ESSAYS ON CREATIVE IDEATION AND NEW PRODUCT DESIGN

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ABSTRACT

Tojin T. Eapen: Essays on Creative Ideation and New Product Design
(Under the direction of Rajdeep Grewal)

Creative ideation, i.e., the generation of novel ideas, represents the terminus-a-quo in the design and development of innovative products. In my dissertation essays, I examine two approaches employed by firms for creative ideation, (1) channeled ideation, a closed approach, which involves applying replicable patterns or properties observed in historical innovations and (2) idea crowdsourcing, an open approach where firms invite crowds to contribute ideas to solve a specific challenge. In my studies, I clarify how firms can incorporate market-related information in the channeled ideation process and examine how the selection of ideas in crowdsourcing challenges relates to local and global novelty.

In Essay 1, "Attribute Auto-dynamics and New Product Ideation," I introduce a replicable property – attribute auto-dynamics, observed in several novel products, where a product possesses the ability to modify its attributes automatically in response to changing customer, product-system, or environmental conditions. I propose a typology of attribute auto-dynamics, based on an analysis of U.S. utility patents. Based on this typology, I specify a procedural framework for new product ideation that integrates market-pull relevant knowledge and technology-push relevant knowledge. I also illustrate how managers and product designers can apply the framework to identify new product ideas for specific target markets using a channeled ideation approach.

In Essay 2, “Selection in Crowdsourced Ideation: Role of Local and Global Novelty,” I examine how the selection of ideas in crowdsourced challenges depends on the form of novelty – local or global. Firms often turn to idea crowdsourcing challenges to obtain novel ideas. Yet prior research cautions that ideators and seeker firms may not select novel ideas. To reexamine the links between idea novelty and selection, I propose a bi-faceted notion of idea novelty that may be local or global. Examining data on OpenIDEO, I find that the selection of novel ideas differs according to the selector, the form of novelty, and the challenge task structure. I also specify a predictive model that seeker firms can leverage when ideator selection metrics such as likes are unavailable.

To Niky, and my parents.

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CHAPTER 1 – INTRODUCTION

The appropriate use and efficient management of methods ideational methods and tools are essential for the success of new products (e.g., Cooper and Edgett 2008; Dahl and Moreau 2002; Lilien et al. 2002; Tauber 1972; Toubia 2006). Beyond idea generation, the success of the idea management also requires firms to select the right ideas (Beretta 2019; Rietzschel, Nijstad, and Stroebe 2019; Toubia and Florès 2007). Technological developments necessitate the adaptation of appropriate methods for ideation that takes into account emerging technical knowledge as well as market-related information such as the voice of the customer (Cooper and Edgett 2008; Hauser, Tellis, and Griffin; Kornish and Hutchinson-Krupat 2017; Gaimon 2008).

Broadly, it is considered that there are two potential sources of innovation, market-pull (or demand-pull) and technology-push (Di Stefano et al. 2012). Parallel to the above dual sources of innovation, we can identify two broad approaches to ideation. The first is a technology push approach exemplified by methods such as TRIZ (Altschuler 1985) and inventive templates for channeled identified by (Goldenberg, Mazursky, and Solomon 1999). Such approaches involve studying replicable patterns in past inventions to identify patterns that can be applied to new contexts. A second approach is a market-pull approach, where ideas convey the voice of the customer (e.g., Chang and Taylor 2016; Cooper and Edgett 2008). An exemplar of the market-pull approach is idea crowdsourcing, where a seeker-firm organizes idea challenges where crowds can submit new product ideas (e.g., Bayus 2014; Poetz and Schreier 2012)

In Chapter 2, I focus on channeled ideation. I identify and describe a property called attribute auto-dynamics that seen in several innovative products. Thus, this property represents a

replicable property similar to inventive templates (Goldenberg, Mazursky, and Solomon 1999) or TRIZ inventive principles (Savaransky 2000). The key contributions of this study are the following. First, based on the analysis of US Patents, I formulate a typology of attribute auto-dynamics that can provide the basis for future examination of this property. Next, I offer a procedural framework that utilizes the above typology to identify new product ideas. I demonstrate the application of this framework by using the example of smart textile clothing, an emerging product category (e.g., Cheng et al. 2017).

In Chapter 3, I examine the selection of ideas in idea crowdsourcing contests, a market-pull approach to generating ideas. The objective of our paper is to investigate the relationship between the novelty of ideas and selection in the context of idea crowdsourcing, where the number of ideas may be substantial. Our contributions in this are threefold – conceptual, methodological, and empirical.

First on the conceptual front, building on the cognitive science literature recognizes the difference in local and global perception (Kimchi 1992), I propose that novelty can take two forms – local and global, relative to the referential domain of knowledge a focal idea is compared to. I argue that the examination of idea selection in the context of crowdsourcing should involve an examination of both faces of novelty. I suggest that mixed findings regarding the relationship between novelty and outcome measures previous studies might stem from not recognizing the two-faced nature of novelty (Chan, Li, and Zhu 2018; Rietzschel, Nijstad, and Stroebe 2019). For example, the frequency-based approach commonly used in evaluating idea novelty is typically an evaluation of local novelty (e.g., Brown 2014).

Second, concerning methodology, I propose an automated approach to evaluating global novelty which may be more convenient than using idea evaluation scales (e.g., Dean 2006). This

method compares the co-occurrence of words in the idea to a high dimensional word embedding space trained on word co-occurrences in a global domain of information such as Wikipedia (Pennington, Socher, and Manning 2014). I propose that this is an improvement and simplification over methods that use raw words or topics-based representation in evaluating creativity of ideas (e.g., Chan and Schunn 2015; Toubia and Netzer 2017).

Third, based on the analysis of OpenIDEO, I explain how the selection of idea differs based on the form of novelty as well as task structure definition (e.g., Moreau and Dahl 2005; Moreau and Engeset 2016; Newell and Simon 1972; Reitman 1974). I also examine how the selection of locally and globally novel ideas may depend on the selection metric (shortlisting, likes, winning) and order entry of ideas. Overall, I find there is an inverted 'U' relationship between shortlisting of ideas and global novelty of ideas, but find no evidence for a positive association between local novelty and shortlisting. Global novelty, however, is not associated with the probability of a contributed idea winning a challenge. I also find that interaction of local and global novelty with factors such as task structure definition, and order of entry plays a role in the selection of ideas.

The findings from our dissertation furnish implications both for theory and practice. On a theoretical front, our findings highlight the importance of considering both forms of novelty – local and global in examining idea selection. This distinction is critical in the case of crowdsourcing contests, where the evaluation of ideas by seeker firms and other ideators may involve both an explicit comparison to other ideas in the same challenge (local domain), as well as an implicit comparison to other ideas outside the contest (global domain). Our findings imply that even though crowds perform better than experts at generating novel ideas (Poetz and Schreier 2012), highly novel ideas may not be shortlisted, particularly for well-defined tasks. In

such cases, I also suggest that using an automated approach for evaluating ideas, as described in our study may help firms in screening novel ideas.

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CHAPTER 2 - ATTRIBUTE AUTO-DYNAMICS AND NEW PRODUCT IDEATION

Abstract

Some contemporary new product introductions feature attribute auto-dynamics—the property that enables a product to adapt its attributes automatically in response to changing customer, product-system, or environmental (CSE) conditions. In addition to explicating auto-dynamics, I propose a typology of attribute auto-dynamics, based on close examinations of 273 U.S. utility patents published between 2001 and 2017. Attribute auto-dynamics offers an efficient mapping design, applicable to changing conditions and product attribute states, that indicates a four-part (contingent, distinctive, associative, and generative) typology. Building on this typology, I specify a procedural framework for new product ideation by harnessing market-pull–relevant knowledge about CSE conditions, along with technology-push–relevant knowledge about product attributes. Finally, the application of a proposed framework for consumer decision making to pricing strategies for products with auto-dynamics reveals some key implications.

Keywords: attribute auto-dynamics, ideation, innovation, new products, patent analyses.

Introduction

Attribute auto-dynamics refers to a property of a product that enables it to adapt its attributes automatically (i.e., without consumer/user input) in response to changing conditions that might pertain to the customer, the product-system, or the external environment. A product attribute is a variable (Goldenberg, Mazursky, and Solomon 1999; Wilkie and Pessemier 1973), able to be measured on nominal (e.g., color), ordinal (e.g., comfort), interval (e.g., temperature), or ratio (e.g., length) scales, and auto-dynamics applies to all four types. Products imbued with attribute auto-dynamics in turn offer unique value, as the following examples suggest:[1]

- Nike's HyperAdapt 1.0 Self-Lacing Sneaker alters its lacing to match the contours of the wearer's feet. The shoe promises to provide an "ultimate solution to individual idiosyncrasies in lacing and tension preference." Its attributes (lacing tension) adapt automatically to changing *customer conditions* (feet contours).
- The Ember Coffee Mug keeps "your beverages at the perfect temperature from the first sip to the last drop." The product adjusts its attributes (cup temperature) dynamically based on changing internal *product-system conditions* (coffee temperature).
- Cabela's ColorPhase line of camouflage clothing designed for hunters adapts its attributes (color and shading) based on changing *environment conditions* (terrain and temperature).

In the past, products that featured auto-dynamics were frequently visible in science fiction novels and movies;[2] even if they were available in reality, they usually lacked technical or commercial viability. But recent technological, computing, and material science advances (e.g., inexpensive smart sensors, flex circuits, embedded software; Davis 2015) support the incorporation of auto-dynamics into relatively simple products, such as shoes and clothing, and highly complex, multifunctional products, such as aircraft. Thus, the wing surfaces on Boeing's 787 Dreamliner

[1]See https://www.nike.com/us/en_us/c/innovation/hyperadapt; https://ember.com/; https://www.cabelas.com/category/Cabelas-ColorPhase/396159480.uts (accessed June 2019).

[2]For example, the Nike HyperAdapt (U.S. Patent # 8046937) was inspired by the 1985 movie *Back to the Future* (https://www.forbes.com/sites/simonogus/2018/12/28/nikes-self-lacing-hyperadapt-sneakers-are-returning-in-2019/, accessed June 2019), and George R.R. Martin's novel *Dying of the Light* (1977) describes a chameleon cloth that adapts its color based on its surroundings.

(U.S. Patent # 7641152) adjust in flight, according to changing altitudes, to ensure a smoother journey. Auto-dynamics also offer great promise in emerging and innovative product categories, such as smart textiles, wearable devices, and consumer Internet-of-things products (e.g., Mackey et al. 2017; Piwek et al. 2016; Rowland et al. 2015).

Considering these increasing uses, studying auto-dynamics promises to establish some substantial managerial and research implications. On the managerial front, a profound understanding of auto-dynamics can inform new product ideation processes. For example, firms might use auto-dynamics as a replicable structural pattern in innovative products to generate novel ideas in previously untapped contexts, similar to TRIZ principles and inventive templates[3] (Altschuler 1985; Goldenberg, Mazursky, and Solomon 1999; Hauser, Tellis, and Griffin 2006).

On the research front, we note three key avenues. First, we need a clearer view of consumer evaluations and decision making for products that feature auto-dynamics, in contrast with products with static attributes. Product attributes respond automatically to changing conditions, which may be uncertain, so the value derived from such attributes may be latent to customers during their purchase decision process. When activated by changing customer, product-system, or environmental (CSE) conditions, attribute auto-dynamics could lead to positive expectation disconfirmations and thus post-usage customer satisfaction (Oliver 1977). Consider safety features as an example. Carmakers might not promote the availability of automatic emergency braking,[4] in an effort to avoid overwhelming customers with too much

[3]TRIZ (Teoriya Resheniya Izobretatelskikh Zadatch, or theory of inventive problem solving) provides 40 inventive principles for technological problem solving, derived from patent analyses (Altschuler 1985). An inventive template is an "identifiable, objectively verifiable, widely applied, and learnable" pattern found in new products (Goldenberg, Mazursky, and Solomon 1999, p. 200). According to Hauser, Tellis, and Griffin (2006), studying patterns such as TRIZ principles and inventive templates and their relation to customer needs constitutes a key research need at the intersection of innovation and marketing.

[4]See https://www.safercar.gov/Vehicle-Shoppers/Safety-Technology/AEB/aeb (accessed May 2019).

product complexity (Rust, Thompson, and Hamilton 2006). However, when activated, this feature may surprise and delight customers by keeping them safe (Oliver, Rust, and Varki 1997). Smart fashion products that generate surprising design patterns automatically, based on changing conditions, might positively disconfirm the expectations of both wearers and observers.[5]

Second, auto-dynamics offer opportunities for developing novel usage- or performance-based pricing models. If attribute auto-dynamics is latent during the purchase phase, the firm might leverage a static upfront price, then charge for variable consumption upon activation. The carmaker thus might install an automatic drowsy driver detection system onboard at no upfront cost, but then charge any customers (possibly a steep price) who fall asleep while driving and activate the system.

Third, research must address ethical and safety issues related to products with auto-dynamics, especially when users are unaware of changing conditions or the product adapts its attributes by overriding human inputs. For example, the Maneuvering Characteristics Augmentation System, which incorporates auto-dynamics, has emerged as a probable cause of two fatal Boeing 737 MAX 8 crashes in October 2018 and March 2019.[6]

Because auto-dynamics is an important emerging property, facilitated by recent technological developments and distinct from extant constructs, it merits systematic study. In particular, we need conceptual frameworks to support systematic investigations of auto-dynamics, as well as managerial decisions and continued research. Auto-dynamics are evident in innovative products and emerging product categories, so to derive a generalizable conceptual

[5]See https://www.businessoffashion.com/articles/intelligence/the-rise-of-smart-fashion (accessed June 2019).

[6]This type of attribute auto-dynamics is "activated without pilot input and commands nose down stabilizer to enhance pitch characteristics during step turns with elevated load factors" See https://theaircurrent.com/aviation-safety/what-is-the-boeing-737-max-maneuvering-characteristics-augmentation-system-mcas-jt610/ (accessed June 2019).

framework, we need contextual insights into novel and emerging product concepts across many product categories. Therefore, we apply grounded theory (Ding 2014; Glaser and Strauss 1967), as a database-supported approach to theory development that emphasizes contexts and interactions (Corbin and Strauss 2008). In turn, we analyze utility patents awarded by the U.S. Patent and Trademark Office (USPTO) during 2001–2017. By sampling more than 3000 patent abstracts and closely analyzing 273 shortlisted patents, we establish a typology of auto-dynamics, with three main contributions to extant literature.

First, we confirm that auto-dynamics provides an efficient mapping structure, moving from changing conditions to product attribute states. The proposed typology of auto-dynamics comprises four types: contingent, distinctive, associative, and generative. We illustrate each type with ideal cases, drawn from USPTO utility patent data. Second, we detail a managerial application for auto-dynamics and the typology for new product ideation. Consistent with an approach by Goldenberg, Mazursky, and Solomon (1999), we specify a procedural framework that firms can use to identify new product ideas by harnessing *market-pull*–relevant knowledge about CSE conditions together with *technology-push*–relevant knowledge related to product attributes. Third, we build on the notion of auto-dynamics and our proposed typology to suggest a framework for consumer decision making, and we draw implications for this framework by applying it to pricing strategies for products that contain auto-dynamics.

Background

Dynamic adaptation is not new. Most biological systems are highly dynamic (Kitano 2002) and respond automatically to stimuli. Yet most human artifacts and manufactured products possess static attributes. Only recently have technological developments allowed for enhanced attribute auto-dynamics, in single-function products such as shoes (e.g., Nike HyperAdapt 1.0)

and complex, multifunctional products such as aircraft (e.g., Boeing 787 Dreamliner). To study this emerging, increasingly prevalent, and influential property in innovative new products systematically and assess its relevance for consumer and managerial decisions, we build on previous theoretical and empirical research in marketing related to new products and product attributes that details the relationship between attributes and customer preferences and the role of attributes in product design.

Attributes and Customer Preferences

Marketing and consumer research often represents products as bundles of attributes (e.g., Chung and Rao 2003; Huber 1975; Wilkie and Pessemier 1973). Multi-attribute models typically assume that attributes are static and can satisfy customer needs; even if their importance can change over time (e.g., McAlister 1982; Mittal, Kumar, and Tsiros 1999), the attributes themselves are assumed to remain stable and time-invariant. In contrast, attribute auto-dynamics imply that the product changes its attributes, in response to changing conditions, which represents a clear advantage in relation to customer preferences for different types of attributes.

It even is possible to classify attributes according to how they relate to *consumer preferences* (Golder, Mitra, and Moorman 2012). That is, some relationships between an attribute and consumer preferences are monotonic; more (less) of the attribute is always better, and customers have homogenous attribute preferences. Familiar examples include the lifespan of a light bulb or the quantity of emissions produced by a vehicle; a longer lasting bulb and a car with lower emission levels consistently have greater utility for customers. For other attributes though, consumers may develop different ideal points (Day 1972; Golder, Mitra, and Moorman 2012), so the attributes evoke heterogeneous preferences. For example, people who are near-sighted (myopic) have different ideal points for their corrective lenses. If that ideal point remains

stable, the consumer's preference for products with attributes constructed close to this ideal point is predictable.

Changing Conditions and Shifting Ideal Points

In many plausible scenarios and changing conditions, the ideal point for a product attribute is not static though, and a consumer even might maintain multiple ideal points. When CSE conditions change, the appropriate ideal point also can shift over time, whether related to the single use of a product or longer-term changes over multiple uses. If the ideal point shifts over time, a product attribute constructed with a single ideal point will be unsatisfactory, a situation we refer to as the shifting ideal point problem. We examine such shifts in ideal points in terms of changing CSE conditions encountered by the customer.

Changing Customer Conditions. When customer conditions, such as physiology or health, change, the ideal points likely shift too. For example, upon receiving a diagnosis of presbyopia (age-related eye condition that affects the ability to focus), patients establish different ideal points for the focal length of their corrective lenses, depending on the object they need to view. Furthermore, customer preferences may change over time due to endogenous factors such as learning, habit formation, or addiction, so ideal points can shift over time.

Changing Product-System Conditions. Changes in product-system conditions also shift ideal points, such as when changes to a product attribute alter the ideal point for another product attribute. Enhanced engine speed in a new model sports car, and the resulting increase in noise, would shift the ideal volume level for the car's music system, for example. In response, auto-dynamics can provide solutions, as exemplified by Speed Dependent Volume Control systems that adjust audio volume according to the car's speed (U.S. Patent # 9118290).

Changing Environment Conditions. Ideal points may shift over time based on changing environmental conditions, whether related to the physical environment (e.g., weather), other related products, or human users. Exogenous factors such as fashion also can lead to shifting ideal points over time; people's ideal points for a clothing aesthetic often depend on choices and preferences expressed by friends.

Therefore, to deal with shifting ideal points, firms have three options: (1) develop multiple products with attributes at different ideal points, such as multiple eyeglasses with lenses of different focal lengths; (2) devise products that allow customers to modify the product attributes manually to suit different ideal points, such as adjustable-focus glasses (U.S. Patent #3598479); or (3) incorporate attribute auto-dynamics into the products, such as eyeglasses developed by Deep Optics (www.deepoptics.com) that adjust the focal length automatically (U.S. Patent #10036901). In several scenarios though, the first two options cannot adequately address the shifting ideal point problem. First, the customer may be unaware of changing conditions (e.g., physiological conditions of a drowsy driver). Second, changing conditions often materialize rapidly, making it inconvenient or even impossible for the customer to switch between multiple products or adjust the attributes (e.g., changing environmental conditions outside an aircraft). In these cases, a product with attribute auto-dynamics likely offers the best solution to the shifting ideal point problem, because the adaptation process is automatic.

Attributes in New Product Design

Effective product design requires incorporating attributes that contribute to both functional and aesthetic (form) elements (e.g., Luchs and Swan 2011; Srinivasan, Lilien, and Rangaswamy 2006), both of which inform consumers' overall evaluations of new product designs (Chitturi, Raghunathan, and Mahajan 2007; Homburg, Schwemmle, and Kuehnl 2015).

As a functional property, studying attribute auto-dynamics may help reveal optimal approaches to the design of innovative new products. Although attribute auto-dynamics, and its key implications for marketing scholars and practitioners, relates to constructs explored in previous studies, it differs in notable ways, and we lack systematic insights into how firms can employ attribute auto-dynamics to design customer-focused new products and marketing strategies.

Data Analysis

To understand consumer and managerial decision making in interaction with attribute auto-dynamics, we first establish a detailed conceptualization of the various forms and manners in which attribute auto-dynamics might be manifest. Because attribute auto-dynamics relate to products, and many products that incorporate attribute auto-dynamics are new and innovative, we examine patents for new products that feature attribute auto-dynamics in our effort to develop a data-grounded typology. Patent data (1) refer to new products across multiple categories, (2) specify customer needs satisfied by a new product, (3) provide technical details about product attributes and design, and (4) detail the interactions between customers and the product. The data we use include patents published by the USPTO between 2001 and 2017. We leverage the rich contextual information available in patents by applying a grounded theory approach (e.g., Ding 2014; Glaser and Strauss 1967).

Grounded Theory

Grounded theory provides a means to examine dynamic interactions among actors and their environment (Charmaz 2006; Corbin and Strauss 2008; Glaser and Strauss 1967). Its epistemological basis derives from pragmatism and symbolic interactionism (Corbin and Strauss 2008). In contrast with hypothetico-deductive models, in which hypothesis development precedes the data analysis, this approach requires their simultaneity, so the resulting grounded

theory is developed and tested at the same time. It has informed research pertaining to marketing strategy (e.g., Gebhardt, Carpenter, and Sherry 2006; Noble and Mokwa 1999), consumer behavior (Epp, Schau, and Price 2014; Fournier 1998), and new product development (Burchill and Fine 1997). Ding (2014) and Fischer and Otnes (2006) provide useful overviews of grounded theory methods as applied in marketing.

Glaser and Strauss (1967) propose certain elements of grounded theory that subsequent research has challenged or expanded. For example, they present the method as consistent with a positivistic view of reality, yet scholars with interpretive views also have used grounded theory methods (Charmaz 2006). Similarly, Glaser and Strauss define grounded theory as an inductive approach, whereas other researchers argue it is epistemologically closer to "abduction," a concept that denotes the creative production of novel hypotheses based on surprising evidence (Reichertz 2007). Glaser and Strauss also call for researchers to discard previous theory and review data without any biases, but subsequent scholars acknowledge the importance of incorporating previous knowledge (Suddaby 2006). Although primarily a qualitative methodology, grounded theory also can encompass qualitative and quantitative data (Corbin and Strauss 2008), because as Glaser (2001, p. 145) acknowledges, "all is data." Accordingly, some applications of grounded theory include both primary and secondary data (e.g., Andrews et al. 2012), derived from interviews, field observations, and archives. Grounded theorists also emphasize the value of data richness (Charmaz 2006) to support its two central features, namely, theoretical sampling and constant comparative analyses.

Theoretical Sampling. Theoretical sampling proceeds according to "the theoretical relevance for furthering the development of emerging categories" (Glaser and Strauss 1967, p. 97), with the objective of identifying data variations that might inform theory development.

Researchers sample data not according to specific groups of individuals or units of time but rather in terms of theoretical concepts and their dimensions (Corbin and Strauss 2008).

Constant Comparative Analyses. Grounded theory researchers collect and analyze data at the same time. Concepts provide the fundamental units of analysis. The first step is to identify concepts from data. Then the act of theorizing "commences with comprehending frequently minute episodes or interactions that are examined for broader patterns and processes" (Deshpande 1983, p. 107). Concepts can be linked to form categories at a higher, more abstract level. Researchers constantly compare the concepts and categories, to one another and with new data, to reveal similarities and differences that might provide a basis for new concepts or categories (Corbin and Strauss 2008).

Analysis of Attribute Auto-Dynamics using Grounded Theory

We apply grounded theory to understand attribute auto-dynamics, such that we (1) study recent patents to obtain insights into attribute auto-dynamics, (2) empirically derive a typology of attribute auto-dynamics, and (3) identify ideal types for comparison with emerging cases.

Data and Theoretical Sampling. Patents awarded by the USPTO are the primary data source. They are ideal for this study, because patents must describe (1) the need or problem faced by the customer/user, (2) vital functional and technical specificities of the product design, and (3) the interactions between the customer/user and the product. Initially, we randomly sampled utility patents published by the USPTO between 2001 and 2017, using keyword searches to sample additional cases that feature attribute auto-dynamics. We searched across product categories and obtained a sample of more than 3000 patents. We then created a shortlist of 273 patents for further analysis (Appendix 1.1 lists the specific shortlisted patents).[7]

[7]As part of theoretical sampling, and to gain a deeper understanding of the relevance of attribute auto-dynamics in a single product domain, we conducted a sector-specific analysis of patents for vehicles published during 2017–2018.

Coding and Constant Comparative Analysis. Coding is the fundamental analytic procedure for grounded theory (Corbin and Strauss 2008). From the initial sampling of patents, we determined that we should examine attribute auto-dynamics according to the interactions of three key elements: the customer (user), product-system, and environment. We employ open, axial, and selective coding to develop the categories (Charmaz 2006; Corbin and Strauss 2008).

First, with open coding, we analytically break down descriptive data in the patents into concepts; an abstract concept "must be developed in terms of its properties and dimensions of the phenomenon it represents, conditions which give rise to, the action/interaction by which it is expressed, and the consequences it produces" (Corbin and Strauss 1990, p. 7). Therefore, we examine three facets associated with each analyzed patent: (1) the conditions, which indicate the consumer need and how it emerges; (2) actions/interactions described in the patent; and (3) the consequences, or how the product resolves the consumer need. We accordingly identify and code different concepts according to these three facets, leading us to combine the concepts to form broader categories. While sampling new data, we compare the categories, to one another and with fresh data, to identify any new categories. The initial categorization revealed several categories and dimensions for classifying patents (see Appendix 1.3). We continued the open coding until we analyzed 273 patents, at which point we reached saturation, with no new categories emerging from the data (Corbin and Strauss 2008). Second, the axial coding step links the categories together, while eliminating any categories that do not help distinguish or classify most cases (Corbin and Strauss 2008). We thus combine key categories to form core categories

The search uncovered more than 16,000 patents awarded in this period. We applied a topic modeling approach with latent Dirichlet allocation (Blei 2014; Blei, Ng, and Jordan 2003) to assess patent similarity, then employed model-based clustering to group the patents into six clusters. Among 300 patents (50 samples × 6 clusters), we could classify 47 (16%) that involved attribute auto-dynamics. Appendix 1.2 details this analysis and the findings, which match those from our main analysis.

(e.g., changing conditions, product attribute states) but drop others (e.g., degree of interaction between product and user). Third, in the selective coding step, we derive a unifying typological framework according to the two core categories that provide the basis for classifying most of the cases: changing conditions and product attribute states.

Empirical Typology and Ideal Types

Theoretical contributions achieved by studies that use grounded theory in marketing span four main areas: (1) identification of construct dimensions, (2) articulation of typologies, (3) conceptual frameworks, and (4) propositions (Fischer and Otnes 2006; Locke 2001).[8] For studies that focus on a construct, as in our case, the first two contributions are more common (Fischer and Otnes 2006). Accordingly, we identified a two-dimensional taxonomy of varying customer needs (described in the next section), with four types of attribute auto-dynamics. After developing the typology, we applied it to identify ideal types,[9] as abstract ideals against which to compare new cases (Blalock 1969; Doty and Glick 1994; Perren and Kozinets 2018). We identify four ideal types from the analyzed patents, one for each type of attribute auto-dynamics.

Typology

As we reveal subsequently in Figure 1, attribute auto-dynamics depends on how the changing conditions, whether discrete or continuous, map on to product attribute states (i.e., the distinct values that an attribute can take), which are few or many in number. These two dimensions (changing conditions and product attribute states) produce the typology with four

[8]Fischer and Otnes (2006) classify grounded theory studies in marketing according to whether they (1) question the nature of a new construct, (2) challenge the conceptualization of a well-known construct, (3) examine unrecognized facilitators or implications of a construct, or (4) consider the adequacy of previous conceptualizations of the facilitators or implications of a construct. Our study falls into the first category.

[9]An ideal type is "A hypothetical construct made up of the salient features or elements of a social phenomenon, or generalized concept, in order to facilitate comparison and classification of what is found in operation" (Oxford English Living Dictionary 2019, https://en.oxforddictionaries.com/definition/ideal_type).

auto-dynamics, which we illustrate by using the running example of a smart textile suit with dynamic attributes (Mackey et al. 2017). The smart textiles product category currently features multiple innovations in progress, seeking to leverage recent technological advances (Cherenack and van Pieterson 2012; Mackey et al 2017), and many of those innovations feature attribute auto-dynamics. By using this product category as a running example, we can identify realistic products across the four types, which appear in both consumer and business markets. Furthermore, many opportunities remain to identify new product ideas for this product category, in diverse industries such as the military, healthcare, fashion, and sports (Gaddis 2014). For example, a dynamic temperature attribute might allow a suit to heat or cool automatically, based on changing CSE conditions—a realistic example, considering that existing smart textiles already can adapt fabric attributes such as temperature, color, and permeability.[10] The four types of attribute auto-dynamics (see Table 1) are:

- **Contingent:** Continuous changing conditions map onto a few product attribute states. A smart suit for use in hospitals could continuously monitor many physiological parameters for patients and change color from blue to red if they enter a critical state.
- **Distinctive:** Discrete changing conditions map onto a few possible product attribute states. A smart suit for construction personnel might change automatically from red in bright light to fluorescent yellow in dark conditions.
- **Associative:** Continuous changing conditions map onto many product attribute states. Smart camouflage wear for soldiers could change color continuously, according to changing environmental conditions.
- **Generative:** Discrete changing conditions map onto many product attribute states. A smart fashion garment might generate a surprising, random design pattern using artificial intelligence algorithms.

Contingent Dynamics

In products with contingent dynamics, discrete changing conditions map onto a few product attribute states. For example, U.S. Patent #6822573 (drowsiness detection system),

[10]See https://heiq.com and http://www.dhamainnovations.com (accessed June 2019) for further details.

assigned to Intelligent Mechatronic Systems Inc., acknowledges that risky drowsy driving behaviors reflect continuously changing conditions (e.g., physiological, road), such that

> Each year numerous automotive accidents and fatalities occur as a result of sleepy individuals falling asleep while driving. It has been observed that these drivers exhibit certain physiological patterns that are predictable and detectible. The classic "head bobbing" motion, where the driver's head drops and then quickly pulls back upward is one of the patterns that is often exhibited when an individual is becoming drowsy while seated in an upright position. Additionally, a drop in heart rate may also indicate the presence of a drowsy driver.

In an effort to resolve this need by turning to contingent dynamics, the proposed system observes multiple continuously changing conditions and activates an appropriate product attribute state only after reaching a certain threshold of confidence. Formally,

> The drowsiness detection system includes two drowsiness detection subsystems communicating with a control unit. Using sensory fusion, intelligent fuzzy algorithms, and the sensory data, the control unit determines the drowsiness state of the driver. The system non-intrusively monitors multiple characteristics of the driver which introduces redundancy and increases the confidence level of the system's drowsiness determination…. If the driver is found to be drowsy, a signal is outputted from the control unit.

Contingent dynamics often arise in contingent, rare, and emergency conditions, in which it is beneficial for the product to adapt its attributes automatically, independent of the consumer. It typically appears in safety or security-related product attributes.

Products with static attributes cannot provide similar utility. A smart suit that monitors the status of hospital patients and changes colors to signify a health emergency signifies a relevant contingent dynamic solution to continually changing consumer health conditions. The product automatically activates one of two states, based on these changing conditions. Products with contingent dynamics thus provide utility to consumers, by monitoring and activating appropriate attribute states automatically, even if consumers themselves are ill-disposed to meet the needs that arise from changing conditions, such as when they are physically inactive, asleep, or unable to engage in self-control.

Distinctive Dynamics

In products with distinctive dynamics, discrete changing conditions map onto a few product attribute states. For example, U.S. Patent #7331183 (personal portable environmental control system), submitted by the U.S. Navy, describes two extreme conditions often encountered by members of the military: very hot or very cold. Conventional static products cannot meet the users' needs in changing conditions, such that

> Military operations, as well as other similar operations, often require being in extreme environments that can be very cold or very hot. Personal environmental control systems may be very helpful to users in that they may increase comfort to the user as well as allow greater concentration on the mission. In extreme cold, added clothing may be too bulky or not adequate. In extreme heat there are few if any alternatives.

By integrating distinctive dynamics, the proposed activated product attribute state (heating or cooling) changes with the consumer condition (very hot, very cold), using:

> … a personal portable environmental control system, which includes a thermoelectric device, two heat sinks, an exhaust fan for blowing ambient air across one of the heat sinks, and a blower for blowing ambient air across the other heat sink such that the blown air is conditioned (either heated or cooled). It is a feature of the present invention to provide conditioned air (cooled or heated) to personnel involved in varying temperature environments.

This example features two changing consumer conditions (very hot and very cold) that map onto two product attribute states (heating and cooling). Distinctive dynamics is typically associated with such utilitarian attributes.

For consumers, products with distinctive dynamics likely appear comparable to a discrete number of separate products with static attributes. A smart suit for construction personnel that changes color could be replaced by two separate products with static attributes: a red vest for use in bright light and a fluorescent vest for use in the dark. However, it might be more cost effective or convenient for consumers to use a single product with distinctive dynamics as opposed to

multiple static products, especially if switching is difficult (e.g., for a construction worker atop a building, whose alternative vest remains at the ground level of the construction site).

Associative Dynamics

Products with associative dynamics feature continuously changing conditions that map onto a large number of product attribute states. The changing CSE conditions might pertain to locations, weather, products, consumer physiological states, or actions by others. Consider the constantly changing customer needs described by U.S. Patent #9189021 for a wearable food nutrition feedback system, assigned to Microsoft:

> People are generally not aware of the nutritional information on food items they consume. While people may have general knowledge of the food items, calorie content, ingredients, and the benefits and consequences of the food they are presented with, tracking consumption and nutritional information for each meal is tedious. Providing nutritional information is advantageous for people trying to watch their weight, people with allergy restrictions, or strict dietary needs.

Addressing these constantly changing conditions requires a feedback system with several product attribute states that provide continuous information about nutrition, food consumption, and social interactions. Therefore,

> The feedback system includes a see-through, near-eye, head mounted display having a plurality of sensors detecting information in a field of view of the apparatus. Food items are detected in the field of view and various types of feedback are provided to the wearer of the device. Feedback can include warnings based on personal wearer needs, general nutrition information, food consumption tracking and social interactions. The system includes one or more processing devices in communication with display and the sensors which identify food items proximate to the apparatus, determine feedback information relevant to a wearer of the apparatus; and render feedback information in the display.

As the name implies, associative dynamics product attributes change associatively, due to changes in consumer conditions, observed for both utilitarian and hedonic attributes.

Consumers cannot substitute for products with associative dynamics by adopting multiple products with static attributes. For soldiers who need camouflage that adjusts to constantly changing physical conditions, associative dynamics might allow the fabric to change texture or

color automatically. Multiple static products do not represent a viable alternative, because they require the user to monitor the changing situation and actively switch among static products, which would be inconvenient and likely unwieldy for soldiers with limited storage capacities.

Generative Dynamics

For generative dynamics, discrete changing conditions map onto many possible product attribute states. Because there are more product attribute states than changing conditions, the link between conditions and product attribute states is typically uncertain, and the activated attribute state may be surprising to the consumer. Consumers typically are not aware of all the possible attributes that could correspond to the changing conditions, such as those described by U.S. Patent #9174128 (dynamic quests in game), assigned to Zynga. Game players recognize a few changing conditions, corresponding to their desire to play by engaging with certain challenges. But many more product attribute states (possible game challenges) are available that could address this same condition (desire to play a game), so:

> Same games provide challenges to players, where the challenges entail the completion of one or more tasks within the game. As the player completes each challenge, the player receives rewards and new challenges are provided to continue the game...After a while, some experienced players may run out of challenges, causing these experienced players to leave the game. Additionally, some players may dislike some of the challenges offered by the game, causing these players to ignore these disliked challenges and continue looking for new challenges that are more appealing. However, creating challenges is a time consuming task that requires human intervention.

