Journal of the Association for Information Systems

Volume 23 | Issue 5 Article 7

2022

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Recommended Citation
Gal, Uri; Berente, Nicholas; and Chasin, Friedrich (2022) "Technology Lifecycles and Digital Technologies: Patterns of Discourse across Levels of Materiality," *Journal of the Association for Information Systems*, 23(5), 1102-1149.
DOI: 10.17705/1jais.00761
Available at: https://aisel.aisnet.org/jais/vol23/iss5/7

Journal of the Association for Information Systems (2022) **23**(5), 1102-1149
doi: 10.17705/1jais.00761

RESEARCH ARTICLE

ISSN 1536-9323

Technology Lifecycles and Digital Technologies: Patterns of Discourse across Levels of Materiality

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Abstract

The technology lifecycle model is extensively used to study technology evolution and innovation. However, this model was developed for industrial-age material technologies and does not address digital technologies with nonmaterial elements. Therefore, a question emerges as to whether the level of technological materiality is implicated in different dynamics of innovation, as reflected in the technology lifecycle. Digital technologies evolve through discourse that involves interactions among multiple stakeholders that shape the evolutionary trajectory of the technology. Therefore, we set out to examine whether discourse about digital technologies that vary in their level of materiality manifests in different ways throughout these technologies' lifecycles. To do so, we conducted a study comparing the discourse around 10 digital technologies—five highly material and five highly nonmaterial—at different stages of their technology lifecycles. We identified three characteristics of discourse—volume, volatility, and diversity—and examined them for the 10 digital technologies by analyzing their corresponding Wikipedia articles. Our findings show that the discourse around technologies with different levels of materiality is similar in the initial era of the lifecycle but diverges in the two subsequent eras. In addition, we found that the discourse around highly nonmaterial technologies remains elevated for longer time periods, compared to highly material technologies. Based on these results, we put forth propositions that challenge and extend existing research on the relationships between the technological level of materiality, discourse, and trajectories of technology evolution.

Keywords: Technology Lifecycle, Digital Technologies, Technological Level of Materiality, Discourse, Wikipedia.

Ulrike Schultze was the accepting senior editor. This research article was submitted on May 28, 2020 and underwent three revisions.

1 Introduction

To succeed in the digital age, organizations must develop, apply, and continuously navigate new digital technologies. Organizational leaders make sense of new and emerging digital technologies and decide where to build capabilities and dedicate resources to innovating with technologies. In other words, organizations must be able to estimate the likely fate of the digital innovations that they encounter. The technology lifecycle model (Tushman & Anderson, 1990; Tushman & Rosenkopf, 1992) is frequently used to think about technology evolution so that organizational leaders can fruitfully innovate with new technologies. The model posits that technologies evolve in a process of punctuated equilibrium whereby an era of incremental change is disrupted by technological discontinuity. This discontinuity can lead to a period of intense research and development activity, known as the era of ferment, where multiple

designs compete for dominance. The selection of a dominant design for the technology signals the start of another era of incremental change. Drawing on this model and on its practitioner-oriented offshoots, such as Gartner's hype cycle model, organizational leaders can understand strategically when to dedicate resources to a particular technology. For example, if they wish to be market leaders and the technology is critical to their strategic goals, they may decide to engage with it early. If the technology is not critical but they still would like to build capabilities as digital options (Woodard et al., 2013; Sambamurthy et al., 2003), they may choose to wait until the lifecycle is stabilized.

The lifecycle model, however, was developed for industrial-age material technologies, which are different from digital technologies. Unlike fully material technologies, digital technologies are programmable (Yoo et al., 2010) symbol-manipulating systems (Kallinkos et al., 2013) that have an "abstract character" (Simon, 1996, p. 13). Digital technologies can help decouple form from function (Lee & Berente, 2012) and media from content (Yoo, 2010) to create new products and services and allow for innovative reconfigurations of existing products and services (Lyytinen et al., 2016; Kohli & Melville, 2018).

Increasing levels of digitization have made it possible to radically redesign industrial-age products across diverse domains (Lyytinen et al., 2016): from management software to production technologies to consumer products to transportation systems. However, the process of digital innovation also presents new challenges. Digital innovation is unpredictable, dynamic, and loosely structured across space and time (Nambisan et al., 2017), making it difficult to manage. Much of this ambiguity has to do with the ontological nature of digital technologies, which can accommodate both material and nonmaterial elements (Faulkner & Runde, 2019). Material elements have a physical manifestation with attributes such as shape and mass, whereas nonmaterial elements consist of organized systems of symbols, which lack these attributes (Faulkner & Runde, 2019). Different digital technologies can therefore be distinguished based on the proportions of material and nonmaterial elements that they accommodate and range from more to less material. We refer to digital technologies with a relatively high proportion of material elements as *highly material technologies* and technologies with a relatively high proportion of nonmaterial elements as *highly nonmaterial technologies*. Given that the process of digital innovation and its outcomes are intertwined with the level of materiality of the digital technology that is being considered, a critical question emerges as to whether the level of materiality of digital innovations is implicated in different dynamics of innovation, as reflected in the technology lifecycle.

One aspect of this question that is of particular interest is the role that discourse plays in the innovation process of digital technologies. Because of their inherent malleability, digital technologies evolve, in no small part, through discourse. Evolutionary trajectories of digital technologies develop in a social process that involves discursive interactions among multiple individuals, groups, and organizations (Barrett et al., 2013; Davidson et al., 2015). Through discourse, actors interpret, legitimize, and mobilize the necessary resources to embed the technology in existing structures and processes (Swanson & Ramiller, 1997; Miranda et al., 2015). This way, discourse can shape the evolutionary trajectory of the technology (Tushman & Rosenkopf, 1992; Miranda et al., 2015).

Existing research emphasizes how certain characteristics of the discourse, such as its volume, volatility, and diversity, affect technology development and diffusion (Swanson & Ramiller, 1997; Kaplan & Tripsas, 2008; Dokko et al., 2012; Nielsen et al., 2014; Davidson et al., 2015; Miranda et al., 2015). However, the relationship between discourse and technology is not unidirectional but circular—discourse can both shape the enactment of technologies and be shaped by their ontological nature (Kallinikos, 2004; Orlikowski & Robey, 1991). Specifically, the level of materiality of digital technologies can influence the characteristics of the discourse around these technologies (Weick, 1979; Weick, 1993; Iivari, 2017) and manifest in different evolutionary trajectories (Tushman & Rosenkopf, 1992) of development and diffusion (Iivari & Koskela, 1987; Hoppmann et al., 2020). Existing research on technology lifecycle models does not address how varying levels of technology materiality may manifest in systematically different evolutionary trajectories and instead treats all technologies alike. This blunt treatment of technology materiality may result in flawed models of technology evolution. This is problematic because such models are used both to understand the process of technology evolution and inform strategic decisions around technology development and investment. To account for levels of materiality in technology evolution, our study aims to answer the following question:

RQ: How does the discourse around digital technologies with varying levels of materiality manifest in lifecycle trajectories of technology evolution?

To answer the research question, we conducted a computationally intensive study (Berente et al., 2019) to compare the discourse around ten digital technologies: five highly material technologies and five highly nonmaterial technologies. We traced the discourse around these technologies across three consecutive eras of their respective technology lifecycles—incremental change, ferment, and

subsequent incremental change (Tushman & Rosenkopf, 1992)—by analyzing their corresponding Wikipedia articles. Wikipedia is an online user-generated encyclopedia that acts as a public forum in which the discourse around different phenomena evolves through the contributions of multiple editors (Pentzold 2009; Gal et al., 2018; Hansen et al., 2009). The platform allows open access to the revision history of each article, thereby enabling an analysis of the discursive process as it unfolds over time.

We found that while highly material and highly nonmaterial technologies displayed mostly similar discursive characteristics during their initial era of incremental change, these characteristics diverged during the eras of ferment and subsequent incremental change. This finding demonstrates that discursive differences across levels of technology materiality can manifest in varying evolutionary trajectories (Anderson & Tushman, 1990). In addition, we examined the discourse around technologies within each level of materiality during their lifecycle eras. This analysis revealed that the discursive volume, volatility, and diversity mostly decreased for highly material technologies as they transitioned from their first era of incremental change into their era of ferment. On the other hand, the discursive characteristics remained high and even intensified for highly nonmaterial technologies as they entered their era of ferment. Finally, we compared averaged measures of discourse characteristics for the first seven years of the 10 technologies. This analysis supported our initial findings and showed that discursive volume and volatility stabilized more quickly for highly material technologies, which displayed consistently lower levels of discursive diversity.

Our study makes a variety of contributions to research on technological evolution. We demonstrate that different levels of technology materiality can manifest in varying evolutionary trajectories and that these variations are noticeable primarily in the era of ferment and subsequent era of incremental change. This finding provides empirical support for the idea that the fate of digital innovation is, at least in part, contingent upon the level of materiality of the digital technology in question. Importantly, this insight can be used by practitioners to inform nuanced analyses and forecasts of technologies' evolutionary trajectories. Our findings further contribute to the understanding of the relationship between technology and discourse. While existing research implies that a discourse's volume, volatility, and diversity shape technological evolution (Swanson & Ramiller 1997; Klecun-Dabrowska & Cornford, 2000; Dokko et al., 2012; Miranda et al., 2015), we explicate and operationalize these three important characteristics of discourse. We demonstrate empirically that these characteristics vary depending on the level of materiality of the technologies in question.

The rest of the paper is organized as follows. Next, we introduce the technology lifecycle model and highlight the role of discourse in the lifecycle of technologies. We identify volume, volatility, and diversity as characteristics of discourse. We then present our methodology and the results of our analysis. We conclude by generating propositions, outlining the contributions of the study, and suggesting avenues for future research.

2 The Technology Lifecycle Model

The technology lifecycle model describes the process through which technologies change and stabilize over time (Anderson & Tushman, 1990). The model identifies two evolutionary eras—*ferment* and *incremental change*—that are punctuated by two events—the selection of a *dominant technological design* and a radical *technological discontinuity* (Anderson & Tushman, 1990).

The era of ferment is characterized by high levels of technological innovation and variation as well as uncertainty about the nature of the technology and what it can do. Due to the ambiguous nature of technology in the era of ferment, it is likely to garner a lot of attention from producers, potential consumers, and institutional actors as they attempt to negotiate a shared meaning for the technology (Kaplan & Tripsas, 2008). The era of ferment eventually concludes with the selection of a stable dominant technological design. This design is often adopted as a standard that is subsequently elaborated on through gradual improvements during the era of incremental change. This phase of relative stability is disrupted with the introduction of radical technological discontinuity. This discontinuity is marked by the arrival of a new technology with novel capabilities and resources, characteristically by new entrants, start-up firms, or established actors from other industries. The novelty inherent in this disruptive technology marks the beginning of a new era of ferment.

The technology lifecycle model (Anderson & Tushman, 1990) is generally consistent with the other seminal models of technology evolution, such as Rogers' research on the diffusion of innovations (Rogers, 1983), Utterback's work on the dynamics of innovation (Utterback, 1994), and Foster's S-curve model that describes the dynamics of technological change (Foster, 1986). Each of these perspectives proposes some pattern of initial development, followed by widespread and rapid development, leading to standardization, followed by the continued development of a maturing and diffusing technology (Table 1).

The technology lifecycle model, in its various incarnations, has been an influential lens used to inform both theory and practice (Geels, 2002; Dosi & Nelson, 2010; Dedehayir & Steinert, 2016). Technology lifecycle research has been instrumental in unpacking the process of technology evolution.

Table 1. Three Stages of the Technology Lifecycle

	Early development	Widespread rapid development	Mature development
Technology lifecycle model (Anderson & Tushman, 1990)	Era of incremental change	Era of ferment	Era of incremental change
Diffusion of innovations (Rogers, 1983)	Innovators	Early adopters/ majority	Late majority/laggards
Dynamics of innovation (Utterback, 1994)	Fluid	Transitional	Specific
Technology S-curve (Foster, 1986)	Pioneering: exploring, evaluating, inventing	Breakthrough	Sustaining: improving, augmenting, applying

For instance, Tripsas (2008) built on other models of technology evolution to propose factors that can bring about an era of technological turbulence. In their study of the automotive emission control industry, Lee and Berente (2013) showed that, rather than decline, innovation became more concentrated around specific product components during the era of incremental change. Other studies have focused on the relationships between technology evolution, industry dynamics, and organizational success. Cusumano et al. (1992) studied the video cassette recorder industry and demonstrated how late market entrants can strategically maneuver to overtake early technology adopters and establish a dominant market position. Similarly, Khazam and Mowery (1994) examined the rivalry between two competing microchip architectures to suggest strategies that organizations can pursue to establish their products as dominant designs. In a similar vein, Christensen et al. (1998) studied the disk drive industry to suggest that organizational success is a factor of both the establishment of a dominant technological design and of entering the market just before the start of the era of incremental change.

Lifecycle perspectives have also extensively influenced practice. The most widely known practitioner lifecycle models are Moore's (1991) chasm model and Gartner's hype cycle model (Fenn & Blosch, 2018). Whereas the chasm model builds on Rogers' diffusion of innovations model, Gartner's hype cycle model is a combination of two models—an expectations cycle that mirrors speculative, and often sensational, projections for a new technology within a broad discursive field (i.e., "hype"), and the actual development, enactment, and diffusion of the technology (Dedehayir & Steinert, 2016). Executives across the globe utilize the hype cycle and chasm models to think through technological innovation, maturation, and diffusion to help guide their investment, development, and marketing decisions (Fenn & Blosch, 2018). For example, according to the hype cycle model, the timing of investments impacts the risk-reward calculations for technology investors: Investing in early-stage innovations is risky but could produce disproportionately high returns. Accordingly, if one were to draw on Gartner's hype cycle analysis in the early part of the century, the "semantic web" was perennially evolving and never moved on to the mature phases of the lifecycle. An investment in the semantic web was therefore risky and ultimately yielded limited returns because alternatives eclipsed the need for this technology (Mika, 2017). In contrast, "3D printing", which was hyped and emerging in the early 2000s, became a mature technology in the 2010s, and early investments were more likely to pay off. Currently, "generative artificial intelligence" is evolving and has not yet matured; it is therefore still unclear whether investments in this technology will pay off.

These practitioner models reflect and support the broader discourse that reciprocally constitutes technologies as they emerge, and both shape and reflect how practitioners make sense of, develop, and use new technologies. We further examine the relationship between the technological lifecycle and discourse next.

3 Discourse and the Technology Lifecycle

Technologies are more than strictly technical objects; they can be conceptualized as social phenomena that are interpreted and instantiated through discourse (Phillips et al., 2004). By *discourse*, we mean a collection of spoken or written texts which are produced and interpreted by social actors (Fairclough, 2003). Communities make sense of situations through discourse and, in turn, discursive practices shape subsequent community action and continued discourse (Fairhurst & Putnam, 2004). Indeed, key social structures and forms such as technologies, organizations, and institutions, as well as changes in them, are constructed and enabled through discourse (Weick et al., 2005; Heracleous & Barrett, 2001; Taylor & Van Every, 2000). Because discourse is at the core of social action (Habermas, 1984; Wittgenstein, 1969) and technologies are in no small part socially constructed (Latour, 1987; Bijker, 1997), discourse plays a key role in the appropriation and understanding of technologies.

Research has shown that the discourse around a technology is consequential for the diffusion trajectory of the technology (Swanson & Ramiller, 1997). It can affect whether a technology is or is not implemented by

organizations (Pollock & Williams, 2010) and individuals (Hakkarainen, 2012), how it performs in the market (Raffaelli, 2019) and against competing technologies (Kahl & Grodal, 2016), how it is accepted by the general public (Batel & Devine-Wright, 2015), whether it gains legitimacy (Barrett et al., 2013), and how successfully it is integrated into practice (Klecun, 2016; Øvrelid & Bygstad, 2019). Discourse can produce a vision of the technology that articulates "what [the technology] is good for, how it works … and how it should be implemented." (Swanson & Ramiller, 1997, p. 459). Discursively formed visions generate a certain set of expectations about the technology, and this influences the development and use of the technology itself (Lyytinen & Damsgaard, 2011).

This notion is reflected in the technology lifecycle model (Anderson & Tushman, 1990), which emphasizes the importance of discourse in the evolution of technologies (Kaplan & Tripsas, 2008; Dokko et al., 2012). The transition between the stages in a lifecycle is driven by social, political, and technological mechanisms (Tushman & Rosenkopf, 1992). Technology does not stabilize as a dominant design in an industry merely because of its intrinsic features that make it superior to comparable technologies. People must make sense of this technology and, as they interpret the possibilities for its use, the technology itself changes to accommodate perceptions of its potential (Bijker 1997, Kaplan & Tripsas, 2008). Technological standards have as much to do with negotiation and social agreements about the technology as with the technology itself (Williams & Edge, 1996). Thus, discursive practices, such as negotiation and argumentation, are critical throughout a technology's evolution. This may be particularly true for digital technologies because, unlike fully material industrial technologies, digital technologies are ontologically hybrid phenomena. They consist of material hardware components and nonmaterial elements, such as digital data and program logic (Faulkner & Runde, 2019). Digital technologies are therefore uniquely malleable (Kallinikos et al., 2013; Yoo et al., 2010) and have an abstract character (Simon, 1996) that lends itself to multiple interpretations and local accommodations.

It is reasonable to expect that a discourse about a technology will vary during different stages of its lifecycle. The era of ferment is characterized by high levels of technological innovation and variation, as well as an uncertainty about the nature of the technology and what it can do. Due to its equivocality during this era, the technology is likely to draw significant attention from industry stakeholders as they attempt to negotiate its meaning, capability, and significance (Kaplan & Tripsas, 2008). These negotiations are likely to manifest in high levels of discursive activity. As stabilization sets in during the era of incremental change, social dynamics are conventionally thought to settle down (Anderson & Tushman, 1990). The rich discourse leading up to the emergence of a standard will level off as actors accept the standard and move on to incremental innovation. This is what Tushman and Rosenkopf (1992) imply when they indicate that social dynamics stabilize in the era of incremental change. We anticipate that this pattern will be more accurately descriptive of the lifecycle associated with highly material technologies, as compared to highly nonmaterial technologies (see Table 2).

Highly material technologies, such as gaming consoles and fitness trackers, have salient material elements, such as buttons, screens, and computer chips, as well as nonmaterial elements, such as bitstrings (Faulkner & Runde, 2019). They have a tactile interface that can be directly and physically accessed (Faulkner & Runde, 2019). They can be understood "narrowly, precisely, and concretely" (Leonardi & Barley 2008, p. 162) and physically occupy our world (Dourish, 2001). We can have unmediated contact with their functioning and perceive them with our senses in a way that allows us to directly tinker with them and examine how inputs from their environment affect their outputs to gain a holistic understanding of their nature. Moreover, highly material technologies are normally designed to have a defined range of application and accomplish a limited set of purposes. Therefore, we can expect discourse about these technologies to taper off once they have reached the era of incremental change.

