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ABSTRACT

Information and Communication Technologies (ICTs) have been recognized as a type of General Purpose Technologies (GPTs), and thus are considered the "driving force" in corporate technology advance. In this study, we re-conceptualize and re-classify GPTs from a broad field-based approach, based on a two-dimensional construct using patent and patent citation data. The new construct makes connections of ICTs with other technology fields. The new approach takes into considerations that firms are not only "users" but also "innovators" of new technologies. The research results in this paper will serve as a platform based upon which more studies on ICTs and GPTs in technology changes, corporate innovations, international R&D and innovation clusters can be further conducted.

Key Words: Information and Communication Technology, General Purpose Technology, Technology Classification

INTRODUCTION

Firms nowadays face increasingly higher pressure on understanding and building capabilities across a broad range of technologies. Technological diversification is based on the dynamic economies of scope which are generated in a fundamentally important way through the combination and recombination of different technologies. Kim and Kogut (1996) explained the pattern of diversification as linked to a firm's "platform technologies", based upon which potential technology relatedness is generated. "General Purpose Technologies" (GPTs) are such platform technologies. GPTs are defined as technologies that are: "1) extremely pervasive in many sectors of the economy; 2) leading to continuous technical advance; and 3) requiring complementary investment" (Helpman & Trajtenberg, 1998).

As computing, communication and information technologies have been invented and diffused, there has emerged an extended trajectory of incremental technical improvements (Granstrand & Sjolander, 1992; Oskarsson, 1993; Patel & Pavitt, 1991). Such gradual and protracted process of computing-related technology diffusion signals the emergence of a new ICT (Information and Communication Technologies) based paradigm. The new ICT-based paradigm, compared with the old one which is primarily grounded upon energy and oil-related technologies, is characterized by the pervasiveness of ever more complex technologies, the increasing importance of science-based technologies (Dosi, 1982; Freeman & Perez, 1988; Cantwell & Fai, 1999; Cantwell & Santangelo, 2000), and the fusion of formerly separated technologies (Kodama, 1992). At this point, the natures of ICTs are consistent with the main characteristics of GPTs. Therefore, we believe that ICT is an advanced type of GPTs.

There are three main objectives of this study. Firstly, we attempt to revisit the conceptualization of GPTs by discussing their "generality" nature. Prior research defines GPTs as a number of individual innovations (proxied by patents) that have been pervasively utilized in many sectors. In this study, instead, GPTs are referring to some broad technology fields (group of patents). We also suggest that the "pervasiveness" or "generality" need to be measured from a cross-industry approach. In order to do so, we create a dual-dimensional construct. The new construct allows us to bring the ICTs (Information and Communication Technologies) concept which attracts increasingly more attentions in corporation innovation research into the GPT framework. Secondly, we classify GPTs using patent count and patent citation data respectively, and compare and contrast the result in defining GPTs. Such comparison may lead to some interesting discussion on the characteristics of GPTs. Thirdly, we map the pattern of innovations in GPT fields across different industries by tracking the creation and application of GPTs in each sector. Discussions on the change of the underlying trajectory of specific sectors provide some greater in depth insights about the GPT evolution and its implementation on the corporate R&D research in the future.

Following by a brief review on previous literature, we distinguish two approaches – "technology creation" and "technology application" to conceptualize GPTs in the next section. We then construct two measurements based on the USPTO patent count and patent citation data respectively. The next section is dedicated to the discussion of statistical results on the comparison and contrast of the classification based on two different approaches. Our conclusions and some limitations in this study will be presented in the last section.

LITERATURE REVIEW

The Concept of GPTs and ICTs

It has been observed that there exists a set of "'General Purpose Technologies' (GPTs) characterized by the potential for pervasive use in a wide range of sectors and by their technological dynamism" (Rosenberg, 1982; Bresnahan & Trajtenberg, 1992). James Watt's steam engine is an early example of GPT that fulfilled the role in the first industrial revolution. Many other technologies were then suggested as GPTs in the following literature, such as non-electrical machinery (Rosenberg, 1976), instrument and controls, chemical processes, computing (Granstrand et al., 1997) and so on. Scholars try to complement the "generality" nature of GPTs, by charactering it not only with a wide range of users, but with technological cumulativeness, dynamism and complementarity innovations (Bresnahan & Trajtenberg, 1995).

Due to the "tacit" nature of technological innovation (Nelson and Winter, 1982), there are significant barriers to the diffusion of knowledge across organizational and geographical boundaries (inter-firm or inter-location). GPTs and more recently ICTs (Information and

Communication Technology) are believed to make feasible the sharing and fusion of knowledge in different domains on an international scale. It is thus important to classify GPTs and map the pattern of the distribution of GPTs across different sectors in corporate innovation research.