As this patent indicates, new product attribute states (i.e., challenges) must be generated to correspond to discrete changes in the consumer condition (desire to play new game), after a challenge has been completed. Generating new product attribute states is necessary, because the consumer no longer benefits from the previous product attribute state (game challenge) after its initial use. By applying combinatorics (i.e., combination of elementary components to create

many product attribute states; Simon 1995), the proposed product can generate many product attribute states (new challenges):

> … embodiments describe methods, computer programs, systems, and apparatus for creating computer-generated quests in a game. Embodiments provide the ability to generate a large number of quests (e.g., 80,000 or more) without a person having to create each quest manually. The quests may be generated on demand on a server and then propagated to the clients, or may be buffered in advance of the player needing the assignment of a new quest.

The emphasis is on dynamically generating attributes automatically, to surprise the consumer. Even if the changes in condition are discrete (i.e., a game player wants to play a new challenge, after completing the prior one), many possible product attribute states (80,000 game challenges) can correspond to the player's desire. This large number of possible product attribute states and smaller number of discrete changes conditions implies high uncertainty in the link between changing conditions and product attribute states, as well as surprising outcomes for consumers.

Generative dynamics accordingly are effective for satisfying consumers' desires for novelty and variety, typically related to hedonic or aesthetic attributes. Consumers may become bored or dissatisfied with a particular product attribute state once they gain familiarity with its static attributes. For example, they grow dissatisfied with the same aesthetic design for clothing, prompting their desire for novel attribute states (e.g., Bianchi 2002; Hirschman 1980), which can be satisfied by a product that incorporates generative dynamics. Fashion-conscious users might want to wear a different clothing pattern every evening and thus would value a smart suit that can generate a surprising design pattern automatically, using artificial intelligence algorithms.[11]

Procedural Framework

[11]Artificial intelligence technology, such as generative adversarial networks, can facilitate the automatic generation of many design or aesthetic attributes. See https://medium.com/syncedreview/is-the-fashion-world-ready-for-ai-designed-dresses-853a5d419bb2; https://www.logoai.com/; https://www.cnet.com/news/this-website-uses-ai-to-generate-startling-fake-human-faces/ (accessed May 2019).

Because we observe auto-dynamics in novel products and emerging product categories, as an important managerial application, we seek to identify new product ideas with auto-dynamics that firms might potentially develop and market. Goldenberg, Mazursky, and Solomon (1999) assert that a procedural framework can be valuable to firms, managers, and designers; accordingly, noting that auto-dynamics involves mapping among changing conditions (market knowledge) and adaptive product attributes (technological knowledge), we present a procedural idea-generation framework to combine elements of two contrasting paradigmatic approaches to new product ideation: *market pull* and *technology push* (e.g., Goldenberg, Lehmann, and Mazursky 2001; Kornish and Hutchison-Krupat 2017).

A market pull approach begins by identifying a market segment and examining or eliciting market knowledge that can spur new product ideas. For example, during a focus group, firms may obtain feedback from consumers regarding the drawbacks or unmet needs associated with existing products (e.g., Fern 1982; McQuarrie and McIntyre 1986). Such feedback can provide a basis for novel product ideas. In contrast, a technology push approach to ideation commences with a consideration of how existing products might be enhanced by exploiting technological knowledge, without explicit consideration of market knowledge. For example, inventive template-based ideation starts by discovering inventive patterns in other novel products, then applies those patterns in new contexts to generate new product ideas (Goldenberg, Mazursky, and Solomon 1999; Hauser, Tellis, and Griffin 2006). Auto-dynamics entails mapping between changing conditions (market pull–relevant knowledge) and adaptive product attributes (technological push–relevant knowledge), so our procedural framework for ideation incorporates elements of both market pull and technology push approaches.

The first stage (market pull) in our procedural framework involves identifying a customer segment for the product category and changing CSE conditions that affect this customer segment, garnered through market research, observational studies, focus groups, or surveys. The second stage (technology push) instead seeks to identify existing or new product attributes with potentially adaptive properties that the firm can develop. In a third, ideation stage, market pull and technology push knowledge combine to enable mapping the changing conditions together with one or more existing or new adaptive product attributes to generate ideas and ascertaining appropriate auto-dynamics in each case.

Market Pull Stage. Consider a sporting goods manufacturer, such as Under Armour, that wants to design a smart suit with auto-dynamics for athletes participating in triathlons. In the market pull stage of the proposed procedural framework, the firm engages in market research to learn about changing CSE conditions athletes encounter that create a need for the product:

- **Customer Conditions:**
  - The distance of the athlete relative to aid stations
  - The varying heart rate of the athlete
  - Changes in body mass of the athlete over time
- **Product-System Conditions:**
  - Changing levels of moisture content in the fabric
  - Stretching of fabric during use
  - Wear and tear of fabric over time
- **Environment Conditions:**
  - Passing competitors during the race
  - Varying external light conditions over a three-hour race
  - Changing weather conditions during training

For example, the athlete's heart rate varies during training or competition, depending on the effort expended. This changing customer condition is significant, because excessive effort that raises the heart rate close to its maximum can hinder performance, due to the accumulation of

lactic acid in the body (Neufield et al. 2019).[12] The athlete's varying heart rate thus represents market pull–relevant knowledge in our procedural framework (Figure 1).

Technology Push Stage. Next, the firm identifies several possible existing or new product attributes that might possess adaptable properties. For the smart suit for triathletes, such product attributes may include fabric temperature, fabric texture, aesthetic design, and size. The technology pull stage is independent of the market pull stage, executed without taking into account market pull–related information about changing conditions. However, the firm considers its existing or potential technological capabilities to narrow down options for smart suits with different adaptive attributes, such as its display, sound or music-playing capabilities, fabric texture, or temperature.

Ideation Stage. In this third stage, integrating market pull and technology push requires two steps: mapping and type identification (Figure 1). In the mapping step, the firm considers one or more possible mappings between conditions and product attributes to obtain a generic product concept. If there are m changing conditions and n adaptive attributes, $m \times n$ mappings are possible (Table 2). For example, if the firm maps a changing condition identified in the market pull stage (e.g., changing heart rate of the athlete) to the four adaptive attributes from the technology push phase, it would obtain four generic smart suit concepts that can adapt the

- Display based on heart rate.
- Sound or music played based on heart rate.
- Temperature based on heart rate.
- Fabric texture based on heart rate.

Next, the firm ascertains the appropriate type of auto-dynamics (i.e., contingent, distinctive, associative, or generative) to be incorporated to identify more specific product

[12]See http://www.220triathlon.com/training/beginners/the-triathletes-complete-guide-to-heart-rate-zone-training/9437.html (accessed June 2019).

concepts. For example, the generic concept of a smart suit that adapts the sound or music played based on heart rate involves a continuous changing condition (heart rate), rather than a discrete one, so the auto-dynamics typology (Table 1) indicates that contingent or associative dynamics would be appropriate. The firm narrows its focus on two specific concepts with different auto-dynamics types: either a smart suit that buzzes when the athlete exceeds 90% of the maximum heart rate (contingent) or one that alters the music volume continuously based on the heart rate (associative). At the conclusion of this step, the firm may conclude that only the first concept is feasible and discard the second concept. In Table 3, we list four other illustrative concepts that may emerge from different mappings of changing conditions and adaptive attributes. A firm also might repeat the procedure for new market segments. In Table 4, we illustrate product concepts for different market segments: toddlers, construction workers, patients, and firefighters who encounter changing conditions that are unlike those of triathletes.

Decision Making

In this section, to illustrate how consumers make decisions about products with auto-dynamics, we again refer to our running example of a hypothetical smart textile suit with dynamic attributes. If it features a dynamic temperature attribute, this product would be able to heat or cool the fabric automatically, according to changing CSE conditions. We derive a framework for consumer decision making for this product and thereby derive appropriate pricing strategies. Specifically, we represent the smart suit as vector X_t of m dynamic product attributes that take different values at different points in time t.[13] Because the smart suit can heat or cool its fabric automatically, based on changing CSE conditions, $m = 2$, and the two attributes are fabric

[13]Without loss of generality, non-dynamic (static) attributes can be included in X_t, such that for these attributes $X_t = X, \forall\, t$.

cooling (X^C) and fabric heating (X^H). They are independent and activate separate heating and cooling elements, so they take binary values of 0 or 1 when these elements switch on or off in response to changing CSE conditions. The attribute vector is $X_t = [x_t^C, x_t^H]'$. In turn, we define four product attribute states:

- $\boldsymbol{S1}$**,** where $X_{s=1,t} = [1,0]'$, and only the cooling element is active. This state activates when the consumer's body temperature is higher than optimal.
- $\boldsymbol{S2}$**,** where $X_{s=2,t} = [0,1]'$, and only the heating element is active. This state activates when the consumer's body temperature is lower than optimal.
- $\boldsymbol{S3}$**,** where $X_{s=3,t} = [1,1]'$, and both the cooling and heating elements are active. This situation arises when a part of the consumer's body needs to be maintained at a cooler temperature, but another part needs a warmer temperature.
- $\boldsymbol{S4}$**,** where $X_{s=4,t} = [0,0]'$, and neither element is active, because the consumer's body temperature is optimal.

That is, with two dynamic attributes ($m = 2$), the smart suit features four product attribute states ($S = 4$). In general, m dynamic attributes lead to *S* potential states, and we can represent the product attribute vector $X_{s,t}$ at time *t* as $X_{s,t} \in \{X_{1,t}, X_{2,t} \dots X_{S,t}\}$.

For this smart suit, $X_t = [x_t^C, x_t^H]'$, and the importance of the attributes varies over time, so we write the attribute importance vector as $\gamma_t = [\gamma_t^C, \gamma_t^H]$. It varies with changing conditions; as an illustration, we conceptualize three conditions for the smart suit, such that $K = 3$:

- $\boldsymbol{K1}$**,** *running in hot temperature conditions*, $\gamma_{k=1,t} = [1, -1]$. The athlete encounters hot weather conditions while running and needs to be cooled down for optimum athletic performance. The importance weight is 1 for fabric cooling and -1 for fabric heating. The negative importance weight for fabric heating signals that the consumer would obtain a disutility if this attribute were present in this condition.
- $\boldsymbol{K2}$**,** *cycling in mixed temperature conditions*, $\gamma_{k=2,t} = [0.5,0.5]$. This need state arises because part of the bicyclist's body (legs) heats up and needs to be cooled down, but another part (torso) encounters cold, windy conditions and needs to be warmed up for optimum athletic performance. In this condition, the athlete expresses importance weights of $.5$ for fabric cooling and $.5$ for fabric heating.
- $\boldsymbol{K3}$**,** *swimming in cold temperature conditions*, $\gamma_{k=3,t} = [-1,1]$. While swimming, the athlete needs to stay warm for optimum athletic performance, so the importance weights for

are -1 for fabric cooling and 1 for fabric heating. The negative importance weight for fabric cooling highlights the disutility that would arise for the consumer if this attribute were present.

For the general case with m attributes and K conditions, the attribute importance vector is $\gamma_{k,t} = \{\gamma_{1,t}, \gamma_{2,t} \ldots \gamma_{K,t}\}$. For the smart suit, we can combine product attribute states ($S = 4$) with customer conditions ($K = 3$) to define the utility for the customer at time *t* as $u_{s,k,t} = X_{s,t}\gamma_{k,t}$, where $X_{s,t}\gamma_{k,t} = x_{s,t}^{C}\gamma_{k,t}^{C} + x_{s,t}^{H}\gamma_{k,t}^{H}$—that is, the utility a consumer with attribute importance vector $\gamma_{k,t}$ derives from the product with attribute vector $X_{s,t}$ at time t. Table 5 lists the benefits of all potential combinations of product attribute states and conditions.

For a product with attribute auto-dynamics to provide the maximum consumer benefits, an appropriate association must exist between condition K and product attribute states S to maximize the corresponding utility for the consumer, $X_{s,t}\gamma_{k,t}$. From Table 2, we see that for the smart suit to provide the highest benefit, it should map the following changing conditions to product attribute states: condition $K1$ maps to product attribute state $S1$, $K2$ maps to $S3$, and $K3$ maps to $S2$.

Purchase and Consumption Decisions

We use the utility specification for products with dynamic attributes to elucidate purchase and consumption decisions. For the general case, we consider a pricing scheme with a purchase price P_0 and consumption payment at time *t* as P_t (purchase price is the price at $t = 0$, so P_0). This pricing strategy resembles a standard two-part tariff scheme (Iyengar and Gupta 2009). Static pricing arises if $P_0 > 0$ and $P_t = 0, \forall\, t > 0$. If $P_{t|t>0} > 0$, for a consumption decision at time *t*, the payment represents a disutility. For example, software may have several components, and consumers pay P_t for the components they use in a given quarter, beyond the base component.

As is typical in dynamic decision-making studies (e.g., Gowrisankaran and Rysman 2012; Lee 2013), we anticipate that at the time of purchase ($t = 0$), a consumer considers both the instantaneous utility u_0 and the expected utility obtained from future consumption $u_{t|t>0}$. Instantaneous utility is:

(1) $$u_0 = g_0\left(X_{s,t=0}\gamma_{k,t=0}, \psi_{t=0}\right) - P_0,$$

where $\psi_{t=0}$ represents utility from non-product attribute *contextual* factors during purchase (e.g., store displays that provide utility, Bitner 1992; the presence of other consumers, Jacobs 2016), $X_{s,t=0}$ is the product attribute vector, $\gamma_{k,t=0}$ is the consumer importance vector, P_0 is the purchase price, and $g_0(.)$ is a theory-based link function at time $t = 0$ for the purchase (typically, it is an identity link function, to attain a linear utility specification).

At any point in time $t > 0$, c_t can represent a consumer's decision to consume the purchased product, such that $c_t = 1$ if the consumer consumes and $c_t = 0$ otherwise. Consumer utility for such consumption is:

(2) $$u_t = u_{t|t>0} = c_t\,[g_t\left(X_{s,t}\gamma_{k,t}, \psi_t\right) - P_t].$$

Note that we use g_t as the link function, thereby allowing for the possibility that it could vary across consumption occasions. When making a purchase decision, a consumer maximizes the sum of purchase utility (u_0) and the current value of all potential future consumption utilities ($u_{t|t>0}$), subject to budget constraints. Thus, the consumer maximization problem (where δ is the discount factor) reduces to (Cogley and Sargent 2008):

(3) $\max E[(\sum_{t=0}^{\infty}\delta^t u_t)]$, subject to the interposal budget constraint $\theta_{t+1} = \theta_t + \zeta_t - c_t P_t$,

where θ_t represents the consumer's budget, and ζ_t are increments to the budget at time t. The value function $V_t(\theta_t)$ of the Bellman (1957) equation, corresponding to Equation 3, is:

(4) $$V_t(\theta_t) = max\,\{\delta^t u_t(c_t, \theta_t) + \delta\, E\,[V_t(\theta_{t+1})]\}.$$

Equation 4 thus signifies the dynamic decision problem faced by the consumer at time t.

Pricing Strategy Archetypes for Attribute Auto-dynamics

From the preceding model, we identify potentially different pricing strategy archetypes that firms might deploy for products with various attribute auto-dynamics types (see Table 3 for examples). In a two-part scheme, a consumer can expect to pay a static purchase price P_0 at $t = 0$, then make a payments P_t during consumption at time $t > 0$. The payment P_t for consumption at $t > 0$ can change over time, which allows firms to devise strategies to charge different payments for the same product at multiple potential consumption instances. We represent this generic two-part pricing strategy as:

$$(6) \qquad P_t := \begin{pmatrix} P_0 \; if \; t = 0 \\ \varphi_t(X_{s,t}, \gamma_{k,t}, \psi_t, c_t, c_{t-1} \ldots) \; if \; t > 0 \end{pmatrix},$$

where φ_t is the *consumption payment function* that depends on current and historical values of dynamic variables (described in the previous section), such as $X_{s,t}$, the product attribute state; $\gamma_{k,t}$, the attribute importance vector; ψ_t, the contextual factors encountered by the consumer; and c_t, the level of consumption. For a product with attribute auto-dynamics, implementing such strategies requires the firm to have information about CSE conditions, so it must establish systems to collect and monitor such information, whether directly (e.g., sensors that track athletic performance, U.S. Patent # 7771320), with proxies (e.g., observing local weather to activate reminders, U.S. Patent #10019888), or with estimates based on consumer reactions (e.g., analyzing consumers' emotions to modify content, U.S. Patent #9681166). We consider these factors to identify archetypal pricing strategies for the four types of attribute auto-dynamics.

Contingent Dynamics and Condition-Based Pricing

Contingent dynamics frequently involve applications that activate the dynamic attribute in rare or unexpected conditions. In such cases, consumers may not be willing to pay upfront, so firms might implement a dynamic pricing model, requiring consumption-related payment based on changing conditions reflected in the attribute importance vector $\gamma_{k,t}$. In this *condition-based pricing* strategy, the consumption payment function defined in Equation 6, $\varphi_t \coloneqq \varphi_\gamma(\gamma_{k,t})$, depends on $\gamma_{k,t}$.

For example, when selling its drowsiness detection system, a carmaker could charge consumption payments based on the drowsiness of the driver or the road conditions, which are reflected in changes to the attribute importance vector $\gamma_{k,t}$.[14] In some cases, the firm may be able to access consumers' condition directly, such as by tracking physiological data using sensors embedded in the product. In other cases, it might rely on a proxy for the attribute importance vector $\gamma_{k,t}$, such as local weather or traffic conditions. With a condition-based pricing strategy for products with contingent dynamics, under certain predefined conditions, firms can set the consumption payment to a low fixed amount, which would be particularly appropriate in emergency or natural disaster contexts, in which consumers' willingness to pay is high but charging a dynamic price based on changing conditions would be unethical.

Distinctive Dynamics and Attribute-Based Pricing

A firm selling a product with distinctive dynamics usually should charge a static, upfront purchase price, similar to the price for the comparable set of multiple static products. However, for some products, such as rental equipment or large purchases with maintenance contracts, a

[14]See https://www.nytimes.com/2017/03/16/automobiles/wheels/drowsy-driving-technology.html (accessed June 2019).

dynamic pricing strategy could include an upfront price and dynamic consumption payments based on the active product attribute state $X_{s,t}$. For this *attribute-based pricing* strategy, the consumption payment function defined in Equation 6, $\varphi_t \coloneqq \varphi_X(X_{s,t})$, depends on $X_{s,t}$, that is, the product attribute state active at time t.

In the ideal type case of the portable environmental control system patented by the U.S. Navy, charges might reflect which product attribute state $X_{s,t}$, heating or cooling, is active at time t. Attribute-based pricing requires a firm to monitor the active product attribute state constantly, which likely is appropriate if the cost of provisioning, maintaining, or servicing one of the attribute states is higher than the costs for the other states. A smart speaker such as Amazon's Echo Dot with digital assistance[15] (U.S. Patent #9633661) typically charges a higher consumption payment for streaming copyrighted music than for providing local weather information, for example.

Associative Dynamics and Consumption-Based Pricing

Products with associative dynamics often involve both a physical hardware component and a software service maintained by the firm. For example, the GPS-based navigation system developed by TomTom for trucks relies on an in-vehicle physical device, but it also provides dynamic attributes for truck drivers, such as real-time routing based on each truck's size, cargo, and speed.[16] In providing this product, TomTom incurs costs to maintain the service component, and these costs depend on the level of consumption (usage) c_t of such services by the customer. Thus, TomTom may adopt a *consumption-based pricing* approach, for which the consumption

[15]See http://www.amazon.com/echodot (accessed January 2019).

[16]See https://www.tomtom.com/en_us/drive/truck/ (accessed January 2019).

payment function defined in Equation 6, $\varphi_t \coloneqq \varphi_C(c_{t-1}, c_{t-2}, \ldots, c_0)$, depends on $c_{t-1}, c_{t-2}, \ldots, c_0$, representing historical consumption by the consumer.

The nutritional feedback system patented by Microsoft reflects how a firm might charge according to the number of times the nutrition feedback product activates in a given month; these consumption-related payments could be raised or lowered according to consumption patterns. A firm might decide to reward consumer loyalty or pass on the cost efficiencies of increasing scale to the consumer and thus reduce consumption-related payments at higher levels of consumption. Alternatively, it might increase the consumption payment after a certain level of consumption, especially if it confronts capability or capacity constraints. On the flip side, the firm could lower the consumption-based payment or even offer the product for free if the user does not consume for some extended period of time.

Generative Dynamics and Utility-Based Pricing

When they purchase products with generative dynamics, consumers may be unaware of the different product attribute states that could be generated dynamically during their consumption. The pricing thus likely requires at least some of the payment during consumption, to reflect the utility obtained by the consumer. This utility also might depend on contextual factors unrelated to the product, such as the presence of other consumers. Thus a firm could set a required consumption payment as a function of dynamic consumption utility, which depends on contextual factors ψ_t. The utility of the smart suit that generates a new design pattern every evening depends, for example, on the choices of other consumers at a party. The associated pricing strategy is *utility-based pricing*, such that the consumption payment function defined in Equation 6, $\varphi_t \coloneqq \varphi_{X,\gamma,\psi}(X_{s,t}, \gamma_{k,t}, \psi_t)$, depends on $X_{s,t}$, the product attribute state; $\gamma_{k,t}$, the attribute importance vector; and ψ_t, the contextual factors encountered by the consumer.

In massively multiplayer online role-playing games (MMORPGs) such as *World of Warcraft*, gamers often are not aware of the precise specifics of the many quests that get generated dynamically during consumption. The utility of such games also depends on dynamic contextual factors ψ_t, such as the number of other MMORPG players. Therefore, rather than charging a conventional monthly subscription fee, a videogame publisher such as Blizzard Entertainment, which developed *World of Warcraft*, might apply a utility-based pricing strategy, especially if it can find a proxy measure of consumer benefits, such as with video or audio analyses of their usage, emotions, and reactions. Alternatively, the firm could price the product according to contextual factors ψ_t that affect utility, such as the number of other players.

Future Research

Contingent Dynamics and Ethical Implications

The ethical and safety implications of designing products with contingent dynamics is a critical question for researchers. Precommitment devices that feature contingent dynamics could be useful for consumers who lack control in some sense and need the device to take over or define their decision making. This condition implies that the consumer grants others the right to make decisions on his or her behalf (Thaler and Shefrin 1981). Products with contingent dynamics enable precommitment, because the product activates the dynamic attribute according to preset conditions and overrides the consumer's immediate choices. A consumer who recognizes a tendency to overspend might activate a contingent attribute in a wallet to reject any transactions above a preset limit. Similar applications could be relevant for electronic gaming and products that threaten a potential loss of self-control. However, the broader ethical implications of such products and the limitations they place on consumer choice are unclear.

Distinctive Dynamics and Multi-User Products

A single product with distinctive dynamics might be designed to meet the needs of multiple users with distinct consumer need states by automatically adapting its attributes, according to the user engaging with the product at that moment. It arguably would eliminate the challenges created when a single product seeks to serve the needs of multiple users, such as in family decision making or business purchasing. In such cases, one buyer might make a decision that promises to meet the needs of multiple users, or group decision making could allow multiple users to decide jointly on a single product (e.g., Corfman and Lehman 1987; Jackson and Yariv 2015). However, the different users may possess different consumer need states and account for heterogeneous attribute importance vectors. In such contexts, a product that adapts its attributes based on different users may be beneficial to the customer.

Associative Dynamics and New Ownership Models

New models of ownership should account for products with associative dynamics. Such products might be particularly appealing in collaborative consumption settings, such as those evoked by the sharing economy (Belk 2014). Products with associative dynamics blur product–service boundaries (Shoshtak 1977), because they incorporate service features, including intangibility, heterogeneity, and inseparability (Parasuraman, Zeithaml, and Berry 1985). Accordingly, they could be designed to shift product attributes states in reaction to the highly heterogeneous need states resulting from the presence of many owners of a single product.

Generative Dynamics and Customer Satisfaction

Finally, generative dynamics might engender positive disconfirmation that evokes customer satisfaction or delight (e.g., Evangelidis and Van Osselaer 2018; Oliver, Rust, and Varki 1997). Typically, consumers are unaware of the full range of attributes available from products with generative dynamics, because they only activate in relevant consumption

situations. Delivering such hidden attributes requires combinatorics (Simon 1995). Recent artificial intelligence and deep learning developments (Goodfellow, Bengio, and Courville 2016) promise the possibility of novel products with generative dynamics that feature attributes such as music or aesthetic designs that surprise consumers, which may enhance post-usage satisfaction.

Conclusion

Attribute auto-dynamics is an emerging product property, facilitated by recent technological developments, that is highly relevant to both marketing research and practice. Innovative new products increasingly incorporate this property, but we possess little systematic understanding of attribute auto-dynamics. With this article, we seek to describe the property and develop a typology to guide research, as well as assist firms in making decisions about ways to develop and charge for such products. Our typological analysis identifies four types of auto-dynamics (contingent, distinctive, associative, and generative), each of which represents a specific mapping pattern between changing conditions and product attribute states and prompts specific research questions. As an opportunity for further research, we suggest considering the benefits of auto-dynamics for consumers more closely. For example, do generative dynamics, facilitated by deep generative models (Goodfellow, Bengio, and Courville 2016), enhance post-usage satisfaction for a consumer whose tastes vary over time? Research related to the drawbacks of auto-dynamics, such as ethical concerns, also may gain prominence as consumers encounter the possible downsides associated with their increased interactions with attribute auto-dynamics.

For managers, we confirm that auto-dynamics can provide a structural pattern that permits applications to new contexts, as a basis for identifying new product ideas. To facilitate new product ideation around our auto-dynamics typology, we propose a procedural framework that integrates market-pull information about changing conditions with technology-push

knowledge related to adaptive product attributes. In another application of our typology, we illustrate how firms can leverage technology that monitors changing conditions and adaptive attributes to implement novel pricing models, such as condition-based, attribute-based, consumption-based, and utility-based pricing.

Applications of attribute auto-dynamics in marketing also can extend beyond products to other domains, such as designs of advertising systems that change depending on consumers' locations or local weather conditions.[17] With dynamic brand identities, the company brand might shift automatically in accordance with external conditions; for example, the logo for the Nordkyn region of Norway[18] changes with the direction of the wind and temperatures. In conclusion, attribute auto-dynamics provides rich, exciting possibilities for innovative and pricing practices, as well as further research about consumer decision making, managerial decision making, and marketing strategy. For example, Freshness sensors on food products is an innovation that has potential to change how consumers shop as well as providing opportunities for marketing innovation across the different components of the marketing mix, while at the same time reducing food waste.[19] Freshness sensors can be used to develop systems where marketing attribute (product, promotion, price, and placement) can be dynamically modified to reduce food waste and to create customer value. First, the product packaging may be dynamically modified to indicate the ripeness of fruit. Second, promotions may be linked to the true expiry date of the product. Third, the dynamic pricing of the product can reflect the dynamic expiration date of the product. Finally, the appropriate channel for delivering the product may be dynamically altered

[17]See https://patents.google.com/patent/US8138930B1 (accessed January 2019).

[18]See https://visitnordkyn.com/ (accessed January 2019).

[19]See https://www.prnewswire.com/news-releases/reducing-food-waste-and-increasing-sales-through-on-pack-freshness-sensors-301003219.html (accessed March 2020)

based on outputs of the food sensor. The company may switch to a cold-chain if the food is unexpectedly deteriorating during transportation.

Figure 1. Procedural Framework for Ideation

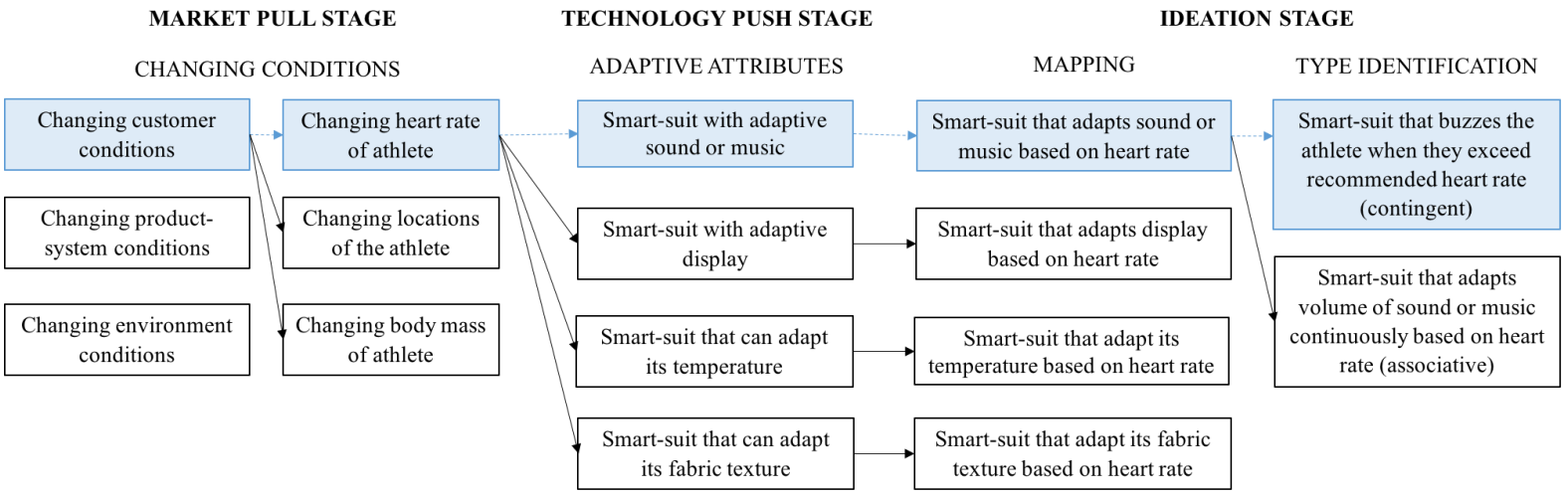

Table 1: Dimensions and Typology of Attribute Auto-dynamics

	Low/Few (Product Attribute States)	***High/Many (Product Attribute States)***
Discrete (Changing Conditions)	**Distinctive** ▪ *Utilitarian* attributes ▪ Static link ▪ U.S. Patent #7331183 (personal portable environmental control system)	**Generative** ▪ *Hedonic or aesthetic* attributes ▪ Uncertain or random link ▪ U.S. Patent #9174128 (dynamic quests in game)
Continuous (Changing Conditions)	**Contingent** ▪ *Security* attributes ▪ Step (threshold) link ▪ U.S. Patent #6822573 (drowsiness detection system)	**Associative** ▪ *Utilitarian or hedonic* attributes ▪ Continuous link ▪ U.S. Patent #9189021 (wearable food nutrition feedback system)

Table 2: Procedural Framework for Ideation with Auto-Dynamics

Market Pull *(Changing Conditions)* Customer/User: Athlete (Toddler) (Construction worker) (Patient) (Firefighter)		***Technology Push*** *(Adaptive Product Attributes)*			
		Display	Fabric Texture	Fabric Temperature	Sound
Customer Conditions	Location	1C			
	Activity		1B		
	Heart rate	2A			1A
Product Conditions	Temperature	2D		1D	
	Moisture				
	Time	2C			
Environment Conditions	Weather				
	Light	2B			
	Terrain				

Note: Similar to Goldenberg, Mazursky, and Solomon (1999), we construct this matrix, with the changing conditions in rows and adaptive attributes in columns. The number in each cell corresponds to the illustrative ideas in Tables 3 and 4.

Table 3: Illustrative Product Concepts: Smart Suit for Triathletes

Product Concept		Type of Auto-Dynamics
1A	Smart suit buzzes an alarm if heart rate increases beyond recommend levels.	Contingent
1B	Smart suit adapts fabric texture/permeability across three states, depending on whether the triathlete is swimming, cycling, or running.	Distinctive
1C	Smart suit generates a new design pattern for each race, partly based on the location of the athlete.	Generative
1D	Smart suit adapts its temperature continuously based on internal temperature.	Associative

Table 4: Illustrative Product Concepts: Smart Suit with Adaptive Display

Product Concept		Type of Auto-Dynamics
2A	Smart suit for hospital patients that changes color in emergencies.	Contingent
2B	Smart suit for construction personnel that is fluorescent yellow in the dark but red in bright light.	Distinctive
2C	Smart suit for toddlers that generates new cartoons every 24 hours.	Generative
2D	Smart suit for firefighters that updates information continuously, based on heat and smoke conditions in the building.	Associative

Table 5: Utility for Different Need States and Product Attribute States for Smart Suit

Changing Conditions *K*	**Product Attribute States *S***			
	$s = 1$ [1,0]	$s = 2$ [0,1]	$s = 3$ [1,1]	$s = 4$ [0,0]
$k = 1, [1, -1]$	**u = 1**	u = -1	u = 0	u = 0
$k = 2, [0.5, 0.5]$	u = .5	u = .5	**u = 1**	u = 0
$k = 3, [-1,1]$	u = -1	**u = 1**	u = 0	u = 0

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CHAPTER 3 - SELECTION IN CROWDSOURCED IDEATION: ROLE OF LOCAL AND GLOBAL NOVELTY

Abstract

The selection of novel ideas is vital to the development of truly innovative products. Firms often turn to idea crowdsourcing challenges, in which both ideators and the seeker firms participate in the idea selection process. Yet prior research cautions that ideators and seeker firms may not select novel ideas. To address the links between idea novelty and selection, this study proposes a bi-faceted notion of idea novelty and probes the role of task structure. Novelty may be local or global, in line with information processing literature. Using semantic analyses of data on 12,079 ideas shared on OpenIDEO during 47 contests held between 2010–2017, I find that the selection of novel ideas differs according to the selector, the form of novelty, and the challenge task structure. The results help explain some paradoxical findings in previous studies, with key implications for both ideators and seeker firms. In particular, this research uses measures of local and global novelty, along with additional linguistic measures, to produce a predictive model that seeker firms can leverage when ideator selection metrics such as likes are unavailable.

Keywords: idea crowdsourcing, ideation, novelty, semantic analysis, text mining

Introduction

[Open innovation] allowed us to open up our problems to the crowd if you will, and we got some novel ideas back.

—Dr. Jeffrey Davis, NASA Johnson Space Center

The selection of novel ideas represents a vital, early step in the development of truly innovative products (Chandy and Tellis 2000; Cooper 2011; Goldenberg, Lehmann, and Mazursky 2001), which in turn drives the wealth of firms and nations (Tellis, Prabhu, and Chandy 2009). As illustrated by the opening quote (Knowledge@Wharton 2013), firms seeking innovation—which we refer to as seeker firms— supplement traditional sources of novel new product ideas, such as lead users (Lilien et al 2002; Von Hippel 1986), with crowdsourcing challenges hosted on open innovation platforms to solicit novel ideas from crowds (e.g., Bayus 2013; Chua, Roth, and Lemoine 2015; Gielens and Steenkamp 2019). The ability of crowds to generate novel ideas relative to experts (Poetz and Schreier 2012) supports the expansion of platforms such as Lego Ideas, My Starbucks Idea, and OpenIDEO that enable both ideators and seeker firms to participate in idea selection.

Because firms rely on idea crowdsourcing to attain novelty, as a key dimension of overall idea creativity (Amabile 1983; Dahl and Moreau 2002; Toubia 2006), it is important to ascertain whether novel ideas actually get selected when ideators and seeker firms collaborate in the idea selection process. Extant research suggests that both parties fail to do so. First, seeker firms appear to exhibit a bias against novelty, due to their uncertainty or fear of failure, and thus do not select novel ideas even when they espouse this effort (Mueller, Melwani, and Goncalo 2012). Second, ideators tend to select feasible ideas over novel ones (Rietzschel, Nijstad, and Stroebe 2010). This apparent inability to select novel ideas is disconcerting, because the quest for novel

ideas provides the primary impetus and rationale for idea crowdsourcing, whereas a conundrum arises, in that firms seek to use idea crowdsourcing for novel ideas but do not select them.