On the other hand, highly nonmaterial technologies, such as software or artificial intelligence, are general processes (Leonardi & Barley, 2008) whose logic and functioning are determined by structured nonmaterial elements, such as bitstrings. These elements do not have a direct physical manifestation. Rather, they are inscribed in material bearers (Faulkner & Runde, 2019) such as integrated circuits and hard drives (Faulkner & Runde, 2019), and are only accessible through highly material technologies, such as an iPad or a self-driving car. Therefore, their structure and nature can only be indirectly approximated. Highly nonmaterial technologies are inherently flexible, open to multiple interpretations, and can inform multiple modes of action (Kallinikos et al., 2013). Compared to highly material technologies, they present users with less precise action paths and have greater interpretative flexibility (Bijker et al., 1987). Because of their general nature, highly nonmaterial technologies can lend themselves to a multitude of emergent uses and purposes (Yoo et al., 2010). We anticipate that because of the uniquely open and abstract nature of highly nonmaterial technologies, the discourse around them will not stabilize readily, as described in the lifecycle model.To further explore how discourse and technology intertwine during a technology's lifecycle, we next introduce volume, volatility, and diversity as three characteristics of discourse**.**

Table 2. Characteristics of Highly Material and Highly Nonmaterial Technologies

	Instantiation	Accessibility	Features	Functional scope
Highly material technologies	Mostly physical	Direct	Well-defined, specific	Narrow
Highly nonmaterial technologies	Mostly conceptual	Indirect	Ill-defined, general	Broad

4 Technology and Discourse Characteristics: Volume, Volatility, and Diversity

Discourse has a number of key characteristics, including the number of people contributing to a discourse and the number of contributions they make; the stability of the discourse in terms of the topics it addresses and the change of such topics; and the variety of viewpoints, perspectives, and disagreement among these perspectives (Miranda et al., 2015; 2016; Swanson & Ramiller 1997; Ramiller & Swanson 2003; Davidson et al., 2015; Barrett et al., 2013). As such, discursive events in a particular domain can be seen as having three general characteristics: volume, volatility, and diversity (Table 3).

Volume reflects the number of discursive utterances about the technology generated by actors expressing their opinions and exchanging views with others in the community, as well as the frequency with which actors contribute to the discourse (Balestra et al., 2016). The volume of the discourse is important because a certain level of critical mass is necessary for discursive communities to influence broader phenomena and maintain relevance (Jones & Rafaeli, 2000). The number of different contributors impacts the vibrancy of the discourse in a community, and influences, for example, whether the discourse around the technology is empowering and emancipatory or not (Miranda et al., 2016). Further, the volume of contributions—especially when any particular perspective constitutes a majority of comments in a discourse—influences how people interpret new technologies and the rate of this view's diffusion throughout the community (Ramiller & Swanson, 2003).

The *volatility* of the discourse manifests in the degree to which a discourse offers a clear, distinctive, and relatively unchanging narrative about the nature of the technology and its possible uses. A stabilized discourse is likely to help legitimize the technology (Kaganer et al., 2010) and lead to its widespread diffusion (Swanson & Ramiller, 1997; Miranda et al., 2015). On the other hand, a volatile discourse will likely remain opaque, undetailed, or unfocused after the introduction of a technology, thereby limiting its widespread diffusion (Swanson & Ramiller, 1997; Davison et al., 2015). Volatile dynamics are often indicative of highly *diverse* discourses, which consist of a broad range of views that compete to define the technology, its significance, and its potential uses and consequences (Davidson et al., 2015; Swanson & Ramiller 1997; Barrett et al., 2013; Miranda et al., 2015).

As noted, we aim to investigate how the characteristics of discourse vary for digital technologies across levels of materiality. In doing so, we complement previous work that characterizes how social and material phenomena are inexorably intertwined (Putnam, 2015; Dourish, 2017). On the one hand, technology is the product of subjective social and discursive action (Orlikowski & Robey, 1991), which can shape its development and diffusion paths. On the other hand, technology is an objective set of rules and resources that condition human action (Orlikowski & Robey, 1991; Kallinikos, 2004), and its ontological nature can influence the very discourse that shapes its own evolution. In this work, we acknowledge the dual nature of the discourse-technology relationship and focus on how technologies' levels of materiality can manifest in divergent discourse characteristics and evolutionary paths. To this end, we next describe the design of our study and analytical approach.

5 Methodology

We examined the discourse around five highly material and five highly nonmaterial digital technologies through a computationally intensive analysis (Berente et al., 2019) of their corresponding Wikipedia articles. Below we provide details about our context of research, sampling process, and analytical approach.

5.1 Research Context: Studying Discourse in Wikipedia

Wikipedia was created in January 2001 and is the largest nonprint encyclopedia in the world. As of January 2022, it contained over 58 million articles in 323 languages that were edited over 3 billion times by almost 100 million contributors.[1]

The English-language Wikipedia alone has over 5.7 million articles and over 30 thousand active contributors (i.e., with more than five edits per month).[2] In January 2022, Wikipedia was ranked the 14th most popular site on the internet,[3] and in December 2021, it received 2.1 billion page-views[4].

[1] http://meta.wikimedia.org/wiki/List_of_Wikipedias# Grand _Total
[2] http://stats.wikimedia.org/EN/SummaryEN.htm
[3] http://www.alexa.com/siteinfo/wikipedia.org
[4] https://stats.wikimedia.org/v2/#/all-projects

Table 3. Three Characteristics of Discourse

Characteristic	Definition
Volume	Number of actors contributing to the discourse and the frequency of their contribution
Volatility	Degree to which the content of the discourse is settled
Diversity	Degree to which the discourse reflects multiple distinct viewpoints

Given its sheer size, Wikipedia is an excellent platform on which to examine the emergence and change of the discourse around technologies. The platform is not just an encyclopedia that holds knowledge about the world. It is also the place where this knowledge is elaborated: a place of dynamic discourse and social engagement where contributors collaborate but also intensely debate and disagree about how to describe events, people, and objects in their world (Hansen et al., 2009). These debates take place as contributors express their opinions by changing article content and participating in discussions on the corresponding "talk pages." Contributors can see and engage with others' views by accessing the revision history and observing previous discussions regarding the article at hand. In doing so, contributors build upon the efforts of others in order to reach, if only temporarily, a collective agreement about the meaning of the topic at hand. This reflects the process whereby discourse unfolds.

5.2 Sampling: Studying Technologies with Varying Levels of Materiality

We selected 10 cases for our analysis that represent five highly material and five highly nonmaterial technologies. Our selection was based on the following criteria: First, the cases had to describe mature digital technologies that have already entered public awareness. This is to ensure that the discourses we examined had had a chance to unfold over time and that they reflected a demonstrable pattern. Second, the technology had to be current in order to avoid "discursive decay" due to the disappearance of the technology (e.g., floppy disks) rather than to the stabilization of its meaning. Third, the discourse about the technology in Wikipedia needed to have sufficient volume, measured by the number of edits and editors, as well as by the number of unique anchors used by editors. This criterion ensured the validity of our analyses and helped us avoid overamplifying the effect of individual discursive changes (see Table 4).

In choosing the cases, we followed a replication logic. Specifically, within each category we sampled cases based on a *literal replication*; namely, each case was selected on the basis that it would predict similar results. Consistent with the logic of maximum variation (Flyvbjerg, 2001), across the two categories, we chose cases based on a *theoretical replication*; that is, on the basis that they would predict contrasting results due to their different level of materiality (Yin, 2003). When replication logic is applied, each case in a multicase design is analogous to an experiment (Yin, 2003) whose results should reflect the sampling logic. In other words, we used the results from each additional case to confirm our expected pattern of discourse: consistent characteristics within each category but distinct characteristics across categories.

In an attempt to isolate the impact of the level of materiality on discourse characteristics, we sampled pairs of cases across the categories that are conceptually associated with each other (each row in Table 4). Specifically, the highly material technologies we selected embody some of the main characteristics of their associated highly nonmaterial technologies, are exemplars of these technologies, or are substantive in their operation: e.g., the Smart TV is a connected device that is characteristic of the Internet of Things; the laptop is one of the many devices through which operating systems manifest; wired gloves are an appliance through which the experience of virtual reality is delivered; many industrial robots embody machine-learning algorithms; and digital cameras are one of the few devices through which 3D printable models can be created.[5]

We started by analyzing highly material technologies in the order presented in Table 4. The discursive patterns we observed in the first case (Smart TV) were replicated four times in the subsequent cases within this category. We followed the same process when we analyzed highly nonmaterial technologies, only now we were looking both for consistency in dynamics within this category and contrast as compared to the material category. We observed these dynamics over the five cases and hence four additional replications.

To ensure that discourse characteristics are similar across all pairs and consistent with overall observed patterns across the two levels of materiality, we ran suppression tests for each pair for the following analytical measures: number of edits and editors, new and removed anchors, anchor dissimilarity, and average anchor strength. These tests showed that the same pattern indeed holds across all pairs and measures.

[5] We settled on these articles after trying out many others that did not meet our selection criteria or simply did not exist in Wikipedia. For instance, while it would have been well-paired with virtual reality, the article "VR Headset" was only edited 57 times by 158 editors who used a mere 15 anchors. Similarly, 3D printing would have been well-matched with an article on the highly material technology of the 3D printer; however, this article did not exist in Wikipedia.

Table 4. Sample Cases

Highly material technologies	Highly nonmaterial technologies
Smart TV	Internet of Things
Laptop	Operating system
Wired glove	Virtual reality
Industrial robots	Machine learning
Digital camera	3D printing

While there is no ideal number of cases in a multicase exploratory design (Baškarada, 2014), six to 10 cases are considered sufficient to establish a pattern (Yin, 2003). Hence, we deemed the observed findings from our 10 cases to be indicative of a consistent pattern (rather than due to chance) and did not examine any additional cases.

5.3 Analytical Approach

5.3.1 Quantifying Discursive Dynamics

Our analysis focused on tracing discourse in Wikipedia articles about our 10 sampled cases. In taking this approach, we consider language not merely as a descriptive system of symbols that correspond to an external reality but rather as a constitutive system through which reality is enacted and rendered meaningful (Phillips & Hardy, 2002). Hence, our analytical approach aimed to foreground the interrelationship between language and social practice (Fairclough, 2003) and examine it in a structured and systematic way. Although various approaches to discourse analysis exist in the literature (e.g., Gee, 1994; van Dijk, 2001; Phillips & Hardy, 2002; Fairclough, 2003), in examining discourse in Wikipedia, we build on what these approaches share, which is the notion that discourse is a social practice that constitutes social reality. Discourses can be studied at the level of utterances, texts, or broad-societal discourses as an aggregation of texts (Fairclough, 2003). In examining Wikipedia articles, we study a dynamic textual discourse that involves utterances that result in an evolving text that both reflects and constitutes an important element of the broad societal discourse. Further, in observing discourse across two categories of materiality, we set out to examine how the material nature of technology may be associated with different discursive characteristics.

Wikipedia's API and transparent structure, which permits easy access to past versions of each article, allowed us to extract relevant data and systematically track change patterns in the discourse within articles. This transparency notwithstanding, the data we accessed through Wikipedia's API are anonymized, aggregated, and publicly available. Hence, our study did not involve any ethical risks concerning data privacy or participants' anonymity. Next, we describe how we operationalized the three characteristics of discourse: volume, volatility, and diversity (Table 5).

Volume—Number of edits, number of editors: To trace fluctuations in discursive volume over time, we examined editing activity within an article by utilizing two measures: number of edits and number of editors. A small *number of edits* and *editors* in a given time period is indicative of low discursive volume whereas a large number is indicative of high volume.

Volatility—Anchor dissimilarity, average anchor strength: To examine the level of content volatility within Wikipedia articles, we employed two measures, anchor dissimilarity and average anchor strength. Both measures trace fluctuations in the stability of anchors within an article over time in order to gauge variations in the meaning of an article. Changes in anchors are a good proxy for variations in the meaning of an article because anchors are sense-giving devices; they are used to familiarize unfamiliar phenomena by positioning them in familiar and relevant conceptual categories (Simon, 1996; Moscovici, 2000; Gal & Berente, 2008). For example, in its early stage, the unfamiliar phenomenon of HIV/AIDS (before acquiring this name) was anchored in terms of a "gay plague" or "gay cancer" (Farr, 1993). Thus, the new phenomenon of HIV/AIDS was initially understood in terms of and took on qualities associated with the plague or cancer.

We traced anchoring in Wikipedia by examining links in one article that point to other Wikipedia articles. These links aim to achieve the same function as anchors: to create an association between a topic that requires elaboration and explanation and another known topic that is perceived to be relevant to understanding the topic at hand. Thus, a link anchors the current unfamiliar topic in terms of an existing familiar one.

Importantly, we only examined anchors in the top lead section of each article because not every link in an article necessarily constitutes a relevant anchor. Wikipedia articles' scope and structure, which users define dynamically, diverge highly and different

sections in an article can include information that is only loosely related to the article's subject.

Table 5. Operationalization of Discourse Characteristics

Dimension	Operationalization
Volume	Number of edits, number of editors
Volatility	Anchor dissimilarity, average anchor strength
Diversity	Unique anchors

However, the top lead section contains information that pertains to the phenomenon of interest: "The lead should stand on its own as a concise overview of the article's topic. It should identify the topic, establish context, explain why the topic is notable, and summarize the most important points"[6] While this policy may not be strictly upheld across all Wikipedia articles, our review of hundreds of articles, among them the 10 articles we analyze in this paper, show that the top lead section is indeed used as prescribed. Namely, that the links in this first section anchor the topic of the article.

Having explained why changes in anchors are a good indication of content volatility and how we identify anchors in Wikipedia, we can now describe the two measures we used to capture content volatility. *Anchor dissimilarity*[7] taps into variations in the meaning of an article by showing the extent to which anchors in a given time period are dissimilar to anchors in the previous time period. The resultant dissimilarity score ranges from 0 to 1. For instance, a score of 0 indicates that anchors are completely similar across consecutive time periods and that the meaning of an article has therefore not changed across these periods. A score of 0.6 indicates that 60% of the anchors in a given month are dissimilar to the anchors present in the previous month. A score of 1 indicates that anchors are completely dissimilar across consecutive time periods and that the meaning of an article has therefore significantly changed across these periods. *Average anchor strength* is extrapolated from *individual anchor strength*, which measures the resilience of individual anchors within a time period. It does so by linearly combining the number of days an anchor was present and the number of revisions it survived during that time period. Individual anchor strength ranges from 0 to 1. Anchors that are present for long periods or that are quickly reintroduced after being removed will have a high score. A score of 1 indicates that an anchor has survived all revisions and was present in the article for the entire measured period. *Average anchor strength* reflects the strength of all anchors present in an article in a given time period. High average scores indicate anchor stability within a certain time frame whereas low average scores indicate anchor volatility.

Diversity—Unique anchors: We understand discursive diversity as the degree to which participants in the discourse draw on a broad range of views, metaphors, and conceptual devices to make sense of the technology, its significance, and its potential uses and consequences. A good proxy for discursive diversity is the number of unique anchors used by Wikipedia editors in a given time period. An examination of the anchors used over time can reveal not only the process whereby a technology is rendered familiar, but also the conceptually substantive bases considered relevant by editors in order to make sense of the technology. The more unique anchors that are used in a given time frame within an article, the more likely are multiple conceptually distinct anchors used by editors. We tracked the number of unique anchors in each article's top lead section for each year, as well as for the article's entire lifespan, within the time frame of our analysis.

5.3.2 Operationalizing Technology Lifecycles

Our analysis involved distinguishing between the different eras in the evolutionary lifecycle of each technology: incremental change, ferment, and subsequent incremental change (Tushman & Rosenkopf, 1992). To identify these evolutionary eras, for each technology we examined the number of publications listed in the Factiva database. We conducted the search by entering the exact name of each technology into the free text search field. Factiva collates information from a broad range of business and industry sources, including an extensive archive of newspapers, magazines, industry publications, newswires (Dow Jones, Reuters and The Associated Press), and news-based websites from around the world. Given its broad scope and industry focus, Factiva is a good proxy for the level of interest in a given technology. Accordingly, we associated periods

[6] Wikipedia:Manual of Style/Lead section. Retrieved December 11, 2019 from https://en.wikipedia.org/wiki/Wikipedia:Manual_of_Style/Lead_section

[7] The formula for calculating anchor dissimilarity is presented in Appendix A.

of increasing growth in interest in each technology with its era of ferment, and periods of reduced interest with an era of incremental change (Maguire, 2004) (see, for example, Figure 1).

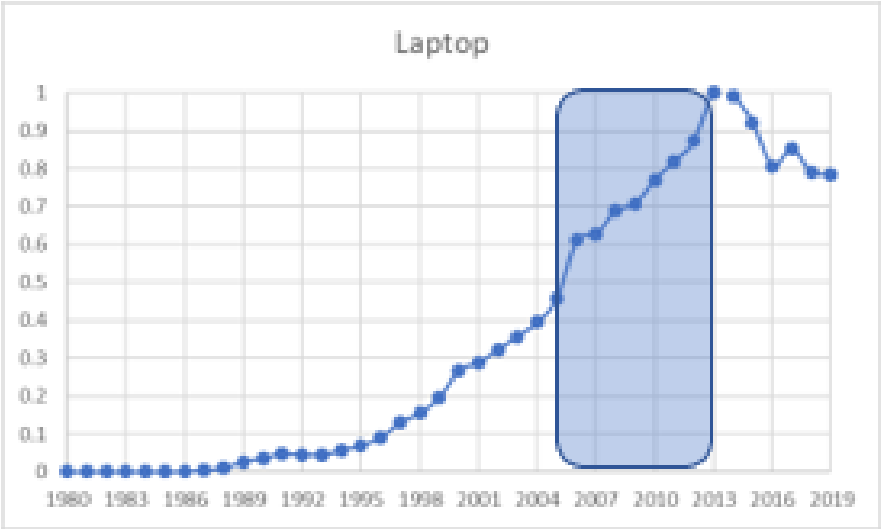


Figure 1. Factiva Publications for "Laptop" (normalized)—Era of Ferment Highlighted in Blue, Preceded and Followed by Eras of Incremental Change.

6 Findings Part 1: Comparing Discourse at Different Eras of the Lifecycle

To answer our research question, we analyzed the discourse for five highly material and five highly nonmaterial technologies (Table 4) during their respective eras of ferment and their preceding and subsequent eras of incremental change (Tushman & Rosenkopf, 1992). Our aim was to establish whether technologies across the two levels of materiality display different discursive patterns as they travel through their evolutionary lifecycles. Below we present two illustrations and a summary of this analysis. We outline the analysis in detail in Appendices B and C.

We found that while all 10 technologies went through an initial era of incremental change and subsequent ferment, only five went through a second era of incremental change following the era of ferment: laptop, wired glove, digital camera, operating systems, and virtual reality—this is because some technologies remained in a period of heightened interest that marks the era of ferment (see Appendix B).

For each technology, we mapped its identified era time frames to its Wikipedia article. In some instances, doing so led to excluding data from our analysis because there was no corresponding Wikipedia data to map it onto. For instance, the first era of incremental change for "Digital Camera" ended in 1994 and its subsequent era of ferment lasted until 2003, when a second era of incremental change started (see appendix B). However, the "Digital Camera" Wikipedia article was only created in May 2002. Therefore, we decided to only examine the second era of incremental change for this technology which took place between 2004-2019.

