

Eye, Robot: Artificial Intelligence and Trade Mark Registers

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1. Introduction: Reading Trade Mark Registers

The edifice of trade mark registration exists primarily to provide useful information. Registers tell us who owns what. They signal the existence of exclusive property rights associated with commercial signs, thereby allowing other traders to plan around that information. These signals exist in ever increasing numbers. According to the World Intellectual Property Organisation (WIPO), an estimated 9.11 million new trade mark applications were filed worldwide in 2017, while in the same year there were an estimated 43.2 million active trade mark registrations at 138 offices worldwide.¹ Until recently, it was axiomatic that registers for marks were directed at human readers – an applicant for a trade mark, trade mark registry examiners, vigilant competitors, employees of search and watching agencies as well as the occasional judge. This list now has a new entrant. What are the implications for the registered trade mark ecosystem, when algorithms begin to efficiently and comprehensively read trade mark registers?

The influence of artificial intelligence (AI) on trade mark registration is more subtle than its impact on patent or copyright law. The creative and inventive domains of IP have to contend with seemingly existential challenges: whether increasingly autonomous computer software ought to be considered an inventor or author and whether the corresponding outputs should be recognised as protectable subject matter.² In the trade mark context, machine learning has developed to the point where AI algorithms can readily assess the similarity between marks as well as goods and services, flagging up potential conflicts. At first glance, this seems like an enhancement which merely allows users of registries to do what they already do, but better. The legal implications of an AI

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¹ WIPO, *World Intellectual Property Indicators 2018* (WIPO, 2018) 88, 95.

² See for e.g. R Abbott, 'I Think, Therefore I Invent: Creative Computers and the Future of Patent Law' (2016) 57(4) *Boston College L Rev* 1079; WIPO *Technology Trends 2019: Artificial Intelligence* (WIPO, 2019); A Ramalho, 'Will Robots Rule the (Artistic) World? A Proposed Model for the Legal Status of Creations by Artificial Intelligence Systems' (2017) 21 *Journal of Internet Law* 1; J Grimmelmann, 'Copyright for Literate Robots' (2016) 101 *Iowa Law Review* 657.

algorithm which ‘reads’ a trade mark register, replicating or entirely replacing human judgment for certain stages of analysis, has not yet been considered in any detail. Machine learning algorithms are involved in identifying potentially conflicting prior rights when selecting a mark, during clearance checks by private service providers or by trade mark registries themselves. The speed and comprehensiveness of coverage, as well as the increasingly routine application of AI, is potentially game-changing. This chapter outlines these recent developments and considers some of their implications.

2. AI and Trade Marks: Setting the Scene

AI is commonly used as an ‘umbrella term to cover a set of complementary techniques that have developed from statistics, computer science and cognitive psychology’.³ According to a White House report, it conventionally refers to ‘a computerized system that exhibits behaviour that is commonly thought of as requiring intelligence. Others define AI as a system capable of rationally solving complex problems or taking appropriate actions to achieve its goals in whatever real world circumstances it encounters’.⁴ The goal is for software to replicate intelligent behaviour and remarkable progress has been made on so called ‘Narrow AI, which addresses specific application areas such as playing strategic games, language translation, self-driving vehicles, and image recognition’.⁵ Recent successes are in part attributable to the advent of big data and improved computing power. Improved data flows form the basis for better-quality machine learning, which ‘is the technology that allows systems to learn directly from examples, data, and experience’.⁶ This technology allows software algorithms to learn from data (or examples), drawing statistical inferences and identifying patterns, rather than by following pre-programmed rules. Machine learning is iterative, so that when an algorithm is exposed to new data, it can adapt. These systems are already ubiquitous. ‘Many people now interact with machine learning-driven systems on a daily basis: in image recognition systems, such as those used to tag photos on social media; in voice recognition systems, such as those used by virtual personal assistants; and in recommender systems, such as those used by online retailers’.⁷

While image recognition technologies are considered below, recommendation systems in the online retail context hint at the broader implication for trade mark infringement.⁸ A

³ W Hall and J Presenti, *Growing the Artificial Intelligence Industry in the UK* (HM Government, Independent Report 2017), 4.

⁴ US Executive Office of the President, *Preparing for the Future of Artificial Intelligence* (October 2016), 6.

⁵ *Ibid.*, 7.

⁶ Royal Society, *Machine Learning: The Power and Promise of Computers that Learn by Example* (April 2017), 16.

⁷ *Ibid.*

⁸ For infringement issues, see L Curtis and R Platts, ‘AI is coming and it will change trade mark law’ (2017) *Managing IP* 9; L Curtis and R Platts, ‘Alexa, “what’s the impact of AI on trade mark law?”’ (2019) *Managing IP* 43.

platform's virtual assistant or AI-powered recommendation system – think Amazon or eBay – might respond to a search query by suggesting an infringing product, based purely on statistical correlations relating to past searches on that platform. Alternatively, the system might treat the trade mark in a search query generically, as shorthand for a product class and offer the products of competitors within that class. Should the platform or online service provider be held liable if an autonomous AI system is making retail recommendations that infringe trade mark rights? Online grocery retailers or supermarkets already recommend substitutes if the desired product is not available and may offer a competing brand in the process. Is this helpful to consumers and competition-enhancing, or damaging to trade mark owners' legitimate interests? Conversely, when virtual assistants shop on our behalf, does the 'average consumer' hypothetical construct, characterised by imperfect recollection and the inability to make side by side comparisons, still apply to AI shoppers when assessing infringement?⁹