The Implication of GPTs (ICTs) in Corporate Management Literature

The long tradition of GPT (ICT) studies has been mainly rooted in economics literature. According to industrial economists, GPTs contribute to the general economic growth (Bresnahan et al., 1995; Helpman et al., 1998, David and Wright, 2003) and are "driving force" in technological progress over eras (Granstrand et al., 1997). However, our understanding of GPTs in the corporate innovation context is still quite limited. Only until more recently, scholars in strategy management fields started to investigate how GPTs may have impact on firm growth. Schumpeter (1934) pointed out that innovation takes place by "carrying out new combinations". Based on this assumption, Granstrand and Sjolander (1992) identified some specific technologies and link them to the change of a firm's technological pattern. In "Multi-technology Corporations" (Kim and Kogut, 1996; Kogut, 1992), technological opportunities are increasingly generated in a fundamentally important way through the combination and re-combination of various technologies. Such technological synergies are facilitated by certain technologies that can be accessed and integrated easily. Combination and recombination of different technologies lie in the heart of corporate technological diversification and consequently to a firm's growth.

GPTs have the long tradition of being studied in the form of ICTs. Such studies have often been taken from managerial control perspective. For instance, ICTs are suggested to facilitate the firm geographical expansion, given that IT and communication technology may help improve the control and coordination among geographically distant organizations (Chari et. al., 2008, Dewan, et al., 1998). Firms as the main actors in the new technological paradigm, tend to further reinforce the development of ICTs to support an even more widely dispersed network of differentiated creativity (Cantwell & Santangelo, 2000). Moreover, SME (Small and Medium Enterprise) literature tried to explain GPTs from a "market transaction" approach, arguing that as many firms are becoming specialized in certain areas, they tend to generate innovations and trade them in the market. For instance, in Biotech and Software industries, some start-ups and university spin-offs tend to modularize their technologies, and such a specialization enables them to sell "general purpose research or production tools" to different buyers – usually large firms (Giarratana, 2004). These studies are based upon the assumption that GPTs are exogenous to firm growth. However, the "connective" and "enabling" nature of these technologies is neglected. According to the RBV, corporate innovation is endogenous to corporate change and needs to be examined within the corporate context. Therefore, to understand GPTs as part of the corporate evolution is essential to the corporate innovation research. There is still lack of research that conceptualizes GPTs within the corporate innovation framework and creates the construct to classify GPTs in a more systematic way. Our study, at this point, is attempted to fill the gap in the literature by establishing a more systematic construct and incorporating GPTs, ICTs and the evolution of technology paradigm into it.

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RECONCEPTUALIZATION AND RE-CLASSIFICATION OF GPTS

The Conceptualization of GPTs

There is only a few literature attempted to develop quantitative measurements to classify GPTs. Most previous studies tried to identify GPTs based on individual cases, such as Bresnahan (et al., 1995)'s study on engine, Rosenberg (1976)'s study on machinery and control system, and David (1990)'s study on computer, etc. Only until more recently, patents become more important research settings to study GPTs. Patent statistics is widely recognized as a reliable source to study questions on technology structure across industries and firms, and countries (Pavitt, 1988; Griliches, 1990). One of the most acknowledgeable works of GPT classification is Hall and Trajtenberg (2004)'s cross-patent study. In this study, the authors selected a group of most frequently cited patents from three million USPTO patents, and classified GPTs through a number of mechanisms such as generality, frequency, size (the patent class growth) and citation lags. This is a single-dimensional construct that it is only focused on the technology classification.

This-single dimensional approach can be risky. The key to find a good construct to measure GPTs is to define the "generality" nature. According to literature (Landes, 1969; Rosenberg, 1982), GPTs are not industry specific, but pervasive "in many sectors" in the economy. GPTs that are classified based on the single dimensional approach are likely to clustering around specific industries, and are thus biased. This is because firms within certain industries may have a higher tendency to cite patents within the industry than to cite from other industries. In other word, this method may result in overweighting the within-industry citations while underweighting the inter-industry citations.

Single-dimensional and Dual-dimensional Approaches

As distinct from Hall and Trajtenberg's (2004) cross-field approach, we propose a dual-dimensional industry-field approach to classify GPTs. More specifically, we define GPTs as some broad technology fields. Compared with patents in other technology fields, innovations in GPT fields tend to be more generally applicable to a wide range of industries (Table 1).

Table 1: The classification of GPTs – The single dimensional vs. dual-dimensional constructs.

	Single dimensional construct	Dual-dimensional construct
Innovations	Technology field	Technology field
Applicable	Technology fields	Industries

According to the new approach, to qualify to be GPTs, innovations in a given technology field need to be created by firms from a broad range of industries. To illustrate, the frequency of within-industry citations of patents in semi-conductor technologies (patents) is extremely high, but that of the cross-industry citations is much lower. Therefore innovations in the semi-conductor field are industry-wide "general technologies", but not GPTs. By contrast, the citations of electronic device technology are not just limited to electronic firms, but are largely developed by firms from a wide range of sectors, such as communication, pharmaceutical, transportation, printing and publishing, and so on. Therefore, the latter is a cross-industry "general technology", and thus are belonging to GPT fields.

Using Patent Citation Data and Patent Count Data to classify GPTs

The classification of GPTs in this study is based on the USPTO (U.S Patent and Trademark Office) patent data. The sample data cover patents granted to the largest Multinational Corporations (MNCs) from year 1969 to year 1995, and their citations back to 1890. Using patents that are granted in a common third country – U.S – allows a more reliable international comparison on a commonly imposed standard. Moreover, the reason we are focused on the period of 1969-1995 is because we observe some tremendous changes in technology structure that is associated with the social and economic environment change during this period. More specifically, traditional sectoral structures that were based on machinery and energy (petroleum) technologies have been replaced by the new technology base which is relying on electronic and information technologies in early 1990s. Being focused on this period allows us to track the change of the underlying trajectory of technological development.

