of the scenario (see Appendix A). Two versions were valence consistent (++, --) and thus uniform, while two were valence inconsistent (+-, -+), and thus non-uniform. Participants only saw one version of each scenario.

As in Study 2, for each scenario, participants answered the question: "How complex do you think a satisfying explanation to this event will be?" (cf. Zemla et al. 2017). Explanation complexity was assessed on a 1-9 Likert scale, anchored by 1 = Extremely Simple, 9 = Extremely Complex. As a manipulation check, participants were also asked to evaluate the complexity of the scenario that they had read, assessed on the same 1-9 Likert scale.

Results

As in Study 2, a mixed model was used to analyze the dependent measures. The four possible versions of scenario valence were condensed into two levels (consistent, inconsistent), and this was entered as a fixed factor, along with scenario (store, baseball team, employee, university). The interaction between scenario valence and scenario was included as a third fixed factor. As before, we modeled the participants as a random factor to control for repeated measurements of each participant.

The manipulation check revealed that, as expected, participants found the inconsistent scenarios ($M = 5.80$, $SD = 1.86$) to be more complex than the consistent scenarios ($M = 5.23$, $SD = 2.06$), $F(1, 935.32) = 28.89$, $p < .001$.

Analysis revealed a main effect of scenario valence, $F(1, 932.77) = 28.01$, $p < .001$. Participants thought that inconsistent scenarios ($M = 5.67$, $SD = 1.78$) required more complex explanations than did consistent scenarios ($M = 5.15$, $SD = 2.03$)[1]. There was also a main effect of scenario, $F(3, 749.30) = 15.58$, $p < .001$), but no interaction between scenario valence and scenario, $F(3, 971.68) = 1.95$, $p = .12$. Thus, in alignment with the complexity-matching hypothesis, participants predicted that valence-inconsistent scenarios would have more complex explanations than valence-consistent scenarios.

Discussion

Study 5 showed that even for a different operationalization of complexity (uniformity), people still exhibited a preference for complexity matching, thus providing further evidence for the complexity-matching hypothesis. In addition, because we held number of details constant in our scenarios, we were able to rule out other factors besides complexity that may have

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[1] While tangential to the main question of complexity matching, it is worth noting that the (- -) scenarios were viewed as being more complex ($M = 5.58$, $SD = 2.01$) than the (+ +) scenarios ($M = 4.88$, $SD = 2.05$), $F(1, 1008) = 16.11$.

contributed to the effect seen. Overall, through two different manipulations of complexity (number of details, valence consistency) and three different dependent measures (prediction, generation, evaluation), the results are consistent with the complexity-matching hypothesis.

Study #6

Amazon.com sells thousands of different products from many product categories varying in complexity, from simple, e.g., water, paper, wigs for dogs (*Rubie's Pet Costume Afro Curly Wig*), to more complex, e.g., laptops, coffeemakers, gummy bear anatomy kits (*4D Master Gummy Bear Skeleton Anatomy Kit*). Consumers can publicly rate these products and write reviews, providing explanations for why they did or did not enjoy their product experience. In this study, we examine whether readers of these reviews exhibit a preference for complexity matching. Specifically, they should find complex reviews to be more helpful for complex products, and simple reviews more helpful for simple products.

Method

We gathered Amazon.com products from five different categories: watches, lightbulbs, scales, showerheads, tape measures. For each category, we found a pair of products, one of which was simple, and the other, complex. All product pairs were pre-tested to ensure differences in complexity; participants were given one product from each pair and asked to rate the complexity of that product. The more complex products (M = 5.49, SD = 1.98) were indeed viewed by participants as being more complex than the simple products (M = 3.64, SD = 2.16), $F(1, 244) = 58.78$, $p < .001$.

For each product, we then obtained twenty-five different reviews. We sifted reviews using the following filters offered by Amazon.com: "Top reviews," "All reviewers," "All stars," "All formats." From there, we retrieved the first twenty-five reviews that Amazon.com provided.

For each review, we recorded the word count, number of stars provided by the reviewer, and the helpfulness score (number of readers finding the review helpful). We then examined: i) whether reviewers wrote more for more complex products, and ii) whether the helpfulness score increased when there was a match between product complexity and review complexity (using word count as a proxy).

