A toolkit for the systematic analysis of patent data to assess a potentially disruptive technology

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Abstract

Technologies can be characterised through exhibited patent characteristics. Previous work has developed a prototype toolkit for characterising potentially disruptive technologies using patent indicators, based on patent data relating to Light Emitting Polymers. This paper describes developing the toolkit to be applied to science-intensive technologies which are visible to horizon-scanning, but not yet widely developed such that opportunities for application and commercialisation may still be unclear, to produce an output score indicative of disruptive potential. A methodology is developed for characterising technologies through patent data analysis and using patent data emergence profiles to determine a point in the technology lifecycle which would have fulfilled the following criteria:

(a) The technology would have been visible to horizon-scanning
(b) The technology would not have been widely patented
(c) The technology would appear to be about to undergo accelerated growth

Technologies fulfilling these criteria are judged to be visible, high potential value, but not widely developed and thus susceptible to intervention and investment. Training and test technologies, including disruptive and non-disruptive technologies, are identified in order to enable the toolkit to be calibrated and validated. By selecting the point in the lifecycle of each technology which would fulfil (a)-(c) above, and retrospectively applying the toolkit, a scoring mechanism was developed to train and validate the toolkit to enable reliable indication and contra-indication of disruptive potential.

Keywords: disruptive technology; science-intensive; patent analysis; emergence profile; proof-of-concept; toolkit

Introduction

Different technologies exhibit different characteristics. Some characteristics are common between different technologies and consequently technologies can be grouped according their characteristics. One of those characteristics is the speed with which and extent to which a technology emerges and enables new applications. If a technology so emerges and as a result disrupts established boundaries of performance, cost or capability it may be labelled a disruptive technology.

This paper follows work by the Patent Informatics Team at the Intellectual Property Office of the UK which identified trends in patent data associated with disruptive technologies. In conjunction with the Technology Strategy Board[1] a retrospective analysis of Light Emitting Polymer technology (LEP) was completed, analysing characteristics of patent data consistent with disruptive innovation. A prototype toolkit for characterising potential disruption using patent indicators was thereby derived.

In the present paper, these indicators are refined, calibrated and aggregated to develop a validated toolkit for the systematic analysis of patent data to assess the disruptive potential of new technology.

The toolkit could assist policy makers to identify emerging technologies with disruptive potential and to make decisions regarding impact, intervention, support and investment.

Science-intensive disruptive technologies

The definition of what is and what isn't disruptive is open to interpretation. In the context of this paper and the toolkit, disruptive technologies are considered to be science-intensive technologies which are fundamentally new (or newly enabled) and which make a non-incremental breakthrough or enable capabilities that were not previously possible. They may also render existing technology redundant[2]. The present interest is in disrupting technological understanding or capability per se rather than disrupting downstream markets or consumer behaviour; although these are not excluded as they often follow the commercialisation of an application or process following a fundamental technical or scientific innovation.

By way of example, this research might aim to identify the enablement of digital photography (which has disrupted the capture, transmission and storage of images), but might not specifically aim to identify the disruptive effect on communications behaviour and the mobile communications market though picture-messaging which arose following commercialisation of 'camera phones'.

The former is enabled through science-intensive technology. The latter is certainly facilitated by technology but the disruption to established methods of communication is significantly attributable to commercialisation and competition between mobile telephone handset and service providers. That is not to say the potential for disruption would not be evident in patent data, but the toolkit is not specifically designed to spot such potential market disruption.

[1] http://www.innovateuk.org/
[2] http://en.wikipedia.org/wiki/Emerging_technology

Pre-emergence

Disruptive technologies can be disruptive at different times, even at multiple times, in their lifecycle. For science-intensive technologies, we believe disruptive potential is evident early in the technology lifecycle i.e. before a product or application is realised, but after the technology has breached contemporary research. This follows the science-push, market-pull theory, where scientific promise is evident before marketable reality.

It is this post-conceptual, pre-emergence period which is of interest; both as a period when characteristic patent activity is observed and as a point in time where identification of disruptive potential may be valuable. The technology will be visible (e.g. via horizon-scanning) but not yet widely adopted; investibility is high risk as potential applications and markets for the technology are speculative. This toolkit aims to assess the disruptive potential of technology at the stage when opportunities for application and commercialisation may still be unclear; pre-emergence.