Next, we analyzed the discourse in each technology's Wikipedia article during each technology's identified eras. Specifically, we examined Wikipedia data to reflect levels of volume, volatility, and diversity. Within each era, we compared these constructs across the two levels of materiality by normalizing each construct's scores to the highest value within that era. For example, Figure 2 below shows that the levels of edits per year (one of two indicators of volume) are similar for highly material and highly nonmaterial technologies during the first era of incremental change.

The full results of this analysis are detailed in Appendix C and summarized in Table 6 below. As can be seen, while the discursive patterns for highly material and nonmaterial technologies mostly converge during their initial era of incremental change

(with the exception of average anchor strength which is higher for highly material technologies), these patterns mostly diverge during the subsequent ferment and second incremental change eras.[8]

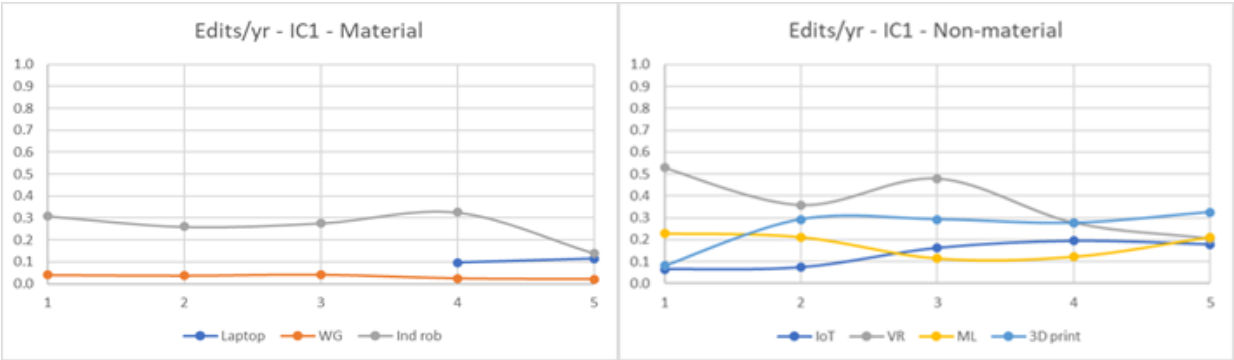


Figure 2. Normalized Number of Edits Per Year for Highly Material and Highly Nonmaterial Technologies during the First Era of Incremental Change

Table 6. Discourse Characteristics for Highly Material and Highly Nonmaterial Technologies over Evolutionary Eras.

		Incremental change I	Ferment	Incremental change II
Volume	Edits/year	Similar	Higher for nonmaterial	Similar
	Editors/year	Similar	Higher for nonmaterial	Similar
Volatility	Anchor dissimilarity	Similar	Higher for nonmaterial	Higher for nonmaterial
	Average anchor strength	Higher for material	Higher for material	Higher for material
Diversity		Similar	Higher for nonmaterial	Higher for nonmaterial

7 Findings Part 2: Comparing Discourse During the Lifecycle

The first part of our analysis was designed to compare discourse characteristics *between* highly material and highly nonmaterial technologies over three lifecycle eras. However, a consequence of this approach is that we were not able to compare discourse characteristics as they unfolded during the three eras *within* each level of materiality. Specifically, because we normalized discursive measures (e.g., number of edits, anchor diversity, etc.) across the levels within each era, we were not able to compare the measures within the levels during the three eras.

In order to trace the discursive characteristics within each level of materiality over the lifecycle eras, we examined the same 10 technologies' Wikipedia articles (Table 4) from their inception until the end of 2017 without normalizing the measures across the levels. Due to the similarity of the analysis process across cases and because discursive characteristics were largely consistent within each level of materiality, for each level, we next present one case in detail and outline the four additional cases in Appendix D.

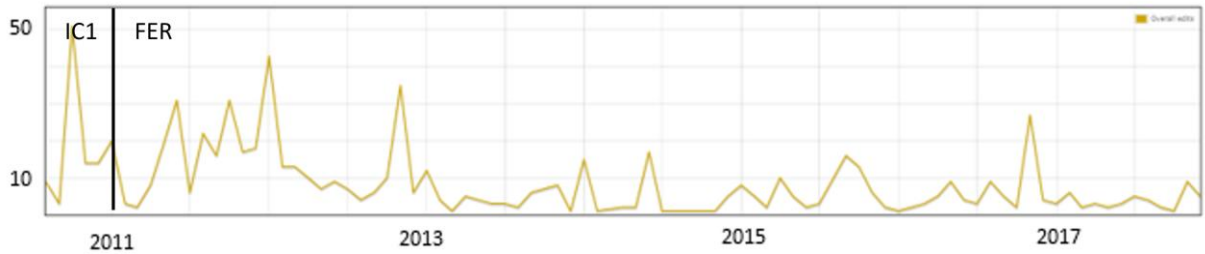
7.1 Highly Material Technology Example: Smart TV

Smart TV refers to devices that merge the functionality of a television set with the internet and interactive features. Smart TVs allow users to browse the web, stream online content, access on-demand videos, and run applications. The basic architecture for this technology was developed in the 1990s with patents filed in the mid-1990s.[9] The smart TV was

[8] The *t*-test results that compare discursive dynamics across the categories of materiality are shown in Appendix E.

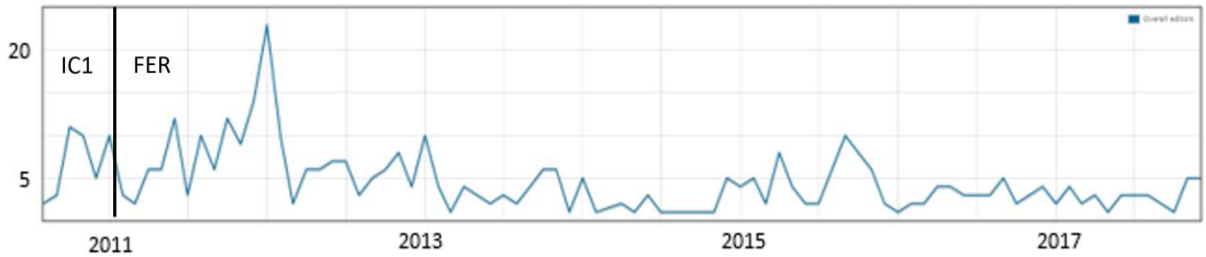
[9] https://worldwide.espacenet.com/publicationDetails/originalDocument?FT=D&date=19960510&DB=EPODOC&locale=en_EP&CC=FR&NR=2726670A1&KC=A1&ND=3#

first commercially introduced in 2008[10] and advanced models of smart TVs continued to be produced by manufacturers throughout the time frame of our study. The Wikipedia article "Smart TV" was created on August 2, 2010. During the time frame of our analysis, the article was edited 778 times by 336 editors. In total, editors used 57 anchors throughout the period of our analysis. As can be seen in Figures 3 and 4, the discursive volume within the article was high until the early phases of smart TV's era of ferment (end of 2012) and later declined.



Note: Each column represents a six-month period. The numbers along the *y*-axis denote the number per day

Figure 3. Number of Overall Edits (volume) for the Article "Smart TV"



Note: Each column represents a six-month period. The numbers along the *y*-axis denote the number per day

Figure 4. Number of Overall Editors (volume) for the Article "Smart TV"

The volatility of the content of the "Smart TV" article is evident in the anchor dissimilarity measure which reached its highest level toward the end of the technology's first era of incremental change, in the second half of 2010, with a score of 0.8 in October, indicating that 80% of the anchors present in this month were different from those present in the preceding month (Figure 5).

The level of content volatility of the "Smart TV" article is also apparent from the average anchor strength graph (Figure 6). We can see that average anchor strength levels shot up within the first few months of the creation of the article as the technology's era of ferment began and hovered above the 0.9 mark throughout the technology's era of ferment until the end of 2017.

Finally, Figure 7 shows that the level of discursive diversity for the article "Smart TV" declined as it entered its era of ferment and remained fairly stable until the end of 2017.

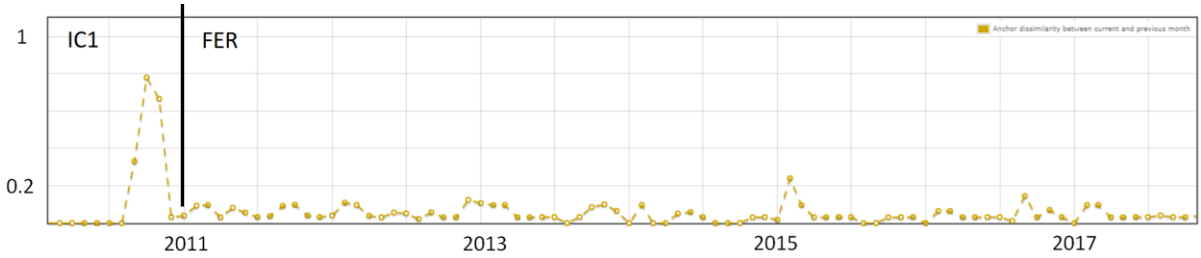
7.2 Highly Nonmaterial Technology Example: Internet of Things

The Internet of Things (IoT) can be defined as everyday devices communicating autonomously with each other through the internet with minimal to no human interaction. The IoT represents a transformation of the internet whereby interconnected objects harvest information from their environment, interact with the physical world, and utilize existing internet standards to transfer, analyze and apply large-scale data (Gubbi et al., 2013). Although the term IoT was coined in 1999 (Ashton, 2009) and became increasingly applicable with the commercialization of the internet, the first IoT devices were created in the early 1980s.[11] IoT's long stable interface architecture, which involves sensors and actuators communicating across networks and streaming data to acquisition systems, stabilized throughout the 1990s. In recent years, IoT has been commonly regarded as one of the key technologies underpinning the fourth industrial revolution, which is characterized by ubiquitous,

[10] http://www.bbc.com/news/technology-16483715

[11] https://www.cs.cmu.edu/~coke/history_long.txt

intelligent, and algorithmic technologies (Floridi, 2014). The Wikipedia article "Internet of Things" was created on July 2, 2007. During the time frame of our analysis, the article was edited 2666 times by 1211 editors who used 128 anchors during this period. As can be seen in Figures 8 and 9, the discursive volume within the article was low until 2013, the end of this technology's first era of incremental change, when it picked up and remained high until the end of 2017.



Note: Each column represents a six-month period. The *y*-axis represents the dissimilarity scores and ranges from 0 to 1.

Figure 5. Anchor Dissimilarity (volatility) for the Article "Smart TV"

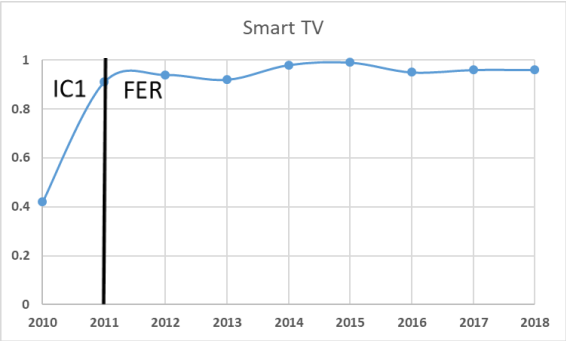


Figure 6. Average Anchor Strength (volatility) for the Article "Smart TV"

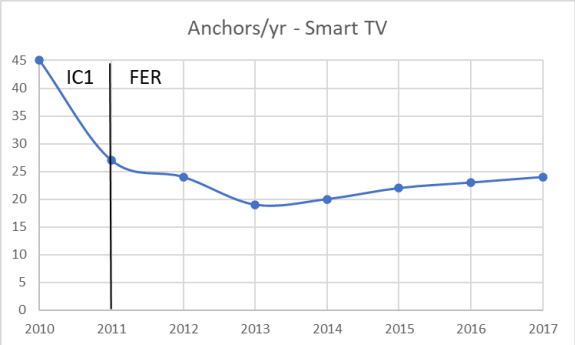


Figure 7. Number of Unique Anchors per Year (diversity) Used for the Article "Smart TV"[12]

[12] The figure shows unique anchors per year, but anchors may not be unique over years.

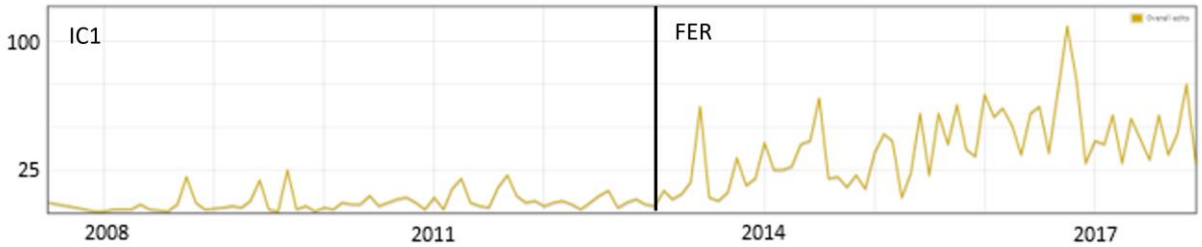


Figure 8. Number of Overall Edits (volume) for the Article "Internet of Things"

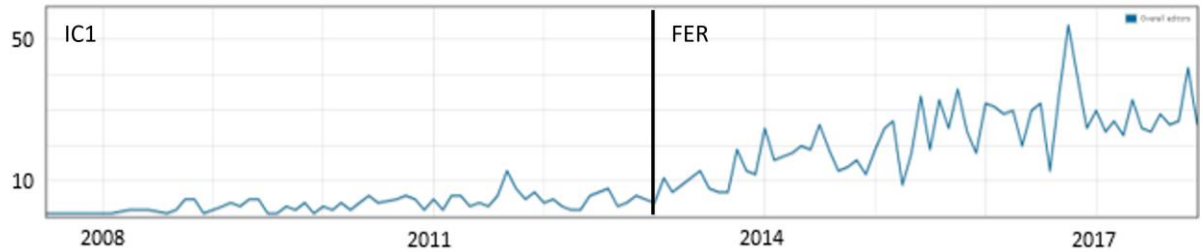


Figure 9. Number of Overall Editors (volume) for the Article "Internet of Things"

The ongoing forming of the meaning of IoT can be inferred from fluctuations in the content of the article. These fluctuations are evident in the anchor dissimilarity measure which had multiple spikes (Figure 10). In May 2011, dissimilarity peaked at 0.80, indicating that 80% of the anchors present in this month were different from those present in the preceding month. This peak was followed by a bumpy pattern that lasted throughout the ferment era until the end of our analysis time frame.

The average anchor strength (Figure 11) further reflects the ongoing volatility in the content of the article. This is evident from the average anchor strength levels which stayed within the 0.35-0.7 range throughout both the first incremental change and ferment eras. Finally, Figure 12 shows that the article's discursive diversity spiked as it entered its era of ferment, and diversity levels remained higher throughout the era of ferment than they were during the first era of incremental change.

7.3 Comparing Averaged Measures Of Discursive Characteristics during the Lifecycle

The analysis described in Section 7 to this point has focused on individual technologies and their associated Wikipedia articles and found differences in discursive characteristics across levels of materiality. To further corroborate these findings, we averaged the measures of discursive characteristics within each level of materiality and compared these averages across the levels for all 10 technologies for the first seven years of their associated Wikipedia article.[13] This analysis supported our previous findings and found that discursive characteristics were markedly different across levels of materiality but generally consistent within levels of materiality.

As can be seen in Figure 13, the average volume of discourse, measured by the number of edits and editors, initially increased for both levels, presumably as individuals were trying to make sense of the different technologies. After this phase, the two levels diverged: the number of edits and editors dropped for highly material technologies but kept increasing for highly nonmaterial technologies.[14]

[13] To ensure that our comparison included all 10 articles, we determined the analysis time frame based on the most recently-created article, "Smart TV," which was created on August 2, 2010. Since our analysis time frame ends on December 31, 2017, our comparative analysis spans seven years.

[14] The total number of editors and edits during the time frame of our analysis was lower for material technologies (6,641 editors, 13,278 edits) as compared to nonmaterial technologies: (10,347 editors, 21,784 edits).

We further observed this divergent pattern across levels of materiality in the content volatility of the 10 technologies' articles (Figure 14). Average anchor dissimilarity levels were consistently lower for highly material technologies, and the gap between the levels widened after five years from the creation of the articles. This indicates that, compared to highly material technologies, anchors in articles associated with highly nonmaterial technologies were replaced more regularly, reflecting ongoing content volatility.

Further evidence of this trend can be seen in the average levels of average anchor strength. Average anchor strength measures the durability of all anchors present during a period of time, which is a quantitative measure of the level of consensus among Wikipedia editors regarding the meaning of the technology at hand. With highly material technologies, we observed an initial period of mid-level average anchor strength across the five articles. However, within approximately 1-3 years, average anchor strength levels climbed to the 0.8-0.9 range, indicating a consolidation of anchors and convergence of views among editors (in the article "Laptop" these dynamics were a bit slower and more punctuated, although the same pattern was observed). With highly nonmaterial technologies, average anchor strength levels were consistently lower and continued to hover around the 0.4-0.6 mark.