Patent Citation and Patent Count Approaches

An important contribution of this study is to take into consideration the fact that firms are not just "users", but also "creators" (inventors) of GPTs. The "general purpose" can thus be explained from two perspectives - being "generally created" or being "generally used" by firms from many industries. Previous GPT classification based upon patent citation data is based upon the assumption that GPTs are "widely applied (utilized)". Our study, relying on patent count data instead, suggests that GPTs can also be understood as technologies that are "generally invented" by firms across many industries. We will compare and contrast the classification results based on the two approaches in the following section.

Classifying GPTs Using Patent Count Data

In this study, we use the USPTO (U.S Patent and Trademark Office) patent data compiled at University of Reading and Rutgers University. Patent statistics has been widely recognized as a reliable source to study the questions on technology patterns (Freeman, 1982; Pavitt, 1988). The use of patent stocks is not limited to the direct measure of new technology creation, but can be extended as a proxy for the underlying pattern of technological change, given the cumulative, incremental and path-dependent process of technological evolution (Nelson and Winter, 1982; Rosenberg, 1982; Dosi, et al, 1988). Patent data have been used in empirical studies covering many industries, such as semiconductor industry (Kim & Kogut, 1996), pharmaceutical industry (Chuang & Alcacer, 2002) and biotechnology industry (Shan and Song, 1997).

We study 948,190 patents created by all largest industrial firms in the world from 1969 to 1995. The data are organized as a panel of patents indexed by the year they are generated, the industry of each patent, the technology classification the patent is belonging to, and the countries of origin the patents have been originally invented. The country of origin of each patent will be identified in accordance with the location of the first inventor(s). Our sample includes patents which are created by firms originated from 46 countries and have foreign stands in 62 countries. Patents are then consolidated into corporate groups, initially on the basis of the structure of ownership of groups in 1982. Most of the effects of subsequent merger and acquisition activity (after 1982) are built into the data through the practice of centralizing the patent application procedure in the parent company.

Each corporate group is in turn allocated to an industry on the basis of its primary field of production (Cantwell and Andersen, 1996). All firms are then assigned to one of the 16 industrial groups (Table 2). Moreover, to study various technologies created by each industrial group, each patent is allocated to one of 399 technological sectors (the type of technological activity with which each patent is most associated), which in turn belong to one of the 56 technological fields (Cantwell and Andersen, 1996), see Table 3.

Table 2: The description of 56 technology fields.

Tech56	Technological Field Description	Tech56	Technological Field Description
1	food and tobacco product	29	other general industrial equipment
2	distillation processes	30	mechanical calculators and typewriters
3	inorganic chemicals	31	power plants
4	agricultural chemicals	32	nuclear reactors
5	chemical processes	33	telecommunications
6	photographic chemistry	34	other electrical communication systems
7	cleaning agents & other compositions	35	special radio system
8	disinfectants & preservatives	36	image and sound equipment
9	synthetic resins and fibers	37	illumination devices
10	bleaching and dyeing	38	electrical devices and systems
11	other organic compounds	39	other general electrical equipment
12	pharmaceuticals and biotechnology	40	semiconductors
13	metallurgical processes	41	office equipment
14	miscellaneous metal products	42	internal combustion engines
15	food drink and tobacco equipment	43	motor vehicles
16	chemical and allied equipment	44	aircraft
17	metal working equipment	45	ships and marine propulsion
18	paper making apparatus	46	railways and railway equipment
19	building material handling equipment	47	other transport equipment
20	assembly and material handling equipment	48	textile, clothing and leather
21	agricultural equipment	49	rubber and plastic products
22	other construction and excavating equipment	50	non-metallic mineral products
23	mining equipment	51	coal and petroleum products
24	electrical lamp manufacturing	52	photographic equipment
25	textile and clothing machinery	53	other instruments and controls
26	printing and publishing machinery	54	wood products
27	woodworking tools and machinery	55	explosives, compositions and charges
28	other specialized machinery	56	other manufacturing and non-industrial

Each patent class is assigned to one distinct technological sector, but in some case classes are sub-divided between fields, thus the fields to which a given class contributes may fall under quite different technological groups. To illustrate, a chemical company increasingly needs to draw on knowledge and skills in many diverse areas, such as mechanical, electronics and biotechnology to further develop its own process system, even if it has no intention of entering markets that are primarily based on these technologies. Therefore, the sectoral classification of patents and the industry of the firms to which patents were assigned are recorded separately. In our study, the use of the term "technology (ies)" or "technology field (s)" is referring to one of the 56 technology fields, and the term "industry" or "industrial group of firms", referring to groups of firms are differentiated. Most large firms have engaged in the development of more than one technological sector. Patents in each industry group will therefore distribute across many technological fields. Similarly, because technologies could be combined and adopted to serve various products and markets, patents within each technological field are usually across many industries.