Literary review

The prototype toolkit was previously developed following literary research to identify existing studies seeking to characterise science-intensive and disruptive technologies through patent data analysis. The results of the research were collated and included:

- ‘Double boom’ profile characteristic of patent filings over time[3]
- Relatively greater rate of patents granted (and/or filed) in a disruptive technology than rate of grants or applications over all technologies[4]
- In the growth stage of a first boom, high numbers of new applicants enter the technology field[5]
- Relatively large number of different applicants for a given number of initial filings (inc. many single applications)[6]
- In the early stages of disruptive technology growth (the first boom), many applicants will have few patents each[7]
- As technology emerges, number of applications per applicant increases[8]
- Significant increase in the number of classification terms assigned to applications between growth stages of first and second booms[9]
- Citation trees having short branches (high proportion of small numbers of forward/backward citations) indicate an immature field. Low numbers of longer branches indicate technical potential merit[10]

3 [1] p.7
4 [2] p.500
5 [3] p.1007
6 [1] p.6
7 [3] p.1007
8 [1] p.6
9 [3] p.1007
10 [1] p.9-10

It was further noted that intense early publication of academic journal articles corroborates early phase research activity[11], although non-patent literature publications stagnate about 2-3 years before the first patent boom[12]. However, non-patent literature analysis is currently outside the scope of the toolkit.

Prototype toolkit methodology

The prototype toolkit was derived by identifying each of the researched characteristics in published patent data relating to the development of Light Emitting Polymers (LEP), extensively analysing this data at different periods and deriving indicators based on observations. Essentially, the indicators reflected the relative extent to which each characteristic was observed in the data, pre-emergence.

LEP technology is widely accepted as being disruptive for its scientific basis rather than for any external strategic or commercial influence[13] e.g. marketing, liquidity or monopoly. Its disruptive effect is a result of science developing a promising discovery to enable new technological capability. In this sense it is a ‘science-intensive’[14] disruptive technology. It exemplifies the nature of disruption which the toolkit is designed to indicate.

The derived indicators may be rationalised as follows:

- Patent application filings over time
- Profile of inventors listed on patent applications
- Patent portfolios by applicant type sector
- Technology sub-sectors/areas
- Forward and backward citation analysis

Development methodology

The indicators were integrated into an algorithm, scored and initially weighted based on observations in the LEP dataset, so as to produce an output score indicative of disruptive potential. However, in order to calibrate and validate these indicators for other applications, it was necessary to identify technologies which could be used to train and test the algorithm. These technologies would need to cover a range of both disruptive and non-disruptive technologies, although all were science-based.

Of course the toolkit is designed to be applied to analyse current and future pre-emergent technologies, but for the purposes of training the toolkit, it was necessary to retrospectively analyse mature technologies which can be deemed to have been disruptive or not. This allowed the toolkit to be trained to indicate and contra-indicate disruption accordingly.

Two important aspects of the selection of training technologies are the selection of the technology itself, and crucially the selection of the point in time at which the toolkit should be applied, pre-emergence. By applying the toolkit in this manner, the toolkit could be trained to perform so as to correctly indicate or contra-indicate disruptive potential, had it been applied at the time that particular technology was visible but pre-emergent.
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[11] [1] p.7
[12] [3] p.1007
[13] From internal discussions with the Technology Strategy Board
[14] [3] p.1006

As well as training technologies, test technologies were selected on the same basis. These were used to test the toolkit following calibration using the training data.

Double boom technologies

Schmoch[15] notes that half of all 'science-intensive' technologies exhibit 'double boom' growth in patent data. A further 25% exhibit a weak double boom or potentially a delayed second boom. In other words, 75% of 'science-intensive' technologies exhibit two peaks of patenting activity over time. The science-push, market-pull phenomenon gives rise to the double boom profile. Double boom is therefore an indication of science-intensive nature but not necessarily disruptive potential. It is, however, likely to be a characteristic of the technologies to which the toolkit may be applied; those resulting from universities and research programs. Double boom technologies, then, are ideal test and training technologies and being science-intensive, may share certain characteristics of disruptive technologies, whether they result in disruption or not.