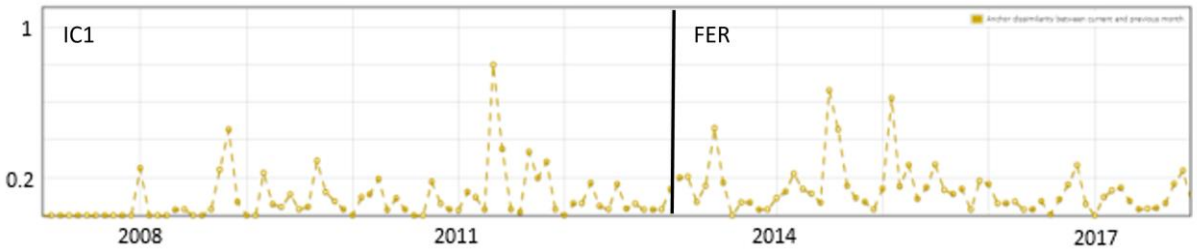


Figure 10. Anchor Dissimilarity (volatility) for the Article "Internet of Things"

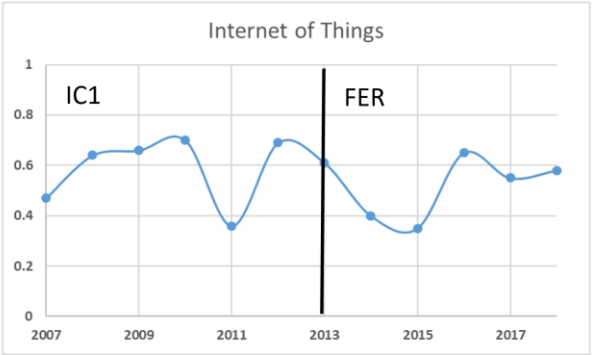


Figure 11. Average Anchor Strength (volatility) for the Article "Internet of Things"

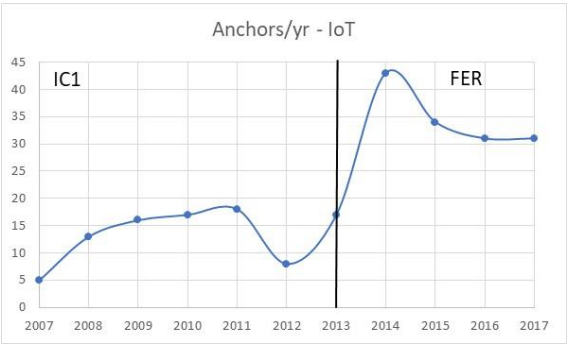


Figure 12. Number of Unique Anchors Per Year (diversity) Used for the Article "Internet of Things"

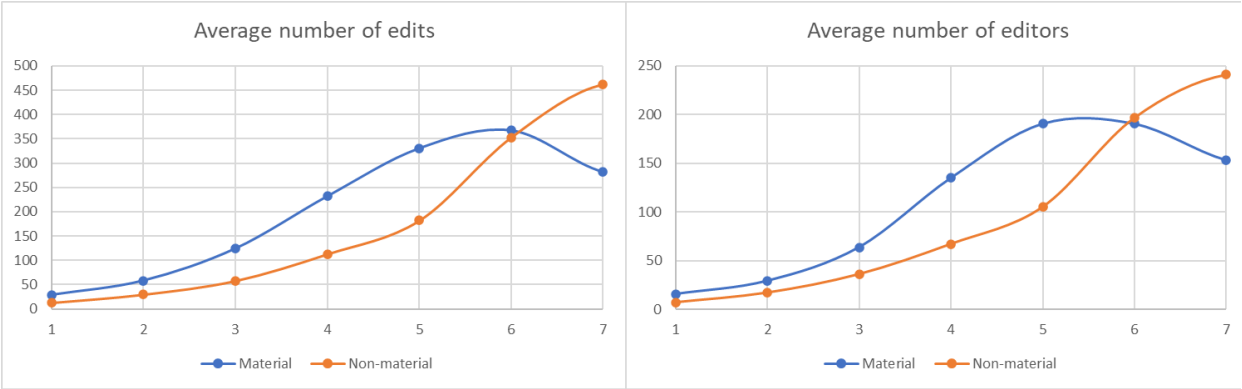


Figure 13. Average Discourse Volume across Highly Material and Highly Nonmaterial Technologies, Measured for the First Seven Years of Each Article

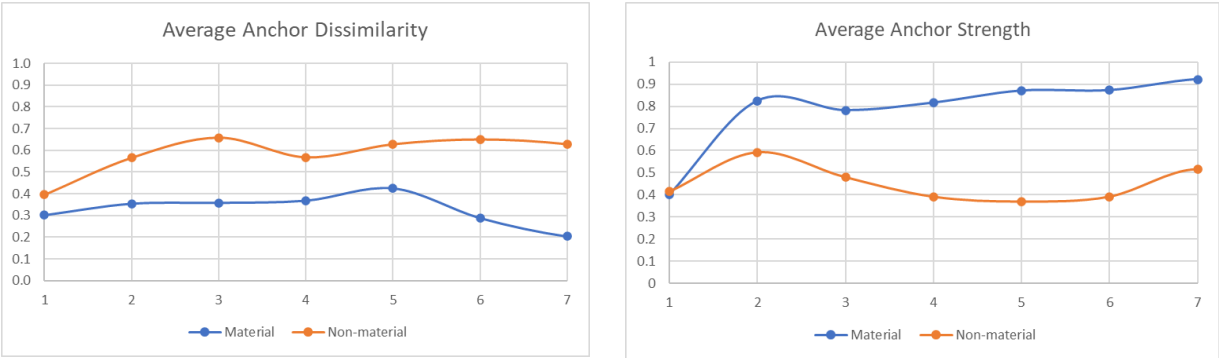


Figure 14. Average Discourse Content Volatility across Highly Material and Highly Nonmaterial Technologies, Measured for the First Seven Years of Each Article

Both indicators—anchor dissimilarity and average anchor strength—suggest that there was a limited generation of new meanings associated with highly material technologies after an initial phase of heightened anchoring activity following the creation of the articles. These indicators further suggest that the negotiation of meaning for highly nonmaterial technologies was a more extended process that did not end during the time frame of our analysis.[15]

Another finding that emerges from our study is that, on average, editors drew on a smaller number of unique conceptual anchors to negotiate the meaning of highly material versus highly nonmaterial technologies for each of the first seven years of the articles (see Figure 15).

Looking beyond the first seven years of the 10 articles and examining the number of unique anchors used during the lifespan of each article (Table 7), we can see that, on average, editors used 64.8 unique anchors to represent highly material technologies, compared to 171 unique anchors that they used to represent highly nonmaterial technologies—a difference of close to 164%. When accounting for the duration of analysis for each article, the average number of anchors per year that was used to render highly material technologies meaningful was 5.18

[15] Importantly, the patterns we observed across the 10 articles cannot be explained by any relevant exogenous news events that overlapped in time with the lifespan of each article that may have shaped their discursive dynamics. To empirically examine this possibility, for each of the 10 technologies, we compared the number of publications on the Proquest Newsstream International databases with the technology's number of edits and dissimilarity scores during the lifespan of its Wikipedia article. The Proquest databases cover more than 3,000 of the world's news sources and are therefore a good reflection of the international news landscape as it changes over time. The findings of the analysis show little to no correlation between the volume of news stories and spikes in editing and dissimilarity scores. This finding therefore confirms that the discursive patterns we observed do not contain much external "noise" and are likely due to varying levels of materiality. In addition, the prolonged editing and anchoring activity we observed for nonmaterial technologies cannot be attributed to fundamental shifts in the nature of these technologies since the broad technical approaches that underlie the Internet of Things, operating systems, virtual reality, machine learning, and 3D printing, were mostly established before the Wikipedia articles for these technologies were created (although incremental innovations within these approaches remained in later years).

compared to 11.98 for highly nonmaterial technologies—a difference of more than 131%.[16]

8 Discussion: Digital Technologies, Materiality, and Discursive Characteristics in the Technology Lifecycle

At the outset of this paper, we asked about the likely fate of digital innovation when digital technologies are more or less material. Specifically, we examined how the discourse about digital technologies that vary in their level of materiality manifest in lifecycle trajectories of technology evolution. To facilitate this examination, we compared the discursive characteristics of five highly material and five highly nonmaterial technologies across three eras of their respective technology lifecycles (Tushman & Rosenkopf, 1992). We found that while highly material and highly nonmaterial technologies displayed mostly similar discursive characteristics during their initial era of incremental change, these characteristics diverged during the eras of ferment and second incremental change. This analysis demonstrates that, while discursive characteristics differ for technologies across levels of materiality, these differences are not evident throughout the entire lifecycle (Anderson & Tushman, 1990).

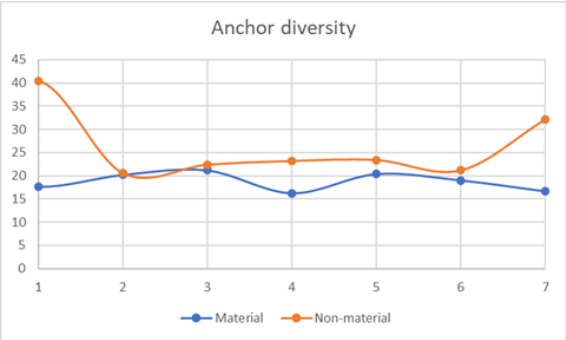


Figure 15. Average Discourse Diversity across Highly Material and Highly Nonmaterial Technologies, Measured for the First Seven Years of Each Article

Table 7. Number of Unique Anchors Used per Article across Levels of Materiality

	Article	No. of anchors	Ave. no. of anchors	Days	Anchors/year	Ave. no. of anchors/year
Highly material technologies	Smart TV	57	64.8	2708	7.68	5.18
	Laptop	123		5401	8.31	
	Wired Glove	35		4490	2.85	
	Industrial Robots	45		5524	2.97	
	Digital Camera	64		5703	4.09	
Highly nonmaterial technologies	Internet of Things	128	171	3835	12.18	11.98
	Operating System	320		5890	19.82	
	Virtual Reality	154		5933	9.48	
	Machine Learning	123		5334	8.42	
	3D Printing	130		4758	9.98	

Specifically, we saw that during the first era of incremental change the volume of the discourse (number of edits and editors) was similar for both levels. Content volatility was partially similar—dissimilarity scores were consistent across the levels but average anchor strength levels were higher for highly material technologies. Finally, diversity levels were similar across the levels of materiality. The discursive differences between the levels fully played out during the era of ferment. During this era, highly nonmaterial technologies showed higher discursive volume, volatility, and diversity. These differences

[16] These differences cannot be fully explained by differences in the length of the articles from the two categories. On average, HNTs articles were only 24.8% longer than HMTs articles. The length of each article was measured through a word count of the last version of the article within our period of analysis.

between the levels—with the exception of discursive volume—remained during the second era of incremental change (see Appendix C).

The technology lifecycle model posits that discourse about a technology is likely to vary during different stages of the lifecycle (Kaplan & Tripsas, 2008), and our research supports this. However, our finding that discourse is also patterned along levels of materiality is not addressed by the model and requires further explanation. In the first era of incremental change, much of the activity around both highly material and highly nonmaterial technologies is performed by a relatively small number of homogeneous stakeholders. Tushman and Anderson's (1990) technology lifecycle model is rooted in the models of technological evolution of Rogers (1983) and Foster (1986). These models emphasize that in the early stages, technology development and its discursive framing are shaped by technology entrepreneurs, innovators, and early adopters (Rogers, 1983; Foster, 1986), all of whom share an affinity for and interest in technology. Thus, it is likely that we will see a relatively stable discourse with moderate diversity in the early stages of technology development because of the small group of similar stakeholders that drive the discourse, and this holds true for all types of technologies. As technologies enter the era of ferment, the community of actors that shape their discourse grows to include other more diverse stakeholders (Rogers, 1983). Accordingly, discourse itself changes, and more so for more highly nonmaterial technologies, which have greater equivocality and are subject to wider interpretations from a greater variety of stakeholders. Thus, we arrive at the following propositions:

P1a: Highly material and highly nonmaterial technologies have similar discursive volume, volatility, and diversity during the first era of incremental change.

P1b: During the eras of ferment and subsequent incremental change, highly nonmaterial technologies display greater volume, volatility, and diversity, compared to highly material technologies, as their discourse is driven by a larger and more diverse group of stakeholders.

While the first part of our analysis compared discourse *across* levels of materiality, its second part aimed to examine how discourse unfolded *within* each level of materiality over each technology's lifecycle (Appendix D). Our analysis showed that discursive volume for the highly material technologies of "Smart TV," "Wired Glove," and "Industrial Robot," reduced as they entered their era of ferment ("Laptop" is an exception to this pattern, and we did not have sufficient data on the era of ferment for the Wikipedia article "Digital Camera"). Similarly, the content volatility for highly material technologies (excluding "Digital Camera") was lower during their era of ferment as compared to their first era of incremental change. This is evident in their lower dissimilarity scores and higher average anchor strength scores. Finally, highly material technologies (excluding "Digital Camera") displayed lower discursive diversity during their era of ferment, compared to their first era of incremental change, as is evident in the lower number of anchors used in their respective Wikipedia articles in their ferment years.

On the other hand, discursive volume for highly nonmaterial technologies remained elevated throughout their respective eras of ferment and, in most cases (with the exception of "Virtual Reality"), it was higher than during the first era of incremental change. Similarly, the content volatility for highly nonmaterial technologies remained high during their eras of ferment. This can be inferred from the high dissimilarity scores and low to medium average anchor strength levels, particularly for the Internet of Things, machine learning, and 3D printing. Finally, most highly nonmaterial technologies displayed higher discursive diversity during their era of ferment as compared to their first era of incremental change.

These findings point out that a longer time horizon may be needed to understand the evolutionary dynamics of digital technologies—particularly highly nonmaterial digital technologies. Existing research shows that discourse can influence the diffusion of particular technologies over windows of time of a year or less (e.g., Miranda et al., 2015), but our findings show that fully appreciating how discourse intertwines with technological evolution may require extending the examination to account for multiple years—particularly for highly nonmaterial technologies. This observation may also shed light on work that shows how discourse, in some cases, remains dynamic for years, whereas in other cases it stabilizes more quickly (Davidson et al., 2015). Our findings suggest that the materiality of the technology can offer an explanation for this divergence.

Additionally, our findings challenge research that indicates that the era of ferment for technologies is marked by radical technological innovation coupled with heightened social interactions and discursive activity (Anderson & Tushman, 1990; Tushman & Rosenkoph, 1992), and show that this tends to be the case for highly nonmaterial more than for highly material technologies. These findings can also help to explain more recent studies which show that discourse remains elevated throughout the technology lifecycle (Lee & Berente 2013; Dokko et al., 2012; Kaplan & Tripsas 2008): technologies' level of materiality may be associated with the characteristics of their corresponding discourse, specifically its volume, volatility, and diversity. This leads to our second set of propositions:

P2a: Discursive volume, volatility, and diversity for highly material technologies tend to decrease in level as they enter their era of ferment.

P2b: Discursive volume, volatility, and diversity for highly nonmaterial technologies remain elevated, or intensify, as they enter their era of ferment.

Our research also demonstrated that the average volume of discourse, measured by the number of edits and editors, showed an upward trend for all 10 technologies in the first seven years of the articles, although scores were initially a little higher for highly material than for highly nonmaterial technologies. After this initial phase, the two levels diverged: the number of edits and editors dropped for highly material technologies but kept increasing for highly nonmaterial technologies (Figure 13).

A possible explanation for the higher discursive volume for highly material technologies in the first few years of each article is that their direct accessibility, well-defined features, and narrow scope were readily identifiable for editors and provided them with ample concrete "discursive hooks" to drive their discussions. By the same token, the indirect accessibility, generally defined features, and broad scope of applicability of highly nonmaterial technologies only provided limited discursive cues initially, which translated into a more muted discourse. However, the lack of concreteness of highly nonmaterial technologies required a more extensive process of debate and negotiation involving a larger group of participants, as compared to highly material technologies. This reasoning is consistent with previous research which has shown that making sense of abstract nonmaterial phenomena is a more elaborate process than making sense of tangible phenomena because we have few existing resources and rules to interpret nonmaterial phenomena and rely on extensive communication cycles with a greater number of people to cope with their inherent abstraction (Weick, 1979; Putnam & Sorenson, 1982). This leads to our third set of propositions:

P3a: Compared to highly nonmaterial technologies, a larger number of stakeholders are more actively involved in constructing the meaning of highly material technologies in the first years of their respective Wikipedia articles.

P3b: After this initial period, a larger number of stakeholders are more actively involved in contributing to the construction of the meaning of highly nonmaterial technologies.

Our findings further show that while the average content volatility of highly material technologies decreased in the first seven years of their respective articles—seen in the decreasing levels of anchor dissimilarity and increasing levels of average anchor strength—the volatility of highly nonmaterial technologies did not diminish, as is evidenced in the persistent medium levels of anchor dissimilarity and average strength (Figure 14). This reflects the open-ended ambiguity of nonmateriality (Kallinikos et al., 2013); the meaning, nature, possible uses, and business and social significance of these technologies remain a subject of ongoing discursive negotiation and debate.

These patterns indicate that the way we collectively make sense of highly nonmaterial technologies is different than for highly material technologies. Many technologies are interpretatively flexible (Pinch & Bijker, 1987); they carry diverse meanings to different groups of users, developers, and observers, and these meanings may change over time. Moreover, they may afford different action possibilities (Gibson, 1986) to different involved stakeholder groups. However, more than being merely interpretatively flexible, highly nonmaterial technologies are sets of techniques and processes that allow for a multiplicity of uses, activities, interactions, and potentialities. Highly nonmaterial technologies are like icebergs floating in the sea (Dourish, 1995); the logic of their operation is hidden from sight and it remains unknown how they perform requested activities (Dourish & Button, 1998). Therefore, they are not easily interpretable and are likely to be perceived as equivocal black boxes (Weick, 1993). Accordingly, there is an extended period of time during which people continue to engage in making sense of them (Weick, 1993; Swanson & Ramiller, 1997; Moscovici, 2000; Davidson et al., 2015).

Existing literature has devoted significant attention to the inherent ambiguity and ongoing enactment of technology through situated use. The discussion has varied from emphasizing the role of practices in enacting technology (Orlikowski, 2000) to focusing on secondary design processes that continue past primary architectural design stabilization (Germonprez et al., 2011) to addressing the ontological inseparability of technology and social practices (Cecez-Kecmanovic et al., 2014; Putnam, 2015). Our work complements this literature by highlighting that technology takes shape and becomes meaningful not only through situated use, practice, and secondary design, but also through ongoing discourse that unfolds over an extended period. This leads to our fourth proposition on the stabilization of the discourse:

P4: Compared to highly material technologies, the negotiation and solidification of the meaning of highly nonmaterial technologies is a more extended process, as evidenced by the persistently volatile content of their discourse.

As noted above, we make sense of unfamiliar phenomena by anchoring them in phenomena that we already know and that we deem to be relevant to the newly encountered phenomena (Weick, 1993; Simon, 1996; Moscovici, 2000). Therefore, more than a trivial structural component of discourse, anchors are conceptual metaphors (Lakoff & Johnson, 1980) that are indicative of the manner in which each of the technologies that we examined was rendered

meaningful. The difference in the average number of unique anchors across the two categories (Table 7) demonstrates that the discursive range that editors brought to bear to make sense of highly nonmaterial technologies was wider than that used for highly material technologies.

Existing research has suggested that discursive diversity reflects the complexity of the vocabulary knowledge and the language proficiency possessed by speakers (Jarvis, 2013), as well as the variety of perspectives held by members of a discursive community (Jovchelovitch, 2001). Our work extends this previous research by proposing that discursive diversity may also be associated with the subject matter of the discourse itself, specifically its level of materiality.

The inherent ambiguity of highly nonmaterial technologies can lead to ongoing negotiations between editors about their meaning, function, potential benefits, and whether they can be clearly distinguished from other similar technologies. Thus, a sensemaking process unfolds whereby multiple actors create "visions" for the technology that are generated and validated across actors (Swanson & Ramiller, 1997). This process involves relating the technology to an analogous technology, or a "parallel case" to the phenomenon that is already known to the actors, and different actors may draw on different reference phenomena (Berente et al., 2011). In the absence of clear-cut answers to questions about the nature of highly nonmaterial technologies, their consideration resulted in elaborate and diverse articulation dynamics, during which a broad metaphorical range was employed—actors anchored the highly nonmaterial technologies in a variety of other phenomena. This leads to our final proposition about the diversity of the discourse:

P5: The discursive dynamics of highly nonmaterial technologies are characterized by greater diversity than that of highly material technologies.

This final proposition extends work that emphasizes how power dynamics manifest in discourse (e.g., Doolin, 2002; Fairclough, 2003). Those who study power in discourse have highlighted that discourse is not merely sporadic and fleeting but reflects and constitutes deeply held social structures, often rooted in foundational ideologies (Barrett et al., 2013). Highly material technologies offer less flexibility for a diversity of perspectives, as key actors lead in their development and patterns of use over time (Miranda et al., 2016). Highly nonmaterial technologies, however, allow for multiple ideologies to be reflected simultaneously in their discourse. Overall, our research shows that the materiality of the digital technology (Faulkner & Runde, 2019) needs to be considered when analyzing power dynamics within the discourse.