Two explanations might suggest why this conundrum exists. The first pertains to the conceptualization of the novelty construct, which reflects domain settings. The second might involve the idea generation context, such that the selection of novel ideas could differ according to the nature of the task (i.e., the problem being solved). Therefore, we propose a bi-faceted conceptualization of novelty and seek to define the task structure to understand when and how ideators and seeker firms might select novel, crowdsourced ideas. Building on cognitive science evidence that people's perceptions and acquisition of information differ according to whether they process local or global structures (Kimchi 1992; Navon 1997), we argue that idea novelty might be local or global. Local novelty is the degree to which the information content contained in the idea is unique relative to competing ideas proffered in the challenge. Global novelty instead reflects the degree to which this informational content is unique relative to global human knowledge. Then we examine how the task structure might moderate the relationship between local/global novelty and idea selection, depending on the degree to which the task description contains restrictions that the ideators must take into consideration while generating ideas (Moreau and Engeset 2016; Newell and Simon 1972; Reitman 1964).

For our empirical analysis, we obtain data from OpenIDEO (openideo.org), an open innovation platform focused on solving sustainability-related challenges. The two outcome variables are likes, which represents an ideator selection metric, and shortlisting, as a seeker firm selection metric. The linear positive relationship between global novelty and likes overall suggests that ideators perform well at selecting novel ideas; however, the seeker firm's novel idea selection depends on the task structure. Local novelty has no evident influence on idea

selections by either the ideator or seeker-firm. These findings help clarify previous evidence that ideators and seeker firms perform poorly, by specifying differences according to idea novelty (local or global) and task structure.

Accordingly, in the next section we provide a conceptual basis for our study, in which we highlight the significance of local and global novelty and task structure definitions for selecting novel ideas. After we propose an automated approach to evaluating idea novelty and its benefits, we describe the study data and specify the operationalization. We then outline the empirical analysis and results, before concluding with a discussion of the implications of our findings for ideators and seeker firms.

Literature Review

Our study is focused on examining the relationship between idea novelty and selection. A close evaluation of the above link is important because the rationale for investment in idea crowdsourcing challenges lies in the desire on the part of firms for novel ideas, and the ability of crowds to generate more novel ideas compared to experts (Poetz and Schreier 2012). In this section, we examine some of the relevant literature relating to novelty and idea selection.

A standard definition of creativity is the production of ideas that are both novel (original) and useful (e.g., Ambaile 1983; Dean et al. 2006; Rietzschel, Nijstad, and Stroebe 2019). Even though there is considerable divergence regarding the meaning of novelty, it is generally considered the most significant feature of creativity (e.g., Brown 2014). For example, Diedrich et al. (2015) find that novelty predicts creativity better than the usefulness dimension. One definition framed in the context of product design is, “novelty is a measure of how unusual or unexpected an idea is compared to other ideas” (Shah, Vargas-Hernandez and Smith 2003). Thus, the evaluation of novelty requires a comparison set or referential domain of information.

Another definition (Litchfield, Gilson, and Gilson 2015, p.242), recognizes that the evaluation of novelty depends on the referential domain of information, since "ideas are considered to be novel to the extent that they are uncommon in terms of either their task or social context."

The literature around selection of ideas in group creativity describe a tension involving originality (i.e., novelty) and feasibility, and that highly novel (or original) ideas are likely to be rejected because of factors such as risk and ease-of-understanding (Blair and Mumford 2007; Rietzschel, Nijstad, and Stroebe 2010; Reiter-Palmon et al. 2019). While a few studies have found a correlation between originality and feasibility, most find that the two are inversely related (Kohn, Paulus, and Choi 2011; Rietzschel, Nijstad, and Stroebe 2019). Given the high negative correlation between novelty and feasibility (r=-4.2; Nijstad et al. 2010), it is unlikely that using an approach to evaluating ideas that involve rating both novelty and feasibility is likely to lead to the most appropriate choices.[20] One possible consequence is that firms are less likely to invest in novel R&D projects (e.g., Criscuolo et al. 2017), leading to fewer breakthrough innovation which is associated with above-normal stock returns (Sorescu and Spanjol 2008).

Idea selection in crowdsourcing is different from that of organizational idea selection at least two crucial ways. Firstly, there is feedback from the crowd, who are involved in the idea selection process by liking or voting on the ideas (e.g., Schemmann et al. 2016; Stephen, Zubcsek, and Goldenberg 2016). The crowds may be more favorable to novel ideas, given that they face no implementation-related risks that result from the low levels of feasibility associated with novel ideas. Thus, we might expect that firms may be more favorable to novel ideas if

[20]Novel ideas may be made more feasible over time by providing additional specificity regarding how the idea may be implemented. Thus, it is incumbent that highly novel ideas are not rejected early on if truly creative products (both novel and feasible) have to be developed.

crowds also such ideas. Moreover, on crowdsourcing platforms, ideas are competing for attention. In such cases, novel ideas are more likely to obtain attention (e.g., Chai and Menon 2019). Secondly, the number of ideas contributed to crowdsourcing challenges tend to be much higher than those in an organizational ideation setting (e.g., Acar 2019). When the number of ideas are large, idea selection is a cumbersome process (e.g., Acar 2019; Toubia and Florès 2007). Past research indicate that when firms are faced with the task of evaluating a large number of ideas, they are likely to choose ones that are more familiar and reject ideas that are distant (Piezunka and Dahlander 2014). Since distant ideas are more likely to be novel, we expect based on this argument that novel ideas are likely to be rejected. Moreover, novel ideas are likely to be less developed and less elaborate. The elaboration of an idea is associated with selection by firms. Therefore, novel ideas that measure low in elaboration (or specificity) may be less likely to be selected (e.g., Beretta 2019).

Conceptual Background

Selection of Novel Ideas: Background

The selection of novel product ideas is part of a two-stage process (Figure 2), comprised of internal ideation, in which novelty influences idea selection by a seeker firm or ideators, and marketplace acceptance, when the novelty of the resulting product influences consumer selection and choice. Two research streams pertaining to novelty and idea selection and reflecting these two stages thus are relevant to our research question, as we summarize in Table 6.

The links between new product novelty and customer selection, leading to market success, have been well established (Table 6) and generally appear nonlinear in nature (Goldenberg, Lehmann, and Mazursky 2001; Nakata et al. 2018), moderated by product complexity (Steenkamp and Gielens 2003). Studies that ignore this nonlinearity of the

relationship fail to find a link between novelty and market performance (e.g., Im and Workman 2004). Similarly, we anticipate that the internal ideation selection phase might feature some complexity, and specifying moderating effects might help explain prior research findings that both seeker firms and ideators fare poorly when it comes to idea selection (Mueller, Melwani, and Goncalo 2012; Rietzschel, Nijstad, and Stroebe 2010).

In particular, because a novel idea describes or specifies a solution to a given challenge that is new or unusual (e.g., Amabile 1983; Massetti 1996), examinations of idea novelty arguably should involve considerations of both the *content* and *context*. That is, to evaluate novel idea selection during crowdsourced challenges, we might consider the novelty of the content or information contained in the idea, as determined by the ideator, and as well as the novelty of the idea context, represented by the challenge task as defined by the seeker firm. Thus, we examine both the *novelty domain* and the *task structure definition*.

Novelty Domain: Local or Global

An idea is novel if the content it contains is new or unusual, so evaluating idea novelty inherently involves a comparison of idea content against a referential information domain. People differ in their perceptions and understanding of information content (e.g., Kimchi 1992; Navon 1977; Sligte, De Dreu, and Nijstad 2011), such that they process local information features in content differently from global information features. Processing of global features in visual content (the forest) tends to precede processing of local features (the trees; Navon 1977). Similarly, novelty might be local or global, depending on whether the domain for the comparative information is local (other ideas in the idea challenge) or global (general human knowledge). In the context of open idea challenges, we predict that idea selection might depend

on how novel the idea content is, whether locally in comparison to other proposed ideas or globally and relative to broad human knowledge.

To assess local novelty, we would evaluate the difference in the content of the focal idea compared with all competing ideas. To do so, we might construct the content of an archetypal idea, using the average semantic content of all ideas proposed in response to a task challenge. Then local novelty would increase with decreasing similarity to the archetypal idea. For global novelty, the idea would be truly globally novel if no similar idea ever has been generated elsewhere. The evaluation of this novelty is challenging, because no access exists to a complete set of all information about all relevant ideas. Instead, a large corpus of information, such as data obtained from search engines or encyclopedias, could predict the degree to which the focal idea content contains novel elements. In particular, rare word combinations or co-occurrences can be informative, such that descriptions of the ideas that use more co-occurring words within the corpus are less globally novel than other ideas with fewer such co-occurrences (Toubia and Netzer 2017).

This distinction in turn appears highly relevant to idea crowdsourcing challenges. First, ideas might offer high levels of one domain of novelty but low scores on the other. A trivial or obvious idea still could be locally novel if its content differs from other ideas. A globally novel idea also might be identified and contributed independently by multiple ideators, which would reduce local novelty, as exemplified by the multiple discovery phenomenon by which scientific discoveries and inventions arise independently and nearly simultaneously (Merton 1961). In addition, a globally novel idea may inspire other ideators to contribute similar ideas, so the original idea would fail to achieve high local novelty.

Second, ideas with varying levels of these two domains of novelty may be evaluated differently and perform dissimilarly in open idea challenges. For example, ideators might refuse to vote for ideas that are similar to their own, to avoid undermining the potential success of their contribution. Alternatively, ideators may be fixated on their own ideas (Jansson and Smith 1991), such that they are unable to appreciate ideas significantly different from their own.

Third, ideators may decide to mimic or differentiate their ideas from others, according to their order of entry. In a version of a copycatting strategy, ideators might mimic initially popular ideas to secure more votes (likes), such as when Crowdspring (crowdspring.com) participants mimic the logo designs of previous contributors (Hofstetter, Nair, and Misra 2018). They also could adopt a differentiation strategy and contribute locally novel ideas, to stand out from the crowd. These copycatting and differentiation strategies seemingly should have different influences on local and global novelty and on idea selection by both seeker firms and ideators.

Significance of Local and Global Novelty in Idea Selection

In this section, we consider how the local and global novelty of ideas can potentially influence the selection of ideas, both by the seeker firm and ideators on the platform. We argue that selection of ideas will be different for local and global novelty. Moreover, we also expect that the selection can also depend on the order of entry of the idea and task structure definition.

Local novelty is the degree to which an idea is new or unusual compared to the local domain, the crowdsourcing challenges. In evaluating an idea, we expect the seeker firm to compare it to other ideas contributed as part of the challenge and make a selection at least partly on the basis of local novelty. There are at two reasons why we believe ideas that rank high on local novelty are likely to be selected. The first may reflect a heuristic regarding decision making on the part of the firm. The second involves a strategic decision to identify diverse ideas with

high levels of variety that cover the whole design space (i.e., the set of all possible ideas). The first concerns availability heuristic (Folkes 1988; Tversky and Kahneman 1973): In many cases, the evaluator, even though and expert, may not possess complete knowledge of the global domain of knowledge.

Moreover, the local domain is more accessible and vivid compared to the global domain that requires costly search or retrieval from memory, which may be imperfect. If there are a large pool of ideas, the evaluator may consider the local domain to be a sufficiently good proxy for the global domain. Thus the seeker firm may find locally novel ideas to be globally novel in the absence of better information. This extrapolation from local novelty to global novelty might stem from the application of availability heuristic given that the ideator is unfamiliar with the global domain of information.

Next, in shortlisting more ideas, the firm might purposefully choose to identify a diverse set of ideas such that the shortlisted ideas show high levels of variety (Brown 2014; Nelson et al. 2009; Verhaegen et al. 2013). If the firms' objective is to shortlist ideas across various locations on the domain of possible ideas (also referred to as design space), then we expect locally novel ideas to have a higher possibility of being selected. Here the objective would be select ideas that are different from each other, not necessarily to select the most creative or novel ideas. In such cases, we would expect locally novel ideas to be selected. Based on the above two reasons, we expect a positive association between local novelty of ideas and selection by the seeker firm (shortlisting).

Global novelty is the measure of how different the idea is concerning the global domain of information. Since evaluators on crowdsourcing platforms are subject matter experts, we expect that such individuals will have access to the global domain of information. Moreover,

given that firms organize idea crowdsourcing contest to obtain novel ideas that they don't have access to within the firm, we expect that globally novel ideas are more likely to be selected. However, based on the evidence in group creativity research, we expect that firms may also be averse to risky ideas. Since novelty and feasibility (risk) are perceived to be inversely correlated, moderately novel ideas may be most likely to be selected. Thus, the selection of globally novel ideas depends on the level of perceived risk on the part of the evaluator. On OpenIDEO, the selection by the firm involves two stages, the shortlisting, and the selection of the winners. Since there is less risk in shortlisting the idea compared to selecting it as a winner, which requires commitment on the part of the firm, we expect that the relationship between global novelty and selection to be more pronounced in the case of shortlisting. One reason why globally novel ideas may not be selected is that such ideas may be perceived as less developed or less specified. Moreover, globally novel ideas may be irrelevant to the challenge and may not be selected. Thus, based on the above considerations, we expect that moderately novel ideas are most likely to be selected by the firm.

In the case of local novelty, in the case of ideator other ideators, there may be both a case of aversion to local novelty and an attraction towards familiar ideas. Individual ideators may also contribute ideas that are different or similar to previous ideas influencing the degree of local novelty. Ideas that are unlike other ideas may be penalized for 'going against the crowd.' Thus we expect that other ideators may dislike locally novel ideas. Moreover, ideators are first involved in divergent thinking, and then convergent thinking, and thus may be unable to select both globally and locally novel ideas. Concerning global novelty, ideators may behave differently from seeker firms since they don't face implementation related risk. Thus, in contrast to seeker firms, ideators selecting ideas may display a higher tolerance for globally novel ideas.

Overall, based on the above reasons, we expect that locally novel ideas to be less likely to be selected (liked) by ideators and globally novel ideas to be selected (liked) by ideators.

Order of Entry and Selection of Ideas

The order of entry of ideas can play a role in the eventual selection of ideas. Ideas that are contributed early on in the challenge have a greater opportunity to be evaluated by other ideators who can 'like' the idea. However, entering and contributing ideas early in the challenges comes with associated drawbacks. Other ideators may copy good ideas contributed early on, reducing the chances that the original idea will be selected. We would expect that ideas that are contributed later on in the contest, which have an opportunity to build on the ideas of multiple earlier may stand a greater chance of being selected. Such ideas would appear less locally novel since it incorporates elements of other ideas. However, copying other ideas may not be an effective strategy if the seeker firm is trying to identify a diverse set of ideas. If the ideators are aware of such an objective, they may attempt to differentiate themselves based by providing locally novel ideas. Based on the above reasons, we expect that ideas that are contributed later on in the challenge (high order of entry) are more likely to be selected, given that they can learn and incorporate information from other ideas. However, if later ideas are novel, they are unlikely to be selected since it represents low levels of incorporation of elements of earlier ideas. Thus, we would expect that both locally and novel ideas are less likely to be selected if they are contributed later in the contest.

Novelty in the Task Structure Definition

The language and instructions used in the task challenge can influence the creativity of ideas (e.g., Gillier et al. 2018; Reiter-Palmon et al. 2019). The novelty of the ideas generated in an idea challenge, and its influence on idea selection, depends on the degree to which the contest

task is ill- or well-defined (Moreau and Engeset 2016; Newell 1969; Newell and Simon 1972; Reitman 1964). This task structure definition establishes any restrictions that the seeker firm places on the solution space of the challenge (Simon 1973). Ill-defined tasks impose fewer restrictions than well-defined tasks, so the domain of possible solutions is greater for ill-defined tasks. In contrast, for well-defined tasks, the domain of possible solutions even could be singular. The task structure definition, in turn, should influence the selection of novel ideas by facilitating divergent thinking, affecting the downstream creativity of serial ideators who contribute multiple ideas, and signaling the seeker firm's preference for novel ideas.

First, asking ideators to solve ill-defined tasks may promote divergent thinking (Guilford 1967; Madore, Addis, and Schacter 2015), defined as an individual ability to come up with ideas that are novel, unrestricted, and spontaneous. However, some restrictions or constraints that encourage ideators to deviate from their path of least resistance also might encourage novel ideas for more ill-defined tasks (Moreau and Dahl 2005; Stokes 2005). Second, the task structure definition can influence the downstream creativity of ideators (Moreau and Engeset 2016), such that a previous task structure definition might influence serial ideators who contribute more than one idea to an innovation platform (Bayus 2013). Such ideators produce a disproportionate percentage of overall ideas, and their ideas might become more or less novel over time, depending on how the task structures have evolved. Third, seeker firms are heterogeneous in their preferences for novel ideas, and they potentially can manage the degree of novelty of ideas they receive by manipulating the degree to which they define the challenge task. Ideators also might use a particular task structure definition as a cue of the seeker firm's preferences.

In general, a problem-solving task, such as open idea challenges consists of three elements: a start state, a goal state, and a transformation function (Reitman 1964; Goel and

Pirolli 2002). In the contest of the idea contests, differences in task structure can be delineated based on the specificity of the constraints or restrictions imposed on the solution space. These restrictions are also termed as operators (Moreau and Engeset 2016). Such restrictions or constraints are a natural way by which ideators identify solutions to ill-defined problems (Newell and Simon 1973). However, the agency itself may introduce such restrictions in the task structure to limit the solution space. We consider that there are three such restrictions for the idea challenges: (1) need specificity (2) target specificity, and (3) mechanism specificity.

Need Specificity (Start State). Need specificity is the degree to task specifies the extent of problem domain itself. The problem owner has the option of making the problem itself ill defined. In the example above, 'poverty' is comparatively ill defined, but broader problem space, compared to 'drought related financial problems'. In some cases, the domain may be a wide-interest domain such as education, or food waste management, which does not require specific domain expertise on the part of the ideator. In other cases, the need may be more highly specified – such as "How might we combat health threats like Zika, SARS, Ebola, and Malaria in bold, imaginative ways." Such challenges also require the ideator to possess some specific domain knowledge to solve the problem.

Target Specificity (End State). Target specificity is the degree to which the target consumer or beneficiary from the solution is indicated explicitly in the challenge description. In the example, 'global' is less specific compared to 'farmers in rural India'. In some of the challenges, the sponsors specify the intended beneficiary. For example, some of the challenges, such as the Amplify challenges, are targeted at specific problems of individuals/groups in developing regions. Thus the task challenge description specifies that the solution should be designed with such target consumers in mind. In other cases, the target consumer is an individual

from a specific age group. For example, some tasks target issues faced by older individuals, such as financial management and health care ("How might we enable older adults to live their best possible life by preventing falls"). Other targets involve members of social groups such as business leaders, refugees, students etc. Some of the challenges do not specify a target ("How might we combat health threats like Zika, SARS, Ebola and Malaria in bold, imaginative ways"). In such cases, the target is implied or a solution open to a broad target is often sought after.

Mechanism Specificity (Transformation Function). The task may also provide a mechanism through which the task is to be solved. In the example above, the first task does not specify a mechanism; however, in the second task, the mechanism, 'blockchain' technology, is well-defined. Broadly, a mechanism can involve a technology, a methodological process, or a facilitating instrument. The provision of such a mechanism in a task rules out the possibility of using other mechanisms, possibly with better results. Thus, mechanism specificity can be restrictive to generation of novel ideas.

Evaluation of Novelty

Standard approaches for evaluating novelty or the overall creativity of ideas rely on trained raters or judges (e.g., Amabile 1983; Dean et al. 2006), which creates several drawbacks, related to the (1) poor consistency among raters, (2) difficulty dealing with large data sets, and (3) lack of independence in idea evaluations, because raters are influenced by their evaluations of previous ideas (e.g., Harbinson and Haarman 2014). To overcome these shortcomings, automated evaluations of the semantic content of ideas provide means to assess novelty (e.g., Forster and Dunbar 2009; Harbinson and Haarman 2014; Toubia and Netzer 2017). Such semantic analyses may rely on vector space models, such as latent semantic analysis (LSA; Deerwester et al. 1990), or else feature similar efforts, as exemplified by pointwise mutual

information (PMI) and latent Dirichlet allocation (LDA) methods (Blei 2014; Blei, Ng, and Jordan 2003; Tirunillai and Tellis 2014). Forster and Dunbar (2009) use LSA to evaluate the creativity of ideas in response to a standard creativity test. Harbinson and Haarman (2014) also compare LSA and PMI evaluations of the originality of the ideas produced in divergent thinking tests. Appendix 2.1 lists extant literature pertaining to automated evaluations of novelty using semantic analyses.

Evaluating Local and Global Novelty

The most common approach for evaluating novelty relies on the distance between ideas in a shared semantic space, or semantic distance (Forster and Dunbar 2009; Kennett 2018). For example, LSA represents ideas in a common vector space, and then uses the distance between the focal idea and an archetypal (average) idea as a proxy of the focal idea's novelty. This approach is effective for operationalizing local novelty, because information about the local domain of information (e.g., competing ideas within a challenge) tends to be accessible. For global novelty though, the comparison is with the global domain of overall human knowledge, which is less accessible. As we noted, one option is to inspect word combinations or co-occurrences in the idea content and compare them against a knowledge corpus representative of overall human knowledge, such as Wikipedia. The prediction that ideas are more novel if they contain unusual combinations of words, relative to the knowledge corpus (e.g., Kaplan and Vakili 2014; Toubia and Netzer 2017), derives from the associative theory of creativity (Mednick 1962; Spearman 1931), which suggests that creative ideas emerge from associations of distinct concepts. Creative thinking then entails the formation of "associative elements into new combinations which either meet specified requirements or are in some ways useful" (Mednick 1962, p. 221). The more distant the domains, more novel the idea likely is (Kaplan and Vakili

2014; Kenett 2018; Mednick 1962). Operationally, words that appear together in a novel idea probably do not occur together in common language usage; the phrase "fish-doctor" is novel because it contains two words that rarely would appear together in everyday language use.

To evaluate the novelty of word combinations, we assess the semantic distance between adjacent words; distance indicates the similarity of two words in their meaning. Ideas described with combinations of words that are semantically distant from one another thus should be more novel. Semantic distances between words can be determine by the shortest path in WordNet-based graphs (e.g., Budanitsky and Hirst 2006; see https://wordnet.princeton.edu/), co-occurrence in Wikipedia pages (Gabrilovich and Markovitch 2007), or word embedding trained with a large text corpus (Hashimoto, Alvarez-Melis, and Jaakkola 2016), for example. In Figure 3, we project a sample of words related to food onto a two-dimensional vector space, similar to the output of a word embedding model such as GloVe (Pennington, Socher, and Manning 2014), trained on words from Wikipedia. In this representation, "bread" is closer to "banana" on the vector space than to "ginseng"; the word combination "bread-banana" appears more commonly together than "bread-ginseng." Ginseng bread as an idea is more globally novel than banana bread. This conception thus does not derive from the novelty of the word itself but rather from the co-occurrence of words (Kaplan and Vakili 2014; Toubia 2017). Toubia and Netzer (2017) provide another illustrative example: A recipe containing chocolate and chicken would be novel, even though the ingredients themselves are not. Therefore, we can estimate the global novelty of idea content by evaluating the rarity of the co-occurrence of words in an idea, relative to their appearance in a global, base corpus such as Wikipedia.

Data and Analysis

We begin this section by providing an overview of OpenIDEO, then describe our data collection and preprocessing efforts. Reflecting our interest in how idea novelty affects selection, we specify the measures of local and global novelty and designate two key selection metrics (likes and shortlisting) as the dependent variables for our analysis.

Overview of OpenIDEO

Set up by IDEO, a storied product design company (www.ideo.com), OpenIDEO's core objective is to tackle prominent social issues by hosting idea challenges that are open to everyone. OpenIDEO collaborates with sponsors[21] such as Acumen, Nike, Unilever, Nokia, and Amnesty International to identify specific sustainability challenges. To contribute ideas, ideators must sign up on the platform by providing basic personal and contact information. This platform offers an appropriate context for our study, because on it, ideators vote for other contributors' ideas, which influence the eventual shortlisting of ideas. In addition, challenges hosted on the platform are diverse, with a broad range of task structure definitions. Due to the open philosophy of this platform, all contributed ideas also are publicly available. Appendix 2.2 lists the 47 OpenIDEO challenges we examine in this study.

A typical task challenge reflects IDEO's design thinking methodology (Kelley 2001), with the following phases: research (or inspiration), ideas (or conception), refinement, feedback, top ideas, and impact (Figure 4). In the research phase, ideators share inspirations, stories, and examples related to the challenge,[22] which are not necessarily their original concepts. Instead, these contributions serve as stimuli and sources of future ideas. In the ideas phase, individual ideators contribute original ideas to the platform, summarized in an abstract together with

[21]See https://www.openideo.com/sponsor (accessed January 2019).

[22]See https://challenges.openideo.com/content/how-it-works (accessed January 2019).

supporting details, drawings, videos, and links. Other participants then can view the ideas and vote for or comment on them. The refinement phase shifts focus to testing the ideas with end users. In the feedback phase, members of the OpenIDEO community share comments and suggestions with the ideators. The top ideas phase creates a shortlist of ideas, according to factors such as potential impact, relevance, and engagement. Finally, the impact phase involves updates on the implementation of winning ideas.

The first challenge, "Jamie Oliver's Food Revolution Challenge," sponsored by the British chef and TED Prize winner Jamie Oliver, is prototypical; it asked, "How can we raise kids' awareness of the benefits of fresh food so they can make better choices?" Of 180 contributed ideas, 40 were shortlisted, and 17 were selected by vote by the community and Oliver (e.g., shopping cart that encourages healthier purchases, kid-friendly recipe cards placed near healthy food choices in the supermarket). The winning ideas were published in a book, available for free downloading.

Data Collection

We collected data from OpenIDEO using a web crawler, from its inception in August 2010 until December 2017. The resulting data set spans 47 challenges that prompted 12,079 ideas contributed by 7,840 ideators. Most ideators (6,117, 78.02%) contributed a single idea, but 1,723 (21.98%) of them are serial ideators (Bayus 2013) who contribute multiple ideas, accounting for 5,962 (49.36%) ideas in our data set. We collected the title and abstract of each contributed idea,[23] the alias of the ideator, date of submission, likes (votes) and comments received by each idea, and whether the idea made the shortlist or won the challenge. In

[23]We evaluate novelty of the ideas using the content in the abstract, which is unlikely to change substantially over time in response to likes or comments.

accordance with its open philosophy, OpenIDEO makes all information contributed on the platform available for public access (as specified in the OpenIDEO Terms and Conditions).

Key Measures and Operationalization

Semantic distance and novelty evaluation. Our evaluation of novelty derives from the concept of semantic distance (Kennett 2019). Ideas that are semantically more distant are more novel, as assessed by vector space models for words (e.g., Blei 2014; Deerwester et al. 1990), such as LSA or LDA (Deerwester et al. 1990). Early applications of LSA to evaluate novelty and creativity (e.g., Forster and Dunbar 2009; Harbinson and Haarman 2014) show that the scores provide a good measure of underlying novelty; others suggest that LDA, a generative probabilistic model related to LSA (Blei 2014), offers a better reflection of underlying perceptions of novelty (Chan and Schunn 2015). The correlations between LDA measures of novelty and human raters' evaluations range from .3 to .6 (Chan and Schunn 2015; Wang, Dong, and Ma 2019).

Operationalization of local novelty. To evaluate local novelty, we use LDA to represent idea abstracts as vectors, then compare each idea to other ideas prompted by the same challenge. We assess the semantic distance between a focal idea and other ideas in the common semantic vector space. In the generative probabilistic model for text corpora in LDA, each document (idea) represents a mixture of topics, and it proceeds as follows (Blei 2014):

1. Draw mixture proportions $\theta \sim Dirichlet(\alpha)$.
2. For each mixture component k, draw $\mu_k \sim \mathcal{N}\ (0, \sigma_0^2)$.
3. For each data point n:
    a. Draw mixture assignment $z_n|\theta \sim Discrete(\theta)$.
    b. Draw data point $x_n|z_n, \mu \sim \mathcal{N}(\mu_{z_n}, 1)$.

This bag of words model ignores the order of words in the document (idea). The Dirichlet distribution is a family of multivariate probability distributions parameterized by a vector α of

positive reals (Blei 2014). For the comparative measure of novelty relative to other ideas, two approaches determine either the distance to an average idea or the average distance from other ideas. Both approaches tend to yield similar results (Wang, Dong, and Ma 2019), so we use the average distance method. In the vector space generated with LDA, we compute the mean Euclidean distance of each idea from other ideas in the challenge as a measure of local novelty. To identify the optimum number of topics ($n = 20$), we tune the parameters using the ldatuning package in R (Murzintcev 2016).

Operationalization of global novelty. To evaluate global novelty, we use the GloVe word embedding model (Pennington, Socher and Manning 2014), an unsupervised learning algorithm for vector spaces of words (Baroni, Dinu, and Kruszewski 2014). The model training relied on aggregated global word–word co-occurrence statistics from a corpus of 6 billion words, using Wikipedia 2014 and Gigaword5.[24] In the vector spaces, words that co-occur more commonly in the corpus appear closer than words that rarely appear together. We thus obtain a measure for global novelty using the word embedding vector space. This approach also uses the associative theory of creativity as its foundation (Mednick 1962; Spearman 1931), along with the biasociative theory of knowledge discovery (Amabile 1983; Koestler 1964), which proposes that novel ideas emerge from associations of components from incompatible domains. Our conception of global novelty, as involving rare combination of words, also is similar to Toubia and Netzer's (2017) in their evaluation of prototypicality (overall measure of creativity) using semantic networks of ideas. However, prototypicality provides an overall measure of the balance between novelty and familiarity, rather than novelty alone, so our approach for estimating global

[24]Gigaword is an archive of newswire text data in English made available by the Linguistic Data Consortium https://catalog.ldc.upenn.edu/LDC2003T05. See https://nlp.stanford.edu/projects/glove/ for details of the GloVe model.

novelty differs somewhat. That is, we expect ideators and seeker firms to have different optimum levels of global novelty. Regarding the semantic distance between two adjacent words, we expect that more novel ideas are those for which the adjacent words are semantically more distant. Thus, we calculate the sum of the distance between adjacent words in an idea.[25] We present an illustrative comparison of the local and global novelty measures in Table 7.

Likes. Ideators can vote for others' ideas, which represents the ideator selection metric. Contributing an idea is not a precondition of voting, though all voters must register on the platform. To indicate their vote, they click on a heart-shaped button, signaling their likes (Figure 5).[26] The number of votes received represents a mediating measure of selection, because the shortlisting step relies on the number of likes. The total number of likes received by an idea also has been used to proxy idea quality in previous studies (e.g., Huang, Singh, and Srinivasan 2014). However, some high quality ideas might not receive many likes if other ideators consider them a threat to their own success.

Shortlisting. Whether an idea eventually is shortlisted by the OpenIDEO team or challenge sponsors provides our seeker firm selection metric. The selection criteria include the number of likes received but also other factors, usually specified by the contest sponsors, that are specific to the challenge, such as idea quality, clarity, and potential for impact.[27] In the 47 challenges in the data set, 13.1% of submitted ideas were shortlisted, ranging from 3.2% to 36.5% for individual challenges. The winners (3.2% of all ideas) all come from the shortlists. Appendix 2.3 provides a descriptive summary of our dataset.

[25]Manhattan distance (L1 norm) is preferable to Euclidean distance (L2 norm) in the case of high dimensional data (Aggarwal, Hinneburg, and Keim 2001) and can reduce the influence of outliers.

[26]See https://challenges.openideo.com/faq and https://www.openideo.com/faq-challenges (accessed January 2019).

[27]See https://www.openideo.com/challenge-briefs/bridgebuilder2 for a brief (accessed January 2019).

Comparison of Key Measures

In Table 8, we present the correlations of key measures. The correlation between global and local novelty is moderate ($\rho = .1587, p < .01$), in line with our expectation that these two constructs represent different but correlated dimensions of idea novelty. See Appendix 2.4 for kernel regression plots for key measures in our study.

To identify control variables, we consider how the focal variables change (1) over time on the platform for different challenges, (2) within challenges based on order of entry, and (3) for individual ideators based on past participation. Figure 6 depicts the focal variables across different challenges on OpenIDEO; Figure 7 indicates the results for the focal measures with different order-of-entry positions. Mean global novelty and likes differ across contests, so the task definition appears to influence these measures. The local novelty of ideas increases with position of entry, implying that earlier ideas are the least locally novel in a contest. Figure 8 shows how past contributions influence the novelty constructs and two selection metrics.

With our data analysis, we examine the effect of local and global novelty on likes and shortlisting, before detailing the moderating influence of the task structure definition. We also present some additional analyses and robustness checks.

Influence of Local and Global Novelty on Selection

To estimate the influence of local and global novelty on likes and shortlisting, the base model specifications are:

$Likes_{ijk} = \beta_0 + \beta_1 GN_{ijk} + \beta_2 GN_{ijk}^2 + \beta_3 LN_{ijk} + \beta_4 LN_{ijk}^2 + \beta_5 LN_{ijk} \text{ x } GN_{ijk} + e_{ijk}$, and

$Shortlist_{ijk} = \beta_0 + \beta_1 GN_{ijk} + \beta_2 GN_{ijk}^2 + \beta_3 LN_{ijk} + \beta_4 LN_{ijk}^2 + \beta_5 LN_{ijk} \text{ x } GN_{ijk} + e_{ijk}$,

Where i denotes the idea, j denotes the challenge, and k denotes the ideator. LN and GN represent standardized measures of local and global novelty; $Shortlist$ is a 0/1 variable that

indicates if the idea is shortlisted or not; and $Likes$ represents number of votes received for the idea. We control for confounding factors that may influence both novelty and the outcome variable of interest, such as the type of challenge, order of entry of the idea, and ideator experience. The modified model for shortlisting is:

$$Shortlist_{ijk} = \beta_0 + \beta_1 GN_{ijk} + \beta_2 GN_{ijk}^2 + \beta_3 LN_{ijk} + \beta_4 LN_{ijk}^2 + \beta_5 LN_{ijk} \text{ x } GN_{ijk} + \beta_6 SerialExp_{ijk} + \beta_7 ChalExp_{ijk} + \beta_8 OrderEntry_{ijk} + \sum_j \gamma_j Challenge_{ij} + e_{ijk},$$

where $SerialExp$ reflects the overall experience of the ideator contributing the idea, $ChalExp$ is the experience of this ideator within the same challenge, $OrderEntry$ indicates the order in which ideas are proposed within a challenge, and $Challenge$ contains the challenge dummy variables (fixed effects). Challenge level fixed effects control for challenge level factors such as number of participants (e.g., Kovacs and Sharkey 2014), differences in promotion of contest by OpenIDEO, and idiosyncratic factors relating to individual challenges that are associated with the outcome variables. We report the ordinary least squares (OLS) and probit regression estimates in Table 9. Then for likes, we estimate the following specification:

$$Likes_i = \alpha_0 + \beta_1 GN_i + \beta_2 GN_i^2 + \beta_3 LN_i + \beta_4 LN_i^2 + \beta_5 LN_i \text{ x } GN_i + \beta_6 SerialExp_i + \beta_7 ChalExp_i + \beta_8 OrderEntry_i + \sum_j \gamma_j Challenge_{ij} + e_i.$$

In addition to the OLS estimates in Table 9, because likes is a count variable, we provide the negative binomial regression estimates. We find no evidence of a link of local novelty with either likes or shortlisting. In contrast, global novelty is linearly and positively associated with likes, as well as nonlinearly related to shortlisting. These results suggest that local novelty does not influence the selection of ideas, but global novelty has an important influence on both ideator and seeker firm selections, such that as global novelty increases, the likelihood of idea selection increases for ideators but not necessarily for seeker firms.

With these findings, we provide pertinent explanations of previous findings that suggest novel ideas are not selected (e.g., Mueller, Melwani, and Goncalo 2012; Rietzschel, Nijstad, and Stroebe 2010), by distinguishing local and global novelty. That is, most studies only investigate local novelty, but a complete picture of idea selection and market success requires considerations of both local and global novelty, as well the possibility of nonlinear relationships.