Training and Test Technologies

Technologies which are alleged to have had disruptive effect were identified through literary research. Science-intensive technologies allegedly exhibiting double boom but not necessarily disruptive effect were identified and selected for training indication and contra-indication.

[15] [3] p.1006

Disruptive Technologies	Technologies exhibiting "double boom" [16]
Microwave heating[17]	Centrifuges with free vortex
Flash memory[18]	Making metallic powder
Cyclonic vacuum cleaners[19]	Metal working by electric current
RFID transponders	Lasers for manufacturing
Fibre-reinforced plastics[20]	Robotics
Laparoscopic surgery[21]	Plies of pneumatic tyres
Telephone[22]	Packaging fragile articles other than bottles
	Composition of optical fibres
	Polymerisation catalysts
	Immobilised enzymes
	Interferons generated by genetic engineering
	Seismology
	Control of optical properties
	Computer systems according to biological models
	Recording by optical means
	Superconductors
	AD conversion

Table 1 Technologies chosen for toolkit development

Published patents for each technology were identified using International patent classification (IPC) codes and keywords in conjunction with the European Patent Office's online patent database. Consequently, a patent dataset was obtained for each technology.

When to apply the toolkit

A plot of the number of published patents per priority filing year was obtained for all training and test technologies in order to establish a method for the determination of when to apply the toolkit. The expectation was that the toolkit would be applied at a point of visibility, pre-emergence. This is consistent with the observation that the prototype toolkit was designed to be applied at a point following scientific development but before commercialisation. It was therefore necessary to develop a method for identifying this point in the patent filing profile.

It might seem obvious to identify the point of toolkit application as the inter-boom period, for double boom technologies. However total published patent filing volumes were frequently identified in excess of 2000 at the peak of the first boom and this is commensurate with greater visibility, or a

[16] [3]
[17] http://en.wikipedia.org/wiki/Microwave_oven
[18] [4] p. 48
[19] [8]
[20] http://en.wikipedia.org/wiki/Disruptive_technology
[21] http://www.neilbaum.com/articles/prac_disrupttech.html
[22] [5] p. 56

broader technology definition, than the anticipated requirement of toolkit application. In other words, by the time the first boom has occurred, the boat has sailed. Furthermore the inherent delay, of at least 18 months in most cases, between patent priority filing and publication means that published patent filing volume will lag visibility. In order to permit toolkit application as early as possible, enabling the largest window of visibility, it was important to identify the point of toolkit application very early in the patent data technology lifecycle and to develop and test the toolkit application at this point.

It was expected that technologies to which the toolkit would be applied might be those visible to a horizon-scanning exercise and rumoured to have disruptive potential. Although such an exercise may or may not take account of patent publications, patent activity is inherently contemporary with early research and publication of results. It is therefore reasonable to assume that the toolkit would be applied when about 200-2000 patents may be published. This range is based on observations of emergence in the LEP and other patent data[23] and is consistent with the method of derivation of the prototype toolkit.

For these reasons it was decided to identify the point of toolkit application independently of the first and second boom profile per se. Consequently, further analysis of emergence profiles was undertaken.

Compressed double boom; pre-boom

During prototype toolkit development, a 'pre-boom' due to very early patenting preceding the "first boom" in LEP technology was observed. Such pre-booms were also observed in presently-studied technology cycles. It is postulated that where research, patenting and investment 'compress' a "double boom" to a protracted rapid rise in activity (perhaps increasing disruptive potential), such a pre-boom may be the best indication of imminent rapid emergence.

Defining the time point for toolkit test application

Consequently a methodology was devised to identify the first protracted rapid rise in priority patent applications (PRRPPA) consistent with the onset of a first boom or protracted pre-boom.

A PRRPPA was defined as:

- A rate of increase of patents published per priority year in excess of the rate of increase of patents published per priority year for all technologies.

- Lasting more than two years.

From the training and test data, the methodology enables identification of the onset of a first boom, a compressed double boom or potentially a pre-boom[24] irrespective of the specific emergence profile. Consequently the point of potential toolkit application was identified earlier in the technology lifecycle. By limiting the point of toolkit application to a period where less than 2000 published patents were available, the technology visibility criteria were also met.