9 Contributions

This research makes a number of contributions to the knowledge of how technologies are discursively shaped. Overall, our findings suggest that we may need to rethink some existing approaches to understanding technology evolution and innovation. Much of our knowledge of technological innovation derives from material technologies rooted in the industrial age, as illustrated in the technology lifecycle model that was developed in the early 1990s (Anderson & Tushman, 1990; Henderson & Clark, 1990). The model stipulates that the era beyond the point of technological stabilization—the era of incremental change—is characterized by limited innovation and social activity and is therefore theoretically uninteresting (Dokko et al., 2012). However, our findings demonstrate that the lifecycle patterns of contemporary digital technologies, particularly highly nonmaterial technologies, diverge from those described in the lifecycle model. Specifically, we have shown that the discourse around highly nonmaterial technologies continues to fluctuate beyond the era of ferment and into the era of incremental change as people negotiate their meaning in an ongoing process. This finding helps bring into sharper focus earlier work that has emphasized the role of social and discursive processes in shaping technology innovation trajectories (Kaplan & Tripsas, 2008, Schubert et al., 2013). For example, Dokko et al. (2012) argued that the stabilization described in the technology lifecycle model is not a dormant phase but more closely resembles Strauss's negotiated order (1978): although social dynamics may reach a state where they appear stable, stability across a diverse set of stakeholders must be continually negotiated in a dynamic process through which the meaning of the technology is shaped. Thus, social stabilization is enabled through a continuous discursive process. Our analysis of discourse characteristics provides a concrete and nuanced account of how this process unfolds over time.

This understanding offers important insights for practice. As noted at the outset of the manuscript, substantial effort has been devoted to identifying technologies' position in their lifecycle and predicting how they may evolve in the future (Christensen et al., 1998; Altuntas, 2015). This knowledge is assumed to help managers make prudent technology investment and development decisions. While this approach assumes universal generalizability, our findings demonstrate that such sweeping predictions may need to be qualified because different types of technologies have different evolutionary trajectories. For instance, a common strategy is to wait for a technology to enter its era of incremental change and stabilize before investing in it (Carr, 2003; Ravichandran & Liu, 2011), and characteristics of discourse can be used to gauge stabilization—the emergence of agreement and consensus is a good signal that a technology has stabilized (Tushman & Rosenkopf, 1992). Our findings indicate that this approach would be effective for highly material technologies, but for highly nonmaterial technologies the

discourse does not stabilize in a similar way: it continues to be volatile past the emergence of a dominant design and into the era of incremental change. Managers would have less luck finding reduced interactions and stabilized interpretations, and if they wait it may be too late to capitalize on technological innovations.

Further, our study contributes to research on the discursive shaping of technology. It has long been understood that technologies are socially constructed, in part, through discourse. In organizational studies, there is a rich body of literature describing how the dynamics around new technologies are manifested through discourse (e.g., Doolin, 2002; Leclercq-Vandelannoitte, 2014; Trusson et al., 2014). Technologies are collectively framed, and this framing takes place through discourse that involves multiple community or organizational members (Gal & Berente, 2008). In the information systems literature, research on the concept of organizing visions has been instrumental in examining how community members engage in discursive activities to render new technologies meaningful, legitimize them, and assemble the required resources to facilitate their adoption and diffusion (Swanson & Ramiller, 1997; Berente et al., 2011; de Vaujany et al., 2013; Miranda et al., 2015; Liao, 2016). However, this existing work does not examine how discursive dynamics may unfold differently depending on the nature of the technology in question. In our research, we take an initial step towards understanding how discourse unfolds over time and varies for digital technologies with different levels of materiality. We characterize these variations in terms of discursive volume, volatility, and diversity.

This insight is important because it demonstrates that technology's material configurations may be important to how it comes to be perceived as well as to its evolutionary trajectory. Thus, we situate previous research that emphasized the discursive shaping of technology in a broader conceptual context by demonstrating empirically that, at least to a degree, this discursive shaping is conditioned by the material nature of the technology. This view helps establish a holistic understanding of the discourse-materiality relationship by emphasizing the mutual influences between the two constituent elements of this relationship (Dourish, 2017). In doing so, we heed calls from other researchers (Putnam, 2015) and transcend unidirectional views that emphasize either the social-discursive construction of technology (Bijker, 1997; Leonardi and Barley, 2010) or its material effects on social and organizational processes (Clemons et al., 1993; Drnevich & Croson, 2013).

This approach can help examine the relationship between discourse and technology from a fresh perspective and shed new light on existing research. For instance, Currie (2004) and Davidson et al. (2015) trace the discourse underlying the organizing visions of application service provision and personal health records, respectively. They document the limited diffusion of these technologies and cite contradictory meanings and rhetorical confusions as reasons for their muted spread. Our research suggests that the contradictions and confusions they found may be a manifestation of the mostly nonmaterial nature of the technologies they studied.

Finally, we contribute with a novel approach to tracing the structural elements of discourse that underpins various social online phenomena. By utilizing computational techniques, we were able to demonstrate variations in the editing and anchoring processes for technologies across levels of materiality. Our operationalization of discursive volume, volatility, and diversity offers an accessible analytical approach that can be used to gauge discourse characteristics as they manifest within large corpora of text, such as social media platforms. This approach departs from the more traditional emphasis on organizational discourse to focus on the way technologies are shaped outside of particular organizational domains. Since an increasing amount of work is taking place on widely available distributed digital products and cross-organizational infrastructure and platforms, it is important to understand how technologies are shaped outside of any particular organizational "container" (Winter et al., 2014).

10 Limitations and Future Research

This study has several limitations that provide opportunities for future research. First, we described discourse characteristics associated with digital technologies across levels of materiality. However, our findings do not fully explain the significance of the identified patterns. Doing so would require adding a qualitative dimension to the current investigation to identify not only the contours of the discursive changes but also their content. Further research could develop rich narrative descriptions that would help to shed more light on the complexity of the discursive process around the meaning of digital technologies and its association with these technologies' evolutionary paths.

Second, in this study, we differentiated between highly material and highly nonmaterial technologies based on their four facets—instantiation, accessibility, features, and functional scope (Table 2)—and observed how the differences in these facets manifested in varying discourses and evolutionary trajectories. However, we did not examine how each of these facets may have uniquely shaped the discursive volume, volatility, and diversity of technologies across levels of materiality. The reason we did not conduct such an analysis is that our data was not sufficiently specific to analytically isolate each of the four facets of technologies and their association with the various discursive characteristics. Future research would be required to identify how individual technology facets may contribute to discursive characteristics in order to

better understand the intertwining of technological materiality, discourse, and technology evolution.

Third, further research is also needed to examine discursive characteristics outside of Wikipedia. While we used data from Wikipedia, the online encyclopedia is only one of many places where the discourse and social-shaping of digital technologies take place. An important assumption implied in our work is that Wikipedia, to an extent, reflects the broader discourse. Future work could test this using other domains of broader discourse, such as news outlets, social media platforms, and the popular press, to determine the extent to which we might generalize about the discourse reflected in Wikipedia data.

Finally, in this study we focused on the patterns of editors' actions and were agnostic to their motivations to contribute to articles. However, previous research has shown that editors have a variety of reasons for engaging with Wikipedia. For instance, Xu and Li found that people are motivated to contribute to articles by reciprocity, self-development, and enjoyment (Xu & Li, 2015). Similarly, Pee found that perceptions of the community's need for knowledge increase people's knowledge sharing intentions because they see the potential value of their contribution to the community (2018). Aaltonen and Seiler demonstrated that people are more motivated to contribute to established and long articles as compared to new and short articles, and that the resultant growth in content drives article quality (Aaltonen & Seiler, 2016), whereas Yenikent et al. showed that familiar and controversial topics increased editors' willingness to engage with Wikipedia articles (Yenikent et al., 2017). While this work focuses on various factors that influence people's motivation to engage with Wikipedia, it also opens up opportunities for future research to examine possible links between people's motivations to contribute to Wikipedia articles and the resultant patterns of editing and anchoring activities.

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Appendix A: Formulas for Anchor Dissimilarity

$$d(t,t-1) = 1 - \frac{\sum_{i=1}^{n} \min\left(f(a_{k_i},t), f(a_{k_i},t-1)\right)}{\sum_{j=1}^{n} \max\left(f(a_{k_j},t), f(a_{k_j},t-1)\right)}, \quad \text{where}$$

$\boldsymbol{a_k} = a_t \cup a_{t-1} = \begin{pmatrix} a_{k_1} \\ a_{k_2} \\ \dots \\ a_{k_p} \end{pmatrix}$: union of anchor name vectors a_t and a_{t-1} in periods t and $t-1$ with $\boldsymbol{a_t} = \begin{pmatrix} a_{t_1} \\ a_{t_2} \\ \dots \\ a_{t_i} \end{pmatrix}$ being a vector of anchor names a_{t_i} in period t,

$\boldsymbol{f}(x,t) = z,\ with\ x \in a_t$ and z being the days survived value for anchor x in t.

Figure A1. Anchor Dissimilarity Formula

Anchor dissimilarity is calculated by dividing the minimum value by the maximum value for the normalized number of days an anchor was present across two consecutive time periods, for all anchors that were present across the same two consecutive time periods, and subtracting the resulting score from 1.

In the formulas above "*ak*" represents the pool of anchors present over two consecutive time periods (*'t'* and "*t-1*") and "*at*" represents an individual anchor at time period "*t.*"

To take a simple example of an article that only had 2 anchors present over July and August; if anchor (1) was present for 20 days in July and 20 days in August, and if anchor (2) was present for 10 days in July and 10 days in August, then the dissimilarity score for August would be:

$$1 - \frac{20+10}{20+10} = 0$$

This means that anchors across the two time periods have not changed.

To take another example of an article that only had 2 anchors present over July and August; if anchor (1) was present for 0 days in July and 20 days in August, and if anchor (2) was present for 0 days in July and 10 days in August, then the dissimilarity score for August would be

$$1 - \frac{(0+0)}{(20+10)} = 1$$

This means that anchors across the two time periods are completely dissimilar.

Appendix B: Factiva Graphs: Publications Per Year (Normalized)[17] [18]

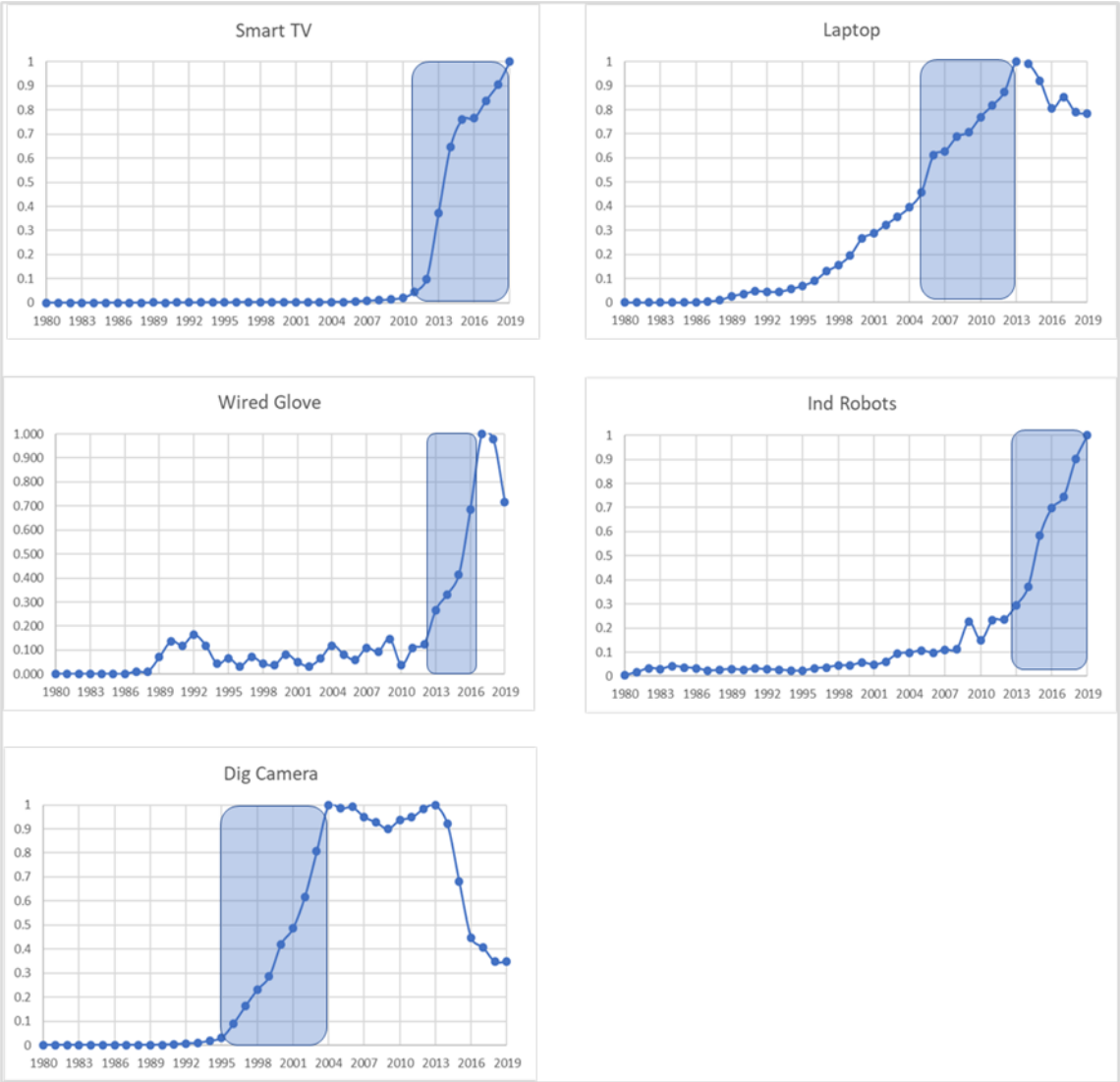

Figure B1. Volume of Publications per Year in Factiva for Highly Material Technologies

[17] We show data from 1980-2019. We start in 1980 because none of the 10 technologies had a substantial number of publications prior to 1980. We finish in 2019 to include the last full year of data at the time we conducted the analysis.
[18] The era of ferment for each technology is highlighted in blue.

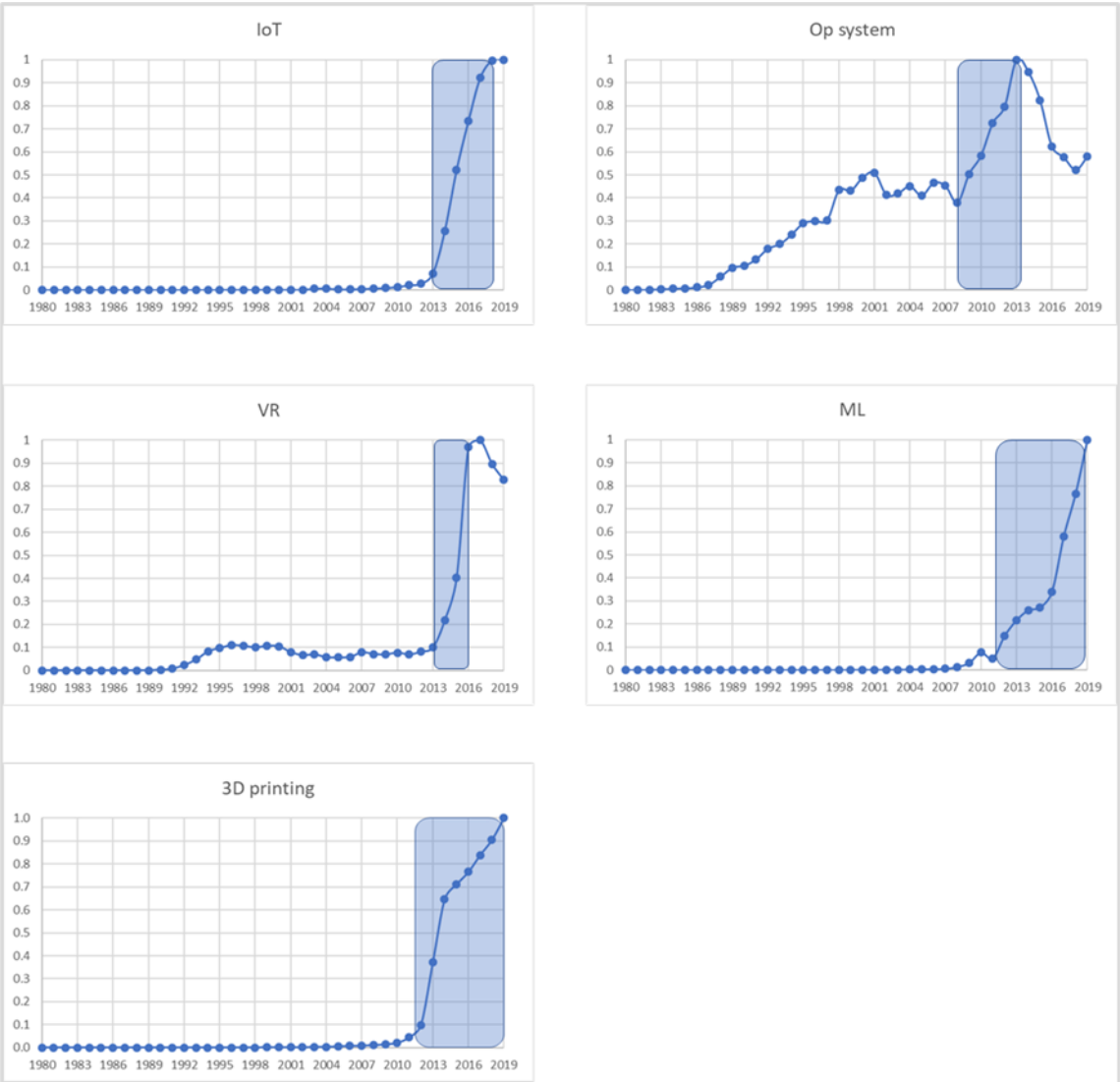

Figure B2. Volume of Publications per Year in Factiva for Highly Nonmaterial Technologies

Table B1. Highly Material and Highly Nonmaterial Technologies' Lifecycle Eras Data (left) and Wikipedia Data (right) Used for Analysis.

		Lifecycle			Wikipedia	
		IC1	**Ferment**	**IC2**	**Start of article**	**End of analysis**
Highly material technologies	**Smart TV**	1980-2010	2011-2019		Aug 2, 2010	Dec 31, 2017
	Laptop	2003-2004	2005-2012	2013-2019	Mar 19, 2003	Dec 31, 2017
	Wired Glove	2005-2011	2012-2016	2017-2019	Sep 15, 2005	Dec 31, 2017
	Industrial robots	2002-2011	2012-2019		Nov 16, 2002	Dec 31, 2017
	Digital camera	1980-1994	1995-2003	2004-2019	May 21, 2002	Dec 31, 2017
Highly nonmaterial technologies	**Internet of things**	2007-2012	2013-2018		Jul 2, 2007	Dec 31, 2017
	Operating system	2001-2007	2008-2013	2014-2019	Nov 15, 2001	Dec 31, 2017
	Virtual reality	2001-2012	2013-2015	2016-2019	Oct 3, 2001	Dec 31, 2017
	Machine learning	2003-2010	2011-2019		May 25, 2003	Dec 31, 2017
	3D printing	2004-2010	2011-2019		Dec 21, 2004	Dec 31, 2017

Note: Highlighted cells were not used for analysis due to a lack of or insufficient corresponding Wikipedia data.