The results also suggest that the ideator selection metric (likes) provides a good proxy and tool for identifying novel ideas in crowdsourced challenges. In this sense, we find evidence of the "wisdom of the crowd" (Galton 1907; Palley and Soll 2019; Surwiecki 2004). Crowds of ideators are better at selecting novel ideas than seeker firms. A firm looking for novel ideas, obtained through crowdsourcing, thus may find it advantageous to shortlist ideas using an ideator selection metric such as likes, rather than directly selecting them itself.

Task Structure Definition

The nature of the task issued by the seeker firms can influence idea selection too. In idea challenges hosted on OpenIDEO, most tasks require solutions to sustainability concerns, defined in collaboration with the challenge sponsors. That is, OpenIDEO works with sponsors to define the degree to which the task structure of a challenge is ill- or well-defined. The task lists a title and a brief; we assess the degree of task structure definition according to the content of the title, which usually takes a form such as, "How can you <solve need> for <target> using <mechanism>?" They range from ill-defined (e.g., "How can you increase your creative confidence?") to moderately well-defined (e.g., "How might we gather information from hard-to-access areas to prevent mass violence against civilians?"). As a specific example, the task "How can you solve global poverty?" is relatively ill-defined compared with "How can you solve drought-related financial problems for farmers in rural India using blockchain technology?" The

varying task structure specifications might arise because the sponsor wants responses from a certain group of potential ideators or else wants to open it up widely; seeks solutions for a specific target group; or aims to generate more novel versus more realistic ideas. The task definitions on OpenIDEO do not change across ideators, regardless of their domain-specific knowledge (Luo and Toubia 2015). However, they might influence the novelty of the ideas and the downstream creativity achieved by ideators (Moreau and Engeset 2016). If we can identify systematic links between the task structure definition and the selection of novel ideas, ideators could use this information in developing their ideas. In this sense, the question of task structure definition is relevant to OpenIDEO, seeker firms, and ideators.

The analysis of how the task structure definition moderates the relationship between novelty and selection (Table 10) relies on a task structure definition rating (TSDR) for each challenge, provided by trained raters on a three-point scale, where 1 indicates an ill-defined challenge task and 3 is well-defined.[28] The relationship between novelty and selection appears linear for the likes measure across all TSDR. The nonlinear influence of global novelty on shortlisting arises only among moderately well-defined and well-defined tasks; for ill-defined tasks, this relationship is linear, such that greater global novelty increases the likelihood of being shortlisted.

We also use an automated approach to operationalize task structure definition based on specificity of of the challenge title. In this approach, the task is considered to be more well defined if it contains more specific informational content. For this operationalization, we consider that information contained by each word equal to inverse of its probability in the

[28]To validate these ratings, we examined the concreteness of the task challenge. The task description of well-defined tasks should contain words that are more concrete. The correlation between TSDR and the concreteness of the words in the challenge task is .259 (Brysbaert, Warriner, and Kuperman 2014).

corpus. Zipf's law is an empirical generalization that states that frequency of a word is inversely proportional to its rank in the frequency table. We obtain probability of the word occurrence from its frequency rank using the Zipf's law, using the following approximation[29]:

$$P\ (r) \sim \frac{1}{r}\ ln(1.78R).$$

The task structure specificity (TS) is calculated as:

$$\sum_i \frac{1}{P(r_i)} = \sum_i \frac{1}{r_i}\ ln\ (1.78R)$$

Here 'r' is the frequency rank of the word, and R is the total number of words in the corpus (e.g., Wikipedia). See Appendix for a complete list of the challenges along with ratings of task structure definition. To evaluate specificity of the challenge task, we first lemmatized the challenge task description and calculated the probability of word occurrence as above. Next, we calculated the task structure specificity by summing the inverse of the probability score for all the words in the challenge task description.

Additional Analysis: Ideator Characteristics

Prior literature suggests that ideator characteristics may influence the relationship between novelty and the selection of ideas they propose (Proudfoot, Kay, and Zoval 2015; Trapido 2015). On an idea crowdsourcing platform, such characteristics may be *personal* and related to the ideator (gender, age, education) or *participative* (experience, motivation). On OpenIDEO though, some personal characteristics, such as age and education, are not available, so they are unlikely to influence idea selection; other ideators and the seeker firm are unaware of such characteristics when making liking or shortlisting choices. However, gender might be

[29]For alculation of probabiltty from Zipf's law see: http://mathworld.wolfram.com/ZipfsLaw.html; https://archive.lib.msu.edu/crcmath/math/math/z/z040.htm (Concise Encyclopedia of Mathematics)

inferred from the name of the ideator, which appears next to the idea. The motivation of an ideator also is not visible to other ideators or seeker firms, so it should not influence the relationship between novelty and shortlisting or liking. However, the ideator's experience, in terms of contributing past ideas, is easily accessible. Therefore, we consider how the ideator's gender, as a personal characteristic, and experience, as a participation characteristic, might affect the selection of novel ideas.

Gender. Gender-related biases arise in quality evaluations of scientific publications and research grant awards (e.g., Bornmann, Mutz, and Daniel 2007; Caplar, Tacchella, and Birrer 2017).[30] Although the gender of the ideator is irrelevant, unrelated to the quality of ideas, such that it logically should not influence idea selection, a gender bias has been documented in attributions of creativity, such that raters evaluate men as more novel than women (Proudfoot, Kay, and Zoval 2015). Such a gender bias then could lead to differences in the nature and strength of the relationship between idea novelty and selection for men versus women. Thus we examine whether gender of the ideator influences the selection of ideas, as well as differences in the relationship between idea novelty and selection. Using the Gender API (https://gender-api.com/), a name-to-gender assignment algorithm that provides a 50–100 probability score that of the accuracy of the predicted gender, we estimate the gender of each ideator. This algorithm also flags names that are difficult to classify; it has been used in similar research applications (e.g., Botelho and Abraham 2017; Leung and Koppman 2018). In our data set, 3,186 ideators (40.64%) were classified as women and 4,505 (57.45%) as men. The Gender API could not classify 149 (1.9%) ideators by gender based on their name.

[30]A bias is an error in identifying "the true quality of the object being rated" (Blackburn and Hakal 2006, p. 378).

Experience. The experience of an author can influence perceptions of scientific contributions (Trapido 2015), likely due to source exposure effects (e.g., Bornstein, Leone, and Galley 1987; Roskos-Ewoldsen and Fazio 1992; Weisbuch and Mackie 2009). Substantial evidence shows that prior exposure to the source of a message or idea influences its persuasiveness (Weisbuch, Mackie, and Garcia-Marques 2003). People tend to demonstrate a more favorable attitude toward messages or ideas from familiar sources (Weisbuch and Mackie 2009); in a similar vein, we expect that repeated exposures to the same source (in our case, ideators) results in favorable attitudes toward their ideas. Moreover, attitudes about the novelty of ideas often depend on experience, because novel ideas contributed by experienced ideators appear less risky (Trapido 2015). Thus, ideators and seeker firms may be more inclined to select novel ideas contributed by experienced ideators. We consider the interaction between novelty and individual experience, both with a specific challenge (challenge experience) and with the general practice of contributing ideas to OpenIDEO across challenges (serial experience).

Results. The relationship between global novelty and likes is positive and linear for both male and female ideators. However, the relationship between global novelty and shortlisting is linear for ideators with female names and non-linear for ideators with male names. In relation to experience, we find that serial experience across multiple challenges improves the likelihood that globally novel ideas are shortlisted. In contrast, increased experience within the same challenge reduces the likelihood that globally novel ideas are shortlisted (see Table 11). The interactions between novelty and experience also differ according to the gender of the ideator. For example, serial experience improves the probability that novel ideas are shortlisted for male names but not for female names.

Robustness Checks: SUR and 3SLS Estimation and Mixed-Effects Models

As robustness checks of the results, we employ both seemingly unrelated regression (SUR) and three-stage least squares (3SLS) to estimate the systems of equations in our models simultaneously. First, SUR accounts for correlation in the error terms across equations, with the acknowledgment that the estimates of the endogenous variables come from the same sample (Zellner 1962). Second, as a combination of 2SLS and SUR, 3SLS addresses both cross-equation error correlation and potential endogeneity arising from the correlation of the explanatory variables with the error term. In the equation with likes as the dependent variable, we introduce comments as an additional covariate that is not present in the shortlisting equation; the identifying assumption is that the number of comments does not directly influence shortlisting. We base this assumption on challenge briefs, which suggest that firms do not use the number of comments as a criterion for shortlisting.[31] The estimates for the coefficients of local and global novelty in the SUR and 3SLS models are consistent with our main specification (Table 12). As an additional robustness check, we also estimate the following multi-level mixed-effects model with ideator and contest random effects (Table 13):

$$Likes_{ijk} = \beta_0 + \beta_1 GN_{ijk} + \beta_2 GN_{ijk}^2 + \beta_3 LN_{ijk} + \beta_4 LN_{ijk}^2 + \beta_5 LN_{ijk} \text{ x } GN_{ijk} + \Phi_{ijk} + \gamma_j + \mu_k + e_{ijk}$$

$$Shortlist_{ijk} = \beta_0 + \beta_1 GN_{ijk} + \beta_2 GN_{ijk}^2 + \beta_3 LN_{ijk} + \beta_4 LN_{ijk}^2 + \beta_5 LN_{ijk} \text{ x } GN_{ijk} + \Phi_{ijk} + \gamma_j + \mu_k + e_{ijk}$$

In the above model, Φ_{ijk} is the vector of control variables and γ_j and μ_k represent challenge and ideator level intercepts.

Predictive Model

In this section, we develop a predictive model of idea selection. Using this model, seeker firms can predict likes or shortlisting, on the basis of content factors such as local and global

[31]As an example, see https://challenges.openideo.com/challenge/gratitude-in-the-workplace/brief.

novelty, along with linguistic features of the idea, such as coherence and use of expert words, which may be associated with overall idea quality. We note at least three scenarios in which such a prediction model would be useful to seeker firms. First, they might use a prediction model to winnow down a large pool of ideas, which makes it cumbersome to make direct selections. From the 47 challenges in our data set, the number of ideas contributed range from 68 to 649. To identify a subset of ideas that are most promising, the firm can use a prediction model trained on past selection data; such a model also can help eliminate junk ideas.

Second, factors unrelated to the idea content, such as order or entry or ideator characteristics, influence idea selection. An idea contributed near the conclusion of a contest likely garners fewer likes than an idea submitted early during the challenge. Similarly, as we showed, gender can influence idea selection, due to the biases of the selectors. A prediction model based solely on idea content, which excludes variables such as gender, provides seeker firms with a more objective measure of idea quality. There are two general approaches to building such a de-biased model. The first produces a predictive model that explicitly incorporates covariates such as gender and excludes any biasing variables from subsequent predictions that use new data. A second approach relies on training with models that exclude biasing variables. We adopt this second approach; Žliobaitė (2017) provides a fuller review of discrimination in algorithmic decision making.

Third, in some idea crowdsourcing challenges such as GE's Open Innovation Challenge or Microsoft's Big Idea Challenge,[32] ideator selection metrics (e.g., likes) are not available, because ideators do not view or vote on others' ideas. Even platforms that allow ideators to view others' contributions have imposed increasingly restrictive practices to prevent full access and

[32]See: https://geinnovationlab.com; https://imaginecup.microsoft.com (accessed May 2019).

voting,[33] in an effort to prevent competing ideators from appropriating earlier proposed ideas. In this case, an ideator selection metric based on likes is not available. However, a predictive model of likes can mitigate this drawback by predicting the number of likes an idea likely would have received in a counterfactual scenario that allows ideators to view and vote on others' ideas.

Noting these potential benefits of being able to predict ideators' valuation of ideas, we move beyond just novelty measures (local and global) and anticipate that idea selection also might be predicted by linguistic features of the idea content, associated with overall idea quality signaled by the use of expert words and textual coherence.

Prediction Using Regularized Linear Regression

A linguistic analysis of idea content results in many putative predictors that would make model selection challenging, so we rely on a subset of the most important predictors. With a lasso model, a regularized linear regression method that penalizes the absolute size of coefficient estimates, we produce the most important predictors of the dependent variable (Frank and Friedman 1993; Tibshirani 1996; Tibshirani, Wainwright, and Hastie 2015). Formally,

$$\hat{\beta}_{lasso}(\lambda) = arg\,min\, \frac{1}{n} \sum_{i=1}^{n} (y_i - x_i' \beta)^2 + \frac{\lambda}{n} \sum_{j=1}^{p} \psi_j |\beta_j|,$$

where λ is the turning parameter that controls the penalty level, and ψj indicates penalty loadings specific to the predictor. Setting $\lambda = 0$ is equivalent to an OLS model, and when $\lambda \to \infty$, it results in a model in which all coefficients are 0. This approach offers two advantages over OLS (Ahrens, Hansen, and Schaffer 2019; Tibshirani 1996). First, it supports variable selection, by setting some of the coefficients exactly to 0 and removing predictors that exhibit the weakest effects. Thus, it results in a parsimonious model that is easier to interpret than a least squares

[33]In 2018, OpenIDEO hosted the NextGen Cup Challenge, aimed at designing the next-generation fiber cup. It was sponsored by multiple seeker firms, including Starbucks, McDonald's, and Coca-Cola, and it allowed ideators to submit their ideas through either a publicly viewable channel, where other ideators could view and vote on their ideas, or a non-viewable channel. In the latter, the seeker firms do not have access to an ideator selection metric.

model. Second, it tends to be more accurate than OLS in out-of-sample predictions, reflecting the bias–variance trade-off, in that OLS estimates often have low bias but large variance.

The selection of variables in a lasso model depends on the choice of the tuning parameter (penalty level) λ. A standard approach to identify the tuning parameter uses an information criterion, such as the extended Bayesian information criterion (EBIC; Chen and Chen 2008). Alternatively, cross-validation methods such as K-fold train the model K times, holding out $1/K$ of the data set for validation purposes, where K is typically set to 5 or 10 (Reid, Tibshirani, and Friedman 2016). However, as a penalized regression model, the lasso approach also introduces an attenuation bias that we handle by applying post-estimation OLS to the lasso-selected first-stage variables (Ahrens, Hansen, and Schaffer 2019; Lee et al. 2016). Therefore,

$$\hat{\beta}_{PE}(\lambda) = \ arg\ min\ \frac{1}{n}\sum_{i=1}^{n}(y_i - x_i'\beta)^2 \ where\ \beta_j = 0\ if\ \tilde{\beta}_j = 0\ ,$$

and $\tilde{\beta}_j$ is the lasso estimator. As covariates, we include linguistic features that may be helpful for predicting idea selection, including the use of analytic words, clout (use of expert words), tone (emotion), and authenticity, all derived from the Linguistic Inquiry and Word Count (LIWC) dictionary (Tausczik and Pennebaker 2010). The LIWC provides a list of word categories, developed from an examination of the writing style of people with different personalities, mental and emotional states, and other traits (Netzer, Lemaire, and Herzenstein 2019; Pennebaker and King 1999). We obtain measures of text cohesion using the tool for the automatic analysis of cohesion (Crossley, Kyle, and McNamara 2016) and measures of lexical sophistication using the tool for the automatic analysis of lexical sophistication 2.0 (Kyle, Crossley, and Berger 2018).

We test for the optimal value of the tuning parameter λ using the EBIC criterion and K-fold cross validation (K = 10). The EBIC criterion (λ = 6441.19) yields a more parsimonious set of predictors than K-fold cross validation (λ = 433.76). The global novelty measure emerges as

the best overall predictor of likes. Furthermore, word count, clout, task structure definition, and semantic overlap with the challenge task evaluated using LSA represent additional, meaningful predictors. Appendix 2.5 lists the lasso first-stage variable selection results and post-estimation OLS estimates of the predictive model. Thus, we show that global novelty together with linguistic measures such as the use of expert words can predict ideator selection in idea crowdsourcing contests if ideator selection metrics such as likes are unavailable.

Discussion

The selection of novel ideas is a *terminus a quo* in the development of really innovative products. Seeker firms rely on idea crowdsourcing through open innovation platforms to generate novel ideas, selected by both seeker firms and ideators. Yet despite reports that 61% of 1,200 executives surveyed in 44 countries embrace open innovation to obtain novel ideas,[34] both seeker firms and ideators perform poorly when it comes to idea selection, and novel ideas might not be selected from idea crowdsourcing platforms. By re-examining the relationship between idea novelty and idea, and considering the role of task structure definition, we determine that the relationship between global novelty and likes is positive and linear. Thus, in idea crowdsourcing challenges, the number of likes provides a strong proxy for the global novelty of ideas. In contrast, the relationship between global novelty and shortlisting is nonlinear and depends on the nature of the task. We do not find any evidence of a relationship between local novelty and the idea selection metrics. Prior studies that fail to find any positive relationship between novelty and idea selection might be examining local novelty alone, ignoring the nonlinear relationship between novelty and selection, or forgetting the potential influence of task structure.

[34]See https://www.pwc.com/us/en/services/consulting/innovation-benchmark-findings.html (accessed March 2019).

In accordance with these findings, studies of outcomes of idea novelty, such as selection or market success, should consider both local and global novelty, along with the influence of task structure. Seeker firms looking to identify novel ideas through idea crowdsourcing should base their selection on ideator selection metrics (e.g., likes), because seeker firm metrics likely are biased against globally novel ideas. As a managerial application, our study provides a predictive model that relies on semantic measures of global novelty, along with linguistic features of the content. Such a model should be helpful if the seeker firm chooses to hide submissions from other ideators (e.g., out of intellectual property concerns), because it still can estimate how ideators likely would have selected such ideas. Predictive models also can prescreen ideas, which is critical when the number of ideas is vast.

Future Research

Future research can consider the broader implications of the local-global novelty distinction in the design, marketing, and purchase of new products. For example, one such area of potential inquiry concerns the differences in marketing-related outcomes (such as sales) based on the level of local and global novelty of a new product. For example, local novelty is a crucial consideration in isolated markets, where consumers may not be familiar with products commonly available in other markets. In such case, it is essential to examine the effects of both local and global product novelty. Consider the introduction of products (such as a smartphone) in new markets with two globally novel features, A and B. Let's consider that in market 1, the majority of the phones have feature A, but not B. In contrast, in market 2, a majority of the phone possess feature B, but not A. If markets A and B are isolated from each other, products with feature A would locally novel in market 1. Products with feature B would be locally novel in market 2.

A similar example of such isolated markets relates to food products: a food item indigenous to one region will be perceived to be locally novel if introduced in another market. Second, consider the case of a consumer evaluating new products inside a store setting. Given that, consumers may display a preference for novel products (e.g., Hirschman 1980), a consumer's evaluation of a product may involve both global novelty (i.e., new to the world), as well as an examination of local novelty by considering differences among competing choices within a store. Thus if several globally novel products with similar globally novel features are displayed together, such features may appear more or less attractive.

Future research can consider automatic assessment of other idea dimensions such as specificity, workability, feasibility, and workability (Dean 2006). One drawback behind our approach is that it does not take into account word sense disambiguation and part-of-speech. In future studies, improved methods to evaluate ideas may be considered that takes into account the above linguistic dimension. It may be helpful to consider intermediate levels of novelty based on the domain of reference. For example, ideators evaluating the novelty of ideas may consider how it is different or unusual compared to other ideas in the specific challenge, on the OpenIDEO platform, and outside OpenIDEO.

Figure 2. Study Framework

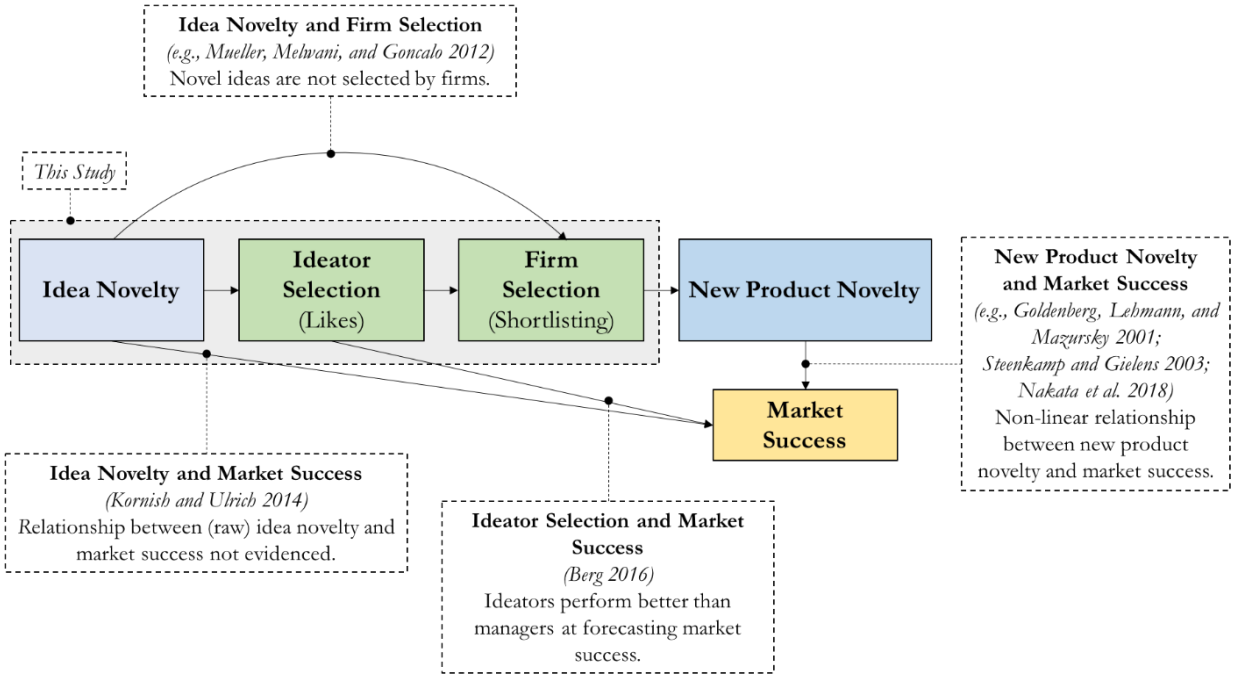


Figure 3. Global Novelty and Semantic Distance

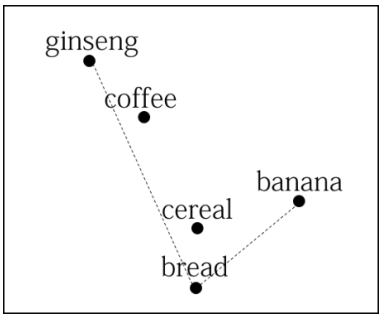


Figure 4. Illustration of OpenIDEO Phases

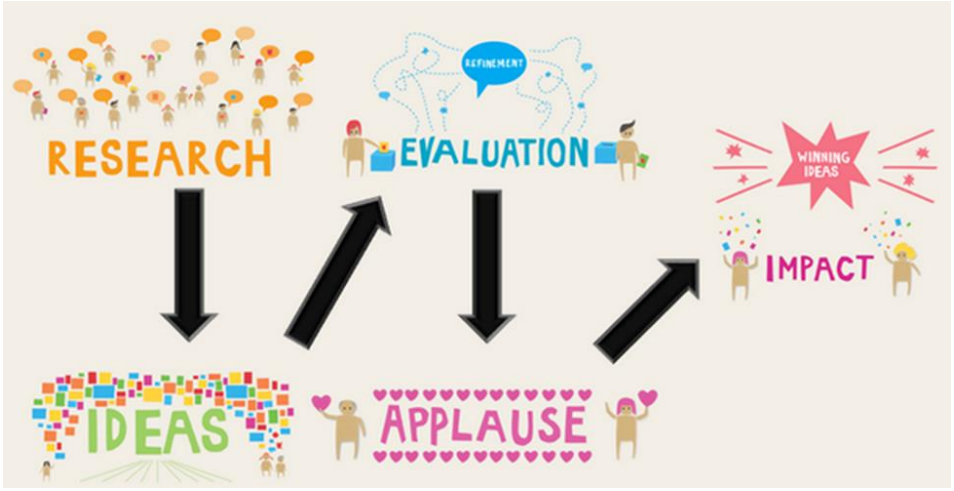


Figure 5. Illustrative Contribution on OpenIDEO

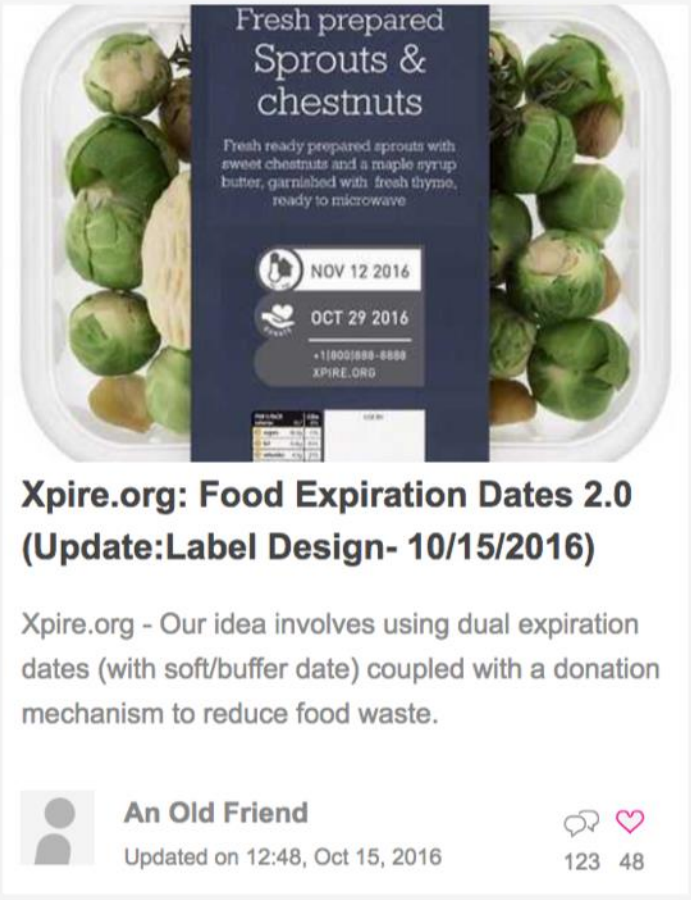
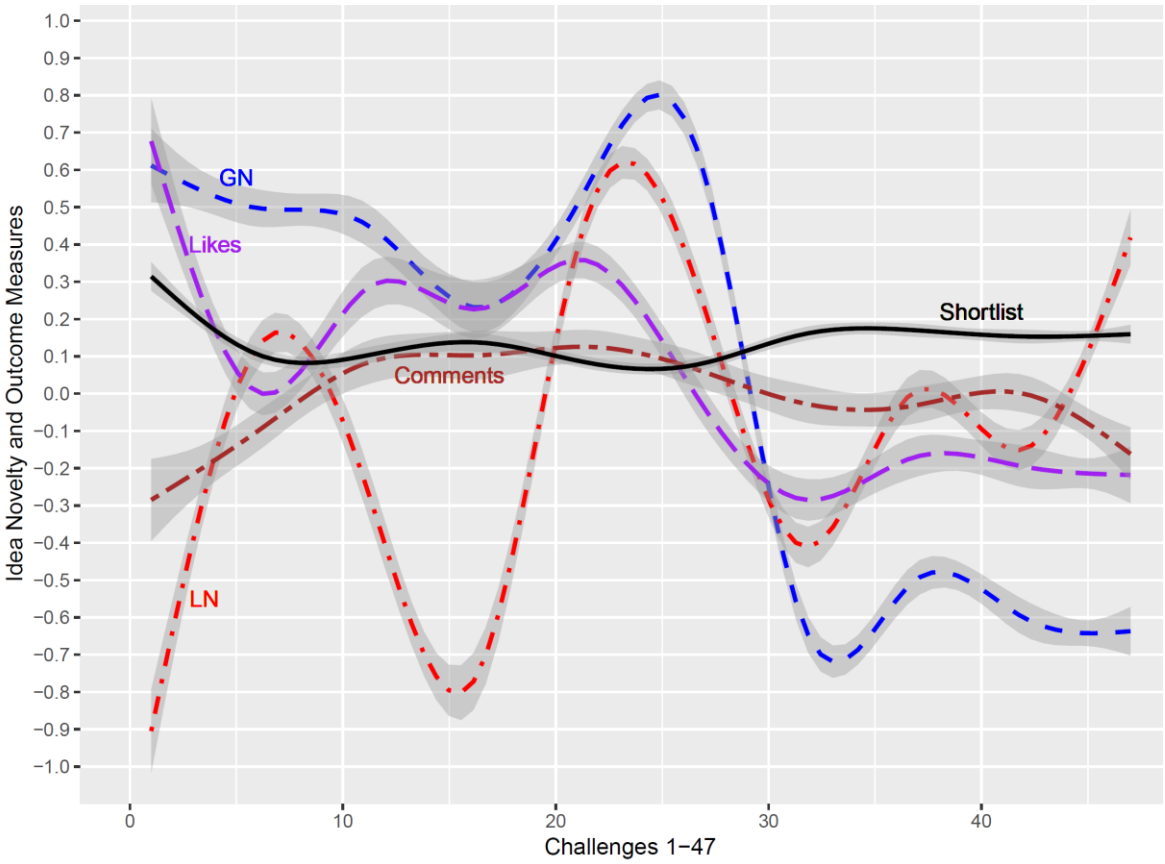
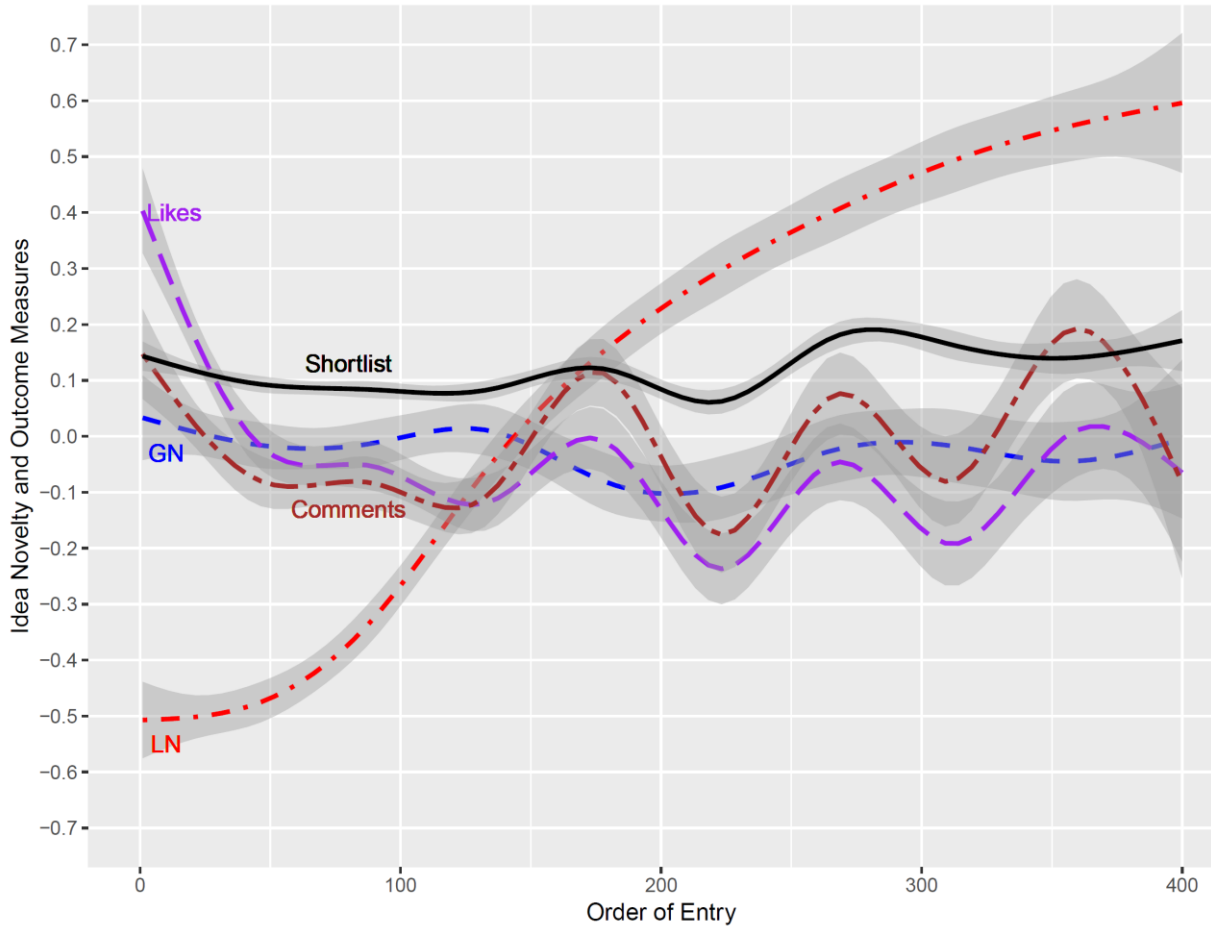


Figure 6. Focal Measures across Challenges



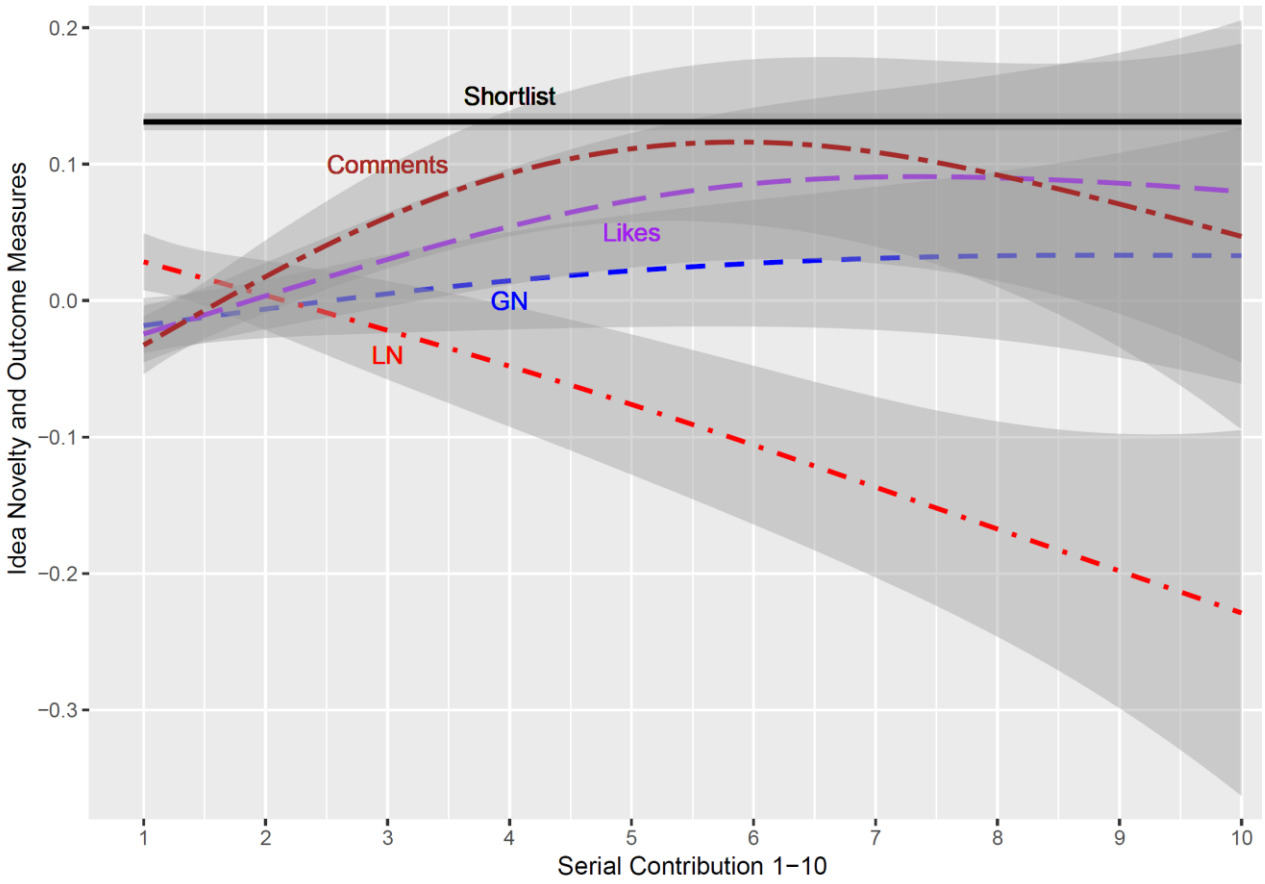
Note: This figure depicts the loess-smoothed plot of focal measures over challenges 1–47 on OpenIDEO.

