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NAVIGATING AI CHALLENGES: EVIDENTIARY, LIABILITY, AND ANTI-COMPETITIVE DIMENSIONS IN LAW

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Abstract:

The increasing integration of Artificial Intelligence (AI) in various domains has brought transformative potential but also raised significant legal and ethical challenges. This research explores the complexities surrounding the use of AI in evidentiary matters, liability frameworks, and anti-competitive behaviour. It delves into the reliability and admissibility of AI-generated evidence, highlighting the need for robust authentication processes to mitigate biases and errors in machine learning algorithms. The paper also examines the accountability of AI creators and users under existing legal doctrines, emphasizing the relevance of vicarious liability and the "deep pocket theory" to address damages caused by AI actions. Furthermore, the study investigates the anti-competitive concerns arising from algorithmic collusion, discussing landmark cases and divergent perspectives on regulating AI-driven market behaviour. By analysing these critical dimensions, the research underscores the need for interdisciplinary collaboration, transparency, and global cooperation to ensure a balanced and forward-looking approach to AI governance. Key suggestions include tailored regulatory reforms, continuous education for legal professionals, and the establishment of clear international standards to address the evolving challenges posed by AI technologies.

Keywords: Algorithm, Tacit Collusion, Artificial Intelligence, Legal Framework, Evidence.

1. INTRODUCTION

In our modern society, electronic evidence has become an integral part of daily life, shaping our perceptions and influencing decisions. From emails to social media posts, we routinely assess the credibility of information encountered. However, the automated creation and dissemination of content, such as phishing attempts and false news, present challenges in determining its reliability, particularly in legal contexts.

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In the case of *Bucknor* v. *R*,[2], the defendant faced charges related to murder as part of a criminal gang. During the trial, the judge admitted photographs from a social networking site depicting the defendant as a member of the gang, along with a YouTube video portraying the gang as violent. The jury was instructed to view this evidence as "background information" if they believed it originated from the defendant, who denied any involvement. However, the English Court of Appeal overturned the conviction, citing the hearsay nature of the social media content and video, particularly since the creators were not identified. The court emphasized that even if the content, assuming it to be true, had probative value, a failure to consider how reliable the maker of the contents was and how many levels of hearsay were involved meant that no consideration was given to the reliability of such content.

Moreover, the widespread adoption of Artificial Intelligence (AI) across various sectors raises important questions about its accountability under criminal law and liability for resulting damages. Discussions surrounding vicarious liability and the "deep pocket theory" underscore the need for clearer governance frameworks. Furthermore, the use of AI algorithms in commercial practices raises anti-competitive concerns, with instances of tacit collusion facilitated by automated mechanisms. Dissenting views on punitive measures for algorithmic usage highlight the complexities of addressing anti-competitive behaviour in the digital era.

This paper endeavours to delve into the gray areas surrounding AI governance and enforcement, aiming to unravel complexities and propose strategies for navigating the evolving landscape of technological integration and legal accountability.

2. RELIABILITY OF AI EVIDENCE

Due to the inherent vulnerability of electronic evidence to manipulation or deletion, it's crucial to prioritise the trustworthiness and reliability of both the evidence itself and the systems responsible for managing it.[3]In law enforcement today, police officers utilise body-worn video cameras and in-car cameras in patrol cars to capture important evidence in real time.[4]In investigative work, police rely on cell phone tracking software and case-management software to simplify the gathering and analysis of evidence they've collected.[5]Prosecutors,

[2]EWCA 2010 Crim 1152.

[3]Stephen Mason & Daniel Seng eds*et.al.*,"*Electronic Evidence"* (Institute of Advanced LegalStudies for theSAS Humanities Digital Library, School of Advanced Study, University of London, 4th Ed,2017)

[4]Ben Bowling & Shruti Iyer, "Automated Policing: The Case of Body-worn Video" 15*Int. J. Law Context*140 (2019); *Director of Public Prosecutions* v. *Young*, 2018 EWHC 3616.

[5]National Criminal Justice Reference Service, Research on the Impact of Technology on Policing Strategy in the21st Century, Final Report(September 2017)

lawyers, and judges utilise case tracking and management systems to handle case filing, organise information, manage caseloads, and maintain dockets effectively.[6]While investigative agencies and courts are transitioning from automated systems to AI systems for various purposes like policing[7], intelligence gathering[8], and dispute resolution[9], the primary concern for prosecutors and courts remains the trustworthiness and reliability of both the evidence and the systems used.

3. MACHINE LEARNING:THE BACKBONE OF MODERN AI

Most AI systems today rely heavily on machine learning (ML) algorithms, which differ from traditional programming by allowing systems to learn from examples, data, and experiences[10] rather than following predefined rules. While ML has facilitated significant advancements and enabled innovative uses of AI, it can sometimes produce unexpected or incorrect results[11]. Moreover, ML is not without limitations.