The ongoing transformation of retail services forms the backdrop for this set of questions. As enticing as they are, we must leave a more detailed consideration for another day. As an initial response, parallels might be drawn with keyword advertising case law, where AI algorithms have offered competing products in response to search terms consisting of trade marks. The answers to infringement questions may turn on how the *results of the search are presented* to consumers, as opposed to *how the AI internally processes the trade mark*. Where product recommendations are provided with suitable clarifications and qualifications, they should be permitted. Where they are misleading or ambiguous, they are likely to be infringing.¹⁰ Putting infringement to one side, the task for this chapter is to highlight the remarkable inroads that AI is making into the everyday processes of trade mark registration, as reflected in its adoption by two very significant institutional actors: (i) trade mark registries, as well as (ii) trade mark clearing, searching and watching agencies.¹¹

The developments described in this chapter are intended to augment existing practices relating to trade mark search, examination and watching. Commercial search and watching agencies have been at the forefront of technological developments. Most of the technology described below is designed to identify prior conflicting rights, as evidenced by similar marks for similar goods. Searching, for the purposes of clearing a potential new mark, is described as:

[T]he critical legal step in the process of selecting a new mark. The search enables a trade mark lawyer to determine whether a mark is available for use and likely to be registrable. For a business to launch a new product or service without first conducting a search is to flirt with commercial disaster. A search is necessary

⁹ On the average consumer, see GB Dinwoodie and D Gangjee, 'The Image of the Consumer in European Trade Mark Law' in D Leczykiewicz and S Weatherill (eds) *The Image(s) of the Consumer in EU Law* (Hart, 2016) 339.

¹⁰ See for e.g. *Cosmetic Warriors and Lush v Amazon.co.uk and Amazon EU* [2014] EWHC 181 (Ch).

¹¹ On the significance of bureaucratic practices such as search and classification in constituting the very objects of trade mark protection, see J Bellido & Hyo Yoon Kang 'In Search of a Trade Mark. Search Practices and Bureaucratic Poetics' (2016) 25(2) *Griffith Law Review* 147; J Bellido, 'Towards a History of Trade Mark Watching' [2015] *IPQ* 130.

because, simply stated, trade mark rights are granted on a first-come, first-served basis.¹²

Searches therefore anticipate objections by the registry or oppositions based on prior rights, allowing applicants to assess the risks of proceeding with a registration. Watching agencies provide a commercial service for clients with successfully registered trade marks, whereby the agencies monitor new trade mark applications by third parties across selected jurisdictions and flag up potential conflicts. The clients can then decide whether or not to oppose them.¹³ Both these processes are primarily concerned with registry level conflicts.

3. Searching for Similarity

In 2018, WIPO convened a review of the experiences of intellectual property offices that had experimented with AI algorithms to increase efficiency and reduce costs.¹⁴ While AI is supporting major IP Offices in a number of specific (e.g. classifying patents according to relevant technology groups for examination purposes) and general ways (e.g. chatbots as part of help desk services, to assist applicants with queries), certain trade mark specific applications have been identified.¹⁵

3.1 Goods and Services Classification

First, AI algorithms are being used to automatically recommend classes for goods and services contained in trade mark applications. Along with the sign being claimed as a mark, the trade mark application also indicates the goods and services identified by that sign.¹⁶ This reflects commercial practice: the Nike ‘swoosh’ logo is applied to athletic footwear, sports clothing and accessories. The international reference point is the Nice Classification system, maintained by WIPO, which consists of a list of headings of 34 classes of goods and 11 classes of services as well as an alphabetic list of goods or services

¹² GA Gundersen, ‘Trademark Searching and Clearance’ (INTA Guide, 2018), 1-2.

¹³ Bellido, ‘Towards a History’ (n 11).

¹⁴ See generally the Meeting of Intellectual Property Offices (IPOS) on ICT Strategies and Artificial Intelligence (AI) for IP Administration, 23-25 May 2018, Geneva (WIPO/IP/ITAI/GE/18). The responses to a survey relating to AI usage is contained in WIPO Secretariat, ‘Original Replies from IPOs in English, French or Spanish’ 29 March 2018 (WIPO/IP/ITAI/GE/18/2 REV).

¹⁵ See WIPO *Index of AI initiatives in IP Offices*, at: https://www.wipo.int/about-ip/en/artificial_intelligence/search.jsp

¹⁶ Case C-3-7/10, *Chartered Institute of Patent Attorneys v Registrar of Trade Marks* (IP TRANSLATOR) ECLI:EU:C:2011:784 (AG Bot), [1] (‘The two essential components of the registration of a trade mark are (a) the sign and (b) the goods and services which that sign is to designate. Each of those components makes it possible to define the precise subject-matter of the protection conferred by the registered trade mark on its proprietor.’)