Figure 7. Focal Measures and Order of Entry



Note: This figure depicts the loess-smoothed plot of focal measures for different order-of-entry positions averaged across all 47 challenges.

Figure 8. Focal Measures and Serial Participation



Note: This figure depicts the loess-smoothed plot of key measures for different orders of serial contributions on OpenIDEO.

Table 6: Summary of Relevant Literature on Selection of Novel Ideas

Study	Outcome	Exam. of Nonlinearity	Evaluation of Novelty	Relevant Findings
Goldenberg, Lehmann, and Mazursky (2001)	Market success	Yes	Human rater	Nonlinear relationship between market novelty and market success
Steenkamp and Gielens (2003)	Market success	Yes	Human rater	Nonlinear relationship between novelty and market success; nature of relationship depends on product complexity
Berg (2016)	Market success	NA	NA	Ideators perform better than managers in predicting market success.
Kornish and Ulrich (2014)	Market success	No	Human rater	No relationship found between idea novelty and market success.
Rietzschel, Nijstad, and Stroebe (2010)	Ideator selection	No	Human rater	Negative relationship between novelty and ideator selection.
Mueller, Melwani, and Goncalo (2012)	Firm selection	No	IAT, Human rater	Negative relationship between novelty and firm selection.
This Study	Ideator selection, firm selection	Yes	Semantic Analysis	Linear relationship between global novelty and ideator selection; nonlinear relationship between global novelty and firm selection.

Table 7: Illustrative Ideas and Standardized Novelty Measures

Challenge Task: “How can we raise kids' awareness of the benefits of fresh food so they can make better choices?”

Idea	Global Novelty	Local Novelty
A kit for kids that contains everything that is needed to start a small farm of edibles at home, even in an urban environment, even in a small space.	-0.8337	-1.3577
Interactive vending machine used to inform, educate and entertain. The thought process is not to replace sugar-laden vending machines, but place it next to them to help children make their own choice while learning about nutrition and where food...	0.5227	-0.3646
Bring together all of the kids ideas’ and recipes into a book and publish it then distribute. Then make fresh vegetables and fruits into sweets, leathers etc.	-0.1437	0.1823
A wiki database of Top Trump style information cards which children can play with to learn more about the nutritional value of different food. The game can be played using either static paper based cards and/or a dynamic electronic version for online	1.6732	0.5106

Table 8: Correlation Table

	Local Novelty	Global Novelty	Likes	Shortlist
Local Novelty	1.0000			
Global Novelty	0.1587	1.0000		
Likes	0.0046	0.1724	1.0000	
Shortlist	-0.0485	0.0223	0.4567	1.0000

Table 4. Results

	OLS Shortlist	OLS Shortlist	Probit Shortlist	OLS Likes	OLS Likes
Local Novelty (LN)	.0042 (.0050013)	.0017 (.0043768)	.0215 (.0291128)	-.4978*** (.1149035)	.1694 (.1652196)
LN^2	-.0038 (.0026797)	-.0013 (.0023454)	-.0118 (.0146216)	-.3051*** (.0674353)	-.1698 (.0885263)
Global Novelty (GN)	.0260*** (.0037362)	.0130*** (.0032766)	.1822*** (.0240312)	1.862*** (.1028237)	.8906*** (.123427)
GN^2	-.0089*** (.0025233)	-.0093*** (.0022081)	-.0546*** (.0151884)	.1500 (.0839661)	.0252 (.0833591)
LN × GN	-.0033 (.0034702)	-.0046 (.0030368)	.0213 (.0200663)	.0721 (.1052919)	.0881 (.1146393)
Serial Exp.	.0031*** (.0006477)	.0009 (.000568)	.0168*** (.0033508)	--	.1520*** (.0213986)
Challenge Exp.	-.0104*** (.001572)	-.0051*** (.0013785)	-.0852*** (.0142775)	--	-.3679*** (.0519325)
Order of Entry	.0008*** (.0000241)	.0007*** (.0000212)	.0056*** (.000182)	--	.0083*** (.0007976)
Likes		.0147*** (.0002416)	--	--	--
Intercept	.1634*** (.0242354)	-.0425* (.0214782)	-1.191*** (.1110403)	6.383*** (.1444414)	14.055*** (.8006291)
Challenge FE	Yes	Yes	Yes	No	Yes
Observations	12,079	12,079	12,079	12,079	12,079
R^2	0.1382	0.3401	--	0.0322	0.0987
Pseudo R^2	--	--	0.2056	--	--

*** $p < .001$, ** $p < .01$, * $p < .05$. Notes: OLS = ordinary least squares.

Table 9: Role of Task Structure Definition

	OLS TSDR=1 Shortlisting	OLS TSDR=2 Shortlisting	OLS TSDR=3 Shortlisting	OLS TSDR=1 Likes	OLS TSDR=2 Likes	OLS TSDR=3 Likes
Local Novelty (LN)	.0082 (.0087135)	-.0031 (.0077852)	.0070 (.0098023)	.2451 (.2971238)	.0090 (.2722059)	.2837 (.2877446)
LN^2	-.0101* (.0049965)	.0017 (.0043552)	-.0038 (.0047196)	-.3769* (.1703764)	-.0290 (.1522787)	-.0746 (.1385436)
Global Novelty (GN)	.0229*** (.0061445)	.0355*** (.0062723)	.0195** (.0071372)	.8074*** (.2095234)	.9438*** (.2193068)	.8363*** (.2095091)
GN^2	-.0031 (.0043338)	-.0124** (.0041556)	-.0101* (.0048052)	-.0531 (.1477807)	.0802 (.1452978)	.1019 (.1410538)
LN × GN	-.0059 (.0059511)	-.0116 (.006004)	.0058 (.0063142)	.3286 (.2029282)	-.0273 (.2099283)	-.2395 (.1853528)
Serial Exp.	.0034** (.0010022)	.0039*** (.0011254)	.0019 (.0013573)	.1847*** (.0341754)	.2040*** (.0393491)	.0887* (.0398443)
Challenge Exp.	-.0122** (.0041938)	-.0089*** (.0020094)	-.0184*** (.0037227)	-.6797*** (.1430056)	-.3193*** (.0702578)	-.4673*** (.1092798)
Order of Entry	.0007*** (.0000383)	.0009*** (.0000407)	.0010*** (.0000489)	-.0002 (.0013061)	.0173*** (.0014219)	.0115*** (.0014365)
Intercept	.3592*** (.0423023)	.3158*** (.0308712)	.1693*** (.0263572)	13.779*** (1.44248)	6.1693*** (1.079395)	13.9013*** (.7737064)
Challenge FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,313	4,109	3,657	4,313	4,109	3,657
R^2	0.1096	0.1666	0.1508	0.0838	0.1184	0.1152

*** $p < .001$, ** $p < .01$, * $p < .05$.
Notes: TSDR = task structure definition rating. OLS = ordinary least squares

Table 10: Gender and Experience Effects

	OLS All Likes	OLS Males Likes	OLS Females Likes	OLS All Shortlist	OLS Male Shortlist	OLS Female Shortlist
Local Novelty (LN)	-.0812 (.1825937)	.1692 (.2496877)	-.2148 (.2991744)	.0000 (.0055274)	.0051 (.0075302)	-.0014 (.0089846)
LN^2	-.1636 (.0888386)	-.0819 (.11495)	-.2687 (.1456745)	-.0040 (.0026893)	-.0041 (.0034667)	-.0038 (.0043748)
Global Novelty (GN)	.9907*** (.1515734)	.8484*** (.2107711)	1.055*** (.2471723)	.0285*** (.0045883)	.0238*** (.0063565)	.0277*** (.0074229)
GN^2	.0358 (.0835935)	.0348 (.1106795)	.0757 (.1334723)	-.0089*** (.0025305)	-.0133*** (.0033379)	-.0021 (.0040084)
LN × GN	.0779 (.1152676)	.0641 (.1496703)	.1010 (.1894155)	-.0026 (.0034893)	.0012 (.0045138)	-.0087 (.0056884)
Serial Exp.	.1691*** (.0234758)	.1245*** (.0263016)	.4155*** (.0586912)	.0028*** (.0007106)	.0020* (.0007932)	.0070*** (.0017626)
Serial Exp. × LN	.0215 (.0192297)	.0296 (.021258)	-.0122 (.0553177)	-.0001 (.0005821)	.0004 (.0006411)	-.0033* (.0016613)
Serial Exp. × GN	.0018 (.0226018)	.0135 (.0256347)	-.0328 (.0544749)	.0017* (.0006842)	.0023** (.0007731)	.0006 (.001636)
Chal. Exp.	-.4619*** (.0597974)	-.4368*** (.1020188)	-.7562*** (.1116431)	-.0118*** (.0018102)	-.0106** (.0030767)	-.0158*** (.0033528)
Chal. Exp. × LN	.1126* (.0545519)	-.0256 (.0912634)	.2113* (.1002759)	.0028 (.0016514)	-.0012 (.0027524)	.0072* (.0030114)
Chal. Exp. × GN	-.0648 (.0598991)	-.0236 (.0927456)	-.0299 (.1069849)	-.0044* (.0018132)	-.0045 (.0027971)	-.0014 (.0032129)
Order of Entry	.0085*** (.0007993)	.0080*** (.0010501)	.0092*** (.0012963)	.0008*** (.0000242)	.0008*** (.0000317)	.0008*** (.0000389)
Intercept	14.092 (.8017525)	15.709*** (1.032805)	11.663*** (1.298371)	.1656*** (.0242702)	.2049 (.0311478)	.0981* (038992)
Challenge FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,079	6,982	4,873	12,079	6,982	4,873
R^2	0.0996	0.0996	0.1131	0.1390	0.1401	0.1591

*** $p < .001$, ** $p < .01$, * $p < .05$.

Notes: OLS = ordinary least squares.

Table 11: SUR and 3SLS Estimates

	SUR			3SLS		
	Model 1 Shortlist	Model 1 Likes	Model 2 Shortlist	Model 2 Likes	Model 1 Shortlist	Model 1 Likes
Likes	.0147*** (.000241)	--	.0175*** (.0002396)	--	.0216*** (.0003877)	--
Local Novelty (LN)	0017 (.0043666)	.1695 (.164843)	.0012 (.0043666)	.1307 (.1262895)	.0005 (.0045148)	.1313 (.1262895)
LN^2	-.0013 (.0023399)	-.1698 (.0883245)	-.0009 (.0023399)	-.0964 (.0676713)	-.0001 (.0024197)	-.0976 (.0676713)
Global Novelty (GN)	.0130*** (.003269)	.8905*** (.1231457)	.0104** (.0032689)	.3724** (.0945036)	.0068* (.00339)	.3810*** (.0945056)
GN^2	-.0092*** (.002203)	.0252 (.0831691)	-.0093*** (.002203)	.1044 (.0637227)	-.0094*** (.0022777)	.1031 (.0637228)
LN × GN	-.0046 (.0030298)	.0881 (.114378)	-.0049 (.0030298)	.0654 (.0876271)	-.0002 (.0024197)	.0658 (.0876271)
Serial Exp.	.0009 (.0005667)	.1520*** (.0213499)	.0004 (.0005667)	.0497** (.0163924)	-.0001 (.0005876)	.0514** (.0163928)
Challenge Exp.	-.0051*** (.0013753)	-.3679*** (.0518141)	-.0040** (.0013753)	-.1712*** (.0397504)	-.0025 (.0014261)	-.1744*** (.039751)
Order of Entry	.0007*** (.0000212)	.0083*** (.0007958)	.0007*** (.0000212)	.0007 (.0006149)	.0007*** (.000022)	.0009 (.000615)
Comments	--	--	--	.4067*** (.0043121)	--	.4000*** (.0043379)
Intercept	-.0425* (.0214284)	14.055*** (.7988043)	-.0824*** (.0214252)	13.328*** (.6120249)	-.1403*** (.0225442)	13.340*** (.6120255)
Challenge FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,079	12,079	12,079	12,079	12,079	12,079
R^2	0.3401	0.0987	0.3325	0.4709	0.2946	0.4710
RMSE	.2741	10.349	.2757	7.929	.2834	7.928
Chi^2	6225.04	1322.66	7858.50	11148.57	5471.53	10754.36

*** $p < .001$, ** $p < .01$, * $p < .05$.

Table 12: Multi-level Mixed-Effects Models

	Shortlist	Likes
Local Novelty (LN)	-.0005405 (.0551222)	.0735026 (.1566304)
LN^2	-.0108661 (.0269534)	-.1597131 (.0835462)
Global Novelty (GN)	.3321802*** (.0477098)	.9100216*** (.1231722)
GN^2	-.0942527*** (.0294416)	.0153081 (.0825349)
LN × GN	.0272107 (.0383364)	.070767 (.1128398)
Serial Exp.	.0315537*** (.0063852)	.1975608*** (.0271454)
Challenge Exp.	-.1508602*** (.027816)	-.3983513*** (.0677721)
Order of Entry	.0133327*** (.0004798)	.0090989*** (.0008222)
Intercept	-3.851131 (.3204634)	5.846351 (.5070086)
Observations	12,079	12,079

*** $p < .001$, ** $p < .01$, * $p < .05$.

Table 13: Random Effects GLS Model

	Shortlist	Shortlist	Likes	Winner	Winner
Local Novelty (LN)	.008366 (.0052037)	.0045384 (.0045216)	.2301154 (.1628773)	.0024083 (.0024395)	.0015014 (.0023227)
LN^2	-.0027943 (.0027914)	-.0006992 (.0024259)	-.1233224 (.0873852)	.0007907 (.0013079)	.0010087 (.0012452)
Global Novelty (GN)	.0334514*** (.003986)	.0187471*** (.0034967)	.9002394*** (.1256485)	-.0001074 (.0018241)	-.0033424 (.0017391)
GN^2	-.011243*** (.002642)	-.0104446*** (.0022988)	-.0430583 (.0828053)	.0002341 (.0012314)	.0020368 (.0011735)
LN × GN	-.0002846 (.0036288)	-.0018446 (.0031508)	.0977494 (.1135135)	-.0021619 (.0016936)	-.0017883 (.0016124)
Likes	-	.0156046*** (.0002532)	-	.0078126*** (.0001339)	.0052963*** (.0001461)
Shortlist	-	-	-	-	.1632634*** (.0046303)
Challenge FE	Yes	Yes	Yes	Yes	Yes
Intercept	13.8684*** (.8380291)	.0068241*** (.0235588)	13.8684*** (.8380291)	-.0210392 (.0119163)	-.0216136 (.0113448)
Observations	12,079	12,079	12,079	12,079	12,079

*** $p < .001$, ** $p < .01$, * $p < .05$.

Table 14: Order of Entry Effects

	Shortlist	Shortlist	Likes	Winner	Winner
Local Novelty (LN)	.0205647** (.0074864)	.0146526* (.0065171)	.3831779 (.2451214)	.0083084* (.0036655)	.0057082 (.0034994)
LN^2	.0074864 (.0029253)	.0020643 (.0025455)	-.0774129 (.0957474)	.0021362 (.0014354)	.0019008 (.0013701)
Global Novelty (GN)	.0493619*** (.0054764)	.0396329*** (.0048061)	.5971609** (.1809577)	.003737 (.0026375)	-.0033898 (.0025259)
GN^2	-.0093291*** (.0025135)	-.0089919 (.0021918)	-.0214978 (.0824739)	.0004426 (.0012284)	.0020124 (.0011733)
LN × GN	.0042102 (.0036441)	.0040416 (.0031727)	.0102436 (.119337)	-.0011066 (.0017824)	-.0017846 (.0017013)
Likes	-	.0147748*** (.0002421)	-	.0077267*** (.000134)	.0052732*** (.0001466)
Shortlist	-	-	-	-	.1666368*** (.0048594)
Order of Entry (OE)	.0009121*** (.0000284)	.0007889*** (.0000252)	.0092263*** (.0009461)	.0001059*** (.0000137)	-.0000195 (.0000136)
LN × OE	-.0001064** (.0000332)	-.0000882** (.000029)	-.0012244 (.0010922)	-.0000384* (.0000162)	-.0000239 (.0000155)
GN × OE	-.0001359*** (.0000217)	-.0001524*** (.000019)	.0011812 (.000716)	-.0000259* (.0000105)	1.41e-06 (.0000101)
Challenge FE	Yes	Yes	Yes	Yes	Yes
Intercept	.1327554*** (.0247787)	-.0643923** (.0223791)	13.09524*** (.8381464)	-.0305505* (.0119419)	-.0202284 (.011402)
Observations	12,079	12,079	12,079	12,079	12,079

*** $p < .001$, ** $p < .01$, * $p < .05$.
Note: Mixed-Effects ML Regression

Table 15: Task Structure Specificity and Order of Entry

	Shortlist (TS = Lo)	Shortlist (TS=Hi)	Likes (TS = Lo)	Likes (TS =Hi)	Winner (TS = Lo)	Winner (TS =Hi)
Local Novelty (LN)	.0092478 (.0091656)	.0199476* (.009212)	.1610136 (.3838359)	.9247309** (.2949278)	.0063706 (.0051262)	.0089499 (.0052149)
LN^2	.0006088 (.0035682)	.0033775 (.0036227)	-.1179263 (.1494156)	.0094683 (.1159819)	.001565 (.0019997)	.0025571 (.0020573)
Global Novelty (GN)	.0422668*** (.0064895)	.0277774*** (.007014)	.0885243 (.1228357)	1.30324*** (.2250211)	.0024739 (.0035772)	.0019191 .0039172)
GN^2	-.0071621* (.0029316)	-.0089533** (.0032633)	.0885243 (.1228357)	-.152999 (.1044492)	.0009696 (.0016357)	.0006822 (.0018491)
LN × GN	.0181776** (.0181776)	.000389 (.0059974)	-.0949862 (.240569)	.3972045 (.1918944)	.0016489 (.0032193)	-.0021843 (.0033947)
Likes	.0121608*** (.0002964)	.020438*** (.0004156)	-	-	.006662*** (.000165)	.01012*** (.0002338)
Order of Entry (OE)	.0008348*** (.0000365)	.0007784*** (.0000341)	.01615*** (.00152)	.0011976 (.0010992)	.0001207 (.00002)	.0001102 (.000019)
LN × OE	-.0000288 (.0000411)	-.0001594*** (.0000405)	-.0005093 (.0017226)	-.003777** (.0012983)	-.0000183 (.000023)	-.000058* (.0000228)
GN × OE	-.000143*** (.0000279)	-.0000849** (.0000308)	.00436*** (.0011695)	-.0025603* (.0009876)	-8.76e-06 (.0000155)	-.0000254 (.0000174)
LN × GN × OE	-.0001029* (.0000302)	-.000016 (.0000332)	-.0009874 (.0012632)	-.0002104 (.001061)	-.0000372* (.0000169)	.0000203 (.0000188)
Ideator RE	Yes	Yes	Yes	Yes	Yes	Yes
Challenge FE	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	-.036978 (.0230857)	.1596381*** (.0275485)	12.724*** (.9597635)	5.92106*** (.8964505)	-.0167407 (.0124821)	.0023203 (.014947)
Observations	6,471	5,608	6,471	5608	6,471	5,608

TS: Task Structure Definition Specificity; Random Effects ML Regression
*** $p < .001$, ** $p < .01$, * $p < .05$.

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APPENDICES

APPENDIX 1.1: LIST OF SHORTLISTED PATENTS

No.	Patent Title	Original Assignee	Pat. No.	Pub. Date
1	Convertible hat and pack apparatus	William P. Connor IV	6167569	Jan 2, 2001
2	Peeler for root vegetables	Rauschnings Maskin Tekniska AB	6167801	Jan 2, 2001
3	Color changing umbrella	Denise Doolan	6196241	Mar 6, 2001
4	Lamp and alarm clock with gradually increasing light or sounds	Verilux Inc.	6236622	May 22, 2001
5	Petroleum production optimization utilizing adaptive network and genetic algorithm techniques	Atlantic Richfield Co	6236894	May 22, 2001
6	Zoned aircraft de-icing system and method	Northcoast Technology	6237874	May 29, 2001
7	Method and apparatus for measuring fetal heart rate	Miklós Török et al	6245025	Jun 12, 2001
8	Compositions for targeted gene delivery	Introgene B.V.	6261554	Jul 17, 2001
9	Adjustable pouch carrier for different size pouches and packaging machine having an adjustable pouch carrier	Klockner Bartelt	6276117	Aug 21, 2001
10	Travel planning system	Ita Software, Inc.	6295521	Sep 25, 2001
11	Method and apparatus for predictively coding shape information of video signal	Hyundai Electronics Industries Co. Ltd.	6301303	Oct 9, 2001
12	System and method providing a restaurant menu dynamically generated based on revenue management information	Walker Digital, Llc	6341268	Jan 22, 2002
13	Separable fastener system	Ppg Industries Glass S.A.	6347491	Feb 19, 2002
14	Method and apparatus for arc welding with melting electrode	Esab Ab	6388233	May 14, 2002
15	Interactive furniture for dieters	Norma Brown	6425862	Jul 30, 2002
16	Navigation system with automatic change of data medium	Mannesmann Vdo Ag	6438489	Aug 20, 2002
17	Seat belt restraint system for vehicle occupants with automatic belt tension compensation	Ford Global Technologies, Inc.	6481750	Nov 19, 2002
18	Arcade game with spinning wheel bonus	Rlt Acquisition, Inc.	6491296	Dec 10, 2002
19	Dynamically Stabilized Contact Lenses	Johnson & Johnson Vison Care, Inc.	6491392	Dec 10, 2002
20	Final minute graphics for digital time displays	Equitime, Inc.	6493290	Dec 10, 2002
21	Apparatus and method for retrieving data cartridge information external to a media storage system	Hewlett-Packard Company	6523749	Feb 25, 2003
22	Food-quality and shelf-life predicting method and system	Emerson Retail Services Inc.	6549135	Apr 15, 2003
23	Temperature-controlled shipping container and method for using same	Nanopore, Inc.	6584797	Jul 1, 2003

24	Image forming apparatus, cartridge detachably mountable to the image forming apparatus, developer remainder displaying method and system	Canon Kabushiki Kaisha	6587649	Jul 1, 2003
25	Treadmill whose speed is controlled by music	Chia-Shen Huang	6605020	Aug 12, 2003
26	Selectable multi-purpose card	Bank One, Delaware, National Association	6631849	Oct 14, 2003
27	Method, system and program for specifying an electronic food menu with food preferences from a universally accessible database	International Business Machines Corporation	6646659	Nov 11, 2003
28	Vehicle communication link automatic diagnostic tool detection	General Motors Corporation	6647323	Nov 11, 2003
29	Consumer interface educational database system for monitoring proficiency, performance and evaluation of student	Alverno College	6651071	Nov 18, 2003
30	Trim-type fastener driving tool	Illinois Tool Works Inc.	6651862	Nov 25, 2003
31	Digital temperature sensor (DTS) system to monitor temperature in a memory subsystem	International Business Machines Corporation	6662136	Dec 9, 2003
32	Circuit cell having a built-in self-test function, and test method therefor	Infineon Technologies Ag	6662326	Dec 9, 2003
33	Dual sensor process pressure switch	Angela E. Summers, Bryan A. Zachary	6704682	Mar 9, 2004
34	Flexible plastic container	David S. Smith Packaging Limited	6715644	Apr 6, 2004
35	Vehicle seat assembly having a cradle seat back	Magna Seating Systems Inc.	6719368	Apr 13, 2004
36	Computer mouse input device with multi-axis palm control	Stephen W. Shaw	6727889	Apr 27, 2004
37	Automated web site creation system	Und Aerospace Foundation	6732332	May 4, 2004
38	Optical path structure for open path emissions sensing with spinning mirror	Spx Corporation	6744059	Jun 1, 2004
39	Proximity safety switch suitable for use in a hair dryer for disabling operation	Ljm Associates, Inc.	6750747	Jun 15, 2004
40	Illuminated motorcycle shifter linkage	Joseph F. Sollitto, Robert Foglia	6761240	Jul 13, 2004
41	Temperature sensor for a warming blanket	Sunbeam Products, Inc.	6768086	Jul 27, 2004
42	Method and system for interfacing with a shipping service	Schneider Logistics, Inc.	6785718	Aug 31, 2004
43	Refrigerator unit with lighted ice dispenser cavity	Whirlpool Corporation	6804974	Oct 19, 2004
44	Multiple plasma generator hazardous waste processing system	Rcl Plasma, Inc.	6817388	Nov 16, 2004
45	Drowsiness detection system	Intelligent Mechatronics Systems Inc.	6822573	Nov 23, 2004
46	Methods and apparatus for model predictive control of aircraft gas turbine engines	General Electric Company	6823253	Nov 23, 2004
47	Method for high resolution magnetic resonance analysis using magic angle technique	Battelle Memorial Institute	6836115	Dec 28, 2004
48	Lens apparatus and camera	Canon Kabushiki Kaisha	6851871	Feb 8, 2005
49	Function values in computer programming languages having dynamic types and overloading	The Mathworks, Inc.	6857118	Feb 15, 2005
50	Beverage container warmer	Hlc Efficiency Products Llc	6870135	Mar 22, 2005

51	Multi component controlled release system for oral care, food products, nutraceutical, and beverages	Adi Shefer, Samuel David Shefer	6887493	May 3, 2005
52	Wavelength-selective photonics device	Quantum Semiconductor Llc	6891869	May 10, 2005
53	Grill assembly for a cyclone-type dust collecting apparatus for a vacuum cleaner	Samsung Gwangju Electronics Co., Ltd.	6896711	May 24, 2005
54	Dental camera utilizing multiple lenses	Schick Technologies	6908307	Jun 21, 2005
55	Addition of power at selected harmonics of plasma processor drive frequency	Tokyo Electron Limited	6917204	Jul 12, 2005
56	Resealable food container	Kraft Foods Holdings, Inc.	6918532	Jul 19, 2005
57	Continuous reactive power support for wind turbine generators	General Electric Company	6924565	Aug 2, 2005
58	Scene representation method and system	Microsoft Corporation	6933941	Aug 23, 2005
59	Music instrument system and methods	Humanbeams, Inc.	6960715	Nov 1, 2005
60	Shock detecting apparatus	Kabushiki Kaisha Toshiba, Toshiba Tec Kabushiki Kaisha	6970277	Nov 29, 2005
61	Method and apparatus for synchronizing data between a watch and external digital device	Fossil, Inc.	6977868	Dec 20, 2005
62	Ink pen for dispensing ink having time-dependent characteristics	Andrew F. Knight	7001091	Feb 21, 2006
63	Adjustable reamer with tip tracker linkage	Howmedica Osteonics Corp.	7008430	Mar 7, 2006
64	Spare tire usage detection	General Motors Corporation	7030745	Apr 18, 2006
65	Kitchen exhaust optimal temperature span system and method	Melink Corporation	7048199	May 23, 2006
66	Razor having thermo-electric shaving aid ejection system and method of ejecting shaving aid	Eveready Battery Company, Inc.	7111400	Sep 26, 2006
67	Smart tray system and method for restaurant inventory management	Prince Castle, Inc.	7132926	Nov 7, 2006
68	Multivariate control of semiconductor processes	Mks Instruments, Inc.	7151976	Dec 19, 2006
69	Generating elevator or escalator installation fault log	Inventio Ag	7172055	Feb 6, 2007
70	Continuously variable transmission	Fallbrook Technologies Inc.	7172529	Feb 6, 2007
71	Slow motion detection system	Intel Corporation	7180429	Feb 20, 2007
72	Derivation and quantization of robust non-local characteristics for blind watermarking	Microsoft Corporation	7181622	Feb 20, 2007
73	Combination shipping carton and twin dispenser boxes	Graphic Packaging International, Inc.	7225930	Jun 5, 2007
74	Source code editor for editing multilanguage documents	Microsoft Corporation	7293232	Nov 6, 2007
75	Personal portable environmental control system	US Secretary of Navy	7331183	Feb 19, 2008
76	Photoelectric controller for electric street lighting	Hendrix Wire & Cable, Inc.	7369056	May 6, 2008
77	Motor-driven decorative spinner for vehicles	Scott B. Baker, Arthur D. Hale, Jr.	7389600	Jun 24, 2008
78	Systems and methods for building a native language phoneme lexicon having native pronunciations of non-native words derived from non-native pronunciations	International Business Machines Corporation	7472061	Dec 30, 2008

79	Method and apparatus for automatically creating a movie	Pinnacle Systems, Inc.	7500176	Mar 3, 2009
80	Using an index to access a subject multi-dimensional database	International Business Machines Corporation	7529727	May 5, 2009
81	Rotatable building	3Sixty Technologies, Llc	7536831	May 26, 2009
82	Apparatus and method for operating a folding machine for a web-fed printing press	Man Roland Druckmaschinen Ag	7569010	Aug 4, 2009
83	Fuel cutoff valve	Toyoda Gosei Co., Ltd., Honda Motor Co., Ltd.	7571740	Aug 11, 2009
84	Fast optical switch	Nortel Networks Limited	7593607	Sep 22, 2009
85	Multiple wash zone dishwasher	Whirlpool Corporation	7594513	Sep 29, 2009
86	Potentiating support with side struts spanning hinge joint	Nordt Development Co., Llc	7615019	Nov 10, 2009
87	Universal water purification system	Christopher Heiss	7632410	Dec 15, 2009
88	System and method for selective adjustment of exercise apparatus	Icon Ip, Inc.	7645212	Jan 12, 2010
89	System and method for downloading software and services	Gateway, Inc.	7657885	Feb 2, 2010
90	Dynamically Providing Newsfeed	Facebook, Inc.	7669123	Feb 23, 2010
91	Disposable absorbent articles with replaceable absorbent core components having regions of permeability and impermeability on same surface	The Procter And Gamble Company	7670324	Mar 2, 2010
92	Methods, systems and devices related to road mounted indicators for providing visual indications to approaching traffic	Spot Devices, Inc.	7688222	Mar 30, 2010
93	Random tumbling washing machine wash chamber for improving cleaning while minimizing mechanical damage to clothes	Whirlpool Corporation	7690063	Apr 6, 2010
94	Warning system for child left unattended in vehicle	James Morningstar	7714737	May 11, 2010
95	Questions and control paradigms for detecting deception by measuring brain activity	Cephos Corp.	7729755	Jun 1, 2010
96	Universal electrical plug	Getac Technology Corporation	7736194	Jun 15, 2010
97	Method and system for identifying keywords for use in placing keyword-targeted advertisements	Amazon Technologies, Inc.	7752200	Jul 6, 2010
98	Search phrase refinement by search term replacement	Collarity, Inc.	7756855	Jul 13, 2010
99	Direct memory access transfer completion notification	International Business Machines Corporation	7765337	Jul 27, 2010
100	Carpet decor and setting solution compositions	S.C. Johnson & Son, Inc.	7780744	Aug 24, 2010
101	Dual depth airbag with active venting	Autoliv Asp, Inc.	7784828	Aug 31, 2010
102	System and method for an interactive security system for a home	Embarq Holdings Company, Llc	7786891	Aug 31, 2010
103	Mechanical ventricular pacing non-capture detection	Medtronic, Inc.	7787942	Aug 31, 2010
104	Controlled release preparation	Takeda Pharmaceutical Company Limited	7790755	Sep 7, 2010
105	Waterfall prioritized payment processing	J P Morgan Chase Bank, N.A.	7792717	Sep 7, 2010

106	System and method for dynamic configuration of replicated database servers	Oracle America, Inc.	7805407	Sep 28, 2010
107	Device and method for automated planning of an access path for a percutaneous, minimally invasive intervention	Siemens Aktiengesellschaft	7809176	Oct 5, 2010
108	Social network augmentation of search results methods and apparatus	Cisco Technology, Inc.	7818394	Oct 19, 2010
109	Variable focus spectacles	Lane Research, Llc	7866816	Jan 11, 2011
110	Infant stroller	AGT Equities, LLC	7878515	Feb 1, 2011
111	Adaptive personalized music and entertainment	James W. Wieder	7884274	Feb 8, 2011
112	Using a shape-changing display as an adaptive lens for selectively magnifying information displayed onscreen	Research In Motion Limited	7890257	Feb 15, 2011
113	Portable intelligent shopping device	International Business Machines Corporation	7890434	Feb 15, 2011
114	System and method for reducing excess capacity for restaurants and other industries during off-peak or other times	Mount Hamilton Partners, Llc	7904334	Mar 8, 2011
115	Apparatus and method for calibrating a variable phase shifter	City University Of Hong Kong	7915942	Mar 29, 2011
116	System and method for tracking assets within a monitored environment	Zebra Enterprise Solutions Corp.	7916023	Mar 29, 2011
117	Sports electronic training system with electronic gaming features, and applications thereof	Adidas International Marketing B.V.	7927253	Apr 19, 2011
118	Methods and apparatuses for navigation in urban environments	Hopstop.com, Inc.	7957871	Jun 7, 2011
119	Updating parameters in a bridged multistandard home network	Thomson Licensing	7984191	Jul 19, 2011
120	System and method of data security in synchronizing data with a wireless device	Good Technology, Inc.	8001082	Aug 16, 2011
121	Methods of assessing and designing an application specific measurement system	Halliburton Energy Services Inc.	8027855	Sep 27, 2011
122	Brightness adjustment method and system for 3D ultrasound	Kabushiki Kaisha Toshiba, Toshiba Medical Systems Corporation	8047992	Nov 1, 2011
123	Zoom lens, image capture apparatus, and method for controlling zoom lens	Sony Corporation	8055126	Nov 8, 2011
124	Hybrid helicopter that is fast and has long range	Eurocopter	8070089	Dec 6, 2011
125	Elevator system with control to allocate a call based on charging status of energy storage, and method of controlling an elevator group	Kone Corporation	8083033	Dec 27, 2011
126	Recommendation system with cluster-based filtering of recommendations	Amazon Technologies, Inc.	8095521	Jan 10, 2012
127	Internal combustion engine control for improved fuel efficiency	Tula Technology, Inc.	8099224	Jan 17, 2012
128	Apparatus and method for securing data on a portable storage device	Sandisk Il Ltd.	8103882	Jan 24, 2012
129	Method and apparatus for FDD and TDD terminal entry into a wireless communication network	L-3 Communications, Corp.	8107982	Jan 31, 2012
130	Motion tracking system for real time adaptive imaging and spectroscopy	The Queen's Medical Center et al	8121361	Feb 21, 2012