As we discussed earlier, our measurement on GPT fields is based on a dual-dimensional construct. This construct takes into consideration of the diverse technology fields that firms in an specific industry innovate, as well as the degree of dispersion (or concentration) of patents in a given technology field that are generated across different industries. Similar methods can be found in Granstrand (1997)'s study on the corporate technological competencies and Cantwell and Andersen (1996)'s work on corporate technological leadership. This dual-dimensional construct allows us to understand the degrees of both "centrality" and "generality" of technology innovative activities within and across different industries.

To identify GPT fields, we create a in which each cell shows the number of patents granted to firms in a given industry and belonging to that technological field. Based on it, the share of patents of each technological field within each industrial group can be calculated. The share of technology fields in each industry (*Tech_Ind*) is defined as:

$$Tech\_Ind = P_{ij} / \sum_j P_{ij} \tag{1}$$

where Pij denotes the number of patents granted in industry i and technological field j. It is found that although almost all industries are developing some technologies from all fields, and in turn almost each of the 56 technological fields is generally used in all 16 industries, but the degrees of concentration of each technology field across industries are different. The patents in some technology fields (ex. Tobacco technology) might be found only in a few industries, while others (ex. Machinery technology) are widely developed in many businesses. Therefore, it helps demonstrate the distribution of patents that have been innovated by firms in different industries. The criteria to identify GPT fields are: firstly, compared with other technologies, the GPT field should be distributed relatively evenly across many industries; secondly, the overall size of activity in that field should be large enough. We select technological fields in which there are more than six (out of sixteen) *Tech_Ind* shares that are greater than or equal to 3%. We chose 3% as the threshold because it is close to the mean value of the share of technological fields across industries (Table 4). In this way, we identified 9 technology fields out of 56 as GPT fields (Table 5). Namely, these GPT fields are tech5-chemical process, tech9-synthetic resins and fibers, tech11-other organic compounds, tech16-chemical and allied equipment, tech29-other general industrial equipment, tech38-electrical devices and systems, tech39-other general electrical equipment, tech41-office equipment and tech53-other instruments and controls.

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It is found that among 9 GPT fields (Table 5), the sectors of office equipment (Tech 41) and other instrument and controls (Tech 53) have relatively higher growth rates compared with the other 7 fields. These two fields are the ICT fields, or the GPTs in the new paradigm. This classification is also consistent with the identification of ICTs in previous literature (Santangelo, 1998; Cantwell & Santangelo, 2000). By contrast, the other 7 technologies are GPTs in the old paradigm given that their growth rate is either negative or lower in the most recent period.

Table 4: The size and generality of each technology fields.

Tech 56	Tech_ind shares	# of ind above avg	Tech 56	Tech_ind shares	# of ind above avg	Tech 56	Tech_ind shares	# of ind above avg
1	0.81%	1	20	1.81%	3	39	4.62%	7
2	0.15%	0	21	0.30%	1	40	1.98%	2
3	1.03%	1	22	0.06%	0	41	5.89%	6
4	0.57%	0	23	0.93%	3	42	1.51%	1
5	3.97%	9	24	0.10%	0	43	0.62%	1
6	2.17%	4	25	0.62%	1	44	0.29%	1
7	2.34%	4	26	0.31%	0	45	0.16%	0
8	0.04%	0	27	0.04%	0	46	0.20%	0
9	5.68%	8	28	1.66%	4	47	0.58%	1
10	0.41%	0	29	4.73%	7	48	0.06%	0
11	7.79%	7	30	0.33%	0	49	1.17%	2
12	4.31%	5	31	0.89%	2	50	3.24%	6
13	2.43%	3	32	0.33%	0	51	1.48%	2
14	2.58%	8	33	2.32%	2	52	1.81%	2
15	0.11%	0	34	1.50%	1	53	8.69%	17
16	3.32%	10	35	0.57%	0	54	0.16%	0
17	1.93%	3	36	2.27%	3	55	0.08%	0
18	0.69%	1	37	1.42%	1	56	0.99%	1
19	0.19%	0	38	5.76%	7			

Table 5: GPT fields and their historical development over Time.

Tech. Field	period	period	period3
5 Chemical Process	4.01	4.30	3.68%
9 Synthetic resins and fibers	5.76	6.03	5.34%
11 Other organic compounds	11.52	7.50	4.97%
16 Chemical and allied equipment	3.56	3.66	2.87%
29 Other general industrial equipment	5.37	4.94	4.04%
38 Electrical devices and systems	6.11	5.40	5.75%
39 Other general electrical equipment	4.43	4.73	4.68%
41 Office equipment	3.21	4.74	8.94%
53 Other instruments and controls	7.18	8.20	10.30

Classifying GPTs Using Patent Citation Data

To compare the results in two approaches, we also classify GPTs using patent citation data. We re-define the GPTs as technologies fields in which patents have cited innovations from a wide range of technology fields. This is how previous studies (i.e. Hall & Trajtenber, 2004) measure GPTs. In this case, the GPT fields are understood as the technology fields in which innovations are grounded upon a broader technology base compared with technologies in other fields.