Where a PRRPPA was not identifiable within a dataset of less than about 2000 published patents, the technology was deemed outside the visibility criteria. The patent datasets were based on researched technologies, but it is quite possible that a technology so identified may be more general than the anticipated subjects of toolkit application and consequently give rise to a larger

[23] E.g. http://ipservices.genericsgroup.com/
[24] Lasting two years or more

dataset. Consequently, the dataset may mask local indications of rapid emergence. In this respect, further work might refine such datasets to identify sub-sectors which meet the visibility criteria.

It was necessary to develop a robust methodology for identifying the correct point in time at which to apply the toolkit. PRRPPA were identified by:

- Normalising the number of patents published per priority year for the technology under consideration.

- Normalising the number of patents published per priority year for all technologies.

- Calculating A - the derivative of the normalised number of patents published per priority year for the technology under consideration. This gives the rate of change of patents published per priority year for the technology under consideration.

- Calculating B - the derivative of the normalised number of patents published per priority year for all technologies. This gives the rate of change of patents published per priority year for all technologies.

- Calculate A-B to give the relative rate of patent publication in the technology under consideration.

- Plotting R, the relative rate of patent publication vs. priority year for each technology under consideration.

The plot of relative rate of patent publication vs. priority year is positive where the rate of increase of patents published per priority year for the technology under consideration is in excess of the rate of increase of patents published per priority year for all technologies.

Where R is greater than 0 for at least two years, this is deemed to be the first period of a protracted rapid rise in patent applications. If the total number of published patents exceeds 2000 during or after this period, then the technology is deemed suitable for intervention and the toolkit may be suitably applied.

Technology plots

Plots of patent publications by priority year, for three example technologies, are shown in the figures below. Each graph also plots the relative rate of patent publication in each technology, for the forthcoming year (i.e. the derivative refers to the rate of patent application in the next year, not the past year).