(a) ML will learn any biases that are contained in the training data, so (for example)an ML system for determining whether a prisoner should be released by theparole board will exhibit racial bias if it has been trained on data that containssuch bias[12] and correlations discovered through ML do not equate to causality.[13]

(b) Datasets will invariably contain hidden biases, as would the choice and use ofML algorithms.[14] This is because the development of datasets and algorithms willinvolve decisions by humans, who, apart from their qualifications (or lackthereof) and inherent biases, will have to consider compromises and trade-offs.[15]

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[6]Marco Fabri & Francesco Contini, *Justice and Technology in Europe: How ICT is Changing the JudicialBusiness* (Kluwer Law International, Hague,1st edn., 2001)

[7]*R* v. *The Chief Constable of South Wales Police*, 20201 WLR 672

[8]Patrick Perrot "What about AI in CriminalIntelligence? From Predictive Policing to AI Perspectives"16 *European Police Science and ResearchBulletin* 65 (2017).

[9] Adam Harkens, "Fairness in Algorithmic Dec is ion-Making: Trade-Offs, Policy Choices, and Procedural Protections"1(1) *Amicus Curiae* 84 (2019).

[10]Royal Society, *Machine Learning: The Power and Promise of Computers That Learn by Example*19 (The Royal Society, 1st edn., 2017).

[11]Will Knight, *AIsLanguage Problem*,(MIT Technology Review 2016)

[12]*State* v. *Loomis*, 881 NW 2016 2d 749; Susan Nevelow Mart, "The Algorithm As a Human Artifact: Implications for Legal 109 *Law Libr J 387*(2017); Anupam Chander,"The Racist Algorithm?" 115 *Mich L Rev.* 1023 (2017).

[13]Frank Pasquale & Glyn Cashwell, "Prediction, Persuasion,and the Jurisprudence of Behaviourism" 68 *U Toronto LJ* 75 (2018).

[14]Cathy O'Neil, *Weapons of Math Destruction: How Big Data Increases Inequality and ThreatensDemocracy* (Crown Publishing Group, 1st edn., 2017);

[15]David Lehr & Paul Ohm, "Playing with the Data: What Legal Scholars Should Learn about Machine Learning" 51 *UC Davis L Rev.* 653 (2017); Solon Barocas & Andrew D Selbst, "Big Data'sDisparate Impact" 104 *Cal L Rev.* 671 (2016); Deven RDesai & Joshua S Kroll, "Trust But Verify: A Guide to Algorithms and the Law" *31 Harv JL Tech*23 (2017).

(c) When our expertise fails, humans fall back on "common sense". But current MLsystems do not define or encode this behaviour. This means that when they fail, they may fail in aserious or brittlemanner. In particular, an ML system may be unstable when presented with novelcombinations of data, so even if it has been trained on past decisions that have beenseparately verified by experts, that may not be enough to justify high confidence in asubsequent decision.[16]

The unique features of AI pose significant challenges regarding the admissibility of electronic evidence, whether it's in the form of real evidence or records generated by AI systems. This raises questions about the reliability of automated systems, challenges how records from AI are categorized as real evidence or hearsay, and necessitates a thorough analysis of their authenticity.

4. PRESUMPTION OF RELIABILITY OF AI EVIDENCE

In common law, there's a key concern regarding the admissibility of electronic evidence, centered around the presumption that computer systems are inherently reliable. InEngland and Wales, this presumption states that: *"In the absence of evidence to thecontrary, the courts will presume that mechanical instruments were in order at thematerial time."*[17]

Commonwealth jurisprudence has shifted away from the necessity for computer systems to be deemed "reliable" before admitting electronic evidence, including evidence generated by AI systems. However, the concept of computer system reliability remains integral to various exclusionary rules of evidence, such as the best evidence rule, hearsay rule, and the authentication evidence rule. The question of who bears the burden of proving or disproving the reliability of the computer system arises in this context.

Section 2(1)(e) of the Bhartiya Sakshya Adhiniyam, 2023, provides a definition of evidence, encompassing statements or information conveyed electronically, as well as documents, including those in electronic or digital format. This definition renders electronic evidence admissible in court. A comparable definition is found within the Indian Evidence Act, 1872.

[16]Nick Bostrom, *Superintelligence: Paths, Dangers, Strategies* (Oxford University Press, 1st edn., 2014).
[17]Law Commission of United Kingdom, CP No. 138 Evidence in Criminal Proceedings: Hearsay and Related Topics (1997); *Castle* v. *Cross*1 WLR 1372 (1984)

In real-world scenarios, many judges haven't consistently sought expert advice or referred to technical literature when assessing the reliability of computers[18]. Instead, they often determine reliability based on whether the systems perform as expected, disregarding challenges from opponents[19]. Unfortunately, this approach mistakenly turns the presumption of reliability into a legal presumption, shifting the burden of proof away from the proponent of electronic evidence and onto its opponent.