To be easy to compare the two approaches, we are focused on a subset of the sample data that we used in the first approach. We investigate the patents that are invented by the non-US firms in the U.S during the same period, and all cited patents linked to these patents back to 1890. It is noteworthy that study citing patents that are only generated by foreign firms won't lower the reliability of our result. It is because compared with the patents that are generated by domestic firms, those that are created by foreign-owned companies tend to have higher quality given that the technologies that can be extended into international market are usually more competitive.

Our sample data in this approach includes 77,851 citing patents and 135,084 cited patents back to 1890s. The citing patents are organized as a panel of patents indexed by the year of being granted, the MNC group to which the patents belong, the industry and the technology field. In addition, the technology class and the granted year for each cited patent are also tracked.

We then create a "Generality Index" (*GI*) that shows the "generality" of citations of innovations in each technology field by examining whether the patent citations to a specific technology field cover a wide range of other sectors. The *GI* is similar to the 'Generality' measurement in Hall and Trajtenber (2004)'s study. It is defined as:

$$GeneralityIndex(GI) = 1 - \sum_{i}^{nj} S_{ij}^{\ 2} \qquad (2)$$

where *Sij* denotes the percentage of citations received by cited patents i in technology class *j*, out of *ni* citing patent classes. We thus obtained the *GI* for each technology field.

Given that we only study the citing patents up till 1995, and by that time some new emerging technologies such as ICTs (Tech 41 and Tech 53) are still in their infant stage, the frequency and broadness of citations in such fields might be underestimated. As an alternative proxy to *GI*, we count the number of technology fields in which any citation activities are found, regardless the frequency of such citations. The latter measures the scope or extension of citation activities of each technology field - *(EX)*.

Table 6 shows the *GI and EX* based upon backward and forward citations respectively. The number of backward citations shows the average number of cited patents that a group of citing patents from the same technology field have cited. The number of forward citations shows the average number of citing patents from a certain technology field that have cited a set of earlier patents. Due to the truncation problem of forward citations, on average the count number of technology fields *(EX)* based on forward citations is lower than that based on backward citations. Moreover, the Generality Indexes *(GIs)* of forward citations of each technology field is also lower than the GIs based upon the backward citations. In addition, we observe some variances when we compare the *EX*s and *GI*s based on backward and forward citations. For instance, we found that Tech26 and Tech53 have high *EX* values based on backward citations, but *GI*s are very low when we look at the forward citations. This is probably due to the reason that the two fields are IT-related and due to the time constraint in our study, innovations in these fields have not yet been applied to a broad range of sectors in the economy until 1990s.

Table 6: Degree of Generality of Each Technology Fields (Citation-Based Approach).

Tech	Backward Citation		Forward citation	
	# of cited fields	Generality Index	# of citing fields	Generality Index
1	27	0.8317	24	0.5209
2	10	0.7950	19	0.6514
3	29	0.8526	30	0.7218
4	23	0.7902	20	0.6024
5	55	0.8974	51	0.7778
6	28	0.7899	26	0.4508
7	47	0.8711	39	0.6826
8	22	0.8995	19	0.8584
9	49	0.7950	39	0.4664
10	24	0.8621	21	0.7153
11	40	0.8227	32	0.6576
12	47	0.7928	30	0.4102
13	44	0.8690	43	0.6836
14	48	0.8696	51	0.6060
15	19	0.9210	20	0.7881
16	53	0.8932	49	0.7222
17	39	0.8706	45	0.6503
18	43	0.8739	35	0.5621
19	17	0.8860	23	0.8151
20	40	0.8762	48	0.5291
21	17	0.7974	23	0.2268
22	8	0.8367	16	0.7221
23	36	0.8754	29	0.4039
24	12	0.8145	12	0.6781
25	28	0.9005	25	0.4916
26	28	0.8959	29	0.6133
27	9	0.8600	10	0.6774
28	44	0.8797	52	0.6958
29	46	0.8629	52	0.6095
30	19	0.8646	22	0.5809
31	34	0.8539	29	0.6703
32	12	0.8249	17	0.6960
33	34	0.8045	29	0.4814
34	36	0.8427	37	0.7378
35	18	0.8393	18	0.6460
36	31	0.7570	37	0.3940
37	28	0.6740	30	0.4141
38	39	0.7858	41	0.5350
39	50	0.8547	47	0.6180
40	29	0.7960	24	0.6226
41	43	0.7317	41	0.3673
42	24	0.8196	24	0.3999
43	24	0.8232	31	0.5808
44	12	0.8673	21	0.8140
45	27	0.8602	21	0.5525
46	15	0.7979	20	0.5060
47	22	0.8469	30	0.7283
48	8	0.7872	16	0.6264
49	39	0.9052	44	0.8123
50	52	0.8958	46	0.7816

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51	31	0.8444	30	0.5345
52	24	0.8717	24	0.6964
53	54	0.8404	52	0.4948
54	13	0.8721	18	0.5492
55	9	0.9620	14	0.7711
56	41	0.8785	45	0.6681