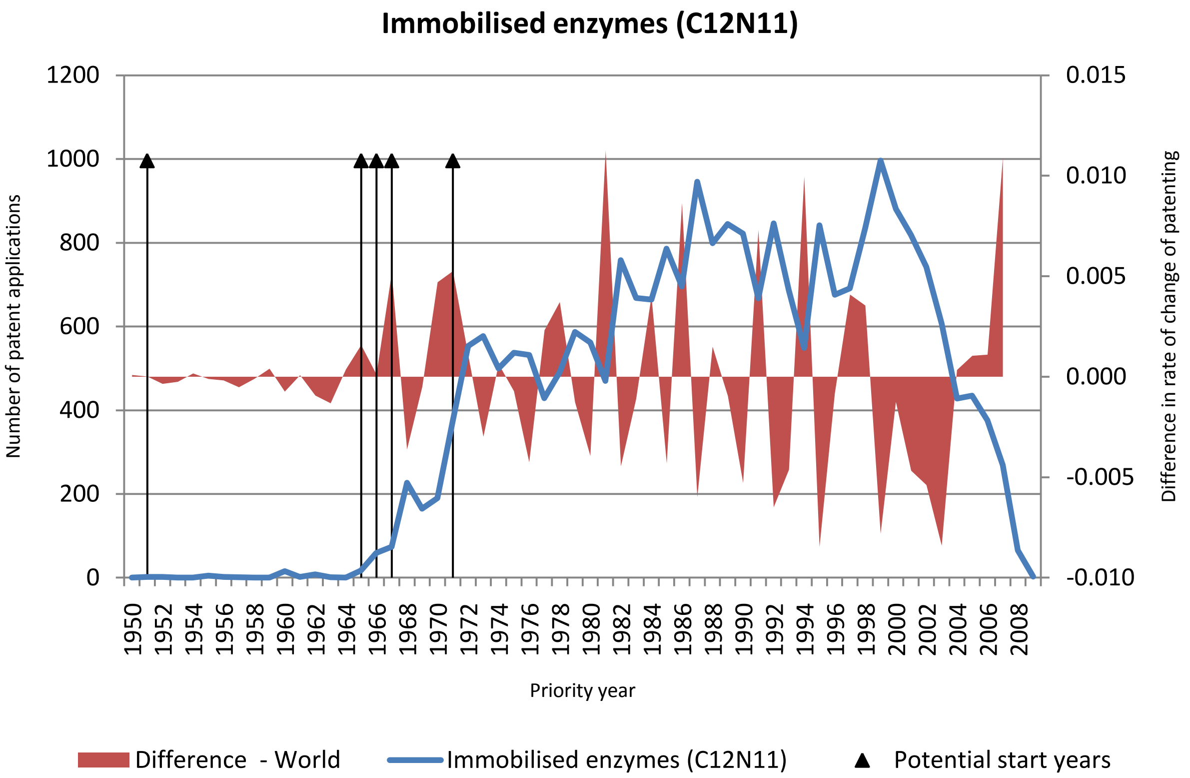

Figure 1 Time series profile showing an incremental technology having a plateau profile

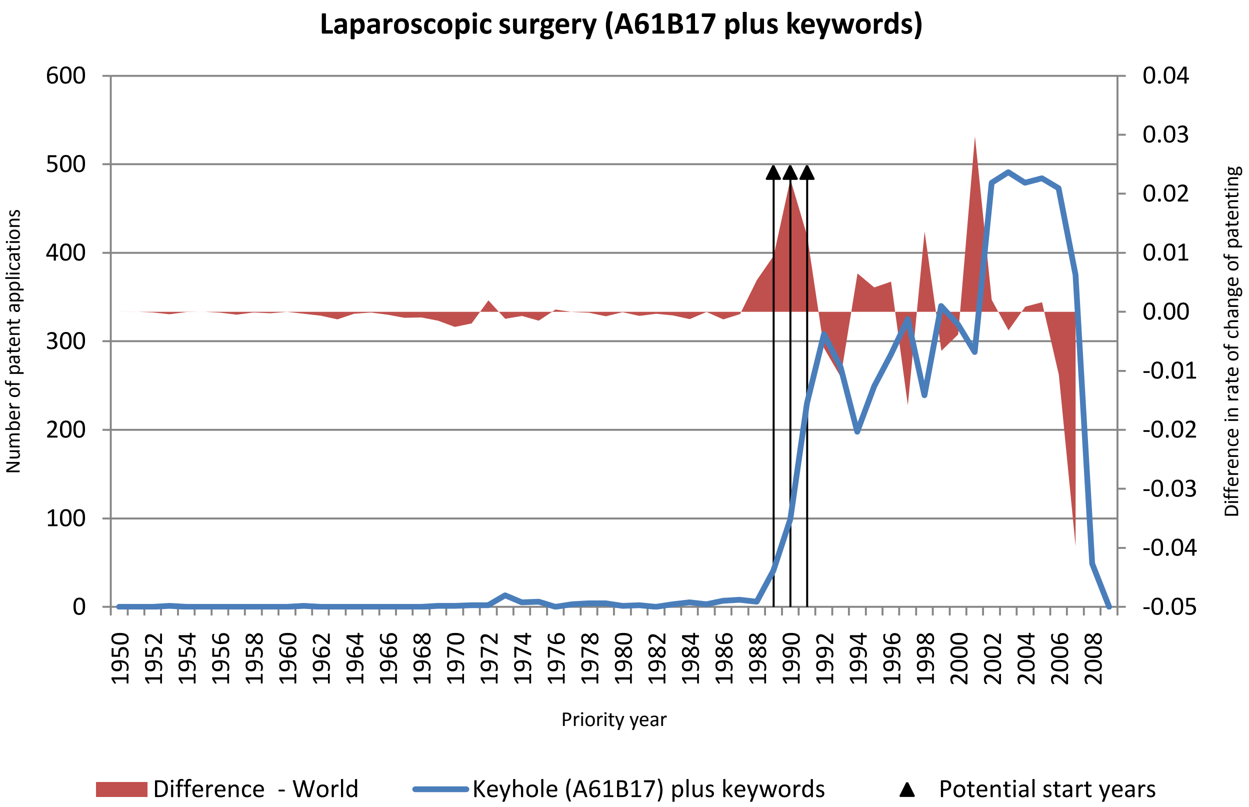

Figure 2 Time series profile showing a disruptive technology having a double boom profile

