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# Mainstream Formation and Competitive Dynamics in the Computer Graphics Industry: Topic modeling analysis of US patents*

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Abstract

This study conducts a quantitative analysis of the relationship between mainstream formation and competition in technological fields. The process of determining the dominant design is crucial in analyzing mainstream formation within specific technological fields, and numerous studies have explored this process. The quantitative analysis conducted in this study indicates that, during the process in which the dominant design is determined, the dominant category, a broader framework than the dominant design, is also established. In this study, we use topic modeling analysis to examine the relationship between the convergence of research and development (R&D) trends among organizations and the number of organizations publishing patents in the computer graphics processing systems industry. Specifically, the number of organizations publishing patents in the industry increased when the degree of convergence among the R&D trends of each organization was relatively low, whereas it decreased when the degree of convergence among R&D trends of each organization was relatively high. Further, the change in the degree of convergence occurred before the change in the number of organizations. These observations suggest that the formation of a mainstream within the industry, which is associated with the convergence of R&D tendencies of specific organizations, affects the competitive environment within the industry.

Keywords: Technological Trajectory, Technology Life Cycle, Industry Life Cycle, Dominant Design, Dominant Category, Patent
JEL classification: L10, L16, O31, O32



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# 1. Introduction

This paper seeks to conduct a quantitative analysis of the relationship between mainstream formation and competition in the market in the technological field. In particular, this study focuses on the determination of the dominant design, a key phenomenon in mainstream formation. In this study, we hypothesize that a broader shared framework than the dominant design may be established before the determination of the dominant design in the technological field, and subject this hypothesis to quantitative analysis. Additionally, this shared framework is examined using the dominant category concept proposed by Suarez et al. (2015). Finally, the study analyzes the relationship between this phenomenon and competition within the technological field.

Previously, discussions on mainstream formation in a technological field have used the concept of technological trajectories (Dosi, 1982). In technological fields, development paths are determined by the chosen technological paradigm, which is established during the field's initial phase. The selection of this paradigm constrains the progress of technological advancement. Dosi (1982) referred to this development process as the "technological trajectory." Moreover, in quantitative investigations into technological trajectories, a number of studies use patent citation network data and conduct main path analysis (Verspagen,2007; Fontana et al., 2009; and Martinelli, 2012). The author has conducted quantitatively analyses of the factors of mainstream formation in the technological field using these methods (Watanabe and Takagi, 2021; Watanabe and Takagi, 2022a; Watanabe and Takagi, 2022b). However, main path analysis focuses on a small subset of patents that exist on the main paths within the entire technological field. While this is an advantage of the method as it extracts only the important aspects of the technological field, it carries the risk of overlooking the field's overall trends as significant portions of the field may be excluded from the analysis. In this study, we employ a machine learning-based natural language processing method called topic modeling analysis to examine patent data, enabling us to visualize the temporal changes in the technological topics that are discussed within the entire technological field. This allows for a nuanced representation of mainstream formation within a technological field. Compared to main path analysis, this method can visualize trends in the entire technological field by analyzing all patents in the field. In particular, topic modeling enables us to analyze the relationship between mainstream formation and research and development (R&D) strategies of all organizations in the field.

This study focuses on the field of computer graphics processing systems. Many manufacturers employ computer-aided design software for product design, necessitating the use of graphics processing units (GPUs). The advancement of computer graphics processing systems is crucial for enhancing productivity in the manufacturing industry. Furthermore, modern supercomputers, autonomous vehicles, robotic systems, and intelligent cameras all rely on GPUs (Dally et al., 2021). Hence, examining the development of computer graphics processing systems is especially pertinent.

## 2. Literature Review

In this study, we conduct a quantitative analysis of the relationship between mainstream formation and competition in technological fields. Therefore, this chapter reviews existing research on two topics, “mainstream formation within a technological field” and “mainstream formation and competition environment.”

### 2.1. Mainstream Formation Within a Technological Field

As previously mentioned, the concept of technological trajectories (Dosi, 1982) has been a key framework for understanding mainstream formation in technological fields. The evolution of technology begins with an initial breakthrough, which sets the course for subsequent incremental improvements. As a result, technological progress is an accumulative process. Dosi (1982) depicted this progression, encompassing initial breakthroughs and incremental advancements, through two key concepts: “technological paradigm” and “technological trajectory.” In technological fields, development paths are constrained by the technological paradigm that is established at the beginning. Future technological advancements must align with this paradigm. Dosi (1982) coined the term “technological trajectory” to describe this paradigm-dependent process and argued that technological development is a selective process where numerous potential development directions exist but only a small subset among these potential directions are realized (Verspagen, 2007). Thus, Dosi (1982) qualitatively described the developmental pathways of technology. These realized development paths, or technological trajectories, are similar to the mainstream within a technological field. Technological trajectories have been widely employed in the field of technological evolution. Since Dosi (1982), researchers have predominantly used qualitative methods, such as case studies, to analyze technological evolution and trajectories (Vincenti, 1994; Possas et al., 1996). In contrast, Verspagen (2007) made a significant contribution to the field by introducing a quantitative approach to identify technological trajectories using citation network datasets. Verspagen (2007) employed main path analysis, originally proposed by Hummon and Doreian (1989), to describe technological trajectories as citation networks. Following Verspagen’s (2007) work, some studies employed main path analysis to identify technological trajectories in several technological fields such as data communication (Fontana et al., 2009) and telecom switching (Martinelli, 2012). Additionally, in recent years, topic modeling analysis of patent documents has emerged as a growing trend as a quantitative methodology to identify technology trajectories (Suominen, 2017; Sun et al., 2021).

## 2.2. Mainstream Formation and the Competition Environment

As implied by the concept of technological paradigms and the formation of technological trajectories, the competitive environment within a market for a particular technology undergoes significant changes with the emergence of a framework for R&D. The technology life cycle represents this framework as the dominant design and encapsulates how the market environment evolves before and after its emergence.