By comparing the *GI* and *EX* across all technology fields, we found that Tech5, Tech16, Tech29, and Tech50 show relatively higher values on both *GI* and *EX*, and the results are consistent in both forward and backward citations. Therefore, these technology fields are considered relatively more "generalized" than other fields. This result is consistent with our classification of GPTs using patent count data in previous section. Meanwhile, Tech9, Tech38, Tech41 and Tech53, especially the last two have relatively lower values in *GI*. A possible reason is that a large proportion of the patents in these fields have cited innovations within their own fields. The intra-field citations may decrease the "generality" of the applications of these technologies. Meanwhile, the *EX* values of these technology fields are much higher than that of other fields, and that makes these fields more "diffusive" than other technologies. A similar argument can be applied to this observation. The innovations in emerging sectors such as in IT, communication and electronics fields (Tech 38, Tech41 and Tech53) were newly emerged in more recent years. Technology development usually takes very long time to diffuse into many sectors in the economy. At this point, the citations due to the constraint of our data might not be fully demonstrated the real generality and propensity of innovations in the newly emerged sectors, and so that we may still want to classify these fields as the GPT fields. With more updated data, we may found some different result in this analysis. Based upon above discussion, we may identify five technology fields as the GPT fields based on patent citation approach. They are Tech5, 16, 29, 50 and 53. All these fields can be found among the GPTs classes in our early classification based on patent count data, except Tech50 – non-metallic mineral products technology.

Among other technologies, we found that patents in Tech27 (wood working tools and machinery) and Tech55 (explosives, compositions and charges) cover least citation fields (both backward and forward) compared with patents in all other fields. In other words, innovations in these fields have very focused implications to a few specific economic sectors.

Table 7: Citation Analysis on GPTs and Other Technology Fields (dropping single citations).

Tech	Backward # of citations	Forward # of	Tech	Backward # of citations	Forward # of citations
1	13.20	2.44	**29**	13.01	2.48
2	10.47	3.01	**30**	12.09	2.11
3	12.26	3.18	**31**	13.75	3.08
4	14.41	2.79	**32**	9.80	2.65
5	13.88	2.97	**33**	13.13	2.47
6	13.78	3.75	**34**	11.68	2.38
7	13.80	3.32	**35**	14.28	2.46
8	13.60	3.00	**36**	12.57	2.83
9	14.33	3.68	**37**	10.29	2.47
10	10.98	2.56	**38**	13.32	2.40
11	13.01	3.22	**39**	12.74	2.76
12	14.94	4.32	**40**	11.53	2.59

13	13.09	2.60	**41**	13.19	2.53
14	13.48	2.42	**42**	14.34	2.75
15	12.78	2.38	**43**	14.80	2.77
16	14.44	3.29	**44**	15.00	2.00
17	13.89	2.58	**45**	11.83	2.85
18	15.61	3.04	**46**	10.18	2.85
19	9.80	2.50	**47**	11.73	2.72
20	14.67	2.32	**48**	9.00	2.91
21	12.89	2.43	**49**	15.66	2.99
22	9.38	2.13	**50**	14.48	2.93
23	19.99	4.17	**51**	16.70	3.30
24	10.67	2.46	**52**	11.30	2.35
25	13.68	2.74	**53**	15.40	3.63
26	14.84	2.77	**54**	12.00	2.23
27	18.50	2.00	**55**	26.00	2.22
28	13.48	2.76	**56**	15.12	3.84

In terms of frequency of citations (Table 7), due to the truncation problem, the average citation numbers on backward citations across all technology fields are much higher than those on forward citations. Moreover, innovations in certain fields such as Tech23 (mining equipment), Tech27 (wood working tools and machinery) and Tech55 (explosives, compositions and charges) are associated with most frequent citations compared with patents in other fields. This result together with what we found in these fields in Table7 leads to some interesting comparison. While Tech27 and Tech55's citation activities cover least technology fields, they show highest frequency of citing other patents (forward citations). This may be explained by the long-standing development of these sectors. Moreover, firms in these sectors have particularly higher tendency to cite innovations within their same industries. We may conclude from this observation that Tech27 and Tech55 are among the least "generalized" technology fields. Results in Table7 and Table8 also suggest that here is no direct linkage between *GI* of a specific field and the frequency of its patents citing others or being cited.

The GPTs identified in our study are not quite consistent with those suggested by Hall and Trajtenberg (2004)'s study. According to our definition, GPTs are technology fields (aggregation of patents), rather than single patents. In addition, the classification of GPTs in Hall and Trajtenberg's study (2004)'s study is based on the 399 technology classes, while we aggregate the 399 classes into 56 technology fields in this study. The large number of single citations associated with many innovations especially those in GPT fields may dilute the citations and consequently lower the generality of these fields. Therefore we drop the citing patents with less than 7.8 backward citations, and the cited patents with less than 1.4 forward citing patents. We found that patents in Tech 11, Tech16 and Tech53 show high frequency in citing other patents and being cited by others compared with innovations in other fields, while citations associated with the patents in Tech 5, Tech 9, Tech29, Tech38, Tech39 and Tech41 are still low (Table 8).

Table 8: The comparison of classifications of GPT fields using patent count and patent citation approach.