131	System and method for facilitating automated dental measurements	Align Technology, Inc.	8126726	Feb 28, 2012
132	Retail system for selling products based on a flexible product description	Groupon, Inc.	8150735	Apr 3, 2012
133	Helmet system with interchangeable outer shells	Kirk Chung, Matthew Chung	8166573	May 1, 2012
134	Retractable needle-safety blood sampling device	Sakharam D. Mahurkar	8167820	May 1, 2012
135	Systems and methods for providing fantasy sports contests based on subevents	Rovi Technologies Corporation	8176518	May 8, 2012
136	Integrated circuit cell architecture configurable for memory or logic elements	LSI Corporation	8178909	May 15, 2012
137	Climate controlled bed assembly	Amerigon Incorporated	8181290	May 22, 2012
138	Temperature responsive smart textile	Malden Mills Industries, Inc.	8187984	May 29, 2012
139	Consumer interface methods and apparatus for processing voice call requests	Motorola Mobility, Inc.	8195177	Jun 5, 2012
140	Writing erasable paper using thermal printhead and UV illumination	Xerox Corporation	8203583	Jun 19, 2012
141	Frequency selective passive component networks for active implantable medical devices	Greatbatch Ltd.	8219208	Jul 10, 2012
142	Method for controlling cleaning device	Industrial Technology Research Institute	8223029	Jul 17, 2012
143	Multi-strategy generation of product recommendations	Richrelevance, Inc.	8244564	Aug 14, 2012
144	Hinge assembly for foldable electronic device	Shenzhen Futaihong Precision Industry Co., Ltd., Fih (Hong Kong) Limited	8245354	Aug 21, 2012
145	Pressure sensing systems for sports, and associated methods	Nike, Inc.	8249831	Aug 21, 2012
146	Adaptive regression test selection within testing environments	Juniper Networks, Inc.	8276123	Sep 25, 2012
147	Power screwdriver having rotary input control	Black & Decker Inc.	8286723	Oct 16, 2012
148	Device for receiving and transmitting mobile telephony	Kathrein-Werke Kg	8289910	Oct 16, 2012
149	Vehicle route selection based on energy usage	Telogis, Inc.	8290701	Oct 16, 2012
150	Jukebox entertainment system having multiple choice games relating to music	Touchtunes Music Corporation	8292712	Oct 23, 2012
151	Net metering apparatus for power generation systems	Chandramouli Vaidyanathan	8295986	Oct 23, 2012
152	Cryptographic module for secure processing of value-bearing items	Stamps.Com	8301572	Oct 30, 2012
153	Firearm	Iwao Fujisaki	8312660	Nov 20, 2012
154	Roll-on, foldable litter and patient handling system for emergency transport vehicles	Air Methods Corporation	8336939	Dec 25, 2012
155	Trigger router and test system including the trigger router	EADS North America, Inc.	8370537	Feb 5, 2013
156	Fully automatic rapid microscope slide scanner	Aperio Technologies, Inc.	8385619	Feb 26, 2013
157	Custom scheduling and control of a multifunction printer	Sharp Laboratories Of America, Inc.	8392924	Mar 5, 2013
158	Method and apparatus for pre-firing cues during a digital cinema presentation	Thomson Licensing	8395751	Mar 12, 2013

159	Method and system for processing a financial transaction	Intuit Inc.	8396794	Mar 12, 2013
160	Apparel with integral heating and cooling device	Dhama Innovations PVT. Ltd.	8397518	Mar 19, 2013
161	Visual ARS service system and method enabled by mobile terminal's call control function	Call Gate Co., Ltd.	8437747	May 7, 2013
162	Dynamic variable-content publishing	Uhlig Llc	8438476	May 7, 2013
163	Wagering game with a table-game configuration	Wms Gaming Inc.	8449372	May 28, 2013
164	Adjustable shoe	Tilag Brands, Llc	8468723	Jun 25, 2013
165	Channel scan logic	Apple Inc.	8471837	Jun 25, 2013
166	Interactive toys and games connecting physical and virtual play environments	Creative Kingdoms, Llc	8475275	Jul 2, 2013
167	Disk drive including an actuator latch having a defeat position	Western Digital Technologies, Inc.	8477460	Jul 2, 2013
168	System, method and apparatus for just-in-time conditioning using a thermostat	Ecofactor, Inc.	8498753	Jul 30, 2013
169	Method and system for associating content with map zoom function	Gabriel Jakobson, Steven Rueben	8504945	Aug 6, 2013
170	Tactile based performance enhancement system	Racing Incident Pty Ltd.	8552847	Oct 8, 2013
171	Garment accessory with electrocardiogram sensors	Medicomp, Inc.	8560044	Oct 15, 2013
172	Composite human physiological stress index based on heart beat and sleep and/or activity history data including actigraphy	Pulsaw Informatics, Inc.	8568330	Oct 29, 2013
173	Apparatus and method for custom cosmetic dispensing	Cosmetic Technologies, Llc	8573263	Nov 5, 2013
174	Tonescale compression for electroluminescent display	Global Oled Technology Llc	8576145	Nov 5, 2013
175	Medical diagnosis derived from patient drug history data	3M Innovative Properties Company	8579811	Nov 12, 2013
176	Content distribution program, content distribution method	Fujitsu Limited	8595139	Nov 26, 2013
177	Cooking temperature and power control	Bose Corporation	8598497	Dec 3, 2013
178	Method, medium, and system for an augmented reality retail application	SeeMore Interactive, Inc.	8606645	Dec 10, 2013
179	Chemically reactive security ink, a method of use of such ink, and security documents incorporating such ink	The Standard Register Company	8622436	Jan 7, 2014
180	Patient selectable joint arthroplasty devices and surgical tools incorporating anatomical relief	Conformis, Inc.	8623026	Jan 7, 2014
181	Variable alarm sounds	Core Wireless Licensing S.A.R.L.	8625394	Jan 7, 2014
182	Surgical stapling systems that produce formed staples having different lengths	Ethicon Endo-Surgery, Inc.	8636187	Jan 28, 2014
183	Method and circuitry to adaptively charge a battery/cell	Qnovo Inc.	8638070	Jan 28, 2014
184	Computer system and method for processing of data related to insurance quoting	Hartford Fire Insurance Company	8655690	Feb 18, 2014
185	Dynamic traffic management	Amazon Technologies, Inc.	8667056	Mar 4, 2014
186	Two stage serviceable safety clip	Ford Global Technologies, Llc	8677573	Mar 25, 2014

187	Dynamic core selection for heterogeneous multi-core systems	Intel Corporation	8683243	Mar 25, 2014
188	Method and apparatus for consumer selection of advertising combinations	Hulu, LLC	8713603	Apr 29, 2014
189	Method of providing consumer-tailored entertainment experience at hospitality location and hospitality media system thereof	Guest Tek Interactive Entertainment Ltd.	8713612	Apr 29, 2014
190	Determining when to drive autonomously	Google Inc.	8718861	May 6, 2014
191	Patient safety system with automatically adjusting bed	Masimo Corporation	8723677	May 13, 2014
192	Digital camera having variable duration burst mode	Apple Inc.	8736716	May 27, 2014
193	Food safety indicator	Food Technologies International, LLC	8747775	Jun 10, 2014
194	Vacuum surge suppressor for surgical aspiration systems	Dana, LLC.	8753323	Jun 17, 2014
195	Control method of a wind turbine generator	Acciona Windpower, S.A.	8759995	Jun 24, 2014
196	Dynamic road gradient estimation	Ford Global Technologies, Llc	8793035	Jul 29, 2014
197	Online volume migration using multi-path input/output masquerading	International Business Machines Corporation	8799594	Aug 5, 2014
198	Dynamic pass phrase security system	Ibiometrics, Inc.	8812319	Aug 19, 2014
199	Adaptive low-battery warnings for battery-powered electronic devices	Apple Inc.	8816868	Aug 26, 2014
200	Surround sound in a sensory immersive motion capture simulation environment	Motion Reality, Inc.	8825187	Sep 2, 2014
201	Targeted marketing to on-hold consumer	Segmint Inc.	8825520	Sep 2, 2014
202	Adjustable memory allocation based on error correction	Seagate Technology Llc	8826100	Sep 2, 2014
203	Systems and methods for controlling energy use in a building management system using energy budgets	Johnson Controls Technology Company	8843238	Sep 23, 2014
204	Methods for handling a file associated with a program in a restricted program environment	Apple Inc.	8850572	Sep 30, 2014
205	Earphone receiving assembly	Scienbizip Consulting (Shenzhen) Co., Ltd.	8861772	Oct 14, 2014
206	Centrifuge	Kensey Nash Corporation	8870733	Oct 28, 2014
207	Gear shift notification apparatus having a preselected notification pattern	Shimano Inc.	8878658	Nov 4, 2014
208	Method and apparatus for dynamic air traffic trajectory synchronization	Lockheed Martin Corporation	8924137	Dec 30, 2014
209	Flexible electronic devices	Apple Inc.	8929085	Jan 6, 2015
210	System and method to adjust insurance rate based on real-time data about potential vehicle operator impairment	State Farm Mutual Automobile Insurance Company	8930269	Jan 6, 2015
211	Communication terminal	Canon Kabushiki Kaisha	8954043	Feb 10, 2015
212	Software license management	Kelce S. Wilson	8966646	Feb 24, 2015
213	Adjustable seat assembly	The Boeing Company	8967723	Mar 3, 2015
214	Point of sale (POS) based checkout system supporting a consumer-transparent two-factor	Metrologic Instruments, Inc.	8976030	Mar 10, 2015

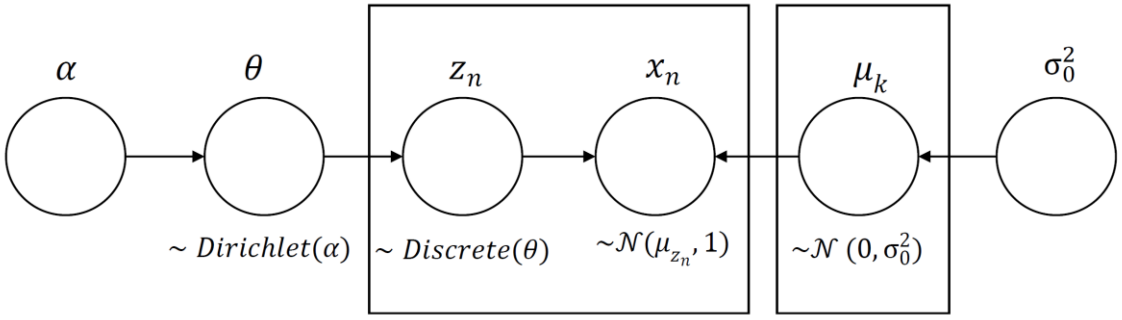
	authentication process during product checkout operations			
215	Method and apparatus for generating flight-optimizing trajectories	The United States Of America As Represented By The Administrator Of The National Aeronautics And Space Administration	8977482	Mar 10, 2015
216	Razor handle with a rotatable portion	The Gillette Company	8978258	Mar 17, 2015
217	Image pickup apparatus, accessory, and imaging system	Canon Kabushiki Kaisha	9001264	Apr 7, 2015
218	Configurable price matrix for mobile billing at a merchant server	Boku, Inc.	9014664	Apr 21, 2015
219	Intelligent board game system with visual marker based game object tracking and identification	Tweedletech, Llc	9028315	May 12, 2015
220	Method for inspecting and testing notification appliances in alarm systems	Tyco Fire & Security Gmbh	9030314	May 12, 2015
221	Controlling vehicle entertainment systems responsive to sensed passenger gestures	Thales Avionics, Inc.	9037354	May 19, 2015
222	Dynamic input at a touch-based interface based on pressure	Google Inc.	9046999	Jun 2, 2015
223	Programming of a robotic arm using a motion capture system	Autofuss	9056396	Jun 16, 2015
224	Risk potential calculation apparatus	Toyota Jidosha Kabushiki Kaisha	9058247	Jun 16, 2015
225	Creating a customized avatar that reflects a consumer's distinguishable attributes	King.Com Ltd.	9058698	Jun 16, 2015
226	Control apparatus for a medical examination apparatus	Siemens Aktiengesellschaft	9078960	Jul 14, 2015
227	Headrest apparatus for multi-purpose vehicle	Kia Motors Corp., Dae Won San Up Co., Ltd.	9108550	Aug 18, 2015
228	Logistic transport system for nutritional substances	Eugenio Minvielle	9121840	Sep 1, 2015
229	Comfort-driven optimization of electric grid utilization	Distributed Energy Management Inc.	9134353	Sep 15, 2015
230	Leakage-modeling adaptive noise canceling for earspeakers	Cirrus Logic, Inc.	9142205	Sep 22, 2015
231	Oral care fluid delivery system	Colgate-Palmolive Company	9144298	Sep 29, 2015
232	Consumer interface for an evidence-based, hypothesis-generating decision support system	International Business Machines Corporation	9153142	Oct 6, 2015
233	Methods and systems for treatment of vestibular disorders	University Of Rochester	9167998	Oct 27, 2015
234	Dynamic quests in game	Zynga Inc.	9174128	Nov 3, 2015
235	Wearable food nutrition feedback system	Microsoft Technology Licensing, Llc	9189021	Nov 17, 2015
236	Method and apparatus for dynamic signage using a painted surface display system	Google Inc.	9195320	Nov 24, 2015
237	Context-based smartphone sensor logic	Digimarc Corporation	9196028	Nov 24, 2015
238	Contextual display of information with an interactive consumer interface for television	Tvworks, Llc	9197938	Nov 24, 2015
239	Haptic feedback devices for surgical robot	Ethicon Endo-Surgery, Inc.	9198714	Dec 1, 2015

240	Adaptive projector	Apple Inc.	9201501	Dec 1, 2015
241	Context sensitive auto-correction	Microsoft Technology Licensing, Llc	9218333	Dec 22, 2015
242	Method and system for creating a customized print	Hewlett-Packard Development Company, L.P.	9218550	Dec 22, 2015
243	Dispensing system and consumer interface	Microsoft Technology Licensing, Llc	9218740	Dec 22, 2015
244	Apparatus, systems, and methods for calibration of microphones	Analog Devices, Inc.	9232333	Jan 5, 2016
245	Systems and methods for monitoring caregiver and patient protocol compliance	Richard Deutsch	9235977	Jan 12, 2016
246	Engine automatic stopping device and engine automatic stopping method	Nissan Motor Co., Ltd.	9249741	Feb 2, 2016
247	Dynamic configuration in cloud computing environments	Citrix Systems, Inc.	9251115	Feb 2, 2016
248	Systems, methods, and computer readable media for copy-on-demand optimization for large writes	Emc Corporation	9256598	Feb 9, 2016
249	Adjustable band mechanism	Microsoft Technology Licensing, Llc	9277791	Mar 8, 2016
250	Carrying device for receiving a baby or an infant	Schachtner Vermoegensverwaltungs Gmbh & Co. Kg	9277830	Mar 8, 2016
251	Real-time improvement method and apparatus for distributed network radio frequency performance	Zte Corporation	9288775	Mar 15, 2016
252	Apparatus and method for automatically activating a camera application based on detecting an intent to capture a photograph or a video	Apple Inc.	9292045	Mar 22, 2016
253	Using a mobile device with integrated motion sensing for customized golf club fitting	Aquimo, Llc	9339707	May 17, 2016
254	Motion actuated fixture illuminator	Jack D. Miller	9345110	May 17, 2016
255	Wearing part with a wear indicator and system for wear testing*	Man Truck & Bus Ag	9355346	May 31, 2016
256	System and method providing protection in the event of current sensing failure	On-Bright Electronics (Shanghai) Co., Ltd.	9362737	Jun 7, 2016
257	System and method for initiating a multi-environment operating system	Google Technology Holdings LLC	9372711	Jun 21, 2016
258	Hybrid satellite and mesh network system for aircraft and ship internet service	Qualcomm Incorporated	9397745	Jul 19, 2016
259	Method, system, and apparatus for providing self-destructing electronic mail messages	AT&T Intellectual Property I, L.P.	9397964	Jul 19, 2016
260	Expert system for prediction of changes to local environment	Christian Humann	9406028	Aug 2, 2016
261	Live timing for dynamic adaptive streaming over HTTP	Qualcomm Incorporated	9426196	Aug 23, 2016
262	Systems and methods of transformer failure detection and control	General Electric Company	9430012	Aug 30, 2016
263	Safety valve control system and method of use	Safoco, Inc.	9441453	Sep 13, 2016
264	Dynamic control of smart home using wearable device	International Business Machines Corporation	9473321	Oct 18, 2016
265	Altering a view perspective within a display environment	Microsoft Technology Licensing, Llc	9498718	Nov 22, 2016
266	Techniques for automatically swapping languages and/or content for machine translation	Google Inc.	9524293	Dec 20, 2016

267	Methods and software for managing vehicle priority in a self-organizing traffic control system	Carnegie Mellon University	9536427	Jan 3, 2017
268	Smart watch and food utensil for monitoring food consumption	Medibotics Llc	9536449	May 23, 2013
269	Method for collecting and aggregating network quality data	Google Inc.	9565578	Feb 7, 2017
270	Authorizing devices based on identifying content distributor	Gracenote, Inc.	9596490	Mar 14, 2017
271	Vehicle system, portable device, and vehicle-mounted device	Denso Corporation, Nippon Soken, Inc.	9599984	Mar 21, 2017
272	Drip bag systems, methods and applications	Thought Streams, Llc	9675062	Jun 13, 2017
273	Color or multi-material three-dimensional (3D) printing	San Draw, Inc.	9688022	Jun 27, 2017

APPENDIX 1.2: ANALYSIS OF VEHICLE PATENTS

To deepen our understanding, we conducted a sector-specific analysis of patents for vehicles published during 2017–2018. The keyword search for relevant patents uncovered more than 16,000 patents. We applied a topic modeling approach with latent Dirichlet allocation (LDA; Blei, Ng, and Jordan 2003) to assess patent similarity. The LDA models document a mixture of topics. The "bag-of-words" models infer topics from their co-occurrence in the document, independent of the order of the words. Each topic is a distribution of words, each document is a mixture of topics, and each word is drawn from one of the topics.



The generative model (Blei 2014) for LDA is as follows:

1. Draw mixture proportions $\theta \sim Dirichlet(\alpha)$.
2. For each mixture component k, draw $\mu_k \sim \mathcal{N}(0, \sigma_0^2)$.
3. For each data point n:
    a. Draw mixture assignment $z_n|\theta \sim Discrete(\theta)$.
    b. Draw data point $x_n|z_n, \mu \sim \mathcal{N}(\mu_{z_n}, 1)$.

Except the documents, the rest of the variable are latent, inferred from the data. The inference comes from a collection of documents: (1) per word topic assignment z_n; (2) per document topic proportion θ; and (3) per corpus topic distribution μ_k. The Dirichlet distribution is an exponential family distribution over the simplex, in which positive vectors sum to 1. We then employed model-based clustering to group the patents into six clusters. Among 300 patents (50 samples; 6 clusters), we were able to classify 47 (16%) that involved attribute auto-dynamics.

Figure A1.2a. LDA Topics for Vehicle Patents

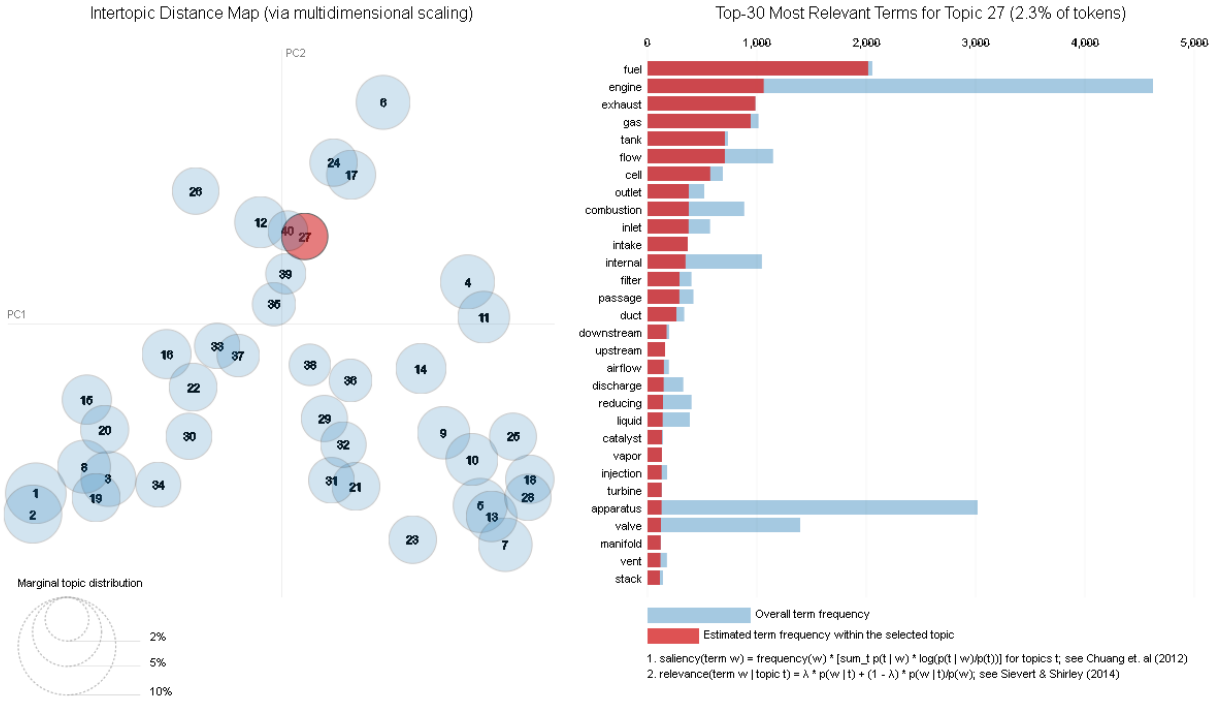


Table A1.2a. Vehicle Patents identified with Attribute Auto-dynamics

1	USP9731417	8/15/2017	5d Robotics Inc.	Vehicle management system
2	USA2017/0123428	5/4/2017	Zoox Inc.	Sensor-based object-detection optimization for autonomous vehicles
3	USP9615213	4/4/2017	Katasi Llc	Method and system for controlling and modifying driving behaviors
4	USP9669840	6/6/2017	Jaguar Land Rover Limited	Control system and method
5	USP9802612	10/31/2017	Toyota Jidosha Kabushiki Kaisha|Toyota Motor Europe Nv/Sa	Vehicle engine activation control system
6	USP9663200	5/30/2017	Ixblue	System and method for the navigation of a movable vehicle, suitable for determining and displaying a safe navigation zone
7	USP9638536	5/2/2017	Alpine Electronics Inc.	Navigation device, route guidance control method in navigation device, and non-transitory computer-readable storage medium storing program
8	USP9846025	12/19/2017	Wabtec Holding Corp	Track data determination system and method

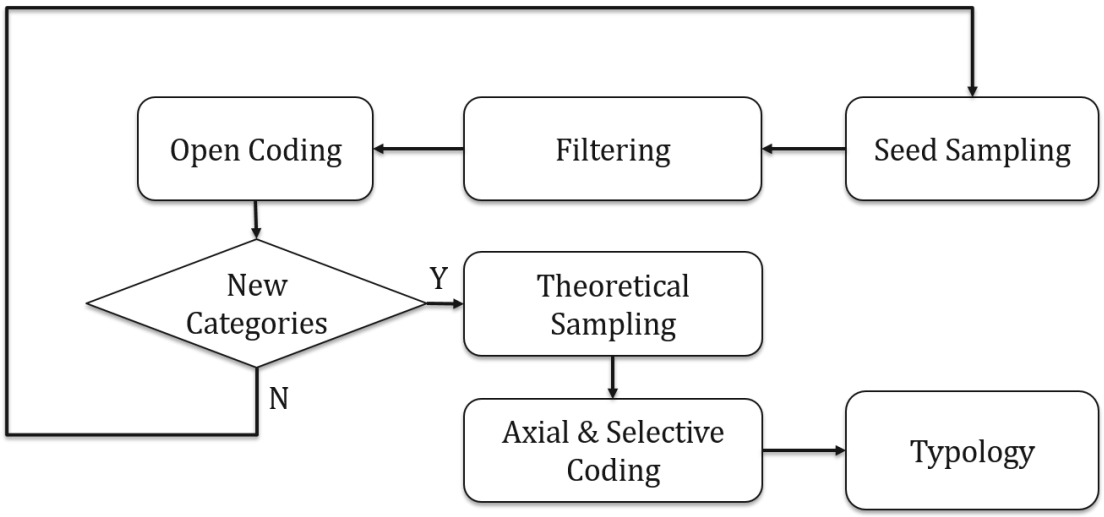
9	USA2017/0282770	10/5/2017	Faurecia Automotive Seating Llc	System, methodologies, and components acquiring, analyzing, and using occupant body specifications for improved seating structures and environment configuration
10	USP9623860	4/18/2017	Toyota Jidosha Kabushiki Kaisha	Hybrid vehicle and control method therefor
11	USP9731722	8/15/2017	Ford Global Technologies Llc	Brake control for stop/start vehicle
12	USP9690296	6/27/2017	Waymo Llc	Avoiding blind spots of other vehicles
13	USA2017/0186315	6/29/2017	Ebay Inc.	Traffic disruption detection using passive monitoring of vehicle occupant frustration level
14	USP9739368	8/22/2017	Robert Bosch Gmbh	Method and device for monitoring a drive of a motor vehicle
15	USP9758005	9/12/2017	Honda Motor Co Ltd	Suspension controller
16	USP9766086	9/19/2017	Rubicon Global Holdings Llc	System having automated route detection and app initiation
17	USP9581610	2/28/2017	Orange Electronic Co Ltd	Position-identifiable tire pressure monitor, monitoring system and method thereof
18	USA2017/0369011	12/28/2017	Honda Motor Co Ltd	Smart entry driver id changing
19	USP9779458	10/3/2017	State Farm Mutual Automobile Insurance Company	Systems and methods for generating vehicle insurance policy data based on empirical vehicle related data
20	USP9673492	6/6/2017	Gm Global Technology Operations Llc	Actively-switched direct refrigerant battery cooling
21	USA2017/0080856	3/23/2017	Toyota Jidosha Kabushiki Kaisha	Vehicle alertness control system
22	USP9682711	6/20/2017	Hyundai Mobis Co Ltd	Apparatus and method for detecting driver status
23	USP9561801	2/7/2017	Toyota Jidosha Kabushiki Kaisha	Vehicle control system
24	USP9604609	3/28/2017	Ford Global Technologies Llc	Emergency in-lane steering assist with braking
25	USP9803412	10/31/2017	Fontanini Isabella D|Wang Kyle H|Kunz Kevin D|Von Borcke Carlos W	In-vehicle carbon monoxide alarm
26	USA2017/0076605	3/16/2017	Denso Corporation	Vehicle recognition notification apparatus and vehicle recognition notification system
27	USP9802487	10/31/2017	Classic Automotive Innovations Llc	Speedometer drive system and method
28	USP9703289	7/11/2017	Toyota Jidosha Kabushiki Kaisha	Vehicle control apparatus and vehicle control method
29	USP9619203	4/11/2017	Insurance Services Office Inc.	Method of analyzing driving behavior and warning the driver
30	USP9560148	1/31/2017	Lg Electronics Inc.	Vehicle terminal and location-based content sharing system having the same
31	USP9829979	11/28/2017	Ford Global Technologies Llc	Automotive touchscreen controls with simulated texture for haptic feedback

32	USP9676391	6/13/2017	Fallbrook Intellectual Property Company Llc	Systems and methods for control of transmission and/or prime mover
33	USP9650053	5/16/2017	The Goodyear Tire & Rubber Company	Slip ratio point optimization system and method for vehicle control
34	USP9815467	11/14/2017	Lg Electronics Inc.	Vehicle assistance apparatus and vehicle
35	USP9818298	11/14/2017	Init Innovative Informatikanwendungen In Transport	Method, evaluating computer, and on-board computer for influencing a traffic light signal system
36	USP9535423	1/3/2017	Adasworks Kft	Autonomous vehicle with improved visual detection ability
37	USP9827993	11/28/2017	Toyota Motor Engineering & Manufacturing North America Inc.	Method and system for improving ride quality in an autonomous vehicle
38	USA2017/0108343	4/20/2017	Google Inc.	Collective vehicle traffic routing
39	USP9805521	10/31/2017	United Parcel Service Of America Inc.	Systems and methods for assessing turns made by a vehicle
40	USP9630624	4/25/2017	Volkswagen Ag|Audi Ag	Method to enhance safe acceleration and lead-vehicle distance keeping performance, by measuring forward vehicle gaps
41	USP9701199	7/11/2017	Nissan Motor Co Ltd	Display control device for vehicle and display control method for vehicle
42	USP9820140	11/14/2017	Driving Management Systems Inc.	Apparatus, system, and method for detecting the presence and controlling the operation of mobile devices within a vehicle
43	USP9809214	11/7/2017	Ford Global Technologies Llc	Battery state of charge control using route preview data
44	USP9669712	6/6/2017	Faraday&Future Inc|Faraday & Future Inc.	Intuitive vehicle control
45	USP9827925	11/28/2017	Toyota Jidosha Kabushiki Kaisha	Driving environment prediction device, vehicle control device and methods thereof
46	USP9630616	4/25/2017	Audi Ag	Method for controlling an autonomous vehicle system and motor vehicle
47	USP9550498	1/24/2017	Ford Global Technologies Llc	Traffic light anticipation

APPENDIX 1.3: TYPOLOGICAL CATEGORIES AND DIMENSIONS

Categories		Dimensions
1	Changing conditions	Discrete, Continuous
2	Number of attribute state	Low, high
3	Attribute measurement	Ordinal, Nominal, Interval, Ratio
4	Attribute state distinctiveness	Low, High
5	Attribute hierarchy	Safety, Utilitarian, Hedonic, Aesthetic
6	Attribute state repetition	Low, High
7	User uncertainty about conditions	Low, High
8	User uncertainty about attributes	Low, High
9	Replaced by adjustable attributes	Yes, No
10	Changes in ideal point	Multiple changes in single use; Single change over single use; Single change over multiple uses
11	Degree of interaction between product and customer	Low, High

APPENDIX 1.4: ANALYTIC APPROACH



APPENDIX 1.5: PATENT SEARCH KEYWORDS FOR AUTO-DYNAMICS

- activating, changing, dynamic, driving, increasing
- sensing, detecting
- adapt, adjust, alter, flexible, modify, re-adjust, selectable
- control, -controlled, optimal, optimize, monitor, regulate, track
- automatic, interactive, self-, process, -dependent, personalized

APPENDIX 2.1: SEMANTIC ANALYSIS OF IDEAS

Study	Operationalization	Context
Bossomaier, Terry, Mike Harré, Anthony Knittel, and Allan Snyder (2009), "A semantic network approach to the creativity quotient (CQ)," Creativity Research Journal, 21(1), 64-71.	Semantic similarity using Wordnet	Ideation fluency and flexibility
Forster, Eve A., and Kevin N. Dunbar (2009), "Creativity Evaluation Through Latent Semantic Analysis," Proceedings of the Annual Conference of the Cognitive Science Society, 602-607.	LSA	Creativity in Uses of Objects Task; Divergent Thinking Tests
Walter, Thomas P., and Andrea Back (2013), "A text mining approach to evaluate submissions to crowdsourcing contests," 46th Hawaii International Conference on System Sciences, IEEE, 3109-3118.	TF-IDF, Clustering	Evaluation of quality of submission on online crowdsourcing platform
Uzzi, B., S. Mukherjee, M. Stringer and B. Jones. 2013. "Atypical Combinations and Scientific Impact." Science 342(6157):468–472.	Rareness of its pairwise combinations of references	Novelty and impact of academic research
Harbinson, J. Isaiah, and Henk Haarman (2014), "Automated Scoring of Originality Using Semantic Representations," Proceedings of the Annual Meeting of the Cognitive Science Society, 36 (6), 1069-7977	LSA, PMI	Evaluation of creativity in tests of divergent thinking
Kaplan, Sarah, and Keyvan Vakili (2015), "The Double-edged Sword of Recombination in Breakthrough Innovation," Strategic Management Journal, 36(10), 1435-1457.	LDA	Evaluation of novel ideas in patents
Chan, Joel, and Christian D. Schunn (2015), "The importance of iteration in creative conceptual combination," Cognition, 145, 104-115.	LDA	Novelty of ideas
Lee, You-Na, John P. Walsh, and Jian Wang (2015), "Creativity in scientific teams: Unpacking novelty and impact," Research Policy, 44(3), 684-697.	Rareness of its pairwise combinations of references	Novelty and impact of academic research
Dasgupta, Tirthankar, and Lipika Dey (2016), "Automatic Scoring for Innovativeness of Textual Ideas," The Workshops of the Thirtieth AAAI Conference on Artificial Intelligence Knowledge Extraction from Text: Technical Report WS-16-10	Entropy, Cosine Similarity, KL Divergence	Novelty of texts
Omari, Adi, David Carmel, Oleg Rokhlenko, and Idan Szpektor (2016), "Novelty based ranking of human answers for community questions," Proceedings of the 39th International ACM SIGIR conference on Research and Development in Information Retrieval, 215-224, ACM.	TF-IDF, Word2Vec, Explicit Semantic Analysis (ESA)	Ranking of answers on community-based question answering (CQA) sites based on novelty.
Cvitanic, Toni, Bumsoo Lee, Hyeon Ik Song, Katherine Fu, and David Rosen (2016), "LDA v. LSA: A comparison of two computational text analysis tools for the functional categorization of patents," International Conference on Case-Based Reasoning.	LSA, LDA	Categorization of patents

Carayol, N., A. Lahatte, and O. Llopis (2018), "The right job and the job right: Novelty, impact and journal stratification in science," Retrieved from: conference.druid.dk/acc˙papers/.	Pair-wise combination of keyword	Novelty of academic papers
Chan, Joel, Pao Siangliulue, Denisa Qori McDonald, Ruixue Liu, Reza Moradinezhad, Safa Aman, Erin T. Solovey, Krzysztof Z. Gajos, and Steven P. Dow (2017), "Semantically Far Inspirations Considered Harmful?: Accounting for Cognitive States in Collaborative Ideation," In Proceedings of the 2017 ACM SIGCHI Conference on Creativity and Cognition, 93-105. ACM.	GloVe	Role of creative ideas in the production of ideas
Christensen, Kasper, Sladjana Nørskov, Lars Frederiksen, and Joachim Scholderer (2017), "In search of new product ideas: Identifying ideas in online communities by machine learning and text mining," Creativity and Innovation Management, 26(1), 17-30.	Support Vector Machine, PLS	Detection and classification of ideas
R. W. Hass, R. W. (2017), "Tracking the dynamics of divergent thinking via semantic distance: Analytic methods and theoretical implications," Memory and Cognition, 45(2), 233-244.	LSA	Tracking dynamics of divergent thinking
Heinen, D. J. P., & Johnson, D. R. (2018), "Semantic distance: An automated measure of creativity that is novel and appropriate," Psychology of Aesthetics, Creativity, and the Arts, 12(2), 144-156	Semantic Distance	Evaluation of novelty and appropriateness
Hoornaert, Steven, Michel Ballings, Edward C. Malthouse, and Dirk Van den Poel (2017), "Identifying new product ideas: waiting for the wisdom of the crowd or screening ideas in real time," Journal of Product Innovation Management, 34(5), 580-597.	LSA	Predicting implement ability of crowdsourced ideas
Skalicky, Stephen, Scott A. Crossley, Danielle S. McNamara, and Kasia Muldner (2017) "Identifying creativity during problem solving using linguistic features," Creativity Research Journal, 29(4), 343-353.	Linguistic Analysis; Linear Mixed Effects Analysis	Creativity in collaborative divergent thinking tasks.
Toubia, Olivier, and Oded Netzer (2017), "Idea Generation, Creativity, and Prototypicality," Marketing Science, 36(1), 1-20.	Semantic Network; Kolmogorov-Smrirnov Statistic	Creativity of ideas
Amplayo, Reinald Kim, SuLyn Hong, and Min Song. "Network-based approach to detect novelty of scholarly literature." Information Sciences, 422, 542-557.	TF-IDF; SVM; Graph; neural network	Novelty of academic papers
Ahmed, Faez, Mark Fuge, Sam Hunter, and Scarlett Miller (2018), "Unpacking subjective creativity ratings: Using embeddings to explain and measure idea novelty," ASME 2018 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference.	Embedding	Novelty of ideas
Ahmed, Faez, and Mark Fuge (2018), "Creative exploration using topic-based bisociative networks," Design Sciences, 4(12), 1-30.	Topic Modeling	Novelty of ideas
Berger, Jonah, and Grant Packard (2018), "Are atypical things more popular?" Psychological Science, 29(7), 1178-1184.	LDA	Novelty of musical lyrics