The technology life cycle has four stages (Anderson and Tushman, 1990; Tushman and Rosenkopf, 1992): technological discontinuity (Kaplan and Tripsas, 2008), ferment (variation), dominant design (selection), and incremental change (retention). Here, technological discontinuity leads to a new era of ferment. Therefore, technology life cycles begin with technological discontinuity or the emergence of a disruptive invention (Taylor and Taylor, 2012), which creates a new technological field. These technologies are referred to as revolutionary, discontinuous, radical, emergent, or step-function technologies (Yu and Hang, 2010). Following such discontinuities, the technology undergoes a period of ferment, during which a dominant design is chosen through competition among the versions of the initial breakthrough (Abernathy and Utterback, 1978). In this stage, the market and the technology are still in their early stages of development; therefore, the ferment period is characterized by intense instability and uncertainty (Kaplan and Tripsas, 2008). The final phase of the cycle is the period of incremental change following the emergence of the dominant design. During this period, there is a gradual evolution of the dominant design that was selected as the dominant configuration following the period of ferment (Taylor and Taylor, 2012). Competition changes because of the emergence of a dominant design (Murmann and Frenken, 2006). During the era of incremental change, further technological advancements are steadily implemented, resulting in improved performance across a stable set of consumer preferences (Kaplan and Tripsas, 2008); these developments are referred to as evolutionary, continuous, gradual, or as “nuts and bolts” technologies (Yu and Hang, 2010). This period of stability is finally disrupted by technological change, which ushers in a new age of ferment (Tushman and Anderson, 1986). Figure 1 summarizes the technology life cycle.

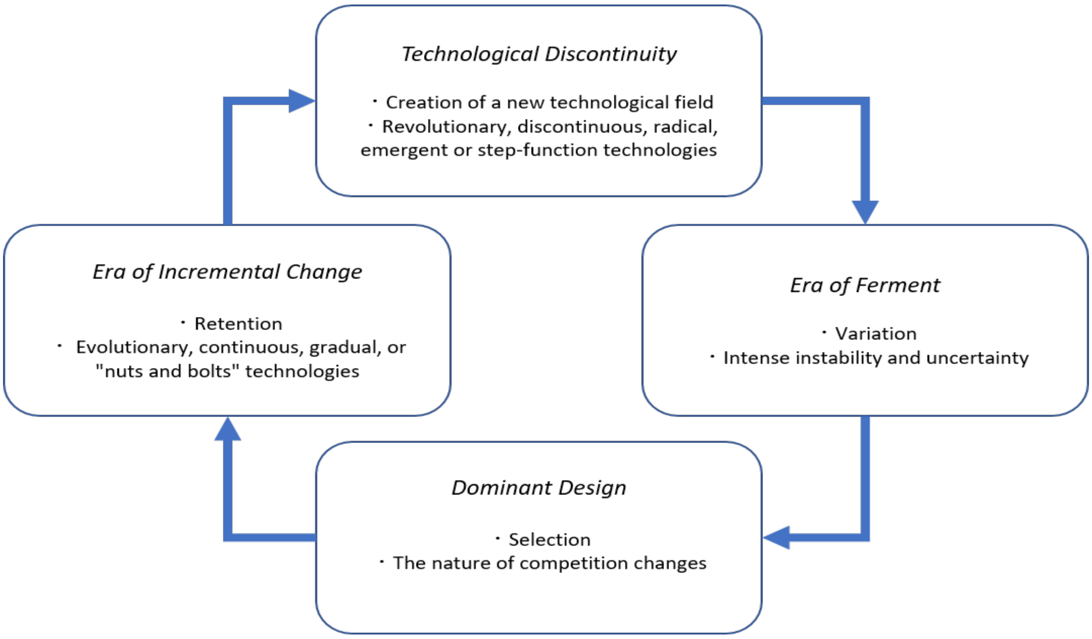


**Figure 1 Technology life cycle**

**(Adapted from Tushman and Rosenkopf, 1992, Kaplan and Tripsas, 2008, and Taylor and Taylor, 2012)**

In addition to these studies, Suarez et al. (2015) introduced the notion of dominant categories alongside the concept of dominant design. While a dominant design is materially constituted and significantly limits subsequent technological evolution, a dominant category is a sociocognitive concept primarily arising from stakeholders’ need to engage in meaningful communication with each other regarding their involvement in the emerging industry (Suarez et al., 2015). Moreover, the dominant category appears before the emergence of the dominant design and signals the possibility of entering into the industry; meanwhile, the emergence of a dominant design implies the disappearance of the possibility of entry (Suarez et al., 2015).

The technology life cycle captures transformations in the competitive landscape within an industry. How do these changes in the competitive environment affect the survival of firms in an industry? Utterback and Suarez (1993) investigated shifts in the number of firms across eight different industries and identified a correlation between these fluctuations and the advent of dominant designs within those industries. Their study revealed a distinct pattern: initially, the number of firms steadily rises at the start of the industry, peaks when a dominant design emerges, and subsequently decreases, eventually stabilizing at a relatively lower number of firms. This observation highlights the interplay between the evolving competitive environment and the viability of firms in the industry.