	Patent creation		Patent citation	
GPT Fields	Pervasiveness	Import	Pervasiveness	Importance
5 Chemical Process	medium	high	High	high
9 Synthetic resins and fibers	High High High	high high	High Medium	Medium high
11 Other organic compounds		medium	High	high
16 Chemical and allied equipment				
29 Other general industrial equipment	Low	high	High	high
38 Electrical devices and systems	high	high	Medium	Medium
39 Other general electrical equipment	Medium	high	High	High
41 Office equipment	High	high Very	High	High
50 Non-metallic mineral products	Low	medium	High	low
53 Other instruments and controls	High	high	High	medium

The Comparison of Classification Results Using the Two Approaches

The comparison of the GPT classifications based on two approaches leads to some interesting discussions. Firstly, there is some discrepancy between the GPT selections using two different approaches (Table 8). The selection of GPTs based upon knowledge creation or patent count approach is more toward reflecting the "dynamic" nature of GPTs, and how these technologies act as the "driving forces" leading to further technology advance in economy. However, such dynamisms may be underestimated in the GPT classification using the citation approach. According to our definition, GPTs are the technology fields usually with a large number of patents, and based on the citation approach, a large proportion of these patents are associated with single citations. The single citation may significantly lower the overall citation frequency and generality values in specific technology fields, and consequently make these fields less "pervasive". On the other hand, technology fields with few patents tend to result in having higher *GI* values given that they are less affected be single citations. For instance, patents in Miscellaneous Metal Products field (Tech 14) has been associated with citations covering a large variety of technology fields (48 fields backwardly and 51 fields forwardly), and with very high *GI* (0.87 and 0.6). However, this field should not be considered a GPT field, given that patents in this field only account for 2.58% of the overall patent pool. In other words, this field is not sufficiently "general".

Another interesting finding is that in the citation approach, ICT fields (ex. Tech41, Tech53) show very low "generality" value. Thus according to the definition, they are not GPTs. However, the result based on the patent count approach draws the opposite conclusion. In the latter case Tech41 and Tech53 are among the fastest growing fields with the most salient characteristics of GPTs. The distinct results suggest that patents in ICT fields are more often "invented" by firms from a broad range of economic sectors, but the citations to these fields are limited to some a few areas. The tacit nature of knowledge may help explain such divergence. More specifically, ICTs are mainly science-based technology in nature (Cantwell & Santangelo, 2002; Nelson & Winter, 1982), and are thus non-codified. Compared with other knowledge which is more public and technology-driven, the science-based technologies tend to be more difficult to transfer across organizations and locational boundaries. Therefore, ICTs are more likely to be developed in-house, and embedded in the combination and recombination of existing competencies with new inputs, and are thus less cited across different fields and sectors.

Thirdly, three characteristics have been emphasized in GPT literature: “pervasiveness, leading to continuous technical advance, and complementarity” (Helpman & Trajtenberg, 1998). Patent citations reflect the linkages between an innovation and its technology ground in the past. At this point, the citation-based approach classification may better interpret the “complementarity” nature of GPTs. On the other hand, the technology “creation” approach is more focused on the “dynamism” of GPT. GPTs are acting as “catalyst”, facilitating the fusion of formerly separate knowledge, and helping increase a firm’s absorptive capacity by establishing a broader technology base within firms. It has always been challenging to answer the question of why firms generate a lot of innovations in GPT areas that are technologically distant from their original cores, and the answer to this question may help explain the dynamism of a firm’s innovative capabilities which have been considered as the driving force of a firm’s growth (Granstrand, Patel & Pavitt, 1997).

Furthermore, we also compare the geographical distribution of GPTs based on the patent creations and citations. Historically, innovations in specific technology fields tend to be constrained within geographical boundary (ex. across different states in the U.S). In more recent years, due to the further cross-industry technological diversification and increasing knowledge flow among firms in geographically distant locations, both innovation and citation activities have become geographically more dispersed (Chart 1 and Chart 2). Corporate R&D becomes increasingly more relying on a widely distributed geographical network. Meanwhile, the degree of geographical dispersion varies across different technology fields. We found that both patent creations and citations in the GPT fields are sited across a broader range of locations (both domestically and internationally) compared with those in non-GPT fields. The only exception is Tech41 (Information Technology) (Table 9) in which patents are generated from a few places. This might be explained by the same argument that we discussed earlier that our study only covers the early stage of the Information Technologies (IT) development, and the fast growth of information technologies didn’t begin until the mid-1990s.

We also found that the geographical distribution of innovations based on patent citations (including that in the GPT fields) is more dispersed than that on patent creations. One possible explanation is that the patent citation activities cover a longer period of time (1890-1995) compared with the patent creations (1969-1995). Meanwhile, such discrepancy may also suggest that firms become increasingly rely on citing other’s technologies across organizational and geographical boundaries to complement their own existing R&D efforts, and it may lead to growth alternatives in the future. The network strategy in corporate innovations includes both intra-firm and inter-firm technology exchanges and transfers, both domestically and internationally.

Chart 1: The average number of states in the U.S covered by patent creations in GPT and other technology fields (1975-1995).

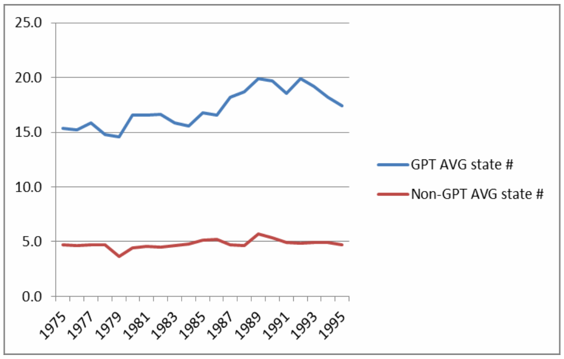

Chart 2: The average number of states in the U.S covered by patent citations in GPT and other technology fields (1975-1995).