Results

Word Count. Word count was analyzed through linear mixed effects regression, with product complexity (simple, complex) as a fixed factor and product category (watches, lightbulbs, scales, showerheads, tape measure) as a random factor. We also included number of stars given as an additional fixed effect, so that we could test the interaction between product complexity and stars given to see if any main effects of product complexity were qualified by the interaction.

There was a trending, but non-significant, effect of product complexity, $F(1, 236.87) = 1.61$, $p = .21$. Specifically, reviewers wrote more for complex products ($M = 119.43$, $SD = 99.61$) than for simple products ($M = 109.10$, $SD = 111.14$). There was no effect of number of stars given by the reviewer, $F(4, 237.59) = 1.17$, p = ns, nor was there an interaction between stars given and product complexity, $F(4, 237.61) = .86$, p = ns. Given that word count featured a skewed distribution, the same analysis was also conducted using the log of the word count variable. Once again, there was a trending effect of product complexity, $F(1, 236.35) = 3.08$, $p = .08$, with no effect of number of stars given, $F(4, 236.68) = 1.45$, p = ns, nor an interaction between stars given and product complexity, $F(4, 236.69) = 1.14$, p = ns.

Helpfulness. Correlations were used to assess the strength of the relationship between word count and helpfulness score for both simple and complex products. For the complex products, there was a moderately strong positive relationship between word count and helpfulness score, $r(125) = .38$, $p < .01$. However, for the simple products, there was a much weaker relationship, $r(125) = .07$, p = ns. In addition, the relationship for the complex products was significantly stronger than the relationship for the simple products, $Z = 2.58$, $p < .01$.

Discussion

As in Study 4, consumers were more satisfied with more complex explanations (i.e., reviews); overall, helpfulness ratings generally increased as review complexity increased. However, this relationship was stronger for complex products than for simple products, providing additional support for the complexity-matching hypothesis. Once again, the data suggests two additive forces working together: a general preference for increased complexity (as evidenced by the consistently positive correlations), in addition to a preference for complexity matching (leading to weaker correlations when products and reviews do not match in complexity).

Of course, the use of naturalistic archival data means that we have less experimental control over stimuli and study design, raising a number of possible confounds. However, these findings, in conjunction with the previous laboratory studies, provide converging evidence for the robustness and generalizability of the complexity-matching hypothesis.

General Discussion

For decades, scholars have been trying to understand what makes for a satisfying explanation. Many factors have been found to contribute to the perceived quality of an explanation, from an explanation’s teleological properties (Kelemen, 1999; Kelemen & Rosset, 2009), to less normatively defensible factors, such as the inclusion of neuroscience (Weisberg et al., 2008) and math (Eriksson, 2012), or appeals to particular scripts and norms (Langer, Blank,

& Chanowitz, 1978). More specifically, we add to the work on explanatory virtues, as first outlined by Thagard (1978) and later carried on by other researchers in the domains of coherence (e.g., Bovens & Hartmann, 2003; Koslowski et al., 2008), breadth (e.g., Read & Marcus-Newhall, 1993; Preston & Epley, 2005), and simplicity (e.g., Read & Marcus-Newhall, 1993; Lombrozo, 2007; Bonawitz & Lombrozo, 2012).

Contributions

In the current work, we focus on the role of simplicity. While many researchers have suggested that simplicity is an explanatory virtue, others have found evidence for the desirability of complexity in explanations. The current work attempts to resolve this apparent discrepancy by showing that both sides have a point— we demonstrate that individuals prefer for events and explanations to match in terms of complexity. Thus, people favor relatively simpler explanations for simple events, and more complex explanations for complex events.

The current work also adds to the emerging literature on matching in causal relationships (Ebel-Lam et al., 2010; Spina et al., 2010; Lebouef & Norton, 2012; Einhorn & Hogarth, 1986). Much of this previous work has examined pure cause-and-effect relationships, where an event A leads to an event B. In the current work, we move the matching principle beyond the lens of cause-and-effect, and into explanations. While explanations and causal relationships are highly related, there are many factors unrelated to perceptions of causal relationships that contribute to the satisfactoriness of an explanation, such as the inclusion of reductive factors (Hopkins, Weisberg, & Taylor, 2016), the teleological structure (Kelemen, 1999; Kelemen & Rosset, 2009), and even length (Kikas, 2003). Thus, to find that complexity matching also contributes to explanatory satisfaction is noteworthy.