## 3. A Brief History of Computer Graphics Processing System Technology

The review in this chapter is entirely based on McClanahan (2011), Das and Deka (2016), Dally et al. (2021), and Singer (2023). The technological field of computer graphics processing systems has advanced along with the evolution of the GPU. A GPU is a single-chip processor, similar to a central processing unit (CPU) (Das and Deka, 2016). As of 2016, the number of cores in a CPU is four or eight, whereas GPUs generally have hundreds of cores (Das and Deka, 2016). GPUs mainly compute three-dimensional (3D) functions which require a proportionally high number of cores; due to the high computational load of 3D calculations. GPUs are designed to help computers run quickly and efficiently (Das and Deka, 2016). GPU designs are based on the graphics pipeline concept, a conceptual model consisting of several stages (Das and Deka, 2016; McClanahan, 2011). Through these stages, 3D space is converted to two-dimensional (2D) pixel space on the screen (Das and Deka, 2016; McClanahan, 2011). Early GPUs relied on host CPUs for most operations comprising the graphics pipeline (Das and Deka, 2016; McClanahan, 2011). Offloading the host CPUs' vertex computations to GPUs enabled higher geometric complexity in games (Dally et al., 2021). GPUs with large floating-point performance are required to conduct such computations (Dally et al., 2021). The earliest GPUs, such as RCA's "Pixie" video chip (CDP1861), were released in the latter half of the 1970s (Singer, 2023). These GPUs were simply 2D accelerators and display controllers that transferred pixel values from the system memory to frame buffer memory and then to a cathode-ray tube screen (Dally et al., 2021). Additionally, they generated addresses and sync signals and provided digital-to-analog conversion (Dally et al., 2021). In the first half of the 1990s, the age of mass-market 3D gaming began with the introduction of 3D video game consoles such as the 3DO, Sega Saturn, and Sony PlayStation; the entire industry of 2.5D and 3D graphics accelerators was driven by the need to enable 3D graphics on PCs for gaming (Dally et al., 2021). This opportunity was so alluring that more than 60 businesses were established to serve it (Dally et al., 2021). One of these firms was the NVIDIA Corporation, established in 1993. An example of an early 3D PC graphics card is the RIVA-128 (NV3), released by NVIDIA Corporation in 1997 (Dally et al., 2021). At this time, 3D graphics cards performed fragment computations for rasterization, color interpolation, texture mapping, Z-buffering, and shading; the host CPU continued to perform vertex computations, which were necessary to convert the vertices from 3D world space to 2D screen space (Dally et al., 2021). In 1999, NVIDIA Corporation released the GeForce 256, one of the first cards to implement all stages of the graphics pipeline (McClanahan, 2011). The GeForce 256 was the first chip with vertex computations for transformation, lighting, and fragment calculations; it was also the first product to be called a

GPU (Dally et al., 2021). Demand for modifying the vertex and pixel computations to provide sophisticated graphical effects increased as PC games became more advanced (Dally et al., 2021). In 2001, NVIDIA Corporation released the GeForce 3, which implemented programmable vertex shaders, and in the following year, it released the GeForce FX, which implemented programmable fragment shaders (Dally et al., 2021). Another example of a GPU in this period is the ATI Radeon 9700 (Das and Deka, 2016; McClanahan, 2011). Since the early 2000s, the programmability of GPUs has occupied a central position in development. The field of general-purpose GPU (GPGPU) programming developed as GPUs with high floating-point calculation ability and programmability became appealing platforms for scientific computing (Dally et al., 2021). NVIDIA Corporation's GeForce 6, launched in 2004, could execute 108 billion single-precision floating-point operations per second (108 GFLOPS) at peak performance; this calculation ability is higher than that of modern CPUs, which provide 8 GFLOPS (Dally et al., 2021). In 2010, NVIDIA Corporation released a GPU architecture called Fermi Architecture, which was designed for GPGPU, allowing programmers to use GPU resources for graphics processing and other purposes (Das and Deka, 2016; McClanahan, 2011). This deep learning revolution was made possible by the accessibility of GPUs with high floating-point performance and programmability (Dally et al., 2021). Thus, GPU hardware has developed from a single-core, fixed-function hardware pipeline implementation developed exclusively for graphics rendering purposes to a group of programmable cores for general computing needs (Das and Deka, 2016; McClanahan, 2011).

## 4. Data and Methodology

This study uses United States Patent and Trademark Office patent data. Next, we process target patent data using latent Dirichlet allocation (LDA), a topic modeling analysis methodology originally developed by Blei et al. (2003).

## 4.1. Data

Patent data have been used as a rich and potentially fruitful source indicating technological change in fields with high levels of R&D (Jaffe and Trajtenberg 2002, 3; Jürgens and Herrero-Solana, 2017). As NVIDIA Corporation and other important organizations in the technological field of computer graphics processing systems are located in the United States, patent publications in the United States can be considered the most suitable data. The technological field of computer graphics processing systems is defined by the technological classes of the US Patent Classification (USPC) under Class 345/501, which has eight subclasses (345/502, 345/503, 345/504, 345/505, 345/506, 345/519, 345/520, 345/522). According to the class definition, patents of "subject matter comprising apparatus or a method for processing or manipulating data for presentation by a computer prior to use with or in a specific display system" (USPC class numbers and titles, Class 345/501) are placed under Class 345/501. However, many other patents outside Class 345/501 are also crucial in advancing computer graphics processing systems. For instance, patents under Class 382 primarily focus on image analysis, a field that is closely tied to computer graphics processing systems. However, this study does not examine patents that do not fall within Class 345/501 to maintain data manageability and focus on a specific subset of patents. The study data were sourced from the US Patent Office's online database, PatentsView, which includes patents published since 1975. For this research, we selected patents from 1975 to 2015. Given that the history of computer graphics processing systems traces back to the 1970s, this timeframe is deemed appropriate for the purposes of this study. A total of 4,032 patents were collected from PatentsView.

## 4.2. Methodology

This study employs LDA, which is a methodology for topic modeling introduced by Blei et al, (2003), because it enables the extraction of underlying technical topics from a text corpus. A comprehensive explanation of the LDA algorithm can be found in Blei (2012). For this study, the text corpus was constructed from the abstracts of patents related to computer graphics processing systems. Common words were filtered using the stop word list provided by the Natural Language Toolkit (Bird et al., 2009). In LDA, the extracted topics are represented as probability distributions over words. Furthermore, each patent document is represented as a probability distribution over the technical topics. The technical topics and their associated probabilities are identified based on the co-occurrence of words in patent abstracts. Previous studies have used LDA to investigate topic evolution within various technological domains. For instance, Chen et al. (2017) explored knowledge transfer between topics and the dynamics of topic evolution in the field of information retrieval by employing LDA to extract technical topics within this domain. Meanwhile, Sun et al. (2021) introduced an empirical approach for identifying potential breakthrough inventions using LDA. Several other studies have applied LDA to analyze patent data, as seen in Suominen et al. (2017) and Kaplan and Vakili (2015). For the LDA analysis in this study, the Gensim Library of Python was used.