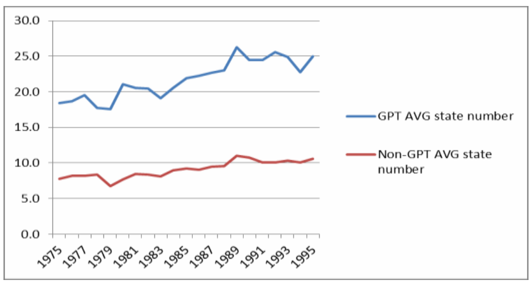

Table 9: The average number of U.S states in which firms have cited patents in a certain technology field.

Tech Field	Average state coverage in patent creations	Average state coverage in patent citations	Tech Field	Average state coverage in patent creations	Average state coverage in patent citations	Tech field	Average state coverage in patent creations	Average state coverage in patent citations
1	5	9.90	**20**	11	17.71	**39**	14	20.76
2	2	4.90	**21**	4	5.38	**40**	5	9.48
3	6	10.90	**22**	1	2.20	**41**	11	16.10
4	4	7.19	**23**	4	7.52	**42**	4	5.62
5	15	24.76	**24**	1	2.29	**43**	3	6.43
6	4	9.95	**25**	4	7.90	**44**	2	2.78
7	12	18.24	**26**	4	9.14	**45**	2	3.65
8	2	3.06	**27**	1	1.46	**46**	2	3.00
9	17	21.10	**28**	13	20.90	**47**	3	6.71
10	5	9.62	**29**	13	21.38	**48**	2	2.80
11	20	24.00	**30**	2	3.81	**49**	8	15.76
12	16	19.95	**31**	3	7.00	**50**	14	23.05
13	12	19.00	**32**	2	2.79	**51**	4	8.86
14	15	23.62	**33**	9	13.52	**52**	3	5.19
15	2	4.90	**34**	7	13.71	**53**	19	24.29

16	15	21.86	**35**	2	4.05	**54**	2	3.14
17	10	17.67	**36**	8	11.62	**55**	1	2.13
18	9	15.00	**37**	5	9.81	**56**	8	14.10
19	2	3.95	**38**	17	21.57			

CONCLUSIONS, IMPLICATIONS AND LIMITATIONS

Firstly, although patent counts and patent citations provide alternative settings to classify GPTs, the findings using both approaches suggest that ICTs have showed some salient natures of GPTs and are considered an advanced type of GPTs. ICTs are thus able to be brought into the GPT framework. The classification construct of GPTs established in this paper may serve as a platform based on which a broad range of research questions such as innovation management, internationalization and inter-firm and intra-firm knowledge flow can be studied. At this point, this study is only part of a wider research agenda that aims to consolidate the understanding of role of GPTs in corporate strategy.

Moreover, the question on whether to classify technology fields based on the knowledge-creation (patent-count) or on the knowledge-application (citation) construct deserves some in-depth investigation. A firm's decision on whether to develop their own GPTs or to apply existing GPTs developed by other firms may lead to some interesting discussions in corporate strategy research.

Furthermore, technological specializations in GPT fields are suggested to be closely associated with the geographical expansion and internationalization of corporate R&D activities. The innovations of GPTs have been spread across geographically distant locations, and the application of these technologies has been even more spatially dispersed. In other words, GPTs may allow firms to overcome their locational constraints to transfer knowledge between technologically and geographically more distant areas. The geographical dispersion of GPTs also suggests that these technologies may act as "catalyst", making feasible the combination and recombination of a firm's existing technologies with new knowledge inputs through intra- firm and inter-firm innovation networks.

This study is also subject to some limitations. Firstly, in this study we rely on USPTO patent class codes to classify technology fields. Like many other studies based on patent data, this method is criticized to fail to interpret the relatedness between different technology classes, and therefore the construct based upon technology class codes may not accurately proxy the "generality" of specific technology fields. In addition, U.S patents do not perfectly reflect the technology development in all industries. Simply relying on patents and citations may overestimate or underestimate the proliferation of some newly emerged sectors. For instance, the practice in the US of protecting software technology through patents is getting more attentions only in more recent years. In addition, innovations that are not codified and cannot be easily patented tend to be neglected in this study. For instance, with the aids of GPTs and especially ICTs, firms largely improve the efficiency of their production process and supply chains. Many of these progresses could not be patented. The "generalized" innovations other than patented technology, at this point, deserve further research.

Another constraint of this study is that there exist some fast growing technology fields more recently, such as the biotechnologies and ICTs. But in this study, we only track the patent creation and citation activities till 1995. The truncated data may affect the accuracy of measuring the "generality" of innovations in specific technology field, especially those in the new emerged ICT fields. Consequently, it may also affect the classification of GPT fields. In addition, although we've taken into concern the evolution of technology paradigms, we still could not find direct evidence on the transition between old and new GPTs (citation lags).

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