in each class.¹⁷ Historically, there has been no mandatory form or prescribed terminology for specifying these goods and services. Applicants are free to choose, based on their own commercial preferences. However the terms selected by an applicant are subsequently slotted into the relevant classification taxonomy adopted by the trade mark registry. Thus an applicant selling remote controlled aerial vehicles might specify ‘toy drones’ on the form but will have to identify Class 28 (‘Games and Playthings’) of the Nice Classification as the relevant class. Accuracy is important here. One of the primary purposes of bureaucratic classification is to enable efficient searching by registries and third parties for conflicting prior marks in relation to identical or similar goods. In order to avoid rejections based on inaccurate terminology or mistaken classifications, the Intellectual Property Office of Singapore (IPOS) has developed an International Classification of Goods and Services (ICGS) Autochecker software tool, which relies on a natural language processing AI system.¹⁸ Applicants can verify their list of selected product terms against the thousands of pre-approved terms in the IPOS database. The software identifies misspellings, duplicated items, terms not found within the database of approved terms and items listed under the wrong class heading. TM Class is another widely used tool which helps applicants to identify appropriate terms and corresponding classes from within a consolidated pre-approved list provided by participating registries.¹⁹ It additionally provides a hierarchical taxonomy of pre-approved terms, thereby enabling applicants to locate their preferred product description within broader or more narrow fields by moving up or down the hierarchy. China is presently developing a ‘Standard Goods System’, which clusters existing terminology relating to goods into groups, based on their similarity, so as to ‘establish the Goods Relation Dictionary. With this dictionary, the system automatically allocate[s] newly-supplied goods into the respective... group. For goods supplied for the first time, a mother goods [sic] would be designated to begin a group’.²⁰ Germany and Japan have also invested in developing such systems,²¹ while WIPO is working on AI that will be used to predict the most relevant Nice classifications, improving on the former text-search matching model.²² These tools reduce examination times and rejection rates based on incorrect classifications, leading to cost savings for registries and users.

3.2 Identifying Similar Marks: Semantic and Image Searches

¹⁷ See: <https://www.wipo.int/classifications/nice/en/>

¹⁸ The instructions are available at: <https://www.ipos.gov.sg/docs/default-source/resources-library/trade-marks/resources/autochecker-user-guide.pdf>

¹⁹ See <http://euipo.europa.eu/ec2/>.

²⁰ WIPO, ‘Summary of the Replies to the Note on Applications of AI to IPO Administration’, 8 Feb 2018 (WIPO/IP/ITAI/GE/18/1), [23].

²¹ Japan Patent Office, ‘Outline of JPO's Activities for Using AI’ 29 May 2018 (WIPO/IP/ITAI/GE/18/P9).

²² Patrick Fiévet, ‘Artificial Intelligence applied to IPC and NICE Classifications’, 25 May 2018 (WIPO/IP/ITAI/GE/18/P18).

Assessing the similarity of marks is at the heart of legal tests for (i) relative grounds of opposition, which allow the trade mark proprietor to oppose the registration of a similar subsequent mark (a registry level conflict), or (ii) trade mark infringement, where that proprietor objects to a similar or identical sign being used in the marketplace by a third party (a real world conflict). Registry level conflicts are the primary focus of this chapter, although the underlying technology is relevant for policing infringement as well. The most widely-used legal test considers whether the similarity of marks, when combined with the similarity of goods or services, is likely to cause confusion for relevant consumers of those products.²³ Marks are assessed in terms of their visual, aural/phonetic or conceptual similarity, also referred to as sight, sound and meaning analysis.²⁴ For complex or composite marks, which combine words and/or figurative elements, the comparison should consider each mark as a whole while also recognising the distinctive and dominant elements that consumers would notice.

Algorithms for assessing the similarity of marks can be distinguished based on the types of mark being compared. Relatively straightforward computerised text searches have been available for several decades.²⁵ In the past, these search systems employed ‘text-based retrieval technology... [which] look for trade marks that match some or all words in a query string text’.²⁶ Text search has improved over the years to incorporate phonetic analogies, synonyms and permutations of letters so that slightly modified marks are also returned in the search results.²⁷ Recent advances have expanded the scope of similarity searching across three dimensions. As regards the first of these, algorithms are being developed to assess the conceptual similarity between marks, on the basis of shared or even oppositional meanings. A simple text search will not flag up the semantic similarity between ‘H₂O’ and ‘water’. On the other hand, signs which look textually or visually similar may relate to different concepts. Homophones sound similar but have different meanings (steel v. steal) while homographs are spelled the same, but the context clarifies the difference in meaning (bass being a type of fish or the lowest frequencies in music). Capitalisation alone can produce significant changes: compare ‘Polish’ (the nationality) with ‘polish’ (for furniture or shoes). Therefore search technology based on semantic or conceptual similarity considers synonyms or antonyms, comparable words in another

²³ I Fhima and DS Gangjee, *The Confusion Test in European Trade Mark Law* (OUP, 2019).

²⁴ USPTO *Trade Mark Manual of Examining Procedure* (April 2016) at §1207.01(b) (Similarity of the Marks); EUIPO *Guidelines for Examination of European Union Trade Marks*, Part C, Section 2, Chapter 4 – Comparison of Signs (v 1.1, Oct 2017).

²⁵ The history of computerisation and the pivotal role of the watching agency Compumark is detailed in Bellido, ‘Towards a History’ (n 11).

²⁶ F Mohd Anuara, R Setchia, Y-K Lai, ‘A Conceptual Model of Trademark Retrieval based on Conceptual Similarity’ (2013) 22 *Procedia Computer Science* 450, 451.