## 4.3. Research Design

LDA enables the representation of each patent document as a probability distribution over technical topics, and these probability distributions can be viewed as probability vectors. To observe the trends of topics within an entire field, one can calculate the average probability vectors for patents published each year in that field (Chen et al., 2017). Similarly, by calculating the average vectors for patents published by each organization in each year in the field, one can describe the R&D tendencies of organizations as probability vectors over topics within that field. In this study, we compute the Euclidean distance between the average topic vector for each organisation in each year and the average topic vector for the entire field in the same year. This distance indicates how closely each organization's R&D activities align with the mainstream in that field for that year. Moreover, we determine the field-wide average of the distances between the topic vectors to represent the R&D trends of each organization and the average topic vector for the entire technological field each year. This average metric can be viewed as an indicator similar to variance in statistical analysis. Effectively, this metric reflects the degree to which the R&D trends of each organization within the field are dispersed. In this study, we refer to this metric as the "variance of topic vectors." Figure 2 illustrates its calculation method. When the "variance of topic vectors" is low, the R&D policies of each organization are converging, which can be viewed as the emergence of a common framework within an industry such as a dominant category or design.

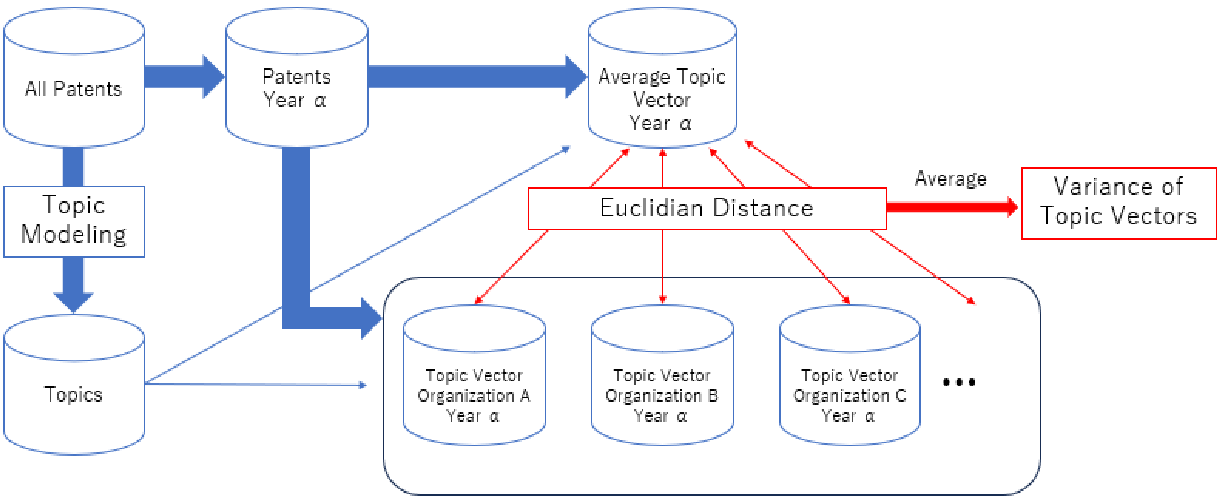


**Figure 2 Calculation of "variance of topic vectors"**

We then compare the temporal changes in the "variance of topic vectors" with those in the number of organizations publishing patents in the technological field each year, signifying alterations in the concentration of the field. These changes are a reflection of the intensity of competition. Meanwhile, the temporal changes in the "variance of topic vectors" indicate shifts in the convergence of R&D trends among organizations in the field, representing some of the dynamics related to mainstream formation within that field. By comparing these two metrics, we can analyze the relationship between competition and the dynamics of mainstream formation.

As mentioned previously, this study focuses on the determination of the dominant design, which is a key phenomenon in mainstream formation. In particular, we propose that the establishment of a broader shared framework than the dominant design may occur before the determination of the dominant design in the target technological field. Suarez et al.'s (2015) dominant category concept is used to examine the broad shared framework, as mentioned previously. Suarez et al. (2015) argued that dominant categories emerge before the appearance of a dominant design. As noted in our review of the technology life cycle, dominant design decisions are considered to occur after the era of ferment. Suarez et al. (2015) argued that there may be more stages in this decision process by making a qualitative argument. This study follows Suarez et al. (2015) and examines the temporal changes in the "variance of topic vectors" and the number of organizations publishing patents in the technological field each year. Specifically, this study observes the phenomenon wherein a decline in the "variance of topic vectors" occurs before the number of organizations publishing patents in this technological field declines. As highlighted by Utterback and Suarez (1993), the emergence of a dominant design in an industry leads to a "shakeout", resulting in a reduction in the number of firms in the field. Therefore, the time when the number of organizations publishing patents in a specific technological field begins to decline indicates the emergence of the dominant design. However, following Suarez et al. (2015), if the decline in the "variance of topic vectors" occurs first, it can be interpreted as the convergence of the R&D policies of each organization due to the formation of the dominant category before the emergence of the dominant design.

## 5. Results

Five topics were extracted from the corpus. The selection of the number of topics in the LDA models is an ongoing challenge. Perplexity and coherence metrics are commonly used to determine the optimal number of topics. According to these metrics, a small number of topics are suitable for the corpus; specifically, the optimal number of topics was two. However, given the scale and complexity of the technological field of computer graphics processing systems, two were considered too small. After several iterations, we ultimately settled on five topics as the most appropriate number.