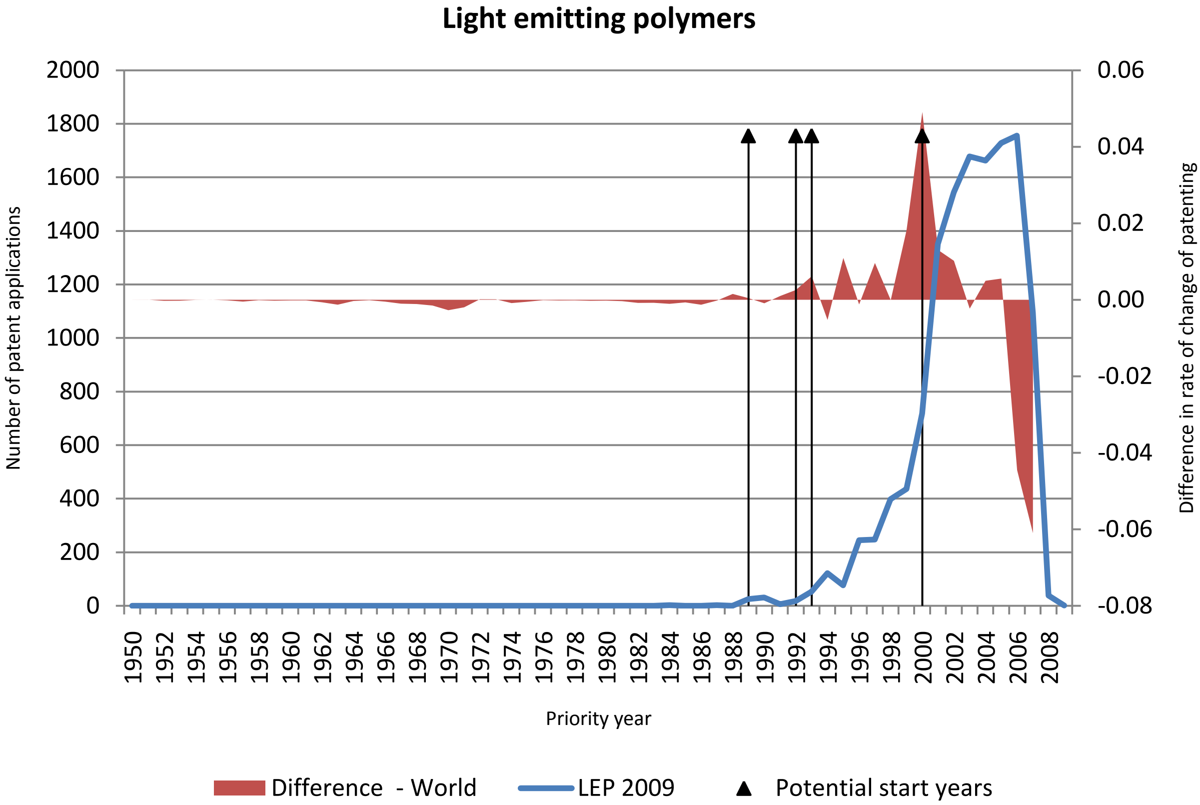

Figure 3 Time series profile showing a disruptive technology having an S-curve profile

To determine the appropriate year of toolkit application, the following methodology was applied:

- Determine where the relative rate of patent publication R is greater than 0 for at least two years.

- If the total patent publications T during this period are less than or equal to 2000 then the technology is suitable and the toolkit should be applied at the last point where R > 0 and T <= 2000.

- If R is never greater than 0 for at least two years then the technology is not regarded as suitable for intervention (and unlikely to be disruptive) but may be suitable for confirming that the toolkit, when applied to such a technology (at a time suitable time in the technology lifecycle), contra-indicates potential disruption.

- If at the beginning of the first time period where R > 0 for at least two years, T > 2000, then the technology is deemed too visible for intervention. Such a technology may be suitable for confirming that the toolkit, when applied to such a technology (at a time suitable time in the technology lifecycle), contraindicates suitable investible disruption.

Training and test technology characteristic summary

Following the application of the methodology derived above, the following table summarises the technologies chosen to train the toolkit algorithm and subsequently test it. In each case an indication of the year of application is given.