²⁷ CJ Fall, and C Giraud-Carrier, ‘Searching Trademark Databases for Verbal Similarities’ (2005) 27(2) *World Patent Information* 135. For an application of text-search technology measuring the distance between word marks and identifying conflicts, in order to assess whether viable word marks are being depleted, see B Beebe and JC Fromer, ‘Are We Running Out of Trademarks? An Empirical study of Trademark Depletion and Congestion’ (2018) 131(4) *Harvard L Rev* 945.

language with similar meanings and so called 'lexical relations' (PINK LADY v. LADY IN ROSE).²⁸

The second domain of similarity comparison, which has seen significant improvements in recent years, is image search. The technology has advanced to the point where a user can directly upload an image in a recognised file format such as JPG, PNG, GIF or TIFF and search for similar images within the relevant registry database. Both WIPO and the European Union Intellectual Property Office (EUIPO) offer this facility.²⁹ National offices are actively incorporating this technology into the internal registry examination process.³⁰ A moment's reflection reveals some of the information processing challenges that need to be overcome. Figurative marks and logos 'are designed to have visual impact... consisting of multiple homogeneous elements, which may be closed regions, lines, or areas of texture. They may represent a given type of object (such as a dog or car) in stylised form, or consist purely of abstract patterns. They may be coloured or monochrome'.³¹ Human observers consider shape to be the single most important feature of an image but image structure (the layout of individual image elements) and their semantic interpretation (the image of a tree evoking trees) are also relevant. Then there is the matter of identifying what counts as an image element – how granular does it get and why?³² It rapidly becomes apparent that there are several, oftentimes subjectively prioritised, parameters according to which similarity might be assessed.

One attempt to respond to these challenges is found in the creation of the International Classification of the Figurative Elements of Marks, also referred to as the Vienna Classification, administered by WIPO.³³ As matters presently stand, figurative marks are manually indexed by trade mark examiners, with codes or keywords being assigned to them.³⁴ The most widely adopted of these coding systems is the Vienna Classification, a hierarchical system proceeding from the general to the particular. It consists of categories, divisions and sections, each of which has been assigned a number. Figurative elements classified within a section are referred to by three numbers: 'the first, which may be any

²⁸ Anuara, Setchia and Lai (n 26) 453.

²⁹ WIPO facilitates images searches in its Global Brand Database: <https://www.wipo.int/branddb/en/>. The EUIPO consolidates registration information via its TMView database, which combines the register of EU-wide European Union Trade Marks with that of 27 national EU member states as well as the WIPO database: <https://www.tmdn.org/tmview/welcome>.

³⁰ (WIPO/IP/ITAI/GE/18/1) (n 20) refers to image search initiatives by the IPOs of Australia, Chile, China, Japan, Norway, Singapore as well as the EUIPO and WIPO.

³¹ J Schietse, JP Eakins and RC Veltkamp. 'Practice and Challenges in Trademark Image Retrieval' (2007) *Proceedings of the 6th ACM international conference on Image and video retrieval* 1, 1.

³² *Ibid.*

³³ See the Vienna Agreement Establishing an International Classification of the Figurative Elements of Marks, 1973. The Agreement entered into force on 9 August 1985. The current (eighth) edition has been available online since 2017 and in force from 1 January 2018. See: <https://www.wipo.int/classifications/vienna/en/>.

³⁴ For an example of a code-based system, see the USPTO Design Search Code Manual, available at: <http://tess2.uspto.gov/tmdb/dscm/index.htm>.

number from 1 to 29, denotes the category; the second, which may be any number from 1 to 19, the division; and the third, which may be any number from 1 to 30, the section. For instance, the representation of "a little girl eating" [02.05.03] belongs to Category 2 (Human beings), Division 5 (Children), Main Section 3 (Girls).³⁵ The result is over 1300 different taxonomic categories. Matching the Vienna codes of a new application with those already in the registry database generates a list of similar figurative marks.

However not all trade mark registries use the Vienna Classification system – it presently has 34 contracting parties – while the allocation of codes (or keywords in some systems) to figurative elements inevitably involves some subjectivity, with the attendant risk of leaving gaps.³⁶ This background helps to explain why recent advances in content-based image retrieval systems, which can be used to directly compare a target image to other images in a database, have been welcomed by trade mark registries and professionals. The search results list (hit list) is prioritized by an AI-assisted process so that only the closest matches and most relevant images are presented. More tightly focussed lists of potential conflicts save reviewing time and therefore reduce costs for trade mark examiners, trade mark attorneys or agents, paralegals, legal practitioners and ultimately clients.

Image recognition systems directly analyse the colours, shapes and textures of images rather than relying on representative keywords or codes.³⁷ Research by WIPO indicates that image searches till date have been more effective in relation to simple geometric shapes, with Vienna Classification searches as the background comparator for measuring effectiveness.³⁸ However there is room for improvement when it comes to complex shapes or logos, combining both figurative elements and text. Nevertheless, the ability to search by directly uploading an image is a significant, potentially tectonic, shift, especially as the technology continuously improves. Thus WIPO's new AI-based image comparison service innovates 'by using deep machine learning to identify combinations of concepts – such as an apple, an eagle, a tree, a crown, a car, a star – within an image to find similar marks that have previously been registered'.³⁹ Meanwhile the United States Patent and Trademark Office (USPTO) has built on its extensive experience with manually coding figurative images to train AI algorithms: 'A six-digit numerical design search code is

³⁵ See <https://www.wipo.int/classifications/vienna/en/preface.html>

³⁶ WIPO, 'Future Development of the Vienna Classification: questionnaire Results' (3 April 2019), 3 (Although most participating registries were satisfied with the system, the following issues were raised: 'a number of Offices reported difficulties with the classification of colours. Codes that are over-used, as well as codes that are not used enough and are simply ignored also lead to an incomplete classification. Modernisation... by adding new codes for commonly used figurative elements and for keeping pace with new technologies was also highlighted').