Table 1 presents the five underlying technical topics extracted from the corpus of the entire technological field of computer graphics processing systems. Each topic's theme was defined by the authors based on the top 30 terms that were most closely associated with that technical topic. As these topics originate from the same technological field, there is a significant overlap in the top terms for each topic. Nonetheless, some distinctive words strongly correlate with individual topics, and these words primarily define the topic's theme. In Table 1, these distinctive words are emphasized using bold letters. Topic 1 is strongly related to the word "apparatus." Therefore, we decided to call it "graphics processing apparatus." Topic 2 is strongly related to the word "pipeline," where the patents assigned to this technical topic can be considered to be primarily related to the idea of a graphics pipeline. Topic 3 is strongly related to the words "bus," "processors," and "stored." We interpreted this topic to be related to data transmission. Topic 4 is strongly related to the words "program" and "application." In the technological field of computer graphics processing systems, software and hardware play pivotal roles in technological evolution. In addition, programmability is an important and relevant concept. The patents assigned to Topic 4 can be considered to be mainly related to graphics processing programming. Topic 5 is strongly related to the words “device” and “controller.” In the early stages of the technological field of computer graphics processing systems, graphics processing chips were called “graphics controllers.” The patents assigned to Topic 5 can be considered to be mainly related to technologies developed in the early stages of the technological field.

**Table 1 Five underlying technical topics in computer graphics processing systems**

| ***Topic No.*** | ***Topic Theme*** | ***Terms*** |
|---|---|---|
| 1 | Graphic Processing Apparatus | data, display, processing, image, unit, memory, system, plurality, one, buffer, control, processor, first, **apparatus**, includes, graphics, video, rendering, information, second, computer, least, command, operation, frame, method, circuit, stored, signal, set |
| 2 | Graphics Pipeline | data, graphics, processing, system, first, processor, video, second, one, unit, may, memory, image, display, method, **signal**, includes, pixel, **pipeline**, buffer, device, plurality, output, input, frame, controller, bus, interface, rendering, address |
| 3 | Data Transmission | image, data, memory, processing, graphics, display, system, video, processor, pixel, first, information, second, method, one, includes, may, unit, **bus**, computer, control, output, command, rendering, device, input, interface, **processors**, **stored**, plurality |
| 4 | Graphic Processing Programming | graphics, processing, system, memory, data, display, information, one, image, unit, video, processor, plurality, method, **program**, device, includes, computer, **application**, process, second, set, **execution**, units, may, user, apparatus, using, pixel, control |

| | | |
|---|---|---|
| 5 | Graphics Controller Devices | display, data, memory, first, **device**, image, second, unit, graphics, system, **controller**, pixel, includes, information, one, processor, output, processing, signal, video, frame, control, plurality, may, input, circuit, buffer, method, object, address |

## 5.1. Mainstream of Topics in the Technological Field

Using LDA, each patent document is represented with a probability distribution over the above-mentioned five technical topics. These probability distributions can be considered as probability vectors with five elements. By calculating the average vectors of the probability vectors of the patents published each year, we can observe the trend of topics in the entire technological field (Chen et al., 2017). This trend can be considered as representing the mainstream of the emerging technical topics. Figure 3 presents the evolution of these topic trends over the years using an area chart. In this chart, the width of the area assigned to each topic reflects its popularity in a given year. It provides a visual representation of how the popularity of topics has changed over time. Meanwhile, Figure 4 utilizes a ribbon chart to visualize the changes; in this chart, the width of the area assigned to each topic corresponds to its popularity, and the position of the ribbons shifts in accordance with the popularity of each topic. The more popular a topic, the closer it appears to the top of the chart.