Appendix C: Lifecycle Analysis Graphs

Figures D6, D7, and D8 show discursive characteristics for highly material and nonmaterial technologies across their respective first era of incremental change (Figure D6), era of ferment (Figure D7), and second era of incremental change (Figure D8).

For each technology, we examined a period of the last five years of their first era of incremental change leading up to the era of ferment. We focused on these five years because in most cases there were only a small number of publications in previous years (see Figures D3 and D4 above). For each relevant technology, we examined a period of the first four years of their second era of incremental change to capture discursive characteristics.

The graphs in the first and second eras of incremental change do not show all 10 technologies. As explained above, the reason some technologies are missing is that their Wikipedia articles did not exist for the duration of this era. For example, IoT, ML, and 3D printing are missing from the nonmaterial graphs during the second era of incremental change because their ferment era extended until 2019 (see Figure D4), which is beyond the end point of our analysis. In other words, their second era of incremental change has not yet begun when we conducted our analysis.

Due to the uneven duration of the era of ferment for technologies within each level of materiality, and because we wanted to capture the discourse during this entire era, we conducted a linear interpolation to fill in missing data values between each two known data points. To do so, we equalized the duration of the era of ferment by "stretching out" eras to the nearest common denominator. For example, for highly material technologies, the era of ferment lasted five years for Smart TV, eight years for Laptop, five years for Wired glove, and eight years for Industrial robot. We therefore stretched out all four eras to 40 years. We then filled in the missing values by inserting the average of each two known adjacent data points (Figure D5).

Time period	Smart TV	Laptop	WG	Ind rob
1	0.91	0.78	0.99	0.98
2	0.93	0.70	0.99	0.98
3	0.93	0.70	0.99	0.98
4	0.93	0.70	0.99	0.98
5	0.93	0.70	0.99	0.98
6	0.93	0.62	0.99	0.97
7	0.93	0.66	0.99	0.95
8	0.93	0.66	0.99	0.95
9	0.94	0.66	0.99	0.95
10	0.93	0.66	0.99	0.95
11	0.93	0.70	0.99	0.93
12	0.93	0.68	0.99	0.97
13	0.93	0.68	0.99	0.97
14	0.93	0.68	0.99	0.97
15	0.93	0.68	0.99	0.97
16	0.93	0.65	0.99	1.00
17	0.92	0.74	0.99	0.95
18	0.95	0.74	0.99	0.95
19	0.95	0.74	0.99	0.95
20	0.95	0.74	0.99	0.95
21	0.95	0.82	0.99	0.90
22	0.95	0.81	0.99	0.99
23	0.95	0.81	0.99	0.99
24	0.95	0.81	0.99	0.99
25	0.98	0.81	0.99	0.99
26	0.99	0.80	0.99	0.98
27	0.99	0.90	0.99	0.98
28	0.99	0.90	0.99	0.98
29	0.99	0.90	0.99	0.98
30	0.99	0.90	0.99	0.98
31	0.99	0.99	0.99	0.97
32	0.99	0.90	0.99	0.97
33	0.99	0.90	0.99	0.97
34	0.99	0.90	0.99	0.97
35	0.99	0.90	0.99	0.97
36	0.99	0.80	0.99	0.96
37	0.99	0.80	0.99	0.96
38	0.99	0.80	0.99	0.96
39	0.99	0.80	0.99	0.96
40	0.99	0.80	0.99	0.96

Note: Known values are shown in blue, inserted values in white.

Figure C1. Linear Interpolation of Average Anchor Strength Values for Highly Material Technologies during Their Era of Ferment

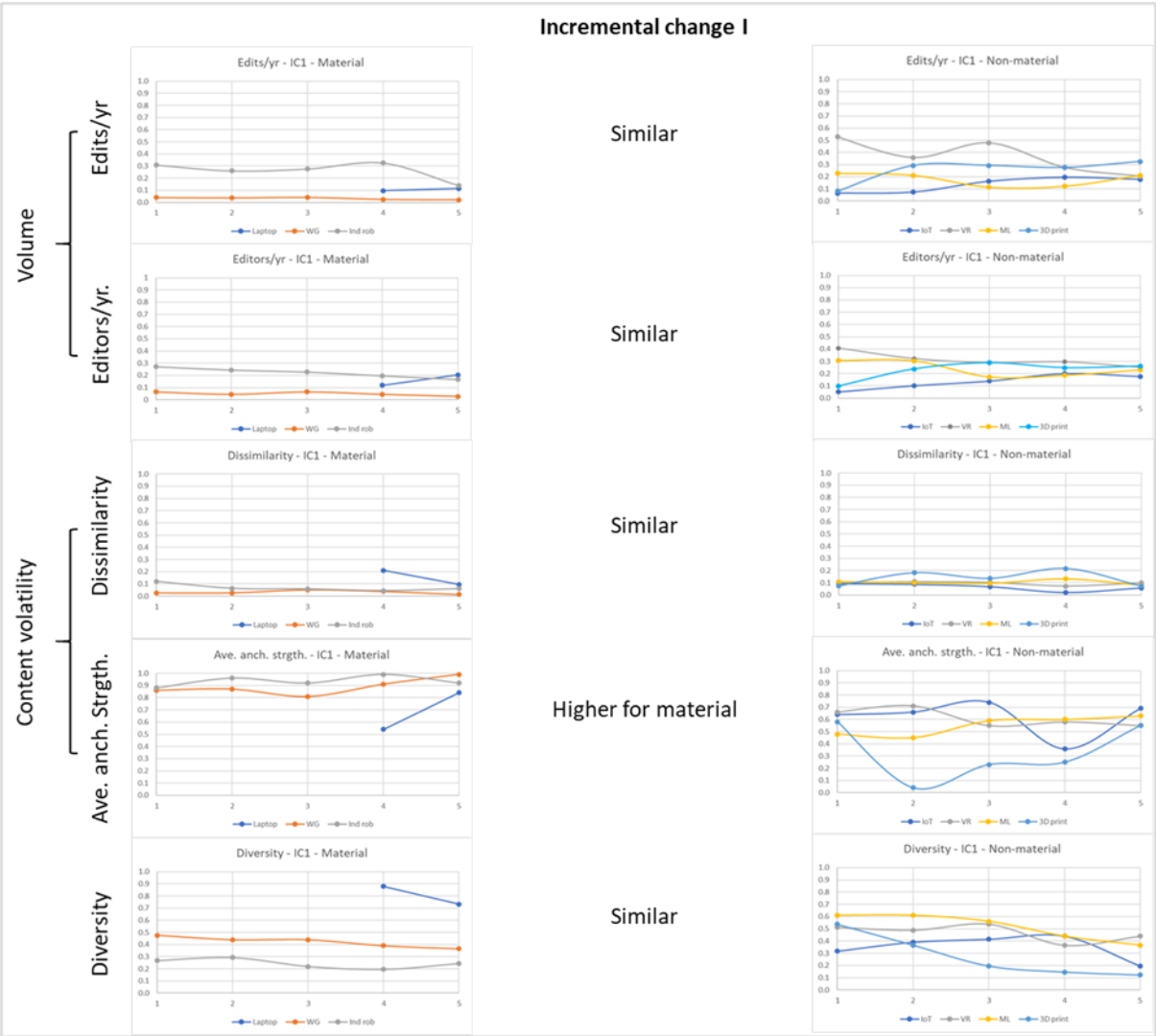

Figure C2. Normalized Discursive Characteristics (volume, volatility, and diversity) for Highly Material (left) and Highly Nonmaterial Technologies (right) during the Initial Era of Incremental Change

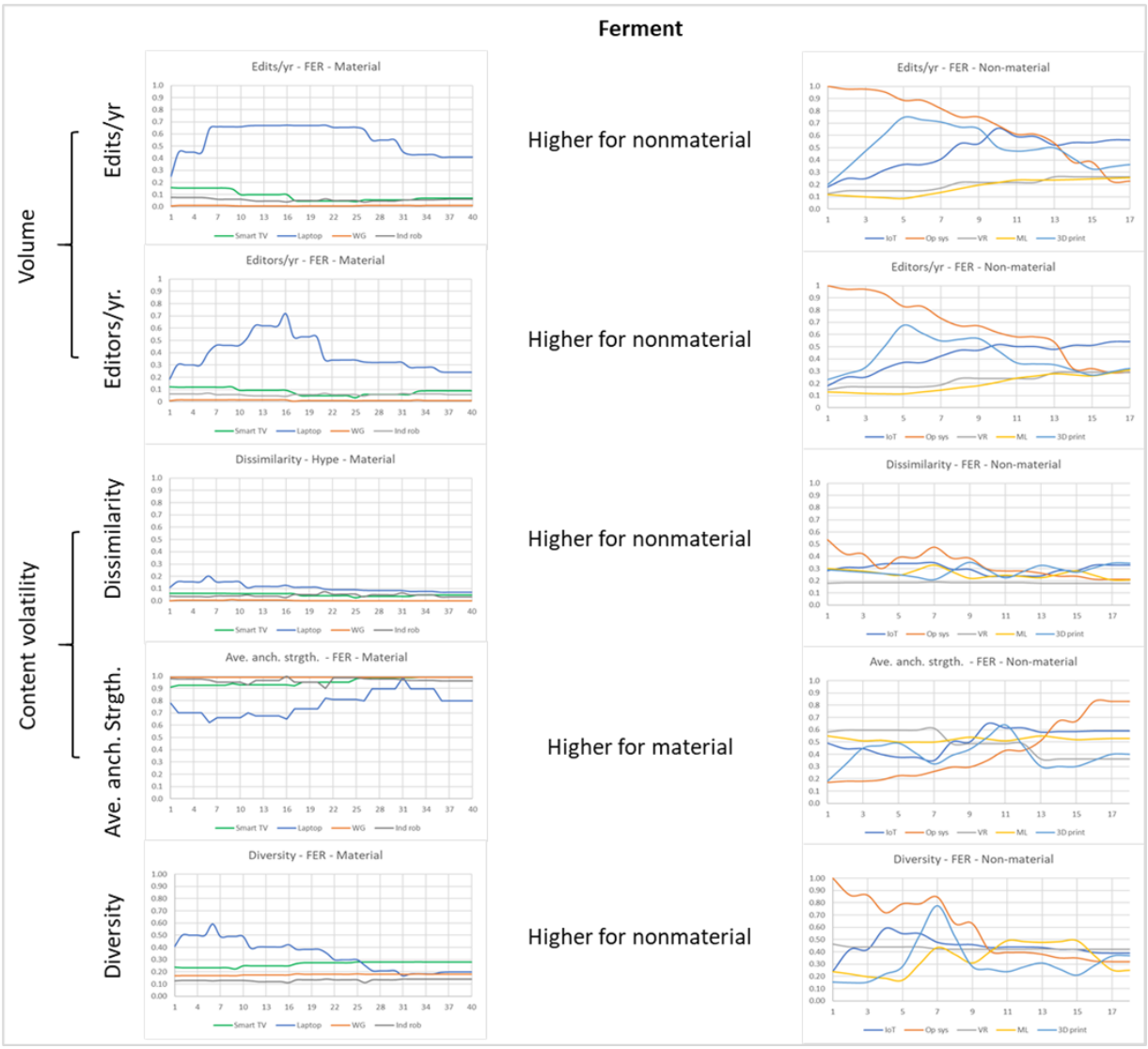

Figure C3. Normalized Discursive Characteristics (volume, volatility, and diversity) for Highly Material (left) and Highly Nonmaterial Technologies (right) during the Era of Ferment

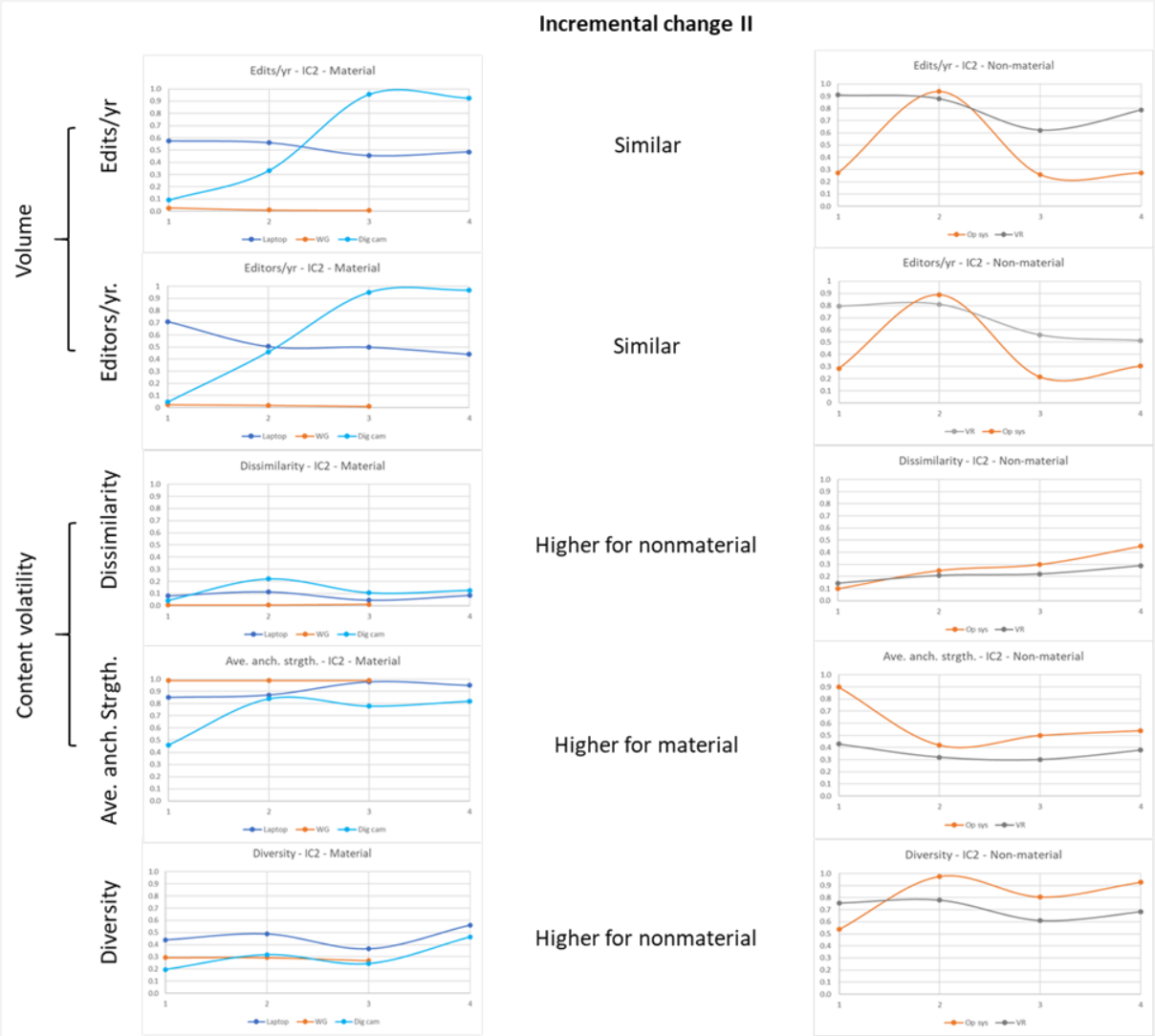

Figure C4. Normalized Discursive Characteristics (volume, volatility, and diversity) for Highly Material (left) and Highly Nonmaterial Technologies (right) during the Second Era of Incremental Change

Appendix D: Discursive Characteristics for Highly Material and Highly Nonmaterial Technologies

Highly Material Artifacts: Laptop, Wired Glove, Industrial Robots, Digital Camera

The laptop is a small, portable, personal computer. Typically containing encased LCD or LED display and keyboard, laptops are meant to capture the core capabilities of a desktop computer and make them available for people on the move. The first laptops were developed in the early 1980s and within the following decade stabilized around the dominant von Neumann architecture (memory, CPU, display, etc.), but in a single-bodied profile. The Wikipedia article "Laptop" was created on March 19, 2003. During the time frame of our analysis, the article was edited 7148 times by 3720 editors, who used 123 anchors during this time.

Wired gloves are an input device for human-computer interaction that is worn like a regular glove.[19] They are equipped with sensors that are capable of measuring joints angles, pressure, tracking and haptic feedback. The wired glove was patented in 1982 and an early version was released to the market towards the end of this decade. Further, and more advanced gloves were developed and commercialized in subsequent years.[20] The Wikipedia article "Wired Glove" was created on September 15, 2005. During the time frame of our analysis, the article was edited 286 times by 226 editors who used 35 anchors.

Industrial robots are automatically controlled, reprogrammable, mechanical devices that operate in three or more axes, which can be either fixed in place or mobile for use in automation applications.[21] They are used across a range of industries to automate processes, reduce production costs, and enhance productivity, often by utilizing machine-learning capabilities. For instance, robotic surgery systems, powered by image-recognition algorithms, enhance the manual dexterity and accuracy of instrument manipulation to support the work of surgeons. Industrial robots were commercially introduced in the 1970s and have gradually gained prominence. The Wikipedia article "Industrial Robots" was created on November 16, 2002. During the time frame of our analysis, the article was edited 1509 times by 628 editors, who used 45 anchors.

The digital camera is a category of cameras that stores photos in digital memory. It is distinguished from film camera which captures and stores images on a physical celluloid film. The first digital cameras were developed in the mid-1970s, released to market in the late 1970s, and became widely commercialized in the late 1990s. The core architecture of the digital camera involving the analog front end (camera, mosaic filter, and image sensor) and the digital back end (digital converter, image processing, buffer, and digital storage), has remained mostly stable throughout the time of the study. The Wikipedia article "Digital Camera" was created on May 21, 2002. However, the article remained mostly dormant until the end of 2004 (as can be seen from the number of edits and editors in Figure C3) and the anchoring process only started in November 2004, when the first anchors were introduced into the article. During the time frame of our analysis, the article was edited 3557 times by 1731 editors, who used 64 anchors.

As can be seen in figures D1-D4, anchoring activity in these four articles displays similar patterns to those observed in the "Smart TV" article. Most significantly, after an initial period of relatively high values, the anchor dissimilarity scores drop and remain fairly low. Additionally, the average anchor strength in all three articles climbs steadily towards the 0.9-1.0 range. Finally, the "Laptop," "Wired Glove," and "Industrial Robots" articles show a general downward trend in the removal and addition of anchors. While the "Digital Camera" article does not strictly follow the same pattern, the mere number of added and removed anchors is very low throughout the lifespan of the article. Consequently, it is difficult to establish any substantive variance over time periods.