Additionally, the past literature on matching has almost exclusively examined physical dimensions, such as magnitude and appearance, which are usually the most easily observable traits for individuals to recognize and use as a cue for matching. Since we focused on explanations and not pure cause-and-effect relationships, it may be worth exploring whether people show a susceptibility to matching in terms of complexity, along with other more abstract factors, when engaging in causal reasoning.

Future Directions

Explanatory Goals

In the current work, we implicitly assume that people's goal in explanation is to gain a sense of understanding (e.g., Achinstein 1983, Wilkenfield 2014). However, beyond understanding, there are a variety of other goals that individuals may come in with when thinking about explanation, such as prediction and control (e.g., Craik 1943, Heider 1958, Gopnik 2000), the desire to "fix" something broken (Graesser & Olde 2003), discovery of underlying causal structure (e.g., Legare & Lombrozo 2014, Amsterlaw & Wellman 2006, Salmon 1984), data interpretation (Koslowski 1996), or simply to obtain a sense of satisfaction (Gopnik 2000). As a result, it is worth asking how people's preferences for simplicity or complexity in explanation will change as their goals shift. For example, if prediction and control is the objective, then individuals may exhibit a stronger preference for complexity instead, as figuring out the nuances of a situation should allow for greater projection of potential outcomes. Thus, future researchers are encouraged to think about the goals individuals have when seeking out explanation, and how these aims may affect their very preferences.

Characteristics of the Event

We examined a key attribute of the precipitating event –complexity– which affected people's explanatory preferences. However, we do not argue that complexity is the only characteristic of an event that matters. For example, previous research has demonstrated that individuals are more likely to think about and elaborate on important issues relevant to them (Petty, Cacioppo, & Goldman 1981). Perhaps the importance or relevance of the event being explained would similarly lead to differences in preferences regarding explanatory complexity, with more important events meriting a stronger preference for more complex explanations. Along with this, there are potentially many other characteristics of a precipitating event that could influence people's explanatory preferences, and future research would do well to explore this area further.

Characteristics of the Explanation

While much research has already been devoted to examining the qualities of a satisfying explanation, there is still much work to be done in this field. Most notably, another key element that must be attended to in most environments is the probability of an explanation (Johnson, Valenti, & Keil 2017; Johnson, Jin, & Keil 2014). Johnson and colleagues (2017) argue that explanations tend to vary in their probability, with simpler explanations being more probable than complex ones. However, complex explanations are often better fits for the event at hand, as they are able to account for the totality of data presented (i.e., the Bayesian likelihood is higher). Thus, attributing a university's success to the confluence of hiring new faculty, adding new majors, and receiving large endowments is a more powerful explanation than any one of these factors alone would be, but it is obvious that having three such events all occur at the same time is much less probable than having any single one take place. As a result, individuals must trade off the probability and likelihood of an explanation as needed in order to obtain an optimal balance for any given event.

Given this tradeoff, it brings up the question: what are the features of any situation that lead people to make this adjustment? Johnson and colleagues (2017) speculated on a couple different environmental characteristics that may lead to a tradeoff: the determinism and the content domain of the causal system. In deterministic systems where causes always led to effects, people favored explanations with lower likelihood (and higher probability), while in stochastic systems where there was variance in whether a cause led to an effect, explanations with higher likelihood (and lower probability) were preferred. The authors reasoned that when causes invariably lead to effects, only one cause is needed in order to account for any given effect. However, when there is some doubt in the causal pathway, people may desire to have more causes, as there will be "more chances" for the causes to explain the effect. Along with the determinism of the system, the content domain also influenced the tradeoff between probability and likelihood. Since people think differently about physical versus social domains (Strickland, Silver, & Keil 2016), reasoning in more complex ways about social events, it seems likely that they will prefer different kinds of explanations for each domain. Specifically, they will favor explanations with higher likelihood (but lower probability) when judging social systems, and explanations with lower likelihood (but higher probability) when assessing physical systems, which is precisely what the authors found.