EVIDENTIAL PRESUMPTION VERSUS LEGAL PRESUMPTION

If the presumption is so established, the consequence is that there is anevidential presumption that the system in question is reliable, and nothing more. Thepresumption does not overturn the basic rule of evidence that the burden of proofremains with the proponent of electronic evidence to prove the evidence.[20] Theproponent of the evidence generated by the system still has to discharge the legalburden in relation to the reliability of the machine, and likewise, the authenticity orintegrity and the trustworthiness of the evidence.

Nor should the absence of evidence of any computer failure suggest systemreliability. After all, *"the fact that a class of failures has not happened before is not areason for assuming that it cannot occur"*.[21] This *"absence of evidence of failure"* maybe because such failures are never recorded in the first place. It is precisely to avoidsuch types of inferences from false negatives that licensing regulations forautonomous vehicles have required that such systems keep records of sensor andother telemetric data to enable the circumstances surrounding vehicle accidents to bereconstructed.

RELIABILITY OF AI AS A SYSTEM

A notable example of an AI system deemed unreliable occurred in the case of the Uber autonomous vehicle that fatally struck a pedestrian. This incident gained widespread attention as the first recorded instance of a pedestrian fatality involving an autonomous vehicle. Investigations by the US National Transportation Safety Board, utilizing recorded telemetry and sensor data, revealed that the primary issue stemmed from the AI system's environmental perception. It struggled to accurately classify the victim, initially identifying her as an unknown object, then as a vehicle, and finally as a bicycle. Each classification resulted in

[18]Bryan H Choi, "Crashworthy Code" 94 *Wash L Rev.* 39 (2019).
[19]*Queen* v. *Dennis James Oland*, 2015 NBQB 245.
[20]Nigel Bridge, "Presumptions and Burdens" 12 *Mod L Rev.* 273 (1949).
[21]S*upra* note 16 at 4.

different predicted collision paths according to the collision detection logic.[22]In the critical moment when emergency braking was deemed necessary, just 1.3 seconds before impact, the vehicular control system failed to initiate an emergency stop autonomously. Moreover, it did not alert the operator, as Uber had disabled this function to minimize the risk of erratic vehicle behavior.[23]

Testing environments for AI systems must replicate a wide array of real-life conditions, including diverse physical environments, road conditions, and situations like emergencies or police interventions. The reliability of an AI system hinges on the extent to which it has been tested and validated across these variations. Given the infinite potential exceptions AI systems may encounter and their inability to be formally proven accurate, assessing their robustness entails examining evidence of errors they cannot handle. This involves scrutinizing the number, frequency, and nature of these errors.[24]

5. THE TREATMENT OF AI EVIDENCE

AI systems can produce many different types of evidence. Voice recognition systems can be automatically activated, and recorded conversation snippets can be stored.[25] Image recognition systems such as those found on traffic enforcement cameras can capture photographs of vehicles[26] and generate traffic violation tickets when linked to number plate recognition systems.[27] Fraud detection systems can monitor credit card transactions and identify anomalous transactions for further investigation. These examples are just illustrative of the wide range of information generated by AI systems that may be admitted in court as relevant and material evidence. But is such evidence allowed under the hearsay rule?

When it comes to AI systems, the main purpose of devices that take in input from humans and generate output is to store and record textual and spoken information created by one or more people. Their main function is to take in human input and store it for later retrieval. The human input is employed testimonially when the information is retrieved and applied to its

[22]National Transportation Safety Board, Preliminary Report, Highway (2018).
[23]*Ibid*.
[24]Peter Bernard Ladkin, "The Law Commission Presumption Concerning the Dependability of ComputerEvidence" 17 *DEESLR*7 (2020).
[25]Zack Whittaker, "Judge Orders Amazon to Turn over Echo Recordings in Double Murder Case" Tech Crunch *available at*<https://techcrunch.com/2018/11/14/amazon-echo-recordings-judge-murdercase/>(last visited on 23 February, 2024);
[26]*Jackson* v. *R*, (2011) EWCA Crim 1870; *Najib* v. *R*, (2013) EWCA Crim 86; *Khan* v. *R*, (2013) EWCA Crim 2230;and*Welsh* v. *R*, (2014) EWCA Crim 1027.
[27]David Pitt, "Iowa Court: Automated Speeding Tickets Not a Public Record" *AP News* (4 January 2020).

content. Thus, hearsay is typically the type of evidence generated by Category 1 evidence. In this case, the statement maker's inputted material can be isolated from the AI system, its data, and its software code.[28]Therefore, the primary goal of any application of such evidence is to look into the veracity of the claim and the identification of the person who made it. The same ruling as in *Aw, Kew Lim v. Public Prosecutor*[29], which determined that the defendants' identities and addresses were not materially altered by the computerised storage of company registration records, would necessitate treating this evidence as hearsay in this particular case.