Technology	Year of toolkit application	Technology type	Type of dataset
LEPs	1993	Disruptive	Initial dataset
Optical fibres	1971	Incremental	Algorithm training
Microwave heating	1969	Disruptive	Algorithm training
Immobilised enzymes	1971	Incremental	Algorithm training
Flash memory	1973	Disruptive	Algorithm training
Cyclonic vacuum cleaners	1998	Disruptive	Algorithm training
Fibre-reinforced plastics	1965	Disruptive	Algorithm training
A-D conversion	1965	Disruptive	Algorithm training
RFID transponders	1988	Disruptive	Algorithm training
Laparoscopic surgery	1991	Disruptive	Algorithm test
Seismology	1953	Incremental	Algorithm test
Computer systems according to biological models	1989	Disruptive	Algorithm test
Optical recording	1977	Incremental / Disruptive (see text)	Algorithm test
Lasers	1980	Incremental	Algorithm test

Table 2 Technologies chosen for toolkit development

Training toolkit indicator algorithm

From the prototype toolkit, the following six indicators were developed, numerical measures established and thresholds initially set to indicate disruption in accordance with the LEP data. A summary of the results used to develop the algorithm is given in the next section, followed by the results of testing the algorithm. For reasons of commercial sensitivity, specific details regarding indicators, thresholds and scoring are not included.

1. Patent application filings over time

Two measures have been developed to reflect the shape of the time series profile. For example, we have noted several different types of profile ranging from a plateau (normally an incremental technology) to an S-curve (normally a disruptive technology).

2. Inventor turnover

Two measures have been used to reflect the increase or otherwise of new inventors being listed on patent applications. It is surmised that a marked increase in new inventors reflects inward investment and imminent rapid technological emergence.

3. Applicant / patent profile

The applicant type profile tends to evolve over a technology lifecycle. For example, early in technology lifecycles, proportionately more patents tend to be held by non-corporate entities (e.g. universities or their IP management bodies).

4. Patent holding

The size of the portfolios held by entities of certain sizes is important. For example, early stage technologies may involve more academic interest, with all applicants having fewer patents. Further developed technologies are likely to be dominated by large corporations having large patent portfolios.

5. Classification term / technology trend

Certain classification terms may indicate that a technology is not well established. Detailed analysis of the spread, hierarchical position, nature and proportion of classification terms applied can enrich assessment of disruptive potential. Furthermore this test could perhaps be applied as a secondary check to filter potential market disruption from science-intensive disruption.

6. Citation analysis

The number of citations and proportion of non-patent literature (NPL) citations to patent citations is postulated to be significant. Detailed citation analysis, which can be performed by in-depth research of search reports on patent applications and determining the citation type (e.g. novelty / inventiveness / background technology) of specific patents, can enrich the analysis of disruptive potential by further understanding the patentability and position of patent applications in the existing technology space.

Aggregate score of weighted indicators

Each of the indicators is weighted differently depending on its observed significance. For example, the inventor turnover indicator is weighted less than patent holding because it has been noted that science intensive disruptive technologies tend to result in smaller portfolio sizes whereas inventor turnover could increase as a result of a change in patenting or commercial strategy[25].

[25] It should also be noted that inaccuracies in the recording of inventor information may also affect the test results and so less weight is given to this test.

Following training of the algorithm, an aggregate score of the weighted indicators was devised. This output score forms the basis for the toolkit result and is expressed as a percentage. 50% is the indeterminate level; higher than 50% indicates disruptive potential. Lower than 50% contra-indicates disruptive potential.

A summary of the results is presented in Table 3 with the cells being coloured to indicate positive indication of disruptive potential (green) or contra-indication of disruptive potential (red).

The three datasets which are contra-indicated are those which are not considered to be disruptive technologies.