What other event characteristics may influence people's tradeoff between probability and likelihood? The current work could lend a clue to another such characteristic –complexity– with the prediction being that for simple events, people will prefer explanations with high probability and low likelihood, but for complex events, they will prefer explanations with low probability and high likelihood. We leave it to future researchers to explore this proposition further.

Motivations for Complexity-Matching

The current work has provided robust evidence for the phenomenon of complexity matching, showing its generalizability across different domains, dependent measures, and operationalizations. However, up to this point we have still not been able to answer *why* people complexity-match to begin with, leading us back to the simplicity versus complexity debate that frames the current work.

On the one hand, it could be the case that individuals have an appreciation for greater complexity in explanation— that complexity, in and of itself, is actually a satisfying quality, a position that theorists such as Zemla et al. (2017) and others would advance. Grasping the nuance and detail of an event may feel rewarding, providing a sense of understanding that is intuitively fulfilling (e.g., Achinstein 1983, Wilkenfield 2014). Thus, a complexity-for-satisfaction account would argue that people have a natural preference for explanatory complexity, one that they adjust downwards for simple events (resulting in an outward appearance of matching), and upwards for complex events (resulting in an explanation that may actually end up over-explaining the event).

However, a competing point could be made that, as Lombrozo (2007) and others have argued (e.g., Lagnado 1994; Chater & Vitanyi 2003; Bonawitz & Lombrozo 2012; Read & Marcus-Newhall 1993), people instead have a natural preference for simplicity. Thus, even though they do exhibit a tendency to match events and explanations in terms of complexity, they are always looking for the most parsimonious explanation possible that is still able to interpret the data. While this complexity-for-necessity account makes sense for simple events, it may seem counter-intuitive for more complex events. However, such an account would argue that when faced with complex events, individuals adjust their preference for explanatory simplicity upwards (leading to an outward preference for complex explanations). In reality though, they are actually looking for an explanation that is just complex enough to meet, as opposed to totally fulfill, their need for understanding. In a sense, while the complexity-for-satisfaction account would propose that people are explanatory satisfiers, the complexity-for-necessity account would argue that they are explanatory satisficers. While we have found preliminary evidence in favor of the latter account, we realize that much work is still to be done to resolve this issue, and we leave it to future researchers to parse between these two accounts further.

Practical Implications

Given the fact that explanations are a pervasive part of everyday life, these findings also have implications across a wide variety of fields, such as medicine, law, and marketing. For example, the American Medical Association notes that one major reason why many patients fail to take their medication is a lack of understanding— "patients may not understand the need for the medicine, the nature of the side effects, or the time it will take to achieve results" ("8 Reasons," 2015). Medical practitioners may thus have better success in reaching their patients if they were to better tailor explanations to patients' perceptions of complexity. Similarly, in law, attorneys may do well to adapt the complexities of their explanations and arguments to the jury's desired level of complexity. In marketing, many public relations crises often involve complex events and outcomes which might make simple explanations seem inadequate, or worse, insulting. Public relations officers and brand managers would thus do well to think about the complexity of the crisis, and to fashion their explanations accordingly.

In the end, our work sheds light on the question of what constitutes a satisfying explanation, by providing complexity matching as a factor worthy of further study. However, there is still much more work that remains to be done to explain explanations. Simply put, the answer to this question can be quite complex.

Appendix A

(+ +)
"Friedman University has been having an interesting year. It was recently christened a top-twenty university by Canadian News & World Report, the first time the school had ever received such an honor. Additionally, upon graduation, 90% of Friedman's senior class this year will either be employed or attending graduate school, the highest such rate in Friedman's history."

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"Friedman University has been having an interesting year. It was recently dropped from the list of top-twenty universities by Canadian News & World Report, the first time the school had ever been absent from the list. Additionally, upon graduation, only 40% of Friedman's senior class this year will either be employed or attending graduate school, the lowest such rate in Friedman's history."

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