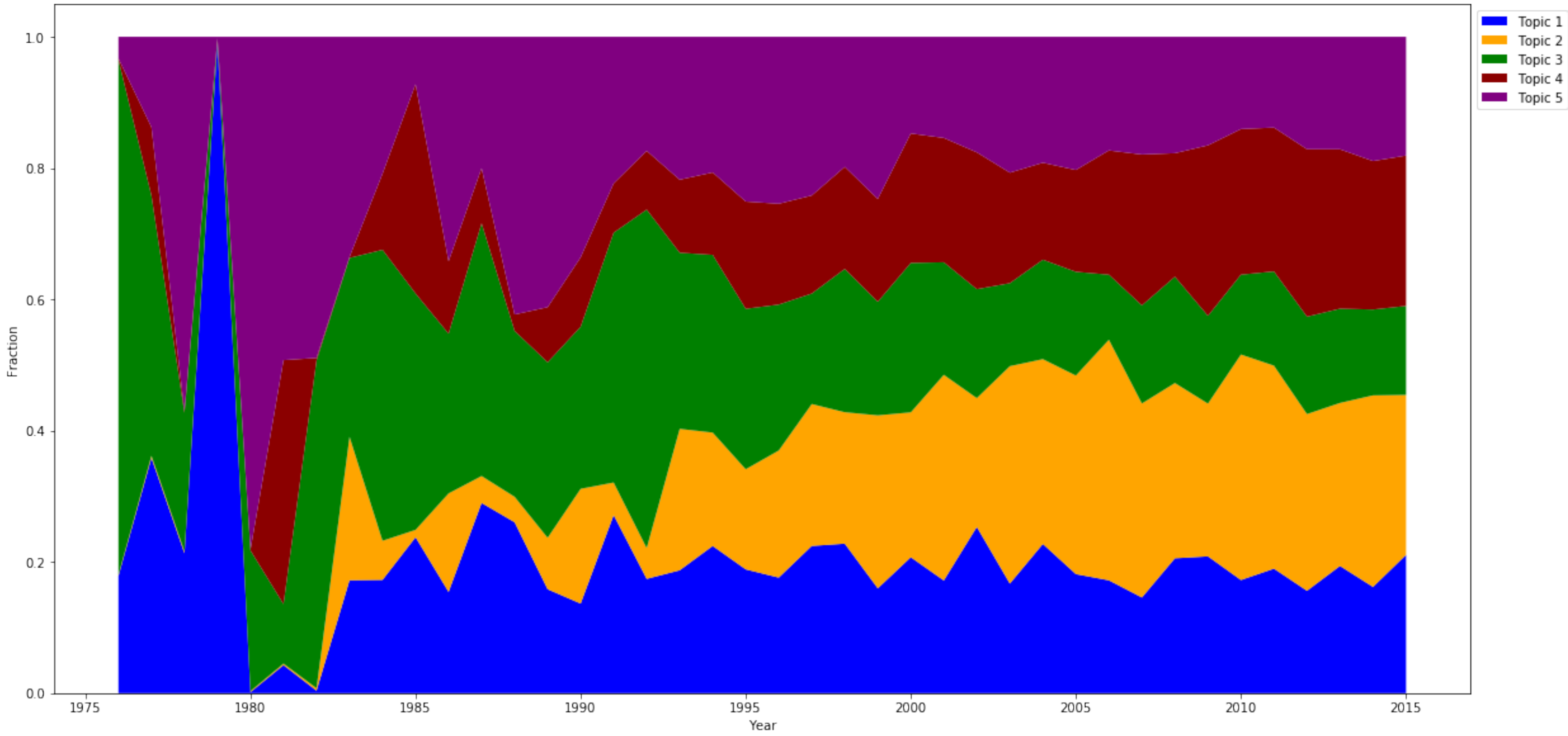


**Figure 3 Change in the trend of topics by years: an area chart**

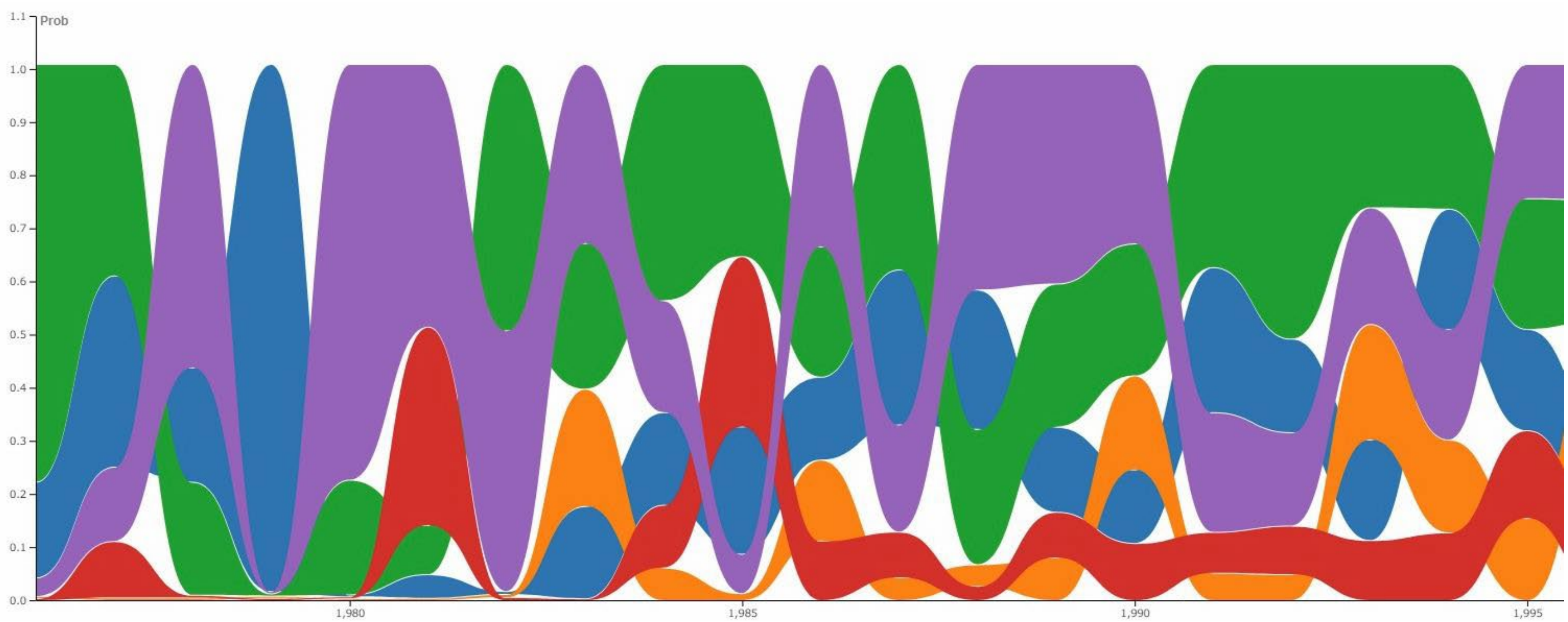


**Figure 4 Change in the trend of topics by years: a ribbon chart**

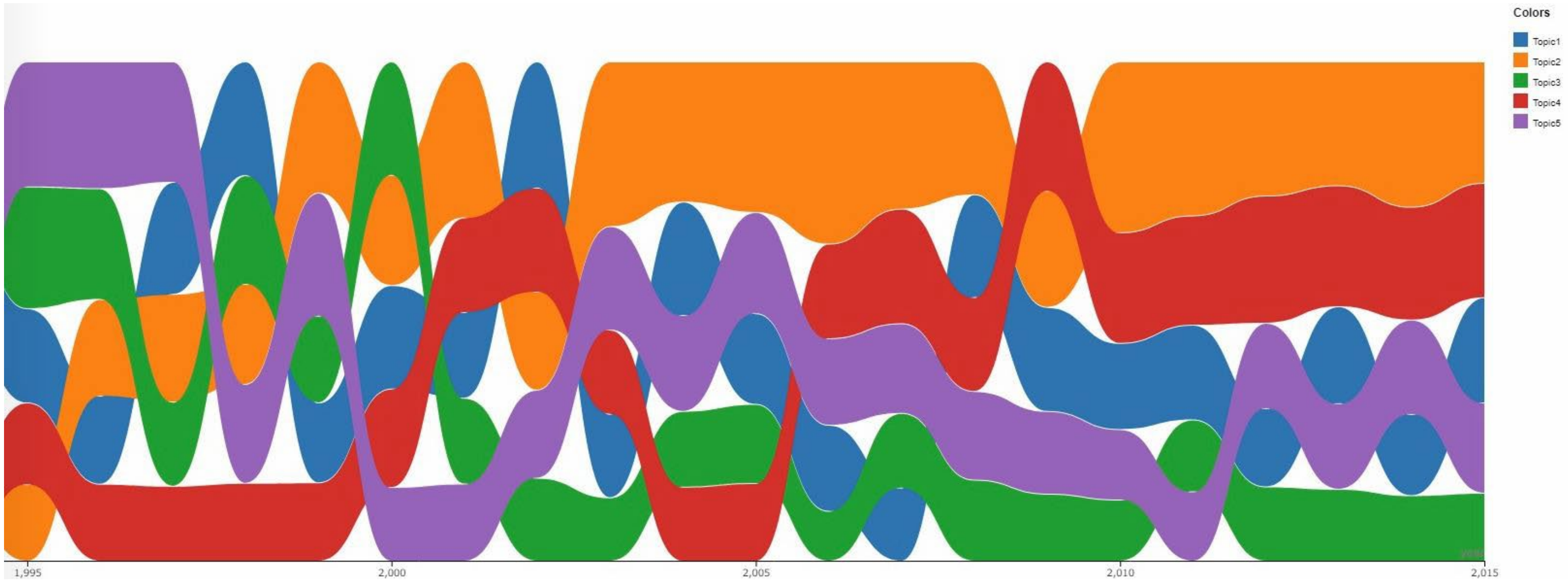


**Figure 4 Change in the trend of topics by years: a ribbon chart**

(continued from previous page)

Figures 3 and 4 reveal a distinct trend in the evolution of topic popularity within the technological field. Some key observations are that until 1996, Topics 3, "Data Transmission," and 5, "Graphics Controller Devices," were the dominant and most popular topics in this technological field. Then, around 2000, there was a shift, with all five topics becoming almost equally popular. During this period, the order of popularity among these topics changed annually. Significantly, during this transitional period, Topic 2, "Graphics Pipeline," began to gain popularity. Starting in 2003, Topic 2 consistently maintained the top position in the ranking order of topic popularity, except in 2009. In parallel, Topic 4, "Graphics Processing Programming," began to increase in popularity around 2005. These observations provide insights into the evolving dynamics of the technological field, with some topics gaining prominence at different times, reflecting shifts in R&D trends and the focus of the industry.

## 5.2. Competition in the Market and the Mainstream Formation

The temporal changes in the number of organizations publishing patents each year represent shifts in concentration within the field and can be regarded as an expression of the changing intensity of competition. Meanwhile, the temporal changes in the "variance of topic vectors" indicate variations in the convergence of R&D trends