³⁷ For technical background, see A Alaei, PP Roy and U Pal, 'Logo and Seal Based Administrative Document Image Retrieval: A Survey' (2016) 22 *Computer Science Review* 47; CA Perez et al., 'Trademark Image Retrieval Using a Combination of Deep Convolutional Neural Networks' 2018 *International Joint Conference on Neural Networks (IJCNN)* (IEEE, 2018).

³⁸ Christophe Mazence, 'Machine Learning applied to Trademarks Classification and Search', 29 May 2018 (WIPO/IP/ITAI/GE/18/P17).

³⁹ WIPO Launches State-of-the-Art Artificial Intelligence-Based Image Search Tool for Brands, 1 April 2019 (PR/2019/831); at: https://www.wipo.int/pressroom/en/articles/2019/article_0005.html.

assigned to each design element of a trade mark, such as a depiction of a star (01.01.03) or flower (05.05.25). Using years of images with corresponding examiner-annotated design codes, we are able to train deep learning systems that can predict design codes of a new trade mark image'.⁴⁰ The USPTO also uses neural networks to retrieve and store features of mark images, that can then be compared, via an image similarity measure, to other marks' features.

Instead of developing their own systems, some registries use commercially developed image search solutions. For instance, IP Australia has an Image Search option within its Australian Trade Mark Search feature, to search for existing trade mark images based on a given image. It uses the commercially available TrademarkVision Image Recognition software for this purpose.⁴¹ The EUIPO uses this system as well. TrademarkVision is now a part of Clarivate Analytics, which had previously acquired a leading trade mark clearance and protection company CompuMark.⁴² The software incorporates a deep learning-based reverse image search, similar to the facial recognition algorithms of Facebook and Google but applied to figurative marks and logos. At the time of writing, the algorithm generates a list of similar figurative marks, which can be filtered by jurisdiction, class of products, status (live or dead), specific goods or services and the owner's name. The system also facilitates proactive monitoring, emailing alerts when similar marks are subsequently discovered.⁴³ TrademarkVision is thus a relatively new entrant in the trade mark search/clearance and watching ecosystems. There are others as well: 'TrademarkVision, MikeTM Suite and LawPanel's Aila are some of the existing AI-powered solutions. With various specialties, they essentially aim to search and monitor words, phrases, and images using various government trademark offices' databases of marks and the internet'.⁴⁴ We return to the implications for search and watching agencies in the next section of this chapter.

The third aspect which is being explored could be described as putting the pieces together or developing a gestalt understanding. Attempts are underway to develop AI algorithms that can combine different measures of similarity – the words *and* images in the two complex marks being compared – to arrive at an integrative assessment. The goal is to mimic the assessment of a human examiner who must synthesise visual, aural and conceptual similarity to arrive at an overall conclusion on whether the marks conflict.⁴⁵ Datasets of past examiners' decisions are a resource for training algorithms to assign different 'weights' to different measures of similarity, depending on the type of mark.

⁴⁰ USPTO, 'Emerging Technologies in USPTO Business Solutions' 25 May 2018 (WIPO/IP/ITAI/GE/18/P5).

⁴¹ Robert Bollard, 'IP Australia Artificial Intelligence Initiatives', 29 May 2018 (WIPO/IP/ITAI/GE/18/P7).

⁴² 'Clarivate Analytics Snaps Up TrademarkVision as New Research Offerings Eyed' World Trademark Review, 31 Oct 2018; at: <https://www.worldtrademarkreview.com/ip-offices/clarivate-analytics-snaps-trademarkvision-new-research-offerings-eyed>

⁴³ See: <https://trademarkvision.compumark.com/solutions/trademarks/>.

⁴⁴ 'How AI Impacts Trademarks' Managing IP Trademark Times, May 19-23, INTA Seattle 2018.

⁴⁵ R Setchi and F Mohd Anuar, 'Multi-Faceted Assessment of Trademark Similarity' (2016) 65 Expert Systems with Applications 16; see also Perez et al (n 37) (assessing the combined visual and conceptual similarities of images).

Another approach presents the relevant measures of similarity in parallel – for e.g. image or pixel similarity, text similarity, automated content similarity and manual similarity – to avoid their significance being diminished or compressed into a single metric.⁴⁶

3.3 Assisting with Examination

The techniques described above, for assessing the similarity of goods or services as well as marks, are assisting registries in processing trade mark applications more efficaciously. For example, the Japanese Patent Office uses an AI-assisted goods and services similarity assessment tool so that its examiners can identify the closest match between a new application and previously registered (approved) terms to describe goods and services. This speeds up the process for checking whether the correct product classes have been indicated in the application, as well as the field of prior marks with which to compare the new application.⁴⁷ IP Australia has been developing a ‘Smart Assessment Toolkit’ for examiners, using machine learning models to flag up potential issues. This includes identifying prior similar word marks for similar goods or services to prioritise conflicting marks. It also incorporates a form of distinctiveness assessment. For example, the candidate sign may be considered descriptive for the goods selected or contain a common or generic term.⁴⁸ The software uses a combination of natural language processors and datasets of historic reports by examiners for learning purposes when evaluating registrability. Meanwhile IPOs has been experimenting with using ‘machine learning to automatically measure the distinctiveness of a given word mark and also to suggest evidence for the measurement (Trade Marks Distinctiveness Checker). This [initial steer] helps officers speed up the examination step of distinctiveness and thus reduces turnaround time. The automatic measurement of this task can be also used by applicants, in order to reduce rejection rate due to [non]distinctive word marks’.⁴⁹

Besides assisting examination, IPOs are developing user assistance tools designed with self-filers in mind. To take one example, in May 2018, IP Australia launched Trade Mark Assist, an online tool that assists users wishing to check whether their chosen sign is a good candidate for registration.⁵⁰ The tool indicates whether prior similar marks exist on the Australian register and whether non-distinctiveness objections might apply to the sign.