[19] https://en.wikipedia.org/ wiki/Wired_glove. Retrieved December 11, 2019.
[20] https://pdfs.semanticscholar.org/3416/9a33e0666bb82fbe927f5d6020e2f28bef96.pdf
[21] http://aei.pitt.edu/93803/1/Working-Paper-AB_25042018.pdf

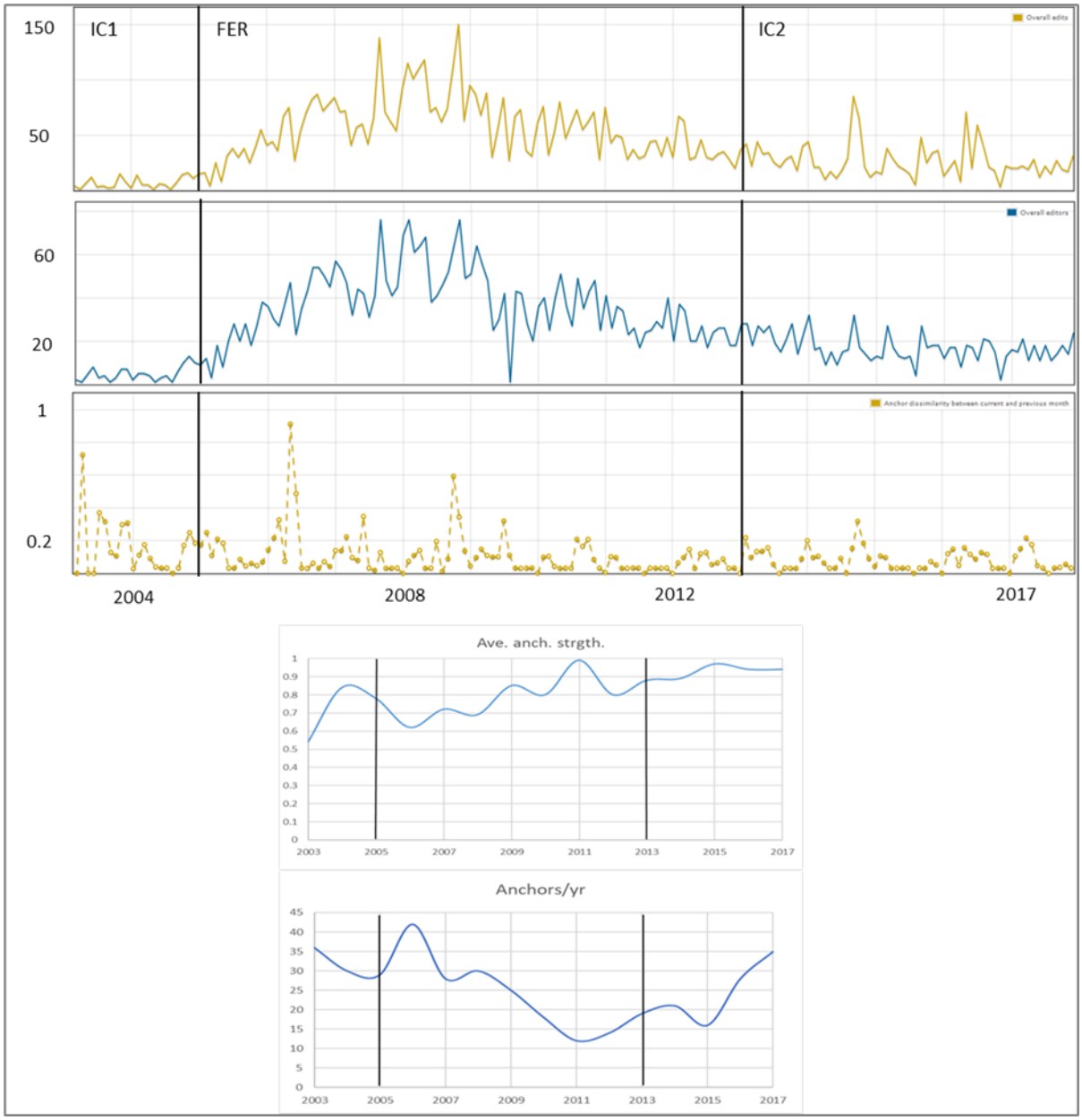

Figure D1. Number of Edits and Editors (volume), Anchor Dissimilarity and Average Anchor Strength (volatility), and Unique Anchors Per Year (diversity) for the Article "Laptop"

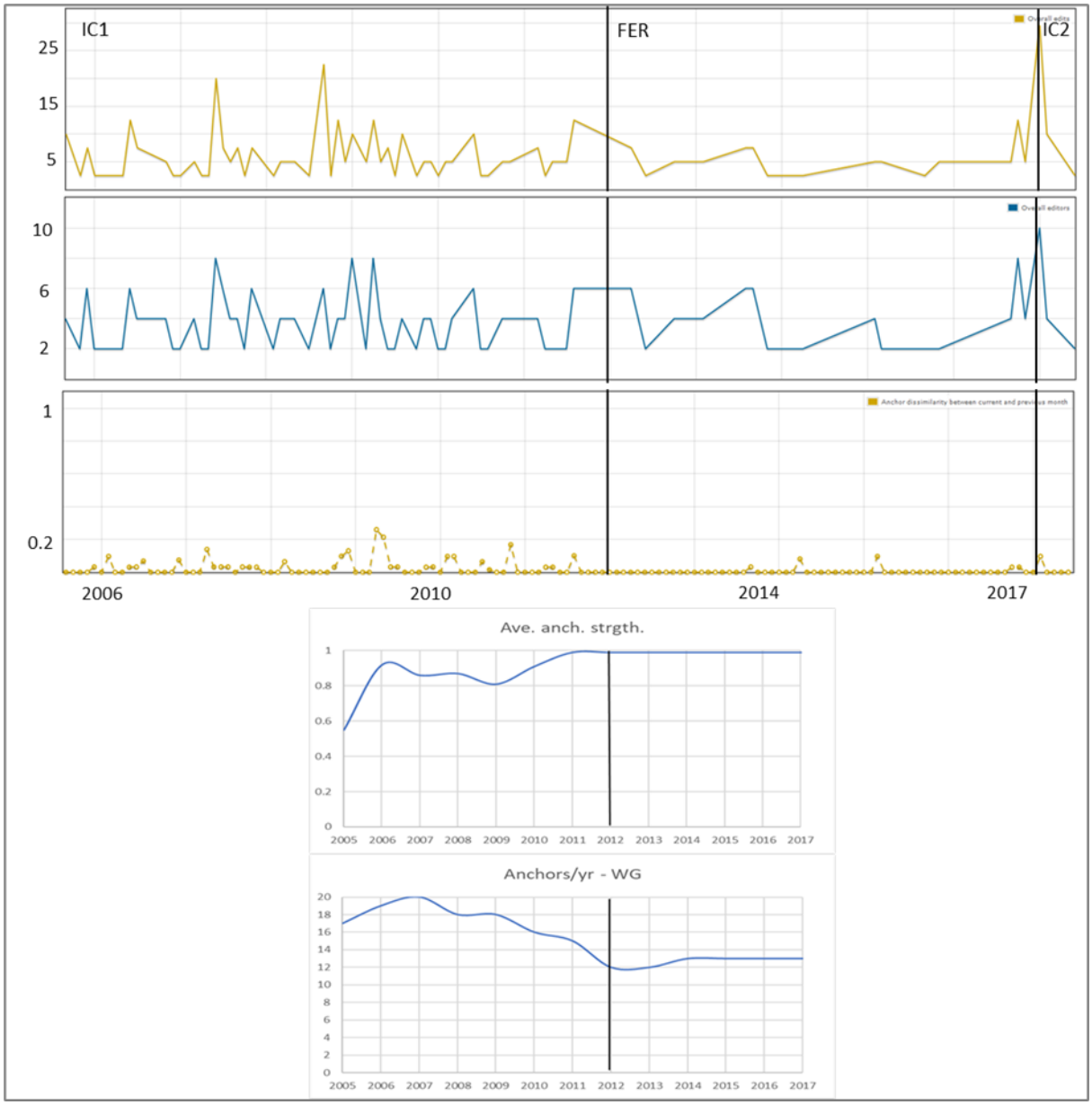

Figure D2. Number of Edits and Editors (volume), Anchor Dissimilarity and Average Anchor Strength (volatility), and Unique Anchors Per Year (diversity) for the Article "Wired Glove"

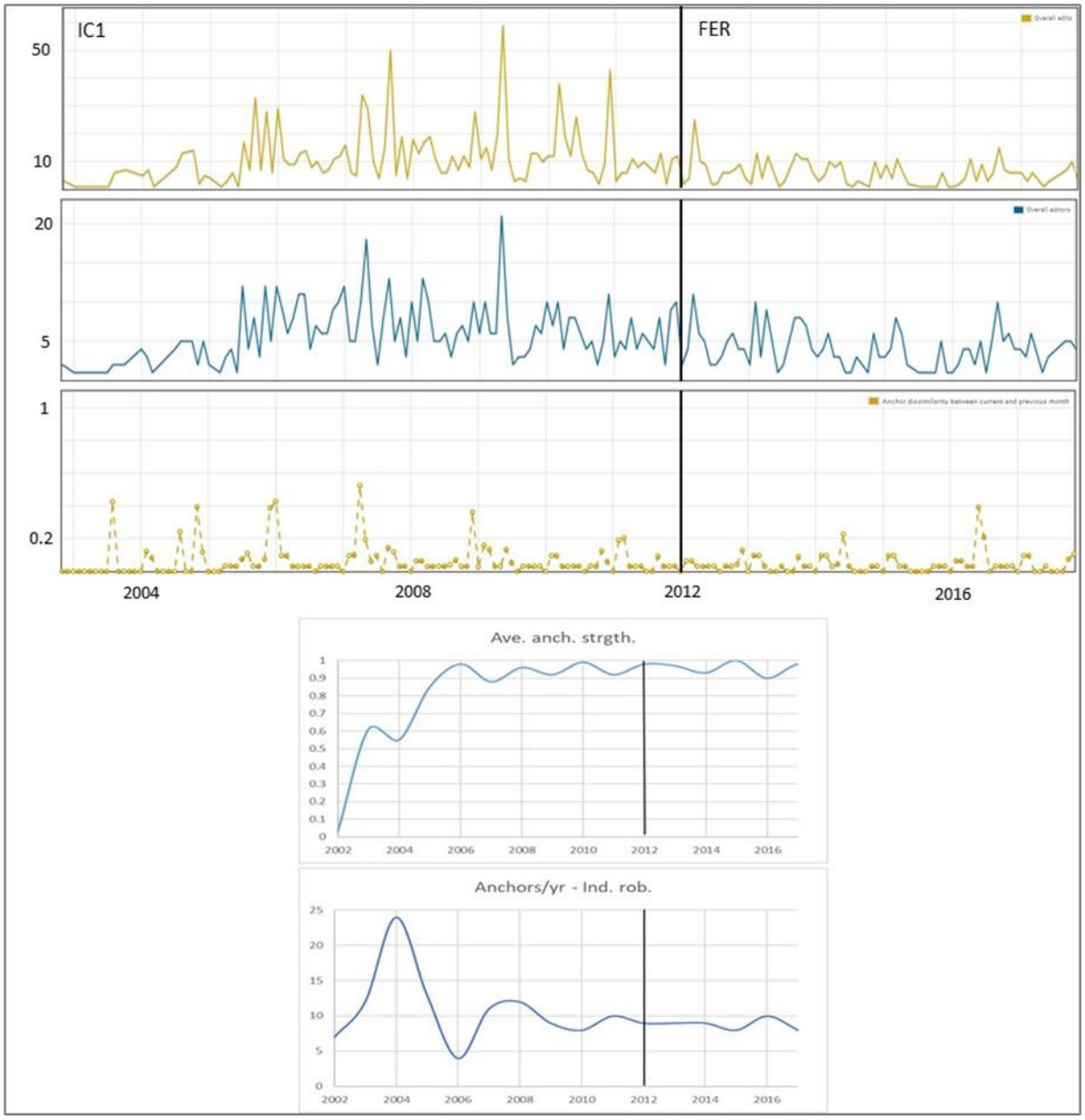

Figure D3. Number of Edits and Editors (volume), Anchor Dissimilarity and Average Anchor Strength (volatility), and Unique Anchors Per Year (diversity) for the Article "Industrial Robots"

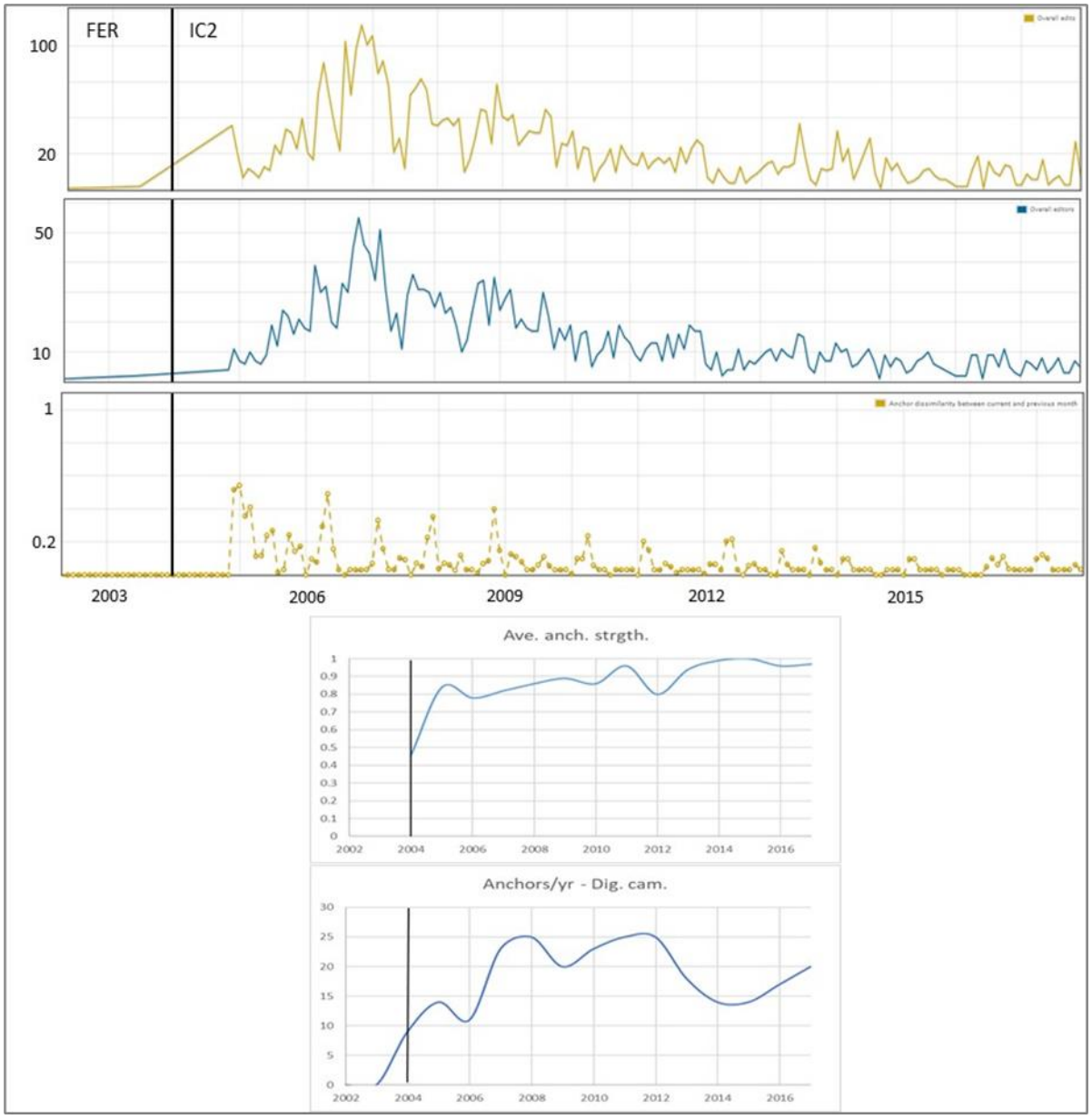

Figure D4. Number of Edits and Editors (volume), Anchor Dissimilarity and Average Anchor Strength (volatility), and Unique Anchors Per Year (Diversity) for the Article "Digital Camera"

Highly Nonmaterial Technologies: Operating System, Virtual Reality, Machine Learning, 3D Printing

An operating system is software that runs on a computer and manages its memory, processes, and other software. The operating system allows users to manage the different applications running on a computer and provides them with a standard user interface.[22] The first operating system was developed in the early 1950s by General Motors to support the operation of mainframe computers and further developments were achieved in subsequent years to develop operating systems for personal computers. The Wikipedia article "Operating System" was created on November 15, 2001. During the time frame of our analysis, it was edited 8280 times by 4084 editors who used 320 anchors.

Virtual reality (VR) is a technology platform that allows its users to experience computer-simulated worlds. This experience is delivered through a head-mounted display unit and wired clothing. Early versions of VR were created through the 1960s and 1970s. The actual term "virtual reality" was coined by Jaron Lanier in the 1980s, and VR became

[22] https://www.open.edu/openlearn/science-maths-technology/computing-ict/introducing-ict-systems/content-section-11.6

commercially widely available during the 1990s. The Wikipedia article "Virtual Reality" was created on October 3, 2001. During the time frame of our analysis, the article was edited 4314 times by 2077 editors who used 154 anchors.

Machine learning is a computing methodology that involves the application of algorithms to data. By analyzing large datasets, machine learning enables systems to extract insights, train, and refine their knowledge without being explicitly programmed to do so. Early applications of machine learning were developed as far back as the 1950s through the work of Alan Turing, Marvin Minsky, and IBM. The core process architecture of machine learning algorithms has stabilized during the 1990s around distinctions between supervised and unsupervised processes which both require learning datasets, feature extraction techniques, modeling approaches, and evaluation criteria (Hinton & Sejnowski, 1999). The Wikipedia article "Machine Learning" was created on May 25, 2003. During the time frame of our analysis, the article was edited 1920 times by 1048 editors who used 123 anchors.

3D printing refers to an "automated additive manufacturing process in which three-dimensional objects are created by laying down successive layers of material."[23] The process starts with the creation of a computerized 3D model. The model is then sent to a 3D printer which breaks it down into successive layers that are then applied on top of each other to create the desired object. Advances in 3D printing technology were made during the 1980s and 3D printers became commercially available in the 1990s, primarily for industrial manufacturing.[24] The Wikipedia article "3D Printing" was created on December 21, 2004. During the time frame of our analysis, it was edited 4604 times by 1927 editors who used 130 anchors.

As can be seen in figures D5-30, the anchoring activity in these four articles displays similar patterns to those observed in the "Internet of Things" article. In particular, the meaning of each of the technologies was negotiated throughout the lifespan of their corresponding articles and editors never seem to have reached a consensus on how to interpret them. This is evident in the dissimilarity scores that continue to fluctuate throughout the articles' lifespans, at times approaching the 1.0 mark, indicating a profound shift in the way an article is anchored and made sense of. The lack of stability in meaning is also apparent in the low average anchor strength scores and in the ongoing removal and addition of anchors.