Fontana, Magda, Martina Iori, Fabio Montobbio, and Roberta Sinatra (2018), "A bridge over troubled water: Interdisciplinarity, Novelty, and Impact," No. dipe0002. Università Cattolica del Sacro Cuore, Dipartimenti e Istituti di Scienze Economiche (DISCE).	Rareness of its pairwise combinations of references	Novelty of academic research
Mei, Mei, Xinyu Guo, Belinda C. Williams, Simona Doboli, Jared B. Kenworthy, Paul B. Paulus, and Ali A. Minai (2018), "Using Semantic Clustering And Autoencoders For Detecting Novelty In Corpora Of Short Texts," 2018 International Joint Conference on Neural Networks (IJCNN), IEEE, 1-8.	LDA, Autoencoders	Novelty of ideas
Dellermann, Dominik, Nikolaus Lipusch, and Mahei Li (2018), "Combining Humans and Machine Learning: A Novel Approach for Evaluating Crowdsourcing Contributions in Idea Contests," (2018).	Topic modeling, Machine learning	Filtering of crowdsourced ideas
Parde, Natalie, and Rodney D. Nielsen (2018), "Exploring the terrain of metaphor novelty: A regression-based approach for automatically scoring metaphors," Thirty-Second AAAI Conference on Artificial Intelligence.	Word Embedding, TF-IDF, SynSet, Psycholinguistics	Scoring novelty of metaphors
Toubia, Olivier (2019), "A Poisson Factorization Topic Model for the Study of Creative Documents (and Their Summaries)," Available at SSRN 3334028.	Poisson Factorization	Novelty of creative content
Wang, Kai, Boxiang Dong, and Junjie Ma (2019), "Towards Computational Assessment of Idea Novelty," Proceedings of the 52nd Hawaii International Conference on System Sciences.	LSA, LDA, TF-IDF	Novelty of ideas

APPENDIX 2.2: LIST OF CHALLENGES

Id.	Challenge Description	TSDR	N
1	How can we raise kids' awareness of the benefits of fresh food so they can make better choices?	3	177
2	How might we increase the availability of affordable learning tools & services for students in the developing world?	2	104
3	What global challenge do you think innovation leaders should work to solve right now?	1	103
4	How can we improve sanitation and better manage human waste in low-income urban communities?	3	68
5	How might we improve maternal health with mobile technologies for low-income countries?	3	172
6	How might we increase the number of registered bone marrow donors to help save more lives?	2	264
7	How might we better connect food production and consumption?	2	598
8	How might we use social business to improve health in low-income communities?	3	95
9	How might we increase social impact with OpenIDEO over the next year?	1	90
10	How can technology help people working to uphold human rights in the face of unlawful detention?	3	162
11	How might we restore vibrancy in cities and regions facing economic decline?	1	322
12	How might we design an accessible election experience for everyone?	1	149
13	How might we support web entrepreneurs in launching and growing sustainable global businesses?	1	156
14	How can we equip young people with the skills, information and opportunities to succeed in the world of work?	1	146
15	How can we manage e-waste & discarded electronics to safeguard human health & protect our environment?	2	104
16	How might we identify and celebrate businesses that innovate for world benefit – and inspire other companies to do the same?	1	89
17	How might we inspire and enable communities to take more initiative in making their local environments better?	1	98
18	How might we create healthy communities within and beyond the workplace?	1	238
19	How might we gather information from hard-to-access areas to prevent mass violence against civilians?	3	166
20	How might we all maintain wellbeing and thrive as we age?	1	133
21	How might we inspire young people to cultivate their creative confidence?	1	599
22	How might we make low-income urban areas safer and more empowering for women and girls?	2	568
23	How might we establish better recycling habits at home?	1	192
24	How might we inspire and engage young people to support older adults through mentorship?	2	114
25	How might we build better employment opportunities and pathways for young people around the world?	1	176
26	How might parents in low-income communities ensure children thrive in their first five years?	3	436

27	How might we rapidly equip and empower the care community to fight Ebola?	3	600
28	How might communities lead the rapid transition to renewable energy?	2	171
29	How might we use the power of communities to financially empower those who need it most?	2	147
30	How might we improve education and expand learning opportunities for refugees around the world?	3	357
31	How might we use technology to inspire all socioeconomic and multicultural groups to lead healthier lives?	2	201
32	How might urban slum communities become more resilient to the effects of climate change?	2	338
33	How might we reimagine the cost of college in the USA and how it's paid for? (The Higher Ed Challenge)	1	271
34	How might we use market-based approaches to expand water and sanitation solutions among low income households in India? (Water and Sanitation Challenge)	3	142
35	How might we improve the livelihoods of small-scale farmers by reducing food waste and spoilage?	3	375
36	How might we reimagine the end-of-life experience for ourselves and our loved ones?	1	290
37	How might we combat health threats like Zika, SARS, Ebola and Malaria in bold, imaginative ways?	2	103
38	How might we dramatically reduce waste by transforming our relationship with food?	2	405
39	How might we expand economic opportunities for youth in East Africa?	3	478
40	How might we create financial services that support the dreams and obligations of those 50 and older?	3	128
41	How might we better prepare all learners for the needs of tomorrow by reimagining higher education?	2	285
42	How might we enable older adults to live their best possible life by preventing falls?	3	201
43	How might we apply new technologies to make agriculture and water systems more resilient in the face of climate threats?	3	100
44	How might we address urgent global challenges at the intersections of peace, prosperity, and planet in radically new ways?	1	649
45	How might we reduce stigma and increase opportunities for people with disabilities?	2	472
46	How might we get products to people without generating plastic waste?	1	612
47	How might we reimagine the new life experience by addressing the diverse challenges of all mothers, babies, and those who care for them?	2	235

Task Structure Definition Ratings (TSDR): 1- Ill-defined challenge task; 2- Moderately well-defined challenge task; 3- Well-defined challenge task.

APPENDIX 2.3: DIMENSIONS OF IDEA CREATIVITY

Several dimensions have been proposed for creativity. A creative idea is one that is novel/original/unusual and useful/feasible (Amabile 1996; Diehl and Strobe 1987). There have been several other attempts to characterize dimensions of idea quality such as:

1. Fluency, flexibility, originality, elaboration (Torrance 1965)
2. unusualness, appropriateness, transformation, condensation (Jackson and Messick 1965)
3. novelty, utility, elaboration (Amabile 1983; 1996; 1997)
4. originality, feasibility (Diehl & Stroebe 1987; 1991)
5. novelty, workability, relevance, specificity (Dean et al 2006)
6. novelty, breadth, depth, thought provoking, interactivity (Toubia MkS 2006)
7. novelty, feasibility, specificity, demand, overall value (Girotra et al 2010)
8. novelty, value, feasibility, elaboration (Riedl et al 2010)

Some of the common dimensions: novelty, feasibility, utility, specificity/elaboration, relevance/appropriateness

APPENDIX 2.4: DESCRIPTIVE ANALYISIS

Table A2.4.1: Summary of Data

	All	Lone Ideator	Serial Ideators (All Ideas)	Serial Ideator (1st Idea)
Ideators (N)	7840 (100%)	6117 (78.02%)	1723 (21.98%)	1723 (21.98%)
Ideas (N)	12079 (100%)	6117 (50.64%)	5962 (49.36%)	1723 (14.26%)
Ideas (Mean)	1.54	1.00	3.46	1.00
Likes (Mean)	6.239	5.81	6.679	6.429
Comm. (Mean)	7.648	7.057	8.255	6.87
ρ(Likes, Comm.)	0.634	0.577	0.6982	0.641
Shortlist (N)	1583	855	728	178
Shortlist (%)	13.1%	13.98%	12.21%	10.33%
Shortlist per Ideator	20.19%	13.98%	42.25%	10.33%
Winner (N)	383	167	216	54
Winner (%)	3.17%	2.73%	3.62%	3.13%

Figure A2.4.1: Boxplot of Standardized Local and Global Novelty

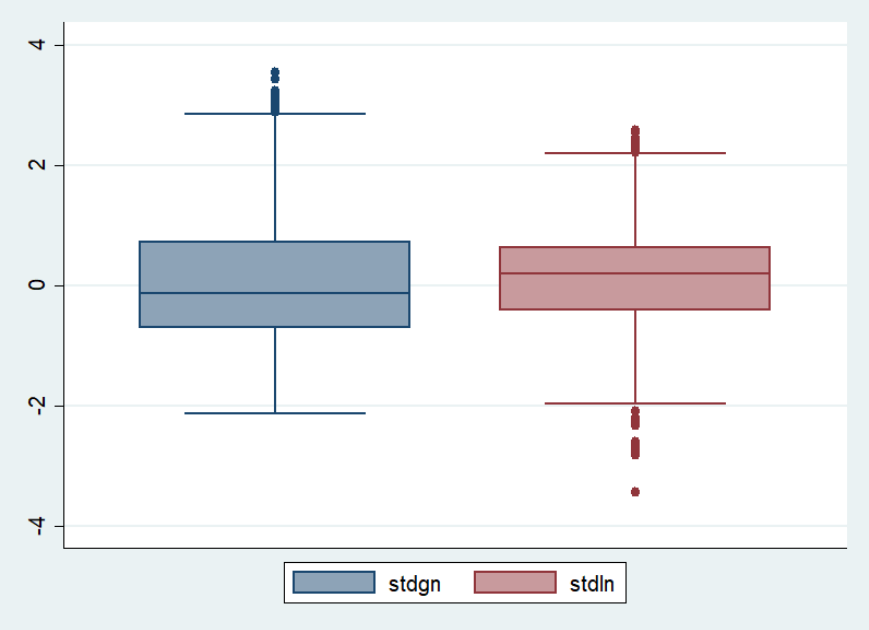


Figure A2.4.2: Kernel regression of local novelty (stdln) and global novelty (stdgn).

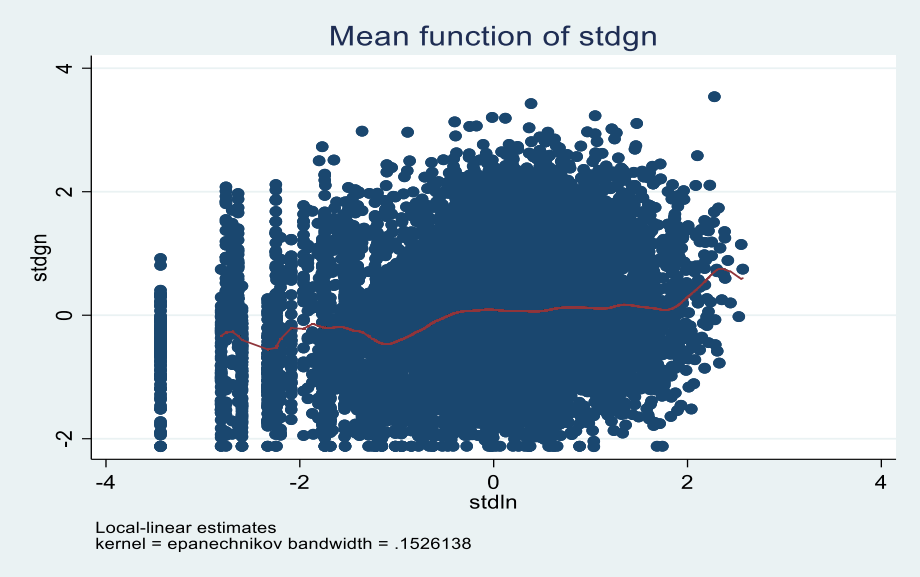


Figure A2.3.3: Kernel regression of likes and shortlist.

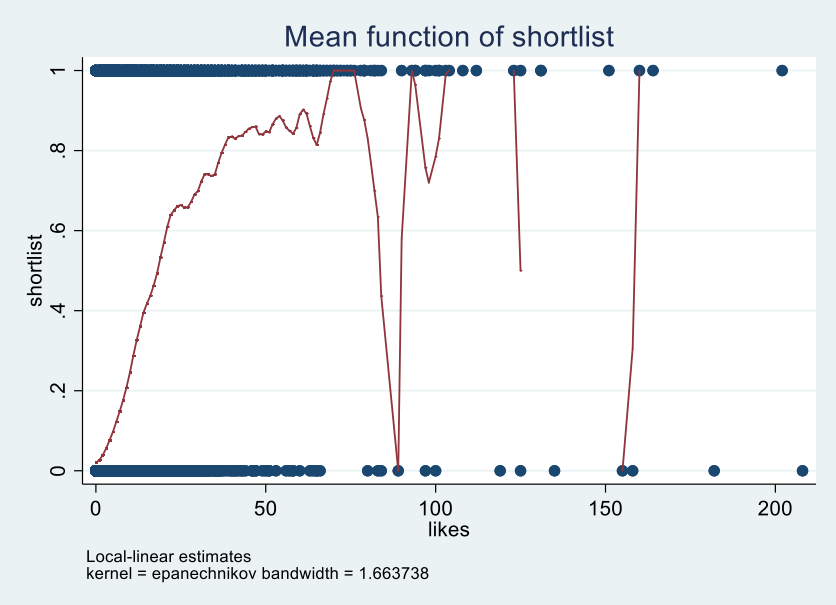


Figure A2.4.4: Kernel regression of standardized local novelty (stdln) and shortlist.

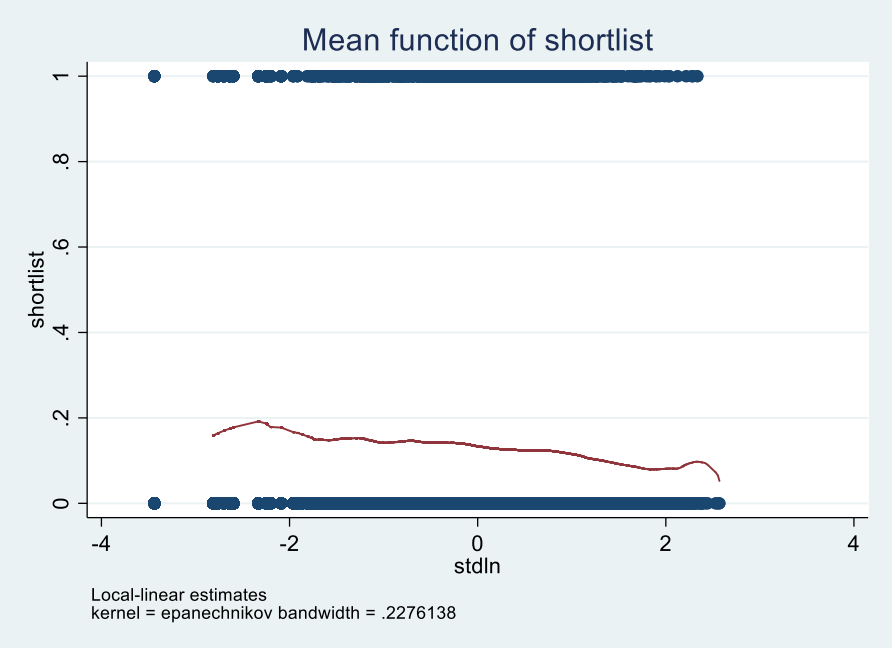


Figure A2.4.5: Kernel regression of standardized global novelty (stdgn) and shortlist.

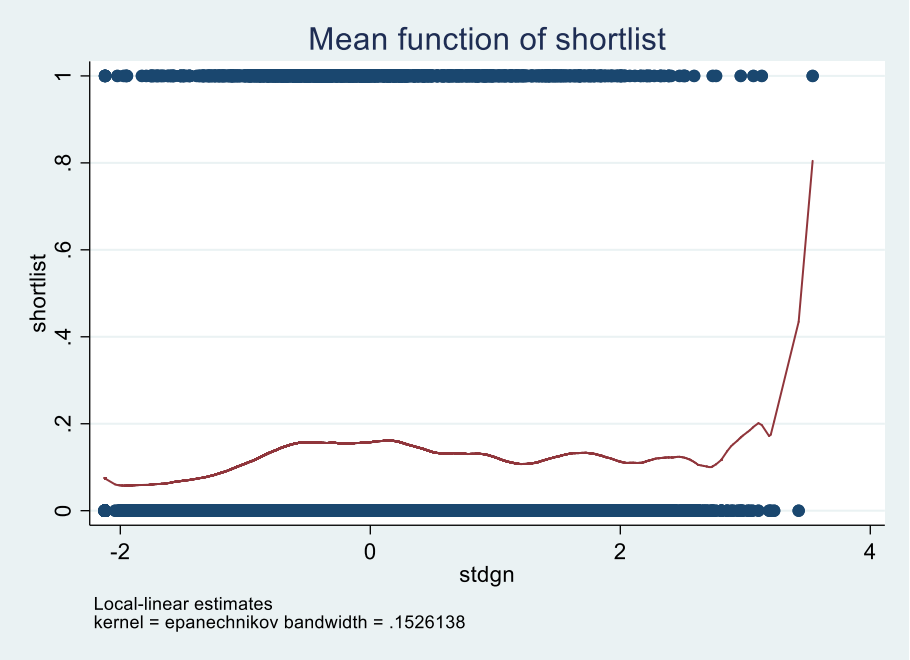


Figure A2.4.6: Kernel regression of stdln and likes.

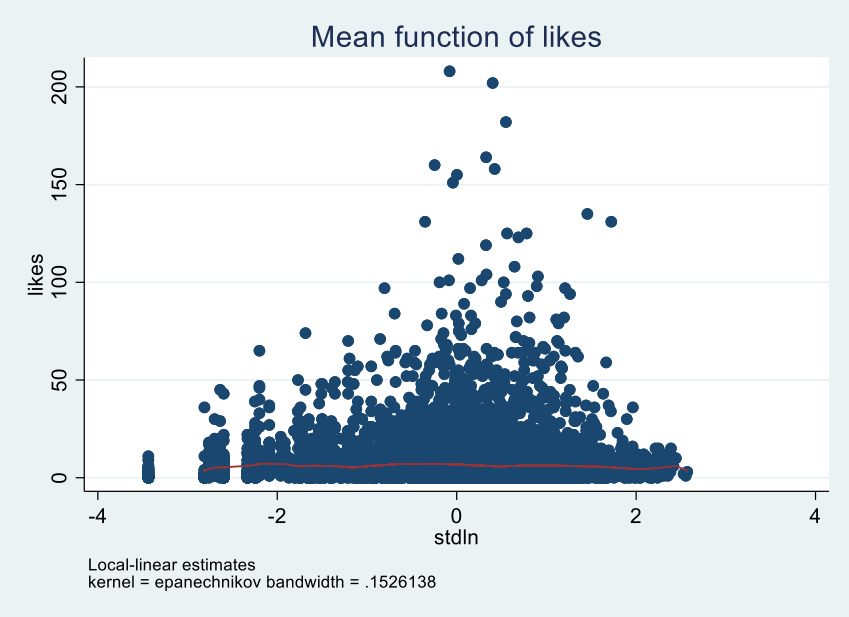


Figure A2.4.7: Kernel regression of stdln and likes.

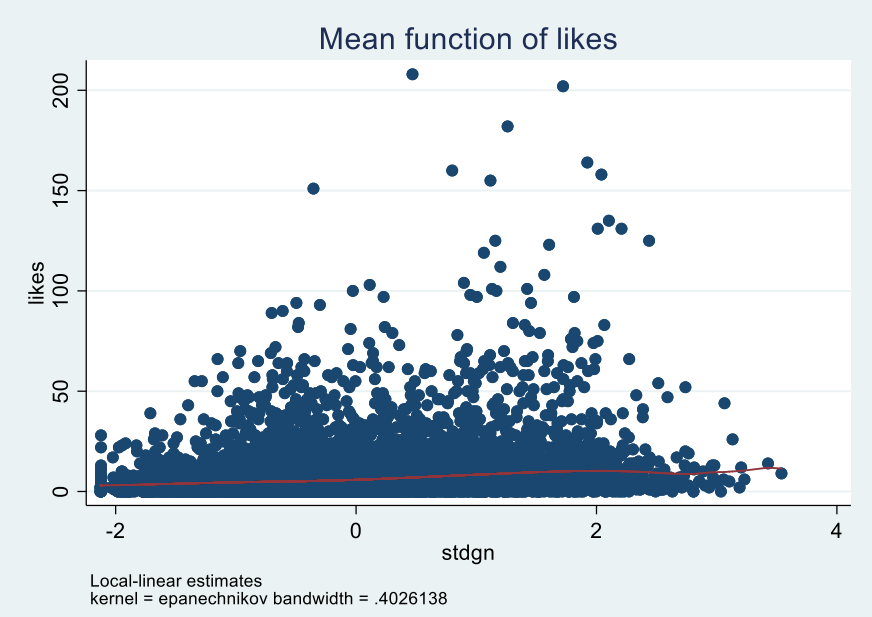


Figure A2.4.8: Histogram of Likes (across all challenges)

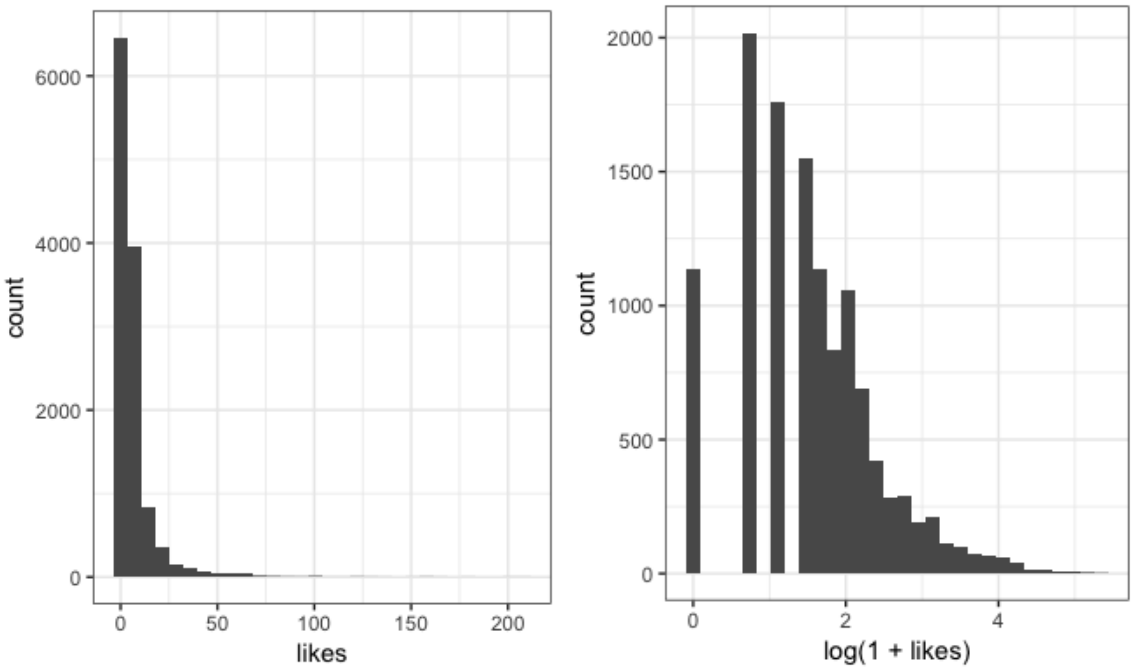


Figure A2.4.9: Histogram of GN and LN (across all challenges)

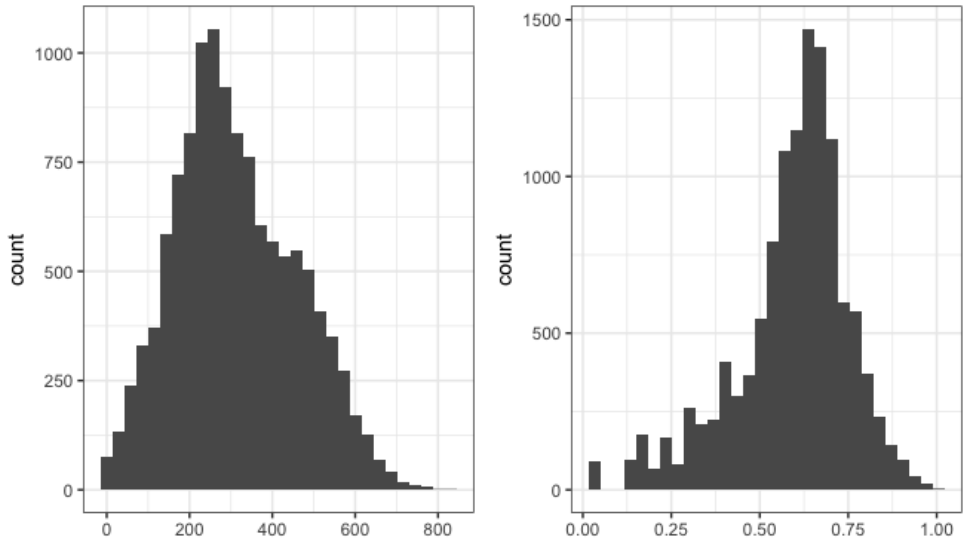
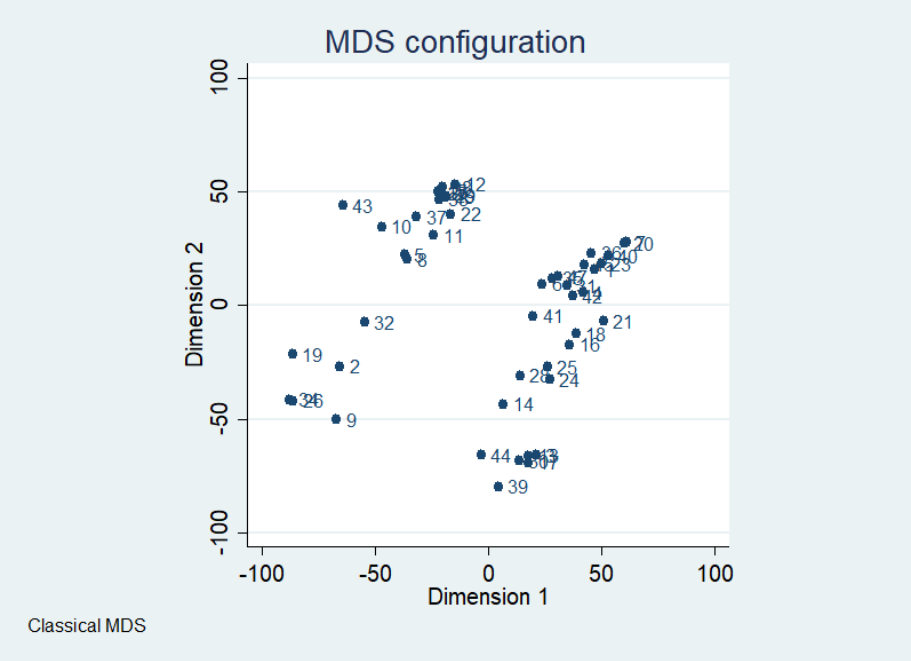


Figure A2.4.10: MDS map of challenge tasks based on textual content



APPENDIX 2.5: DOMAINS AND DIMENSIONS OF NOVELTY

Figure A2.5.1: Local and Global Domains of Novelty

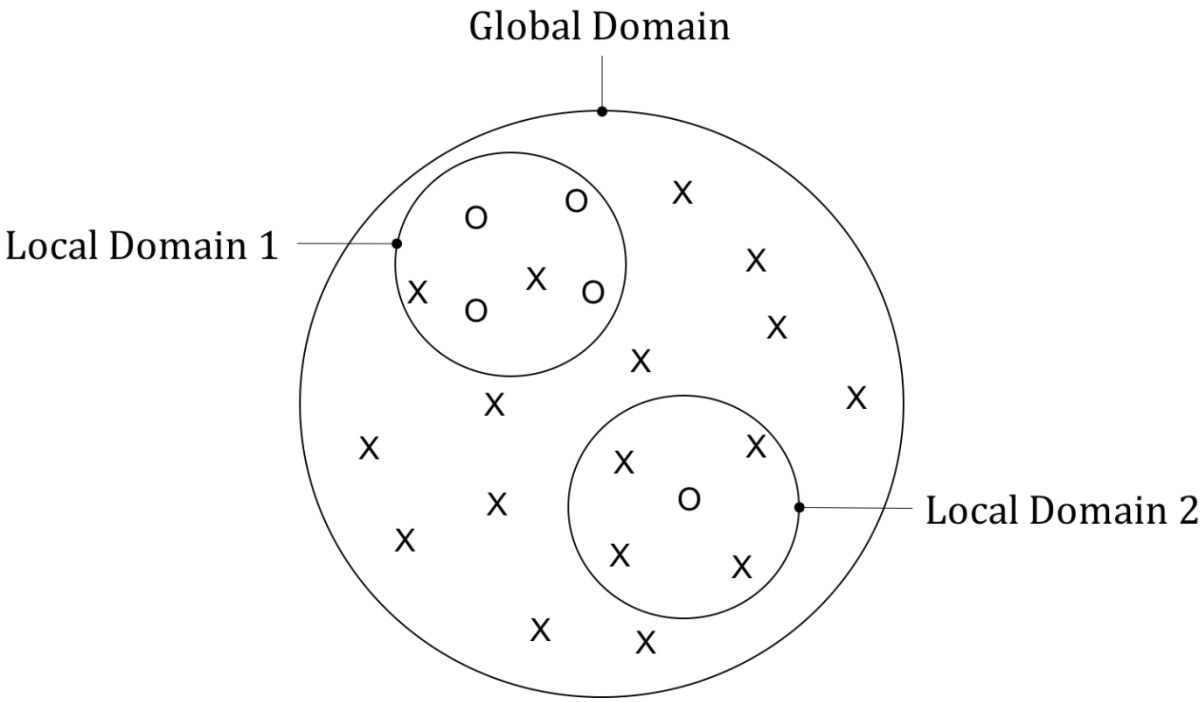


Figure A2.5.2: Comparison of Ideas on Novelty Dimensions

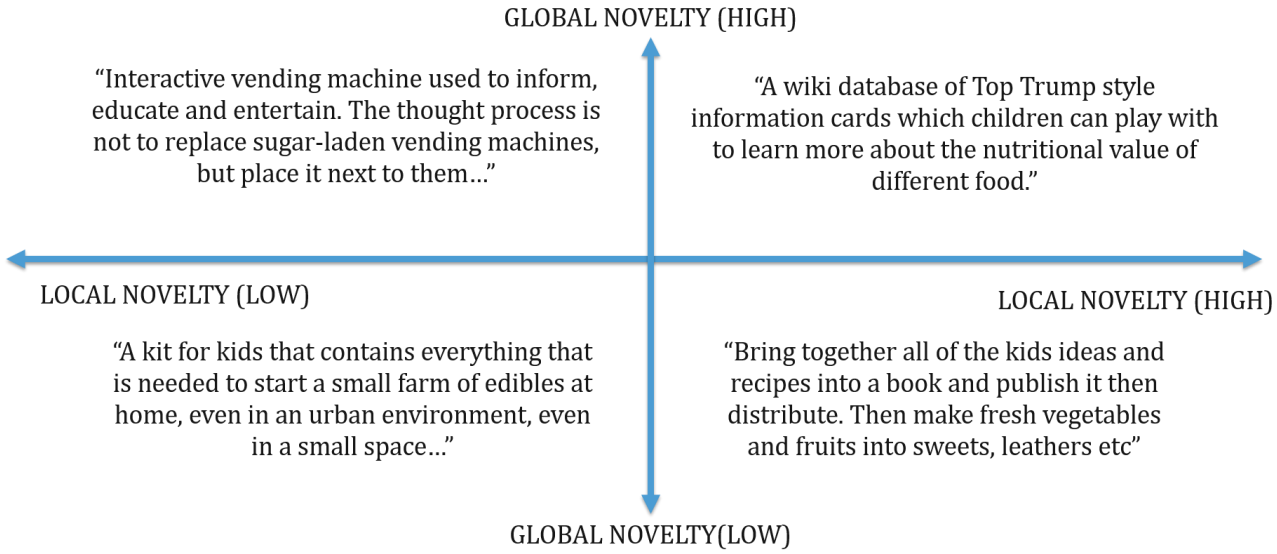


Figure A2.5.2: Shortlisted and Non-Shortlisted Ideas on Novelty Dimensions (All challenges)

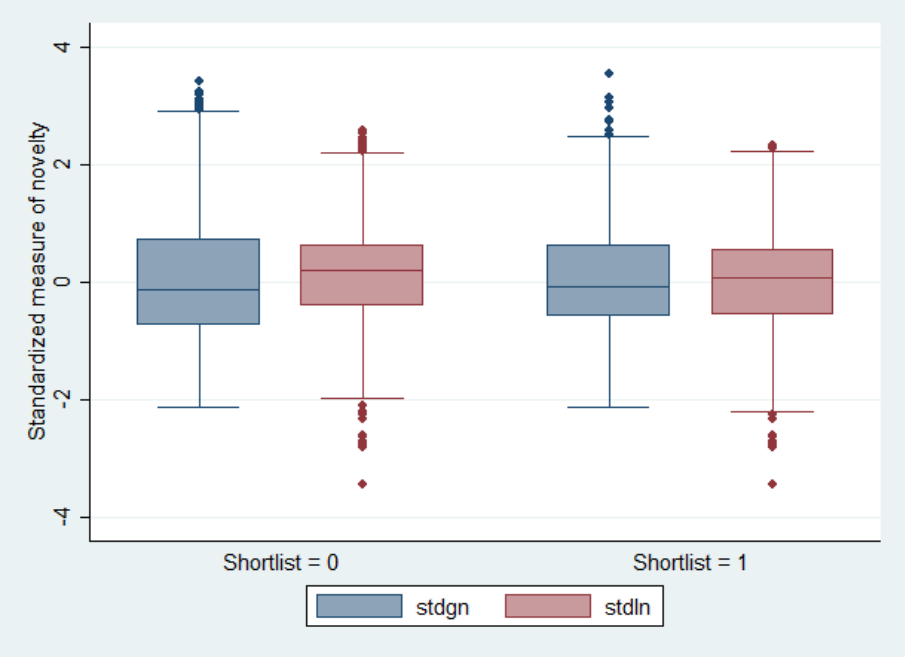
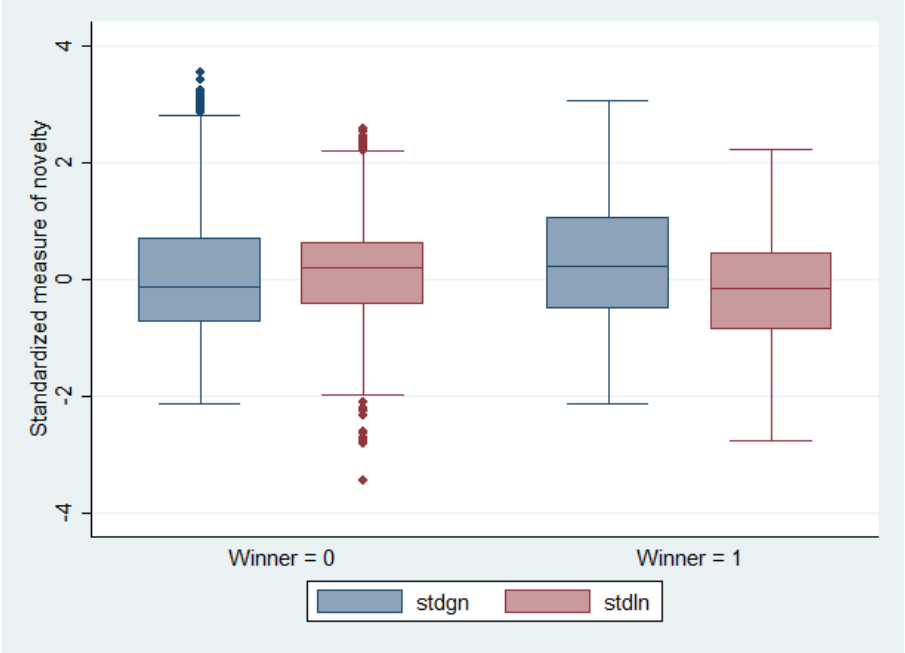


Figure A2.5.2: Winning and Non-Winning Ideas on Novelty Dimensions (All challenges)



APPENDIX 2.6: ROBUSTNESS ANALYSIS

Table A2.6.1: Role of Task Structure Specificity

	Shortlist	Likes	Winner
Local Novelty (LN)	.0070423 (.0085645)	-.5949613 (.3215236)	.0064283 (.0047964)
LN^2	.0003951 (.0034264)	-.2761172* (.1286313)	.0016121 (.001922)
Global Novelty (GN)	.0421142*** (.0062691)	.2719934 (.2360264)	.0023557 (.0034873)
GN^2	-.0083772** (.0028513)	.0722252 (.1071707)	.000534 (.0015957)
LN × GN	.0059159 (.004247)	-.1947245 (.1594867)	-.0028378 (.0023789)
Likes	.014649*** (.0002415)	-	.0077025*** (.0001343)
Order of Entry (OE)	.0007768*** (.0000249)	.0087238*** (.0009393)	.0001057 (.0000137)
LN × OE	-.0000175 (.0000368)	.0041042** (.0013829)	-.000018 (.0000206)
GN × OE	-.0001877*** (.0000245)	.0033953*** (.0009231)	-.0000262 (.0000136)
TS-H × LN	.0171141 (.0123332)	2.18963*** (.4632252)	.0042993 (.0068915)
TS-H × LN^2	.0029546 (.0050501)	.4311179* (.1895782)	.0008524 (.0028335)
TS-H × GN	-.0062286 (.0095774)	.9517003** (.3601665)	.0028247 (.00534)
TS-H × GN^2	-.0015312 (.0044562)	-.2033344 (.167298)	-.0001271 (.0024984)
TS-H × LN × OE	-.0001584** (.0000506)	-.0120136*** (.0019054)	-.0000461 (.0000281)
TS-H × GN × OE	.0000791* (.0000384)	-.005728 (.001444)	1.08e-06 (.0000214)
Intercept	-.0640848** (.0221458)	13.25547*** (.8340348)	-.029445* (.0121173)
Observations	12,079	12,079	12,079

TS: Task Structure Definition Specificity; Mixed Effects ML Regression
*** $p < .001$, ** $p < .01$, * $p < .05$.