⁴⁶ I Mosseri, M Rusanovsky and G Oren, ‘TradeMarker – Artificial Intelligence based Trademarks Similarity Search Engine’ in C Stephanidis (ed), *HCI International 2019 – Posters: Communications in Computer and Information Science*, vol. 1034 (Springer 2019) 97.

⁴⁷ (WIPO/IP/ITAI/GE/18/P9) (n 21).

⁴⁸ At <https://www.govtechreview.com.au/content/gov-tech/news/trademark-applications-streamlined-by-machine-learning-1008018169>.

⁴⁹ (WIPO/IP/ITAI/GE/18/1) (n 20), [44].

⁵⁰ At <http://assist.ipaustralia.gov.au/trademarks/welcome>

4. Implications for Trade Mark Law

An AI-assisted search results in a relevancy ranked list of potential conflicts along with a risk profile, often presented statistically (e.g. a 71% similarity match). This assists registry officials and professional advisers when making recommendations. Experience till date therefore suggests that AI algorithms are intended to augment human judgment – to effectively sift through ever increasing volumes of registration data – and not to replace it. Emphasising the continuing need for nuanced human evaluations, a CompuMark report observes: ‘While AI and neural networks will play an expanding role in CompuMark solutions... they are intended to complement, not replace, human analysts’.⁵¹ As the founder of LawPanel puts it: ‘AI will speed up legal research, but it will not replace advice formulation... [since it] only works on repetitive tasks in a very tightly-defined domain’.⁵² Machine learning technology can comprehensively filter the ever growing numbers of trade mark applications and registrations, displaying the most relevant list of results for human experts to assess.

Yet despite the projection of ‘(enhanced) business as usual’, is a more fundamental set of realignments taking place? A general question, beyond the remit of this chapter but one of interest to decision makers across many legal and regulatory fields, is the extent to which algorithmic decision making differs from human decision making.⁵³ That depends on the nature of the analysis: where the data for a machine learning approach is derived from judicial content analysis – past decisions by human tribunals where factors are coded and correlations derived – the algorithm will behave like the human decision maker it is modelled after, warts and all. On the other hand, when it comes to assessing semantic similarity, algorithms may also stretch beyond the capacities of human analysts and identify alternatives from within a dictionary or thesaurus which might escape human assessors, or, using a historic database of goods and services, identify product similarities that humans would be unlikely to make. At this point, the algorithm may be outperforming a human trade mark examiner. Any resulting match and associated risk indicator may be erring on the side of caution, since real world examiners would not pick up on those similarities. Unless of course registries are using similar algorithms(!). Algorithms may also find patterns which are ‘valid’ but not causally related in a meaningful way to the rules of trade mark law. Peter Keyngnaert provides an example of an irrelevant pattern – where a new company X files 50 new trade mark applications on (say) 14 August 2019 but all contain an error (a reference to class 54 instead of 34) and

⁵¹ Compumark White Paper, *Artificial Intelligence, Human Expertise: How Technology and Trademark Experts Work Together to Meet Today’s IP Challenges* (2018) 5.

⁵² T Lince “‘No Imminent AI Apocalypse’ – Tech Expert Rejects Predictions of Mass Job Losses in Trademark Industry”, 1 Feb 2018, *World Trademark Review*, at: <https://www.worldtrademarkreview.com/brand-management/no-imminent-ai-apocalypse-tech-expert-rejects-predictions-mass-job-losses>.

⁵³ See for e.g. European Parliamentary Research Services, *Understanding Algorithmic Decision-Making: Opportunities and Challenges* (Report PE 624.261, March 2019); Centre for Data Ethics and Innovation, *Interim Report: Review into Bias in Algorithmic Decision-Making* (25 July 2019), at: <https://www.gov.uk/government/publications/interim-reports-from-the-centre-for-data-ethics-and-innovation/interim-report-review-into-bias-in-algorithmic-decision-making>.

are rejected, the algorithm may identify a high risk of rejection associated with company X, or a high risk of rejection associated with 14 August.⁵⁴