among organizations in the field, serving as a representation of the dynamics of mainstream formation. The comparison of these metrics provides an analysis of the relationship between competition and the dynamics of mainstream formation within the field. Figure 5 presents the temporal changes in the "variance of topic vectors" and the number of organizations publishing patents in the technological field.

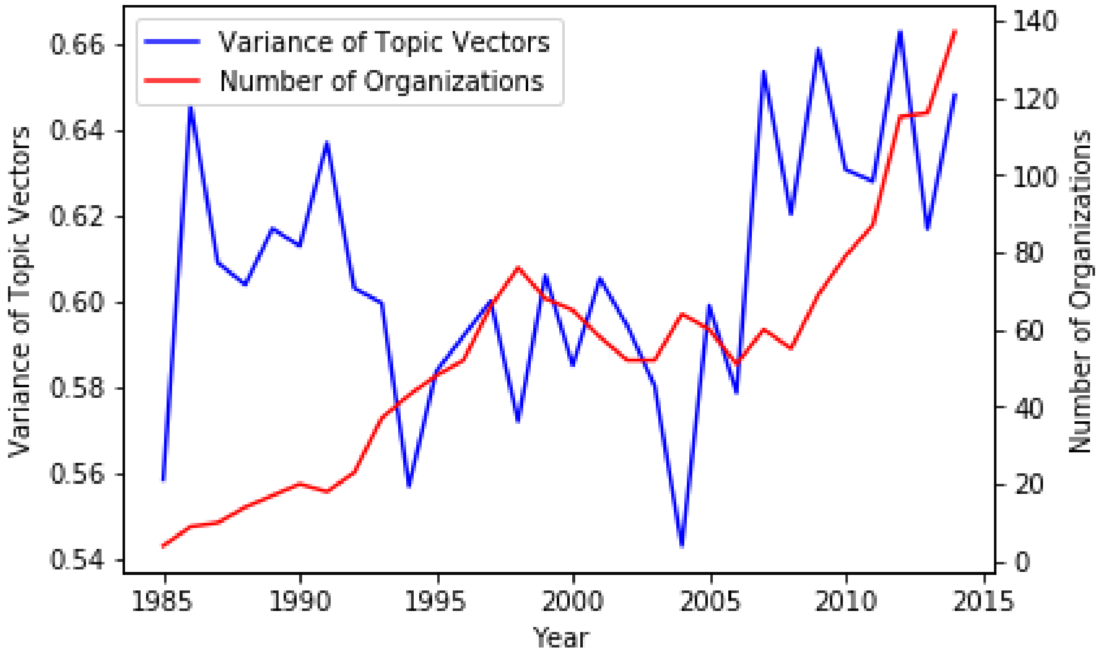


**Figure 5 "Variance of topic vectors" and the number of organizations publishing patents in the technological field**

Upon examining Figure 5, several intriguing trends become apparent. The number of organizations publishing patents in the technological field exhibited a consistent increase until 1998. Afterward, it decreased and then remained relatively constant until 2008, whereupon it resumed the upward trend. In contrast, the "variance of topic vectors" maintained relatively high values until around 1993, after which it declined and continued to exhibit relatively low values until 2006. Subsequently, it returned to relatively high values. In summary, there is an interesting correlation between these two metrics. When the number of organizations publishing patents in the technological field is on an upward trajectory, the "variance of topic vectors" tends to have relatively large values. Conversely, when the number of organizations publishing patents is stagnant or decreasing, the "variance of topic vectors" tends to have relatively small values. Notably, the "variance of topic vectors" transitions between two ranges of values, from relatively large to relatively small, just before the trend of the number of organizations publishing patents shifts from an increase to a decrease, and vice versa.