[23] http://digitalcommons.calpoly.edu/cgi/viewcontent.cgi?article=1090&context=cmsp
[24] http://digitalcommons.calpoly.edu/cgi/viewcontent.cgi?article=1090&context=cmsp

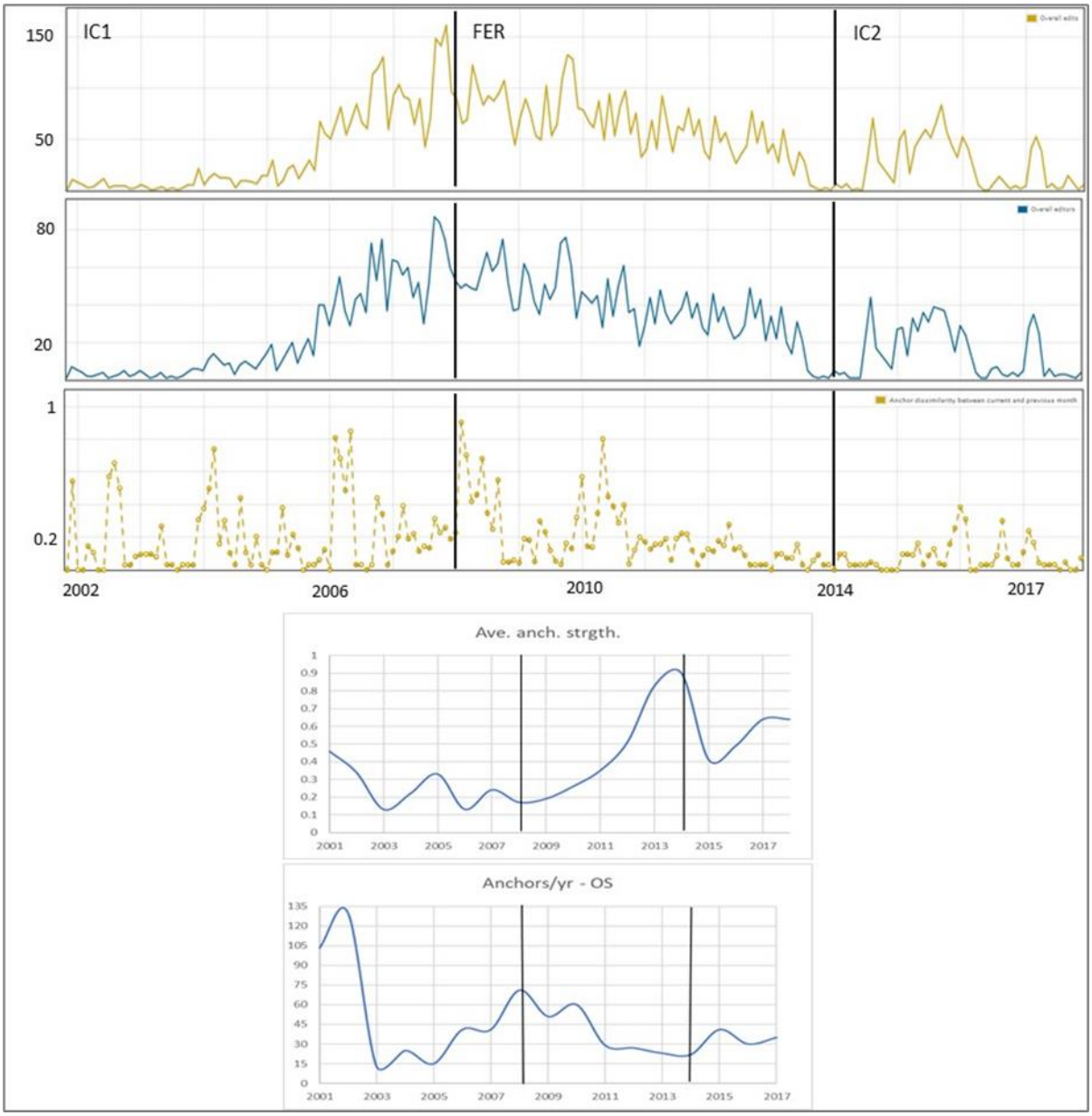

Figure D5. Number of Edits and Editors (volume), Anchor Dissimilarity and Average Anchor Strength (volatility), and Unique Anchors Per Year (diversity) for the Article "Operating System"

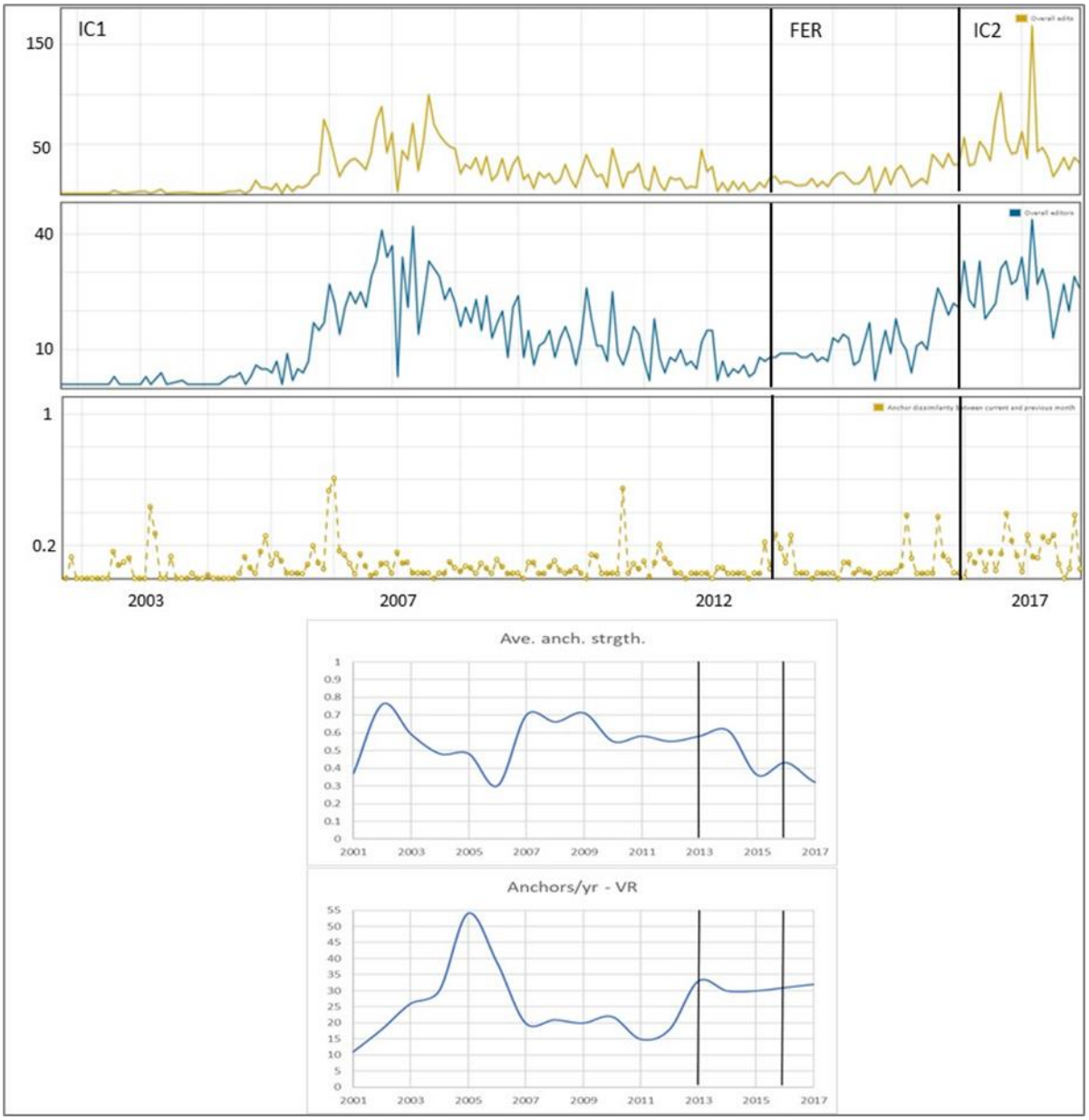

Figure D6. Number of Edits and Editors (volume), Anchor Dissimilarity and Average Anchor Strength (volatility), and Unique Anchors Per Year (diversity) for the Article "Virtual Reality"

Figure D7. Number of Edits and Editors (volume), Anchor Dissimilarity and Average Anchor Strength (volatility), and Unique Anchors Per Year (diversity) for the Article "Machine Learning"

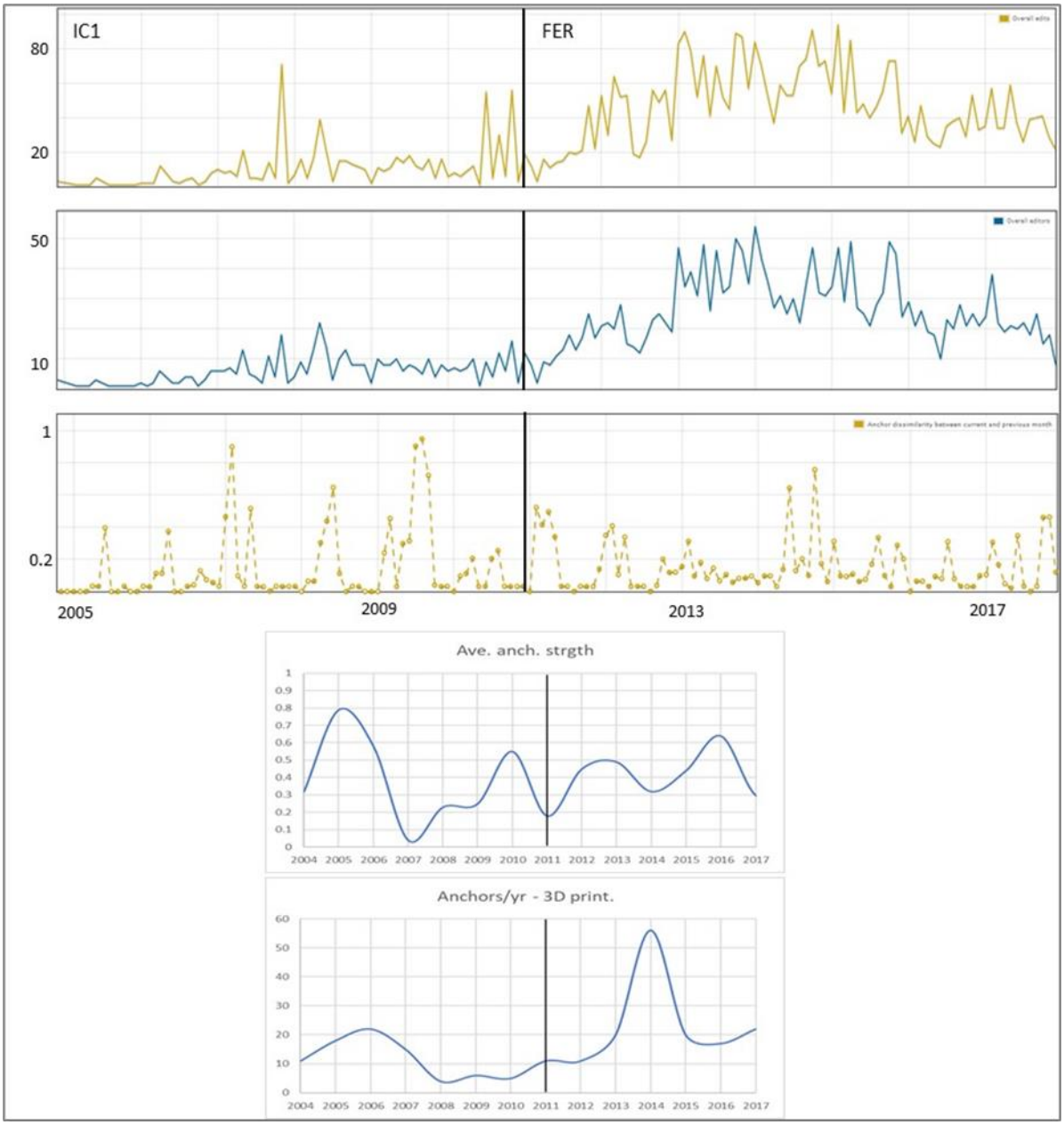

Figure D8. Number of Edits and Editors (volume), Anchor Dissimilarity and Average Anchor Strength (volatility), and Unique Anchors per Year (diversity) for the Article "3D Printing"

Appendix E: T-Tests Across Levels of Materiality Over Three Lifecycle Eras[25]

IC1

Edits - IC1		
t-Test: Two-Sample Assuming Equal Variances		
	Material	*Non-material*
Mean	0.133	0.245
Variance	0.014	0.025
Observations	3.000	4.000
Pooled Variance	0.021	
Hypothesized Mean Difference	0.000	
df	5.000	
t Stat	-1.016	
P(T<=t) one-tail	0.178	
t Critical one-tail	2.015	
P(T<=t) two-tail	0.356	
t Critical two-tail	2.571	

Editors - IC1		
t-Test: Two-Sample Assuming Equal Variances		
	Material	*Non-material*
Mean	0.144	0.228
Variance	0.008	0.005
Observations	3.000	4.000
Pooled Variance	0.006	
Hypothesized Mean Difference	0.000	
df	5.000	
t Stat	-1.397	
P(T<=t) one-tail	0.111	
t Critical one-tail	2.015	
P(T<=t) two-tail	0.221	
t Critical two-tail	2.571	

Diss - IC1		
t-Test: Two-Sample Assuming Equal Variances		
	material	*non-material*
Mean	0.084	0.095
Variance	0.004	0.001
Observations	3.000	4.000
Pooled Variance	0.002	
Hypothesized Mean Difference	0.000	
df	5.000	
t Stat	-0.333	
P(T<=t) one-tail	0.376	
t Critical one-tail	2.015	
P(T<=t) two-tail	0.752	
t Critical two-tail	2.571	

Ave. anch. strgh. - IC1		
t-Test: Two-Sample Assuming Equal Variances		
	Material	*Non-material*
Mean	0.768	0.514
Variance	0.006	0.008
Observations	3.000	4.000
Pooled Variance	0.007	
Hypothesized Mean Difference	0.000	
df	5.000	
t Stat	3.981	
P(T<=t) one-tail	0.005	
t Critical one-tail	2.015	
P(T<=t) two-tail	0.011	
t Critical two-tail	2.571	

Diversity - IC1		
t-Test: Two-Sample Assuming Equal Variances		
	Material	*Non-material*
Mean	0.490	0.402
Variance	0.082	0.012
Observations	3.000	4.000
Pooled Variance	0.040	
Hypothesized Mean Difference	0.000	
df	5.000	
t Stat	0.573	
P(T<=t) one-tail	0.296	
t Critical one-tail	2.015	
P(T<=t) two-tail	0.591	
t Critical two-tail	2.571	

[25] *P*-values (highlighted) above 0.05 indicate averages across levels of materiality are not significantly different; *p*-values below 0.05 indicate that averages across levels of materiality are significantly different.

Ferment

Edits - Ferment		
t-Test: Two-Sample Assuming Equal Variances		
	Material	*Non-material*
Mean	0.151	0.419
Variance	0.045	0.037
Observations	4.000	5.000
Pooled Variance	0.040	
Hypothesized Mean Difference	0.000	
df	7.000	
t Stat	-1.989	
P(T<=t) one-tail	0.044	
t Critical one-tail	1.895	
P(T<=t) two-tail	0.087	
t Critical two-tail	2.365	

Editors - Ferment		
t-Test: Two-Sample Assuming Equal Variances		
	Material	*Non-material*
Mean	0.135	0.381
Variance	0.029	0.031
Observations	4.000	5.000
Pooled Variance	0.030	
Hypothesized Mean Difference	0.000	
df	7.000	
t Stat	-2.123	
P(T<=t) one-tail	0.036	
t Critical one-tail	1.895	
P(T<=t) two-tail	0.071	
t Critical two-tail	2.365	

Diss - Ferment		
t-Test: Two-Sample Assuming Equal Variances		
	Material	*Non-material*
Mean	0.051	0.120
Variance	0.002	0.003
Observations	4.000	5.000
Pooled Variance	0.003	
Hypothesized Mean Difference	0.000	
df	7.000	
t Stat	-2.031	
P(T<=t) one-tail	0.041	
t Critical one-tail	1.895	
P(T<=t) two-tail	0.082	
t Critical two-tail	2.365	

Ave. anch. strgth. - Ferment		
t-Test: Two-Sample Assuming Equal Variances		
	Material	*Non-material*
Mean	0.920	0.469
Variance	0.010	0.003
Observations	4.000	5.000
Pooled Variance	0.006	
Hypothesized Mean Difference	0.000	
df	7.000	
t Stat	8.572	
P(T<=t) one-tail	0.000	
t Critical one-tail	1.895	
P(T<=t) two-tail	0.000	
t Critical two-tail	2.365	

Diversity - Ferment		
t-Test: Two-Sample Assuming Equal Variances		
	Material	*Non-material*
Mean	0.227	0.420
Variance	0.008	0.010
Observations	4.000	5.000
Pooled Variance	0.010	
Hypothesized Mean Difference	0.000	
df	7.000	
t Stat	-2.941	
P(T<=t) one-tail	0.011	
t Critical one-tail	1.895	
P(T<=t) two-tail	0.022	
t Critical two-tail	2.365	

IC2

Edits- IC2		
t-Test: Two-Sample Assuming Equal Variances		
	Material	*Non-material*
Mean	0.275	0.550
Variance	0.054	0.124
Observations	3.000	2.000
Pooled Variance	0.077	
Hypothesized Mean Difference	0.000	
df	3.000	
t Stat	-1.086	
P(T<=t) one-tail	0.179	
t Critical one-tail	2.353	
P(T<=t) two-tail	0.357	
t Critical two-tail	3.182	

Editors - IC2		
t-Test: Two-Sample Assuming Equal Variances		
	Material	*Non-material*
Mean	0.387	0.546
Variance	0.104	0.030
Observations	3.000	2.000
Pooled Variance	0.079	
Hypothesized Mean Difference	0.000	
df	3.000	
t Stat	-0.619	
P(T<=t) one-tail	0.290	
t Critical one-tail	2.353	
P(T<=t) two-tail	0.580	
t Critical two-tail	3.182	

Diss - IC2		
t-Test: Two-Sample Assuming Equal Variances		
	material	*non-mat*
Mean	0.050	0.217
Variance	0.001	0.000
Observations	3.000	2.000
Pooled Variance	0.001	
Hypothesized Mean Difference	0.000	
df	3.000	
t Stat	-5.966	
P(T<=t) one-tail	0.005	
t Critical one-tail	2.353	
P(T<=t) two-tail	0.009	
t Critical two-tail	3.182	

Ave. anch. strgth. - IC2		
t-Test: Two-Sample Assuming Equal Variances		
	Material	*Non-material*
Mean	0.933	0.474
Variance	0.003	0.027
Observations	3.000	2.000
Pooled Variance	0.011	
Hypothesized Mean Difference	0.000	
df	3.000	
t Stat	4.779	
P(T<=t) one-tail	0.009	
t Critical one-tail	2.353	
P(T<=t) two-tail	0.017	
t Critical two-tail	3.182	

Diversity - IC2		
t-Test: Two-Sample Assuming Equal Variances		
	Material	*Non-material*
Mean	0.351	0.756
Variance	0.010	0.005
Observations	3.000	2.000
Pooled Variance	0.008	
Hypothesized Mean Difference	0.000	
df	3.000	
t Stat	-4.968	
P(T<=t) one-tail	0.008	
t Critical one-tail	2.353	
P(T<=t) two-tail	0.016	
t Critical two-tail	3.182	

About the Authors

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