One implication is that the existing gap between the likelihood of confusion test for relative grounds analysis and infringement analysis will continue to expand. An attenuated version of the likelihood of confusion test in trade mark law is applied upstream, at the initial stages of trade mark clearance. Conflict analysis conducted by algorithms focuses on similarity between the marks and goods as they appear on the register. However the broader multifactor likelihood of confusion test for infringement incorporates additional elements. In the US, although the test varies across judicial circuits, significant factors include: the similarity of the marks; the similarity between goods or services; evidence of actual confusion; the strength of the plaintiff's mark (in the form of inherent distinctiveness or acquired repute); the defendant's intent (including bad faith); and consumer sophistication.⁵⁵ In the EU, the assessment proceeds in three interdependent and cumulative stages:⁵⁶ (i) similarity of the marks; (ii) similarity of goods or services; and (iii) does this lead to a likelihood of confusion. Under the third stage, the (hypothetical) average consumer for the overlapping goods or services needs to be constructed, her levels of attention and sophistication established, her linguistic attributes clarified and evidence of market conditions (for e.g. are products likely to be sold over the counter, with professional assistance or via websites) identified. Evidence of actual confusion may also be submitted, in the form of witness statements, trade evidence or consumer surveys. Once these additional factors are incorporated, it may emerge that the similarity between two marks derives from themes common to the product sector (both incorporate the colour green and the image of a tree on environmental products). Consumers might conclude the marks appear similar but they would not be confused about the commercial origin of the respective products, because that similarity could be discounted (motifs common to the sector).⁵⁷ Or a common class heading – such as Class 28 for Games and Playthings – may actually resolve into two very different subordinate categories of products: soft toys aimed at toddlers versus role playing board games for a teenage market. Some of these additional factors – such as constructing the notional consumer perspective – are relevant for relative grounds analysis as well, which is why leading search or watching agencies clarify that human analysts, with the experience to draw these distinctions, remain integral to the services that they offer.

Today conflict analysis for registry clearance purposes is already a thinner, more formalistic version of conflict analysis for real-world infringement purposes, where

⁵⁴ I am extremely grateful to Peter Keyngnaert, Manager Research Scientist at Compumark, for his patient and helpful guidance.

⁵⁵ A representative approach is: *Polaroid Corp v Polarad Electronics Corp*, 287 F 2d 492 (2d Cir 1961).

⁵⁶ For details, see Fhima and Gangjee, *The Confusion Test* (n 23).

⁵⁷ As one US decision memorably puts it: *Paula Payne Prods. Co. v. Johnson's Publ'g Co.*, 473 F.2d 901, 902, 177 USPQ 76, 77 (CCPA 1973) ('[T]he question is not whether people will confuse the marks, but rather whether the marks will confuse people into believing that the goods they identify emanate from the same source').

context can be taken into account.⁵⁸ AI-enhanced similarity searching may serve to further attenuate registry level conflict analysis. Will the test effectively shrink to just two factors (marks and products) in the commercially significant clearance or registry opposition context?⁵⁹ The reactions of a real-world consumer, so often alluded to in trade mark doctrine, may be muted even further as a result. While human expertise continues to assess the conflicts results lists generated by algorithms, for risk-averse commercial clients it is extremely tempting to be guided by clearly defined percentages of similarity. Alongside the attenuation of the multifactor test, a related issue is the increasing legal significance of bureaucratic classification of goods and services by registries. It has been repeatedly emphasised that bureaucratic classification systems such as Nice do not have a bearing on the similarity of goods and services analysis when rights conflict. EU trade mark law confirms that goods and services cannot be assumed to be similar from the fact that they are in the same class and, vice versa, it cannot be assumed from the fact that they are in different classes that they are dissimilar.⁶⁰ However similarity within the Nice classification hierarchy is seemingly considered relevant for risk analysis by algorithms. One is left to wonder whether the algorithmic assessment of similarity will make its way across to infringement analysis, as evidence in a real-world dispute. It has been suggested that businesses might find it attractive if an AI solution were to replace judicial determination, or at least provide a preliminary assessment of confusion even in an infringement context.⁶¹

A second set of concerns relates to the quality of information contained in trade mark registers. In recent years, attention has focused on the problem of clutter or deadwood – the existence of marks on the register that are partly or wholly unused by their owners.⁶² It is not uncommon for trade mark applicants to claim broad swathes of goods and services

⁵⁸ As recognised in *Case C-533/06 O2 Holdings Ltd v Hutchison 3G Ltd* EU:C:2008:339, [66]. See also *Specsavers International Healthcare Ltd v Asda Stores Ltd* [2012] EWCA Civ 24, [78]-[88] (Kitchin LJ).

⁵⁹ Empirical research already suggests that, for (human) tribunals, the similarity of marks and of products may be dispositive. This leads to a ‘stampeding’ of the remaining factors to align them with the more important ones, thereby shaping the outcome of the confusion test. See B Beebe, ‘An Empirical Study of the Multifactor Test for Trade Mark Infringement’ (2006) 94 *California L Rev* 1581; I Simon Fhima & C Denvir, ‘An Empirical Analysis of the Likelihood of Confusion Factors in European Trade Mark Law’ [2015] *IIC* 310.

⁶⁰ See Art 33(7) of the Regulation (EU) 2017/1001 of the European Parliament and of the Council of 14 June 2017 on the European Union trade mark OJ L 154 16.6.2017.

⁶¹ See the discussion during a WIPO and UKIPO conference in 2019, reported at: <https://www.worldipreview.com/news/ai-as-judges-and-patent-destroying-tools-panel-discussion-18237>

⁶² G von Graevenitz, R Ashmead & C Greenhalgh, *Cluttering and Non-Use of Trade Marks in Europe* (UK IPO Report 2015/48); USPTO, *Post Registration Proof of Use Pilot Final Report* (25 Aug 2015); US House Committee on the Judiciary Hearings, *Counterfeits and Cluttering: Emerging Threats to the Integrity of the Trademark System and the Impact on American Consumers and Businesses* (18 July 2019), at: <https://judiciary.house.gov/legislation/hearings/counterfeits-and-cluttering-emerging-threats-integrity-trademark-system-and>.