These observations indicate a potential relationship between competition dynamics, reflected by the number of organizations publishing patents, and the evolution of mainstream trends, indicated by the "variance of topic vectors." The implications of these trends are explored further in the Discussion section.

# 6. Discussion

When the number of organizations publishing patents in the technological field is on an upward trajectory, the "variance of topic vectors" tends to have relatively large values. Conversely, when the number of organizations publishing patents remains stagnant or is decreasing, the "variance of topic vectors" tends to have relatively small values. Additionally, the "variance of topic vectors" shifts between two ranges of values, from relatively large to small, just before the corresponding shift in the trend of the number of organizations publishing patents, and vice versa. In this chapter, we discuss what these observations imply as per the hypothesis.

As noted by Utterback and Suarez (1993), the number of firms operating within a particular technological field tends to peak when a dominant design emerges. Following this phase, a "shakeout" occurs, with the number of firms tending to decrease. Drawing on Utterback and Suarez's (1993) explanation and considering the observations in Figure 5, we can infer that the emergence of a dominant design in this technological field occurred around 1998. Additionally, Figure 5 reveals a substantial decline in the degree of convergence in R&D policies among organizations prior to 1998. This observation supports the hypothesis and suggests that there was a convergence in the R&D policies of each organization in the field before the dominant design emerged.

Here, we reexamine Suarez et al.'s (2015) argument in conjunction with the study's findings. Suarez et al. (2015) argued that dominant categories emerge before the appearance of a dominant design and that a dominant category is a sociocognitive concept primarily arising from stakeholders' need to engage in meaningful communication with each other regarding their involvement in the industry. Therefore, in this field, organizations converged their R&D policies before the emergence of the dominant design. This convergence can be interpreted as a consequence of the emergence of the dominant category. Notably, in the field of computer graphics processing systems. this convergence occurred during the early 1990s, a period marked by the active development of 3D display chips for gaming on PCs. The appearance of the dominant category, specifically, "3D display chips for games on PCs" likely promoted this convergence. Following the emergence of this dominant category, the dominant design, GPUs, emerged in 1999 with NVIDIA Corporation's announcement of the GeForce 256. As mentioned previously, the GeForce 256 was the first product to be introduced as a GPU (Dally et al., 2021). Since the launch of the GeForce 256, the development of graphics processing chips in this technological field has been heavily influenced by the concept of the GPU. This announcement occurred chronologically after 1998, marking the onset of a decline in the number of organizations publishing patents in this technological field. Based on these observations, we can assert that the concept of GPUs performing graphics processing calculations without relying on CPUs indeed emerged as the dominant design in this technological field around 1998. Suarez et al. (2015) qualitatively discuss the emergence of dominant categories; meanwhile, this study presents quantitative observational results that support the existence of this phenomenon, adding novelty to the literature.

Thus far, we have examined the alterations in the competitive environment driven by the alignment of R&D strategies among organizations within the industry. Meanwhile, according to Figure 5, around 2005, there was evidently a divergence in the R&D strategies of organizations. Shortly thereafter, there was an increase in the number of organizations publishing patents in the field. As seen in Figure 4, around 2005, there was an increase in the prevalence of Topic 4, which is related to software within the field. This shift indicates a transformation from an industry heavily reliant on hardware manufacturing technology to software-related innovations, lowering the barriers to entry. The divergence in R&D strategies among organizations within the field observed in Figure 5 can thus be interpreted as an indication of the expansion of business opportunities and a decrease in entry barriers.

This study has analyzed the correlation and causality between changes in the number of organizations publishing patents in a particular technological field and the convergence of R&D policies of organizations within that field. It demonstrates that the convergence of organizations' R&D policies occurred before the shakeout of organizations publishing patents; conversely, the divergence occurred before the increase in new entrants. The study's observations reveal the presence of dynamics related to the formation of the mainstream in the technological field and the consequent uncertainty of mainstream formation, leading to changes in the competitive environment, shakeouts, and new entrants. This study enriches the literature by shedding light on these dynamics in the technological field of computer graphics processing systems.

Suarez et al. (2015) argued that the period between when the dominant category and the dominant design are determined is an opportunity for organizations to enter into that industry because the identification of the dominant category provides a shared framework, fostering effective communication within the industry and reducing uncertainty; meanwhile, the emergence of a dominant design implies the disappearance of the possibility of entry. This study quantitatively depicts the timing of the emergence of the dominant category and design within the computer graphics processing systems industry using patent data. We believe that this study will facilitate evidence-based decision-making for organizations as they shape their entry timing strategies and economic policies to promote such strategies in emerging markets.

While this study shows the correlation and causality between the changes in the number of organizations publishing patents in a particular technological field and the convergence of R&D policies of organizations within that field, it is important to acknowledge that these findings are based on observations. Further in-depth qualitative and quantitative research is necessary. In a future study, we will conduct an empirical analysis of the organization strategies that have influenced the convergence of R&D policies. Furthermore, this study is specific to the field of computer graphics processing technology. To validate the generalizability of the results, research outcomes from other technological fields are required.

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