Table A2.6.2: Models Controlling for Word Count

	Shortlist	Shortlist	Shortlist	Shortlist
Local Novelty (LN)	.0003488 (.0043278)	.0031399 (.0049658)	.0041908 (.004279)	--
LN^2	-.0006891 (.0023213)	-.0027864 (.0026628)	-.0021078 (.0022721)	--
Global Novelty (GN)	.0213616*** (.0046805)	.0398279*** (.005335)	--	.0220166 (.0046225)
GN^2	-.0108572*** (.0022988)	-.0124005*** (.0026329)	--	-.0116258 (.0022169)
LN × GN	-.0035716 (.0030176)	-.0023848 (.0034626)	--	--
Likes	.0147363 (.0002429)	--	.0147932 (.0002428)	.0147367 (.0002428)
Word Count (WC)	-.0013289** (.0004607)	-.0021255 (.0005254)	.0002828 (.0003277)	-.0013537** (.0004602)
Order of Entry (OE)	.0007428 (.0000219)	.0008565 (.0000246)	.0007499 (.0000219)	.0007424 (.0000219)
Intercept	-.0096939 (.0267086)	.2113972 (.0297375)	-.0691359** (.0246366)	-.0085712 (.0266473)
Observations	12,079	12,079	12,079	12,079

Note: Random Effects GLS Regression
*** $p < .001$, ** $p < .01$, * $p < .05$.

Figure A2.6.1: Local Novelty and Word Count

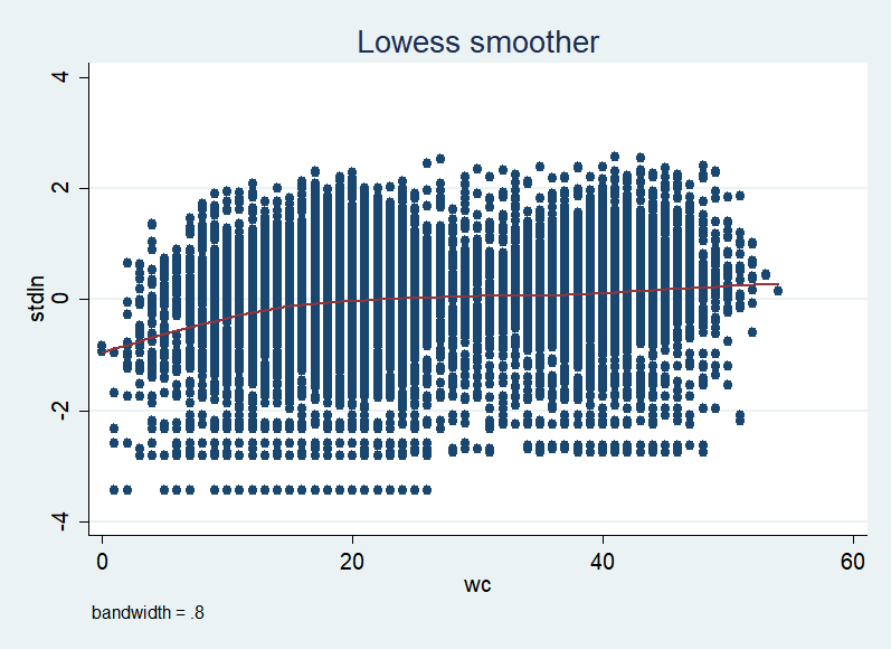
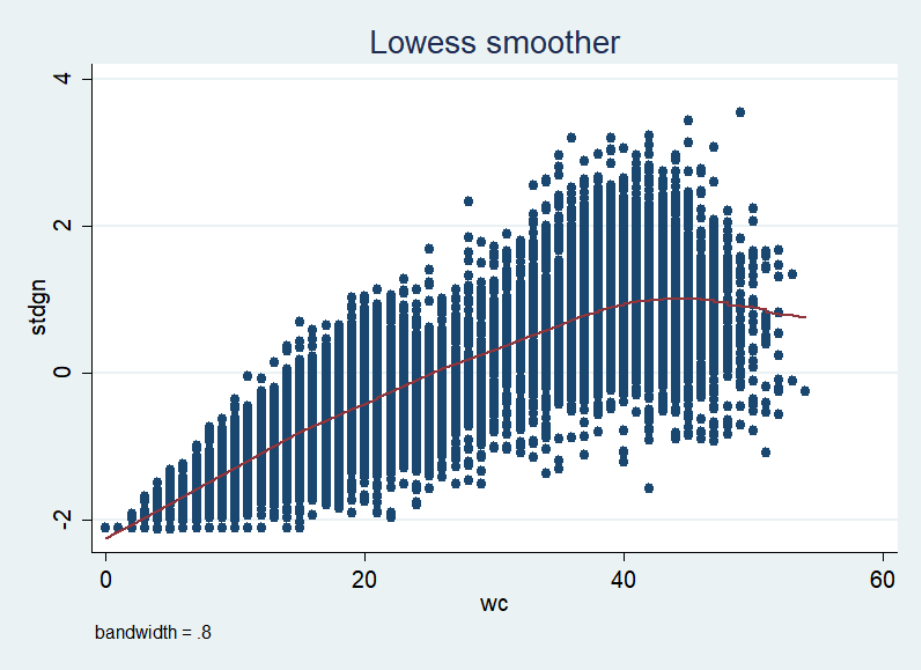


Figure A2.6.2: Global Novelty and Word Count



APPENDIX 2.7: MARGINS ANALYSIS

Figure A2.7.1: Linear Prediction of Likes (Local Novelty)

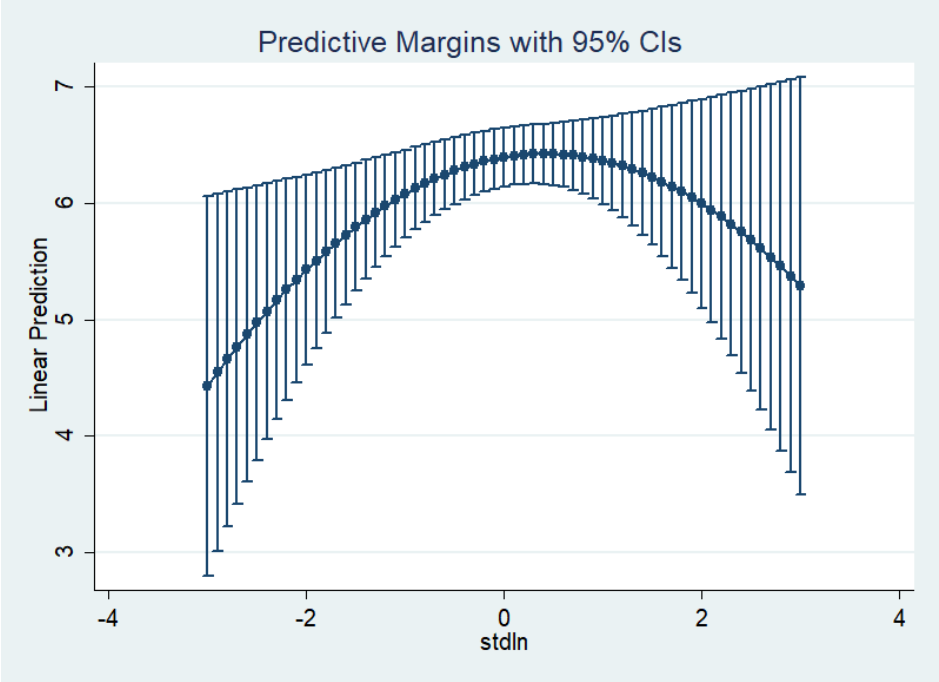


Figure A2.7.2: Linear Prediction of Likes (Global Novelty)

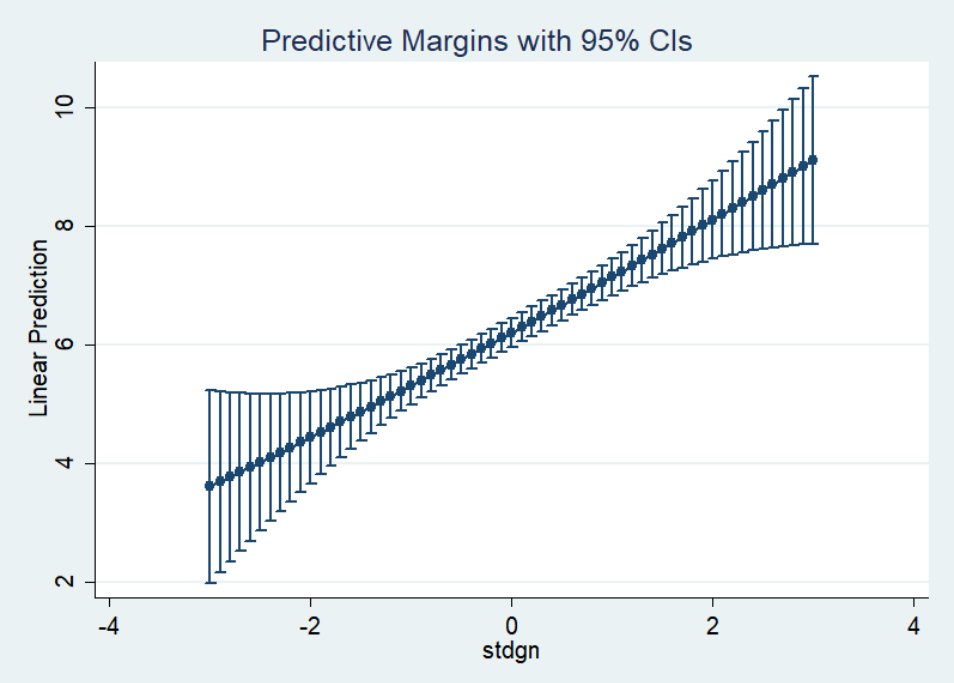


Figure A2.7.3: Linear Prediction of Shortlisting (Local Novelty)

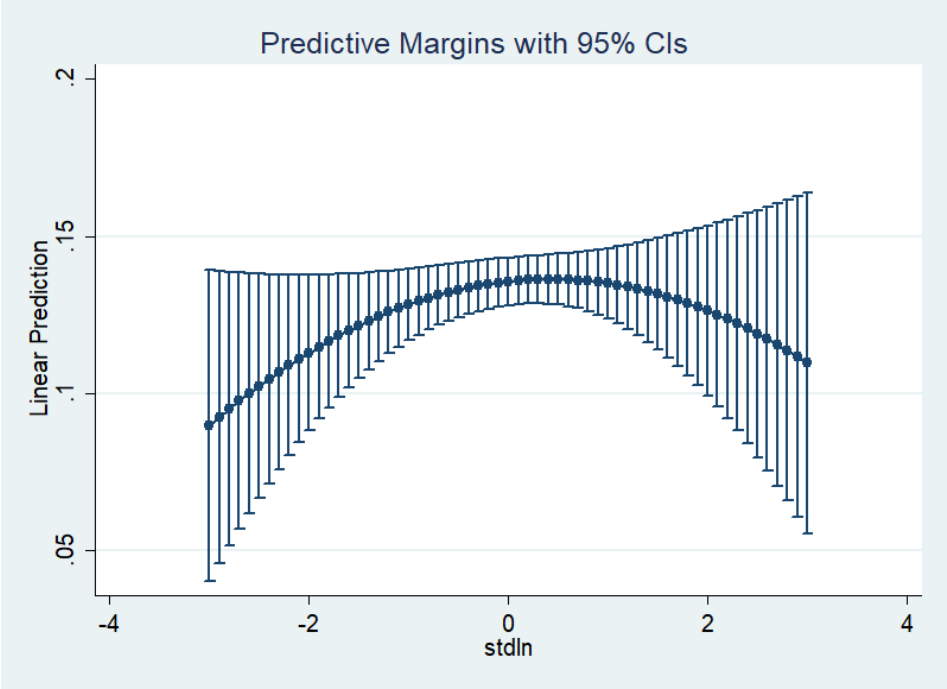


Figure A2.7.4: Linear Prediction of Shortlisting (Global Novelty)

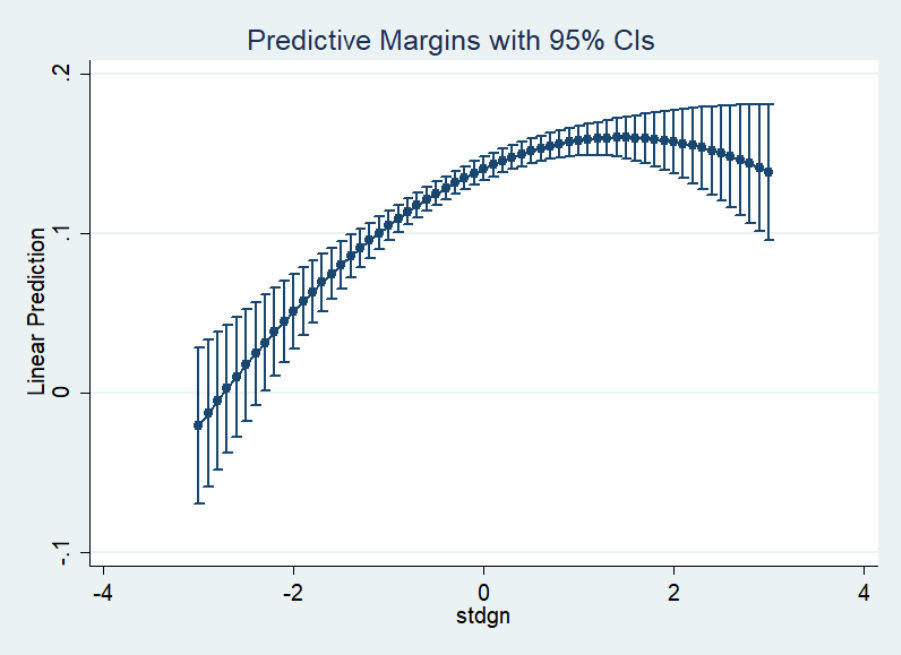


Figure A2.7.5: Linear Prediction of Winner (Local Novelty)

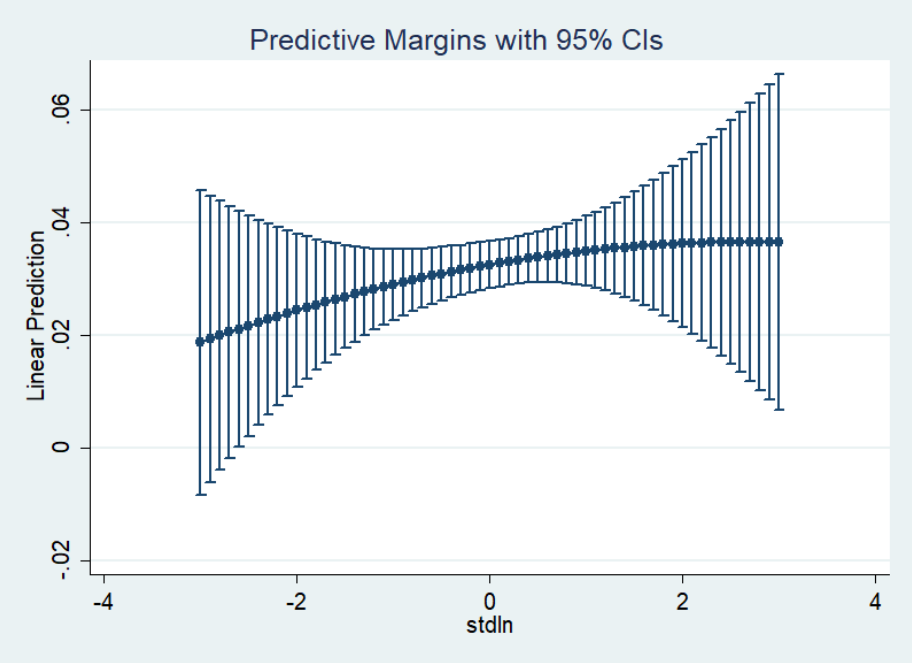


Figure A2.7.6: Linear Prediction of Winner (Global Novelty)

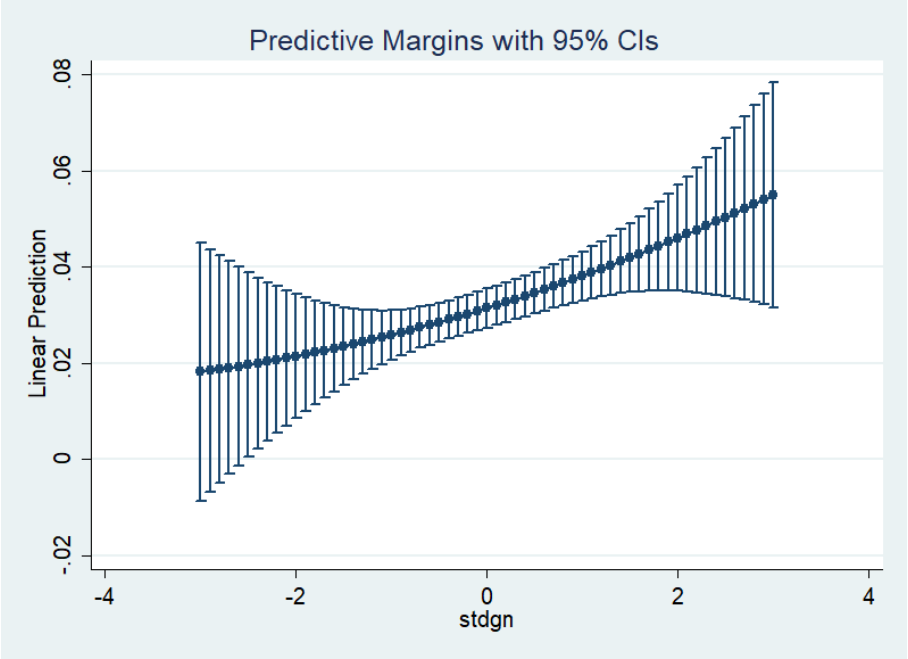


Table A2.7.7: Average Marginal Effects of Global Novelty on Linear Prediction of Shortlisting

	dy/dx	Std. Error	z	P>|z|	95% Confidence Interval	
TS = 1	.0217388	.0051382	4.23	.000	.0116681	.0318094
TS = 2	.0267578	.005434	4.92	.000	.0161073	.0374083

Figure A2.7.8: Average Marginal Effects of Global Novelty

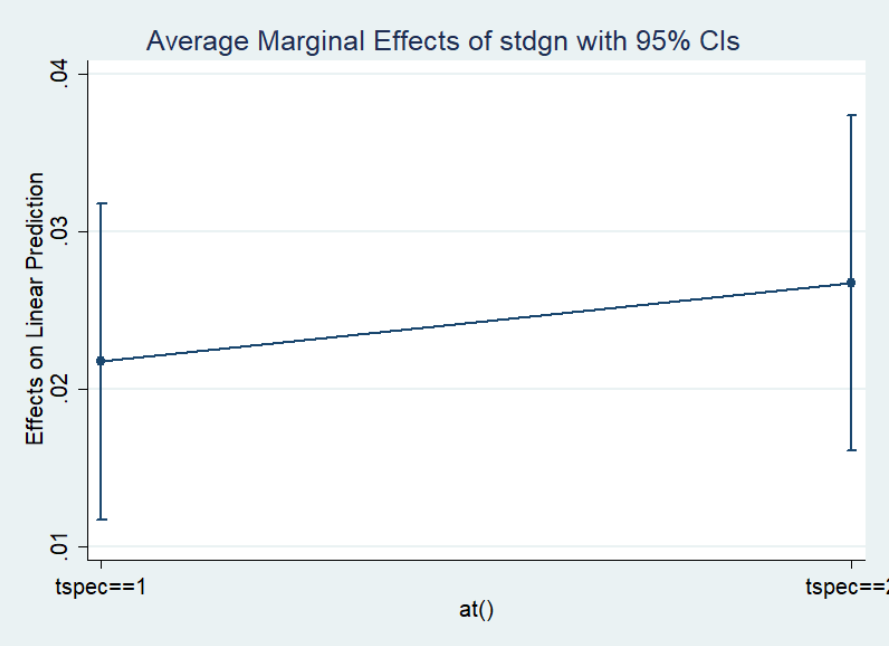
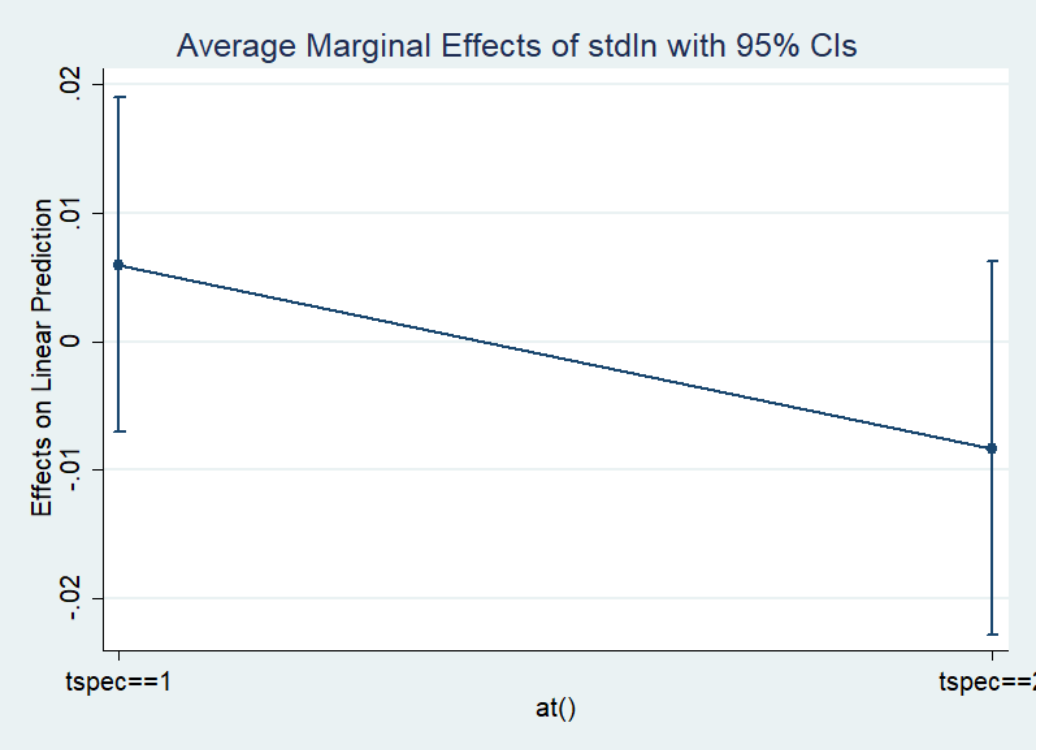


Table A2.7.9: Average Marginal Effects of Local Novelty on Linear Prediction of Shortlisting

	dy/dx	Std. Error	z	P>|z|	95% Confidence Interval	
TS = 1	.005979	.0066413	0.90	0.368	-.0070377	.0189957
TS = 2	-.0082875	.0073991	-1.12	0.263	-.0227896	.0062145

Figure A2.7.10: Average Marginal Effects of Local Novelty



APPENDIX 2.8: PREDICTORS OF IDEA SELECTION

Figure A2.8.1: ROC for Logistic Model for Shortlisting (without Order of Entry)

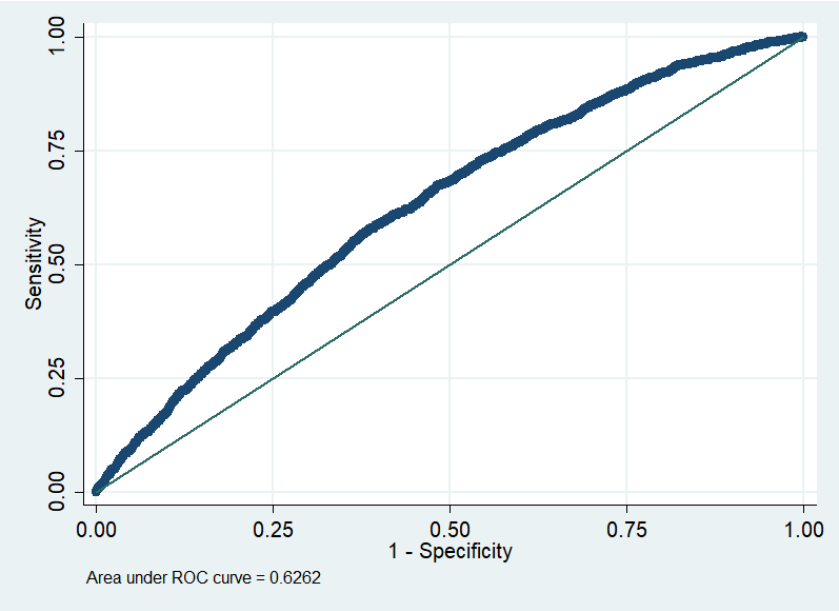


Figure A2.8.2: ROC for Logistic Model for Shortlisting (with Order of Entry)

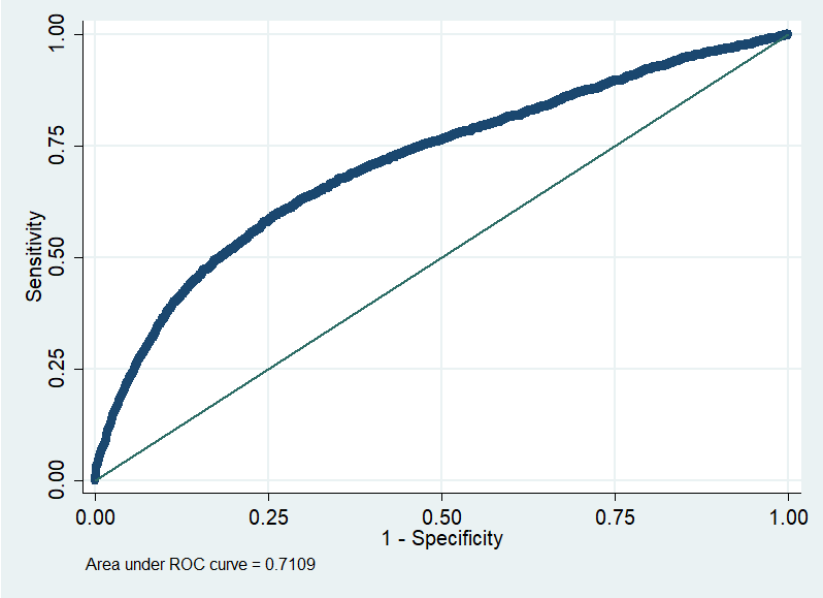


Table A2.8.1: Lasso Predictors of Ideator Selection (Likes)

Knot	ID	Lambda	s	L1-Norm	EBIC	R-sq.	Entered/removed
1	1	4.54E+04	1	0	57705.39	0	Added _cons.
2	2	4.14E+04	2	0.1672	57654.82	0.0051	Added stdgn.
3	3	3.77E+04	3	0.28931	57611.75	0.0095	Added v119.
4	7	2.60E+04	4	0.60003	57461.67	0.0226	Added v62.
5	8	2.37E+04	6	0.67681	57444.36	0.0257	Added v31 v48.
6	9	2.16E+04	7	0.759	57409.05	0.0294	Added v26.
7	11	1.79E+04	8	0.92079	57343.95	0.0355	Added v57.
8	12	1.63E+04	9	1.01302	57320.28	0.0382	Added v25.
9	13	1.49E+04	10	1.14255	57296.87	0.0409	Added tsmain.
10	14	1.36E+04	11	1.29151	57276.21	0.0434	Added v80.
11	16	1.13E+04	13	1.56914	57245.24	0.0475	Added v58 v68.
12	17	1.03E+04	14	1.73959	57226.89	0.0498	Added v107.
13	18	9345.069	16	1.99797	57221.5	0.0519	Added v200 v890.
14	19	8514.879	21	2.37015	57243.34	0.0544	Added v44 v85 v86 v88 v207.
15	20	7758.44	22	2.89829	57214.98	0.0574	Added v87.
16	**21**	**7069.202**	**23**	**3.35945**	**57193.02**	**0.06**	**Added v121 v189. Removed v80.**

Note: lambda = 6441.19, based on EBIC

Table: Lasso Post-Estimation OLS

Predictor	Lasso	Post-est OLS	Predictor description
stdgn	1.0176136	1.095339	Standardized global novelty
tsmain	-0.7860677	-1.6522085	Task-structure definition
v25	-0.0026174	0.0033087	Analytic (Contest); LIWC
v26	0.0754889	0.1070659	Clout (Contest); LIWC
v31	0.0290654	0.0180441	Dic (Contest); LIWC
v44	0.0951935	0.3314514	Adverb (Contest); LIWC
v48	0.0362021	0.0441349	Adj (Contest); LIWC
v57	-0.1142507	-0.0967048	Anger(Contest); LIWC
v58	0.1552004	0.3591812	Sad(Contest); LIWC
v62	0.0659151	-0.0189265	Female(Contest); LIWC
v68	-0.1397684	-0.2833882	Tentat(Contest); LIWC
v85	0.1112336	0.3624185	Risk(Constest); LIWC
v86	-0.2525325	-0.8323976	Focuspast (Contest); LIWC
v87	0.0113073	0.0559447	Focuspresent(Contest); LIWC
v88	-0.0176196	-0.0718194	Focusfuture(Contest); LIWC
v107	-0.0818972	-0.2008829	Comma(Contest); LIWC
v119	0.0192864	0.0006826	Word Count(Idea); LIWC
v121	0.0010582	0.0096909	Clout(Idea); LIWC
v189	0.0124001	0.0759379	Leisure(Idea); LIWC
v200	0.0072215	0.0203809	AllPunc(Idea); LIWC
v207	0.0270806	0.1025051	Dash(Idea); LIWC
v890	0.68419	1.9813673	Source Similarity LSA; TAACO

Table: Lasso Predictors of Ideator Selection (Likes)

Knot	Lambda	L1-Norm	EBIC	R-sq	Predictor Added	Predictor Removed
1	895.74493	0.00000	-2.6233e+04	0.0000	constant	
2	816.16942	0.00029	-2.6247e+04	0.0020	iv9	
3	562.55392	0.00160	-2.6306e+04	0.0078	cv65	
4	512.57818	0.00297	-2.6319e+04	0.0106	cv22 iv41	
5	467.04215	0.00477	-2.6321e+04	0.0133	cv3 cv34 iv20	
6	425.55141	0.00748	-2.6323e+04	0.0160	stdgn-sq cv64 iv89.	
7	387.74660	0.01203	-2.6335e+04	0.0196	cv14 iv7 iv8	
8	321.91404	0.02051	-2.6365e+04	0.0246	stdgn*stdln cv21 cv30	
9	293.31608	0.02525	-2.6355e+04	0.0271	cv19 cv67 iv6 iv29	
10	267.25869	0.03011	-2.6361e+04	0.0293	stdgn cv16 cv93	cv30
11	243.51616	0.03733	-2.6370e+04	0.0325	cv53 iv3 iv45	
12	221.88286	0.04448	-2.6380e+04	0.0350	iv12 iv49	
13	202.17140	0.05220	-2.6370e+04	0.0384	stdln cv8 cv32 iv5 iv46	
14	184.21105	0.06052	-2.6382e+04	0.0411	cv37 cv84	
15	167.84625	0.06827	-2.6389e+04	0.0433	iv73 iv92	
16	152.93525	0.07592	-2.6383e+04	0.0453	cv46 iv18 iv80	
17	139.34890	0.08592	-2.6376e+04	0.0473	cv51 cv54 iv60	
18	126.96953	0.09737	-2.6320e+04	0.0494	cv7 cv39 iv54 iv66 iv67 iv77 iv84 iv86	
19	115.68991	0.11299	-2.6305e+04	0.0516	cv28 cv63 iv34 iv50 iv74	cv46
20	105.41233	0.12837	-2.6329e+04	0.0534	iv38	cv37
21	96.04779	0.14364	-2.6309e+04	0.0552	cv17 cv20 cv62 cv72	
22	87.51517	0.15853	-2.6297e+04	0.0567	cv73 iv39 iv70	
23	79.74057	0.17504	-2.6254e+04	0.0583	cv36 cv37 cv46 cv48 iv28 iv53	
24	72.65663	0.19152	-2.6262e+04	0.0597	cv59 iv22 iv26 iv27	cv32 cv64 cv73
25	66.20202	0.20516	-2.6245e+04	0.0609	iv14 iv40 iv51	

Table: List of Content Predictors for Shortlisting

stdln: local novelty	v18: article	v37: family	v56: ingest	v75: death
stdgn: global novelty	v19: prep	v38: friend	v57: drives	v76: informal
v1: WC	**v20: auxverb**	v39: female	v58: affiliation	v77: swear
v2: Analytic	v21: adverb	v40: male	v59: achieve	v78: netspeak
v3: Clout	v22: conj	v41: cogproc	v60: power	v79: assent
v4: Authentic	v23: negate	v42: insight	v61: reward	V80: nonflu
v5: Tone	v24: verb	v43: cause	v62: risk	v81: filler
v6: WPS	v25: adj	v44: discrep	v63: focuspast	v82: Allpunc
v7: Sixltr	v26: compare	**v45: tentat**	v64: focuspresent	v83: Period
v8: Dic	v27: interrog	v46: certain	v65: focusfuture	v84: Comma
v9: function	v28: number	v47: differ	v66: relative	v85: Colon
v10: pronoun	**v29: quant**	v48: percept	v67: motion	v86: SemiC
v11: ppron	v30: affect	**v49: see**	v68: space	v87: QMark
v12: i	v31: posemo	v50: hear	v69: time	v88: Exclam
v13: we	v32: negemo	v51: feel	v70: work	**v89: Dash**
v14: you	v33: anx	v52: bio	v71: leisure	V90: Quote
v15: shehe	v34: anger	v53: body	v72: home	v91: Apostro
v16: they	v35: sad	v54: health	v73: money	v92: Parenth
v17: ipron	v36: social	v55: sexual	v74: relig	v93: OtherP