on which they never intend to use the mark.⁶³ Once such marks are registered, they occupy space on the register as prior rights in relation to these goods and services. Emphasising that registered trade marks need to be used in order to be maintained, the US Registrar of Trademarks recently summarised the problem at a Congressional Hearing in 2019:

The register itself provides notice to applicants, other trademark owners, and our examining attorneys of the registrant's claim of ownership in a mark and allows them to search the register to determine the availability of marks for registration in the United States. The register is a valuable tool in making business decisions, and its accuracy is paramount. When businesses are selecting names for new products, they turn to the register to figure out whether their chosen mark is available for their use and registration. But, for the register to be useful, it must accurately reflect marks that are in use in the United States for the goods and services identified in the registrations. If the register is filled with marks that are not in use, or features registrations obtained by improper means, it makes trademark clearance more difficult, time-consuming and expensive. An inaccurate register also leads to expensive opposition and cancellation proceedings, or federal court litigation, to correct inaccurate registrations and to enforce rights. And, in turn, it may cause companies to alter business decisions, often at significant cost.⁶⁴

Although these unused categories are vulnerable to a claim for invalidation, this requires costly and time-consuming real-world investigations into the commercial offerings of trade mark proprietors, followed by legal proceedings to revoke the mark. So long as the register unhelpfully generates false positives, AI algorithms will take formally valid registration at face value. Risk profiles are generated based on potentially vulnerable prior rights that won't survive scrutiny.

Conversely, AI algorithms are presently unable to identify conflicts on the basis of trade mark dilution, which is a broader form of infringement protection for marks with a reputation.⁶⁵ It involves the use of an identical or similar mark in connection with non-competing or dissimilar goods or services, where the use by the junior user will generate a link in the minds of consumers to the reputed mark. No confusion need be established. Instead, as a result of that link, the reputed mark might be blurred or tarnished. Alternatively, the junior user might obtain a free ride or unfair advantage, through a form of image transference, based on the mental link between the two signs.⁶⁶ The crucial point is that for reputed marks, protection extends unpredictably (at least for now) beyond

⁶³ A reference on whether such applications should count as being made in bad faith is pending before the CJEU in Case C- 371/18 *Sky plc v Skykick UK Ltd*. For background see: *Sky Plc v Skykick UK Ltd* [2018] EWHC 155 (Ch).

⁶⁴ Statement of Mary Boney Denison, Commissioner for Trademarks, USPTO, *Judiciary Hearings* (n 62) 2.

⁶⁵ R Burrell and M Handler 'Dilution and Trademark Registration' (2008) 17 *Transnational Law and Contemporary Problems* 713.

⁶⁶ These theories of harm may not rest on empirically or doctrinally valid foundations and are contested. See B Beebe, R Germano, CJ Sprigman, JH Steckel, 'Testing for Trademark Dilution in Court and the Lab' (2019) 86(3) *University of Chicago L Rev* 611; M. Handler, 'What Can Harm the Reputation of a Trademark? A Critical Re-evaluation of Dilution by Tarnishment' (2016) 106 *Trademark Reporter* 639.

similar goods and services. Trade mark law also recognises unregistered prior rights which may generate conflicts, such as common law trade marks protected via the tort of passing off, trade names protected under unfair competition or copyright-protected images from which trade mark logos are derived. These exist outside of trade mark registers or indeed any form of registration in some cases.⁶⁷ Therefore while the machine learning technology of today offers clearance assistance for one very significant layer of conflicts – where a similar mark on similar goods would be assessed under the likelihood of confusion test – its limitations must be borne in mind.

Finally, the technology offers the potential to support defensive strategies to narrow the scope of trade mark rights. Visual search now offers users submitting a complex or composite image an in-built editing tool for close cropping a region of interest within the image.⁶⁸ It is possible to use this to claim that certain elements within an image are widely used by other trade mark owners (such as an image of a cow on dairy products) and therefore unlikely to be considered the distinctive elements of the mark by consumers.⁶⁹ They should be discounted from the similarity analysis. These are just some of the implications of the comprehensive, large scale algorithmic reading of trade mark registers that is available today.

5. Conclusion

The algorithmic reading of registers is engineered for completeness, certainty and convenience. As the technology improves, the similarity of marks and goods analysis is a useful resource to augment human expertise. Trade mark registry officials, analysts and lawyers can focus on what is important – analysing relevant results in greater detail – as opposed to spending time on searching for those results through trial and error. Yet the risk is that the genie may escape the bottle. Algorithms designed to produce a heuristically helpful upstream snapshot of conflict risks, based on two dimensions of similarity, may unintentionally edge out the more complex multifactor test in a wider range of situations, including trade mark infringement analysis. The seductive appeal of the all-seeing algorithm should be resisted, since a range of conflicts beyond likelihood of confusion (similar marks on similar goods) is also possible. The seduction is especially powerful since similarity matching algorithms can seemingly keep up with the high-pressure hosepipe of new trade mark applications, bringing a degree of consistency, comprehensiveness and ‘objectivity’ to the intrinsically subjective task of assessing similarity. Their limits should be borne in mind.

⁶⁷ R Burrell and M Handler ‘The intersection between registered and unregistered trade marks’ (2007) 35(3) *Federal Law Review* 375.

⁶⁸ The WIPO Global Brands Database image search has this functionality.

⁶⁹ EUIPO *Guidelines* (n 24) Part B, Section 4, Chapter 3, [8] (Commonplace Figurative Elements).