Test	Optical fibres	Microwave heating	Immobilised enzymes	Flash memory	Cyclonic vacuum	Fibre-reinforced plastics	A-D conversion	RFID transponders
Patent application filings over time 1a (%)	20	3	21	17	42	24	18	33
1b (%)	7	1	9	4	15	15	6	15
Inventor turnover 2a (%)	121	90	-99	187	93	-50	57	-9
2b (%)	933	86	-96	812	394	-97	100	75
Applicant / patent profile 3a (years)	2	3	2	4	2	0	4	4
3b (years)	2	0	1	2	1	0	3	4
Patent holding 4a (%)	0	51	9	55	42	12	26	16
4b (%)	69	24	56	19	24	21	26	27
4c (%)	31	25	36	26	35	67	48	57
Classification term / technology trend 5a - science	7	11	14	14	0	2	3	13
5a - /00s	3	2	3	5	5	4	3	1
Citation analysis 6a (%)	2	0	3	11	3	0	0	2
6b (%)	21	0	59	42	2	0	0	0
Output score (%)	47	32	37	74	68	53	58	63

Table 3 toolkit applied to refinement datasets

Testing the toolkit

Following calibration of the algorithm by adjusting thresholds for individual indicators using training data, the toolkit was applied to the test technology datasets. The results can be seen Table 4 below.

Test	Laparoscopic surgery	Seismology	Computer systems according to biological models	Optical recording	Lasers
Rate of change of patent applications over time 1a (%)	76	36	33	49	33
1b (%)	60	12	14	14	14
Applicant turnover 2a (%)	130	27	952	20	16
2b (%)	202	147	2482	143	93
Applicant / patent profile 3a (years)	3	4	3	4	4
3b (years)	1	0	3	3	4
Patent holding 4a (%)	17	49	18	67	59
4b (%)	18	23	39	13	24
4c (%)	65	28	43	19	17
Classification term / technology trend 5a - science	15	15	1	12	3
5a - /00s	3	1	5	5	3
Citation analysis 6a (%)	9	0	6	3	6
6b (%)	4	0	21	6	11
Total score (%)	63	42	53	47	32

Table 4 Toolkit applied to test datasets

The two technologies which score more than 50%, Laparoscopic Surgery and Computer Systems According to Biological Models, are both considered to be disruptive technologies. Whilst most of the datasets used represent relatively mature technologies, the Laparoscopic Surgery dataset is more recent, and is similar in form, timing and volume to the LEP dataset. Noticeably, it exceeds 50% with the most significant indication of disruptive potential.

Although science-intensive, seismology and laser technologies exhibit generally incremental characteristics and so correctly score under 50%. Specific applications of lasers, however, may be deemed disruptive and may be the subject of further work. Furthermore, by virtue of the way that optical recording patents are classified, audio CD, computer data CD-ROMS and more recently DVD/Blu-Ray technology were all included in the patent dataset in accordance with the researched definition. As such, the dataset encompassed a broad range of optical recording technology, some of which is acknowledged disruptive, some is not. As a result, the overall dataset scores under 50%. However, a more refined dataset, looking at specific sub-sectors of digital recording technology, for example only CD-ROMS, might give a different result.

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Conclusions and further work

Technologies can be characterised through exhibited patent characteristics. Consequently, characteristics in patent data associated with disruptive potential can be identified and incorporated into a systematic methodology for assessing disruptive potential in datasets relating to a specific technology.

By identifying established science-intensive technologies and determining whether or not they were disruptive, it has been shown that a toolkit of suitable patent characteristics can be trained and refined to produce an output score indicative of assessed disruptive potential.

This required designing a methodology for characterising technologies using patent data and developing a definition of the time-period for application of the toolkit within the technology criteria of:

- visibility to horizon-scanning
- not widely patented
- appear to be about to undergo accelerated growth

By training and then testing the toolkit through retrospective application on each technology dataset, a weighted, aggregated mechanism was developed which leads to successful indication and contra-indication of disruptive potential in testing.

Further work could extensively test and refine the toolkit algorithm on the basis of other technology datasets. These could be identified through further research or by sub-sectorising existing broader datasets such as lasers and optical recording.

Further work might also target market disruption. Although the current toolkit is designed to identify disruption to technological capability, a different model may be able to assess potential market or downstream disruption. Potential disruption to society might also be factored in; disruption to behavioural patterns, mobility and networking for example.

The current toolkit focuses on science-intensive technologies, but combinational technology such as ‘camera phones’, which can also lead to disruptive innovation might be the subject of further work.

Although the toolkit has been ‘blind’ tested, real-time application to contemporary horizon-scan events, and subsequent monitoring of emergence will permit thorough assessment of the toolkit.

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