Evidence produced by Category 2 (self-contained data processing devices which obtain input or take recordings from the environment without human intervention) devices is, simply put, evidence that is substantially the product of automation and is not used testimonially. For instance, many criminal prosecutions in England have succeeded through the admission of automatic number plate recognition ("ANPR") evidence to show vehicular location, movement and time.[30] ANPR works by having specially adopted closed-circuit television cameras that are fitted with infrared sensors that can capture the number plates of vehicles, even at night. The images are then fed into M-Systems that "read" the number plates, and that information is sent to the Police National Computer to find a match for the vehicle and its owner.[31]Courts appear relatively sanguine in admitting ANPR evidence, with no noted hearsay challenges raised.[32] Nonetheless, the reason for the absence of challenges is that such evidence is considered real evidence or *"evidence produced purely mechanically without human intervention"* and is outside the hearsay rule.[33]

But while real evidence from these automatic systems does not amount to "assertions" that are caught by the hearsay rule, this does not mean that such evidence is reliable or accurate. Challenges to the reliability and accuracy of such evidence will be by way of authentication. The absence of challenges to ANPR evidence in the courts could be attributed to the fact that, for the large part, the defendants or the parties have admitted to the accuracy of such evidence, and so no real dispute arises.[34] Even so, when a discrepancy arises in relation to

[28]*Supra* note 2 at 2.
[29]1987 SLR(R) 443.
[30]*Supra* note 25 at 6
[31]Primo Reg Plates, "Your Guide to Automatic Number Plate Recognition"*available at* <https://www.primoregistrations.co.uk/article/view/your-guide-to-automatic-number-plate-recognition>(last visited on29February 2024).
[32]*R* v. *Doyle*, (2017) EWCA Crim 340.
[33]*Sapporo Maru* v. *Statue of Liberty*; (1968) 1 WLR 739.

[34]*BV* v. *Talal El Makdessi*(2015) UKSC 67.

ANPR evidence, as in the case of *Re A (death of a baby),* there was other evidence to corroborate the drivers' testimony as to their movements and contradict the ANPR evidence. In other words, the independent verifiability of the vehicular movements enabled the court to exercise its discretion and choose to draw no conclusions from the ANPR evidence.[35]

A large majority of AI evidence, however, will be evidence produced by Category 3 (devices that are hybrids of the two) devices. In this category, the device output will comprise a mix of human-supplied input and data-processed output, which operates without human intervention. As supervised ML systems are trained on human-labelled data to operate autonomously, evidence from ML systems will invariably fall into this category. The line between evidence produced by Category 2 and Category 3 devices can be hard to draw: the difference really is one of degree that represents the relative significance of the contribution level of human-supplied input and pre-programmed autonomous processes to the eventual output.

In *Public Prosecutor v. Aug Soon Huat*[36]("Ang Soon Huat"), for instance, the High-Pressure Liquid Chromatograph and Gas Chromatography-Mass Spectrometer outputs which were adduced to prove the weight of the trafficked drug were admitted as real evidence by supporting such automated output with the oral testimony of the technicians who calibrated and operated the machines, the automated processes were characterised as recording, processing and calculating the information fed into them without human intervention.

If there is no opportunity for the human assertions to be tested – for instance, if the automatically-produced analysis is to be relied on but the programmer who wrote the software that generated the analysis is not called to testify – the analysis becomes hearsay.[37] Given that the product of AI systems will inevitably be based on a multiplicity of, and interplay between, direct and indirect human assertions, not all of which have been validated, let alone completely assessed for their accuracy and correctness[38], it will be near impossible to call all contributors of these assertions to give evidence in legal proceedings. Therefore, considering that these models embed various human assertions and even biases, it is more apt to proceed with caution and subject AI evidence to closer scrutiny for the "human input". Of course, this closer scrutiny can be further assisted with a robust approach to authentication of such evidence and to a more effective stance regarding disclosure.

[35]Re A (death of a baby), (2011) EWHC 2754.
[36](1990) 2 SLR(R) 246.
[37]*Mehesz* v. *Redman*, (1979) 21 SASR 569; and *Holt* v. *Auckland City Council*, (1980) 2 NZLR 124.
[38]*Supra* note 2 at 2.

AUTHENTICATION

There are two qualities to trustworthy evidence: its reliability and its authenticity. The rule of hearsay assesses the reliability of the evidence by determining if the record is capable of representing the facts to which it attests.[39]Authenticity of the evidence on the other hand means demonstrating that the evidence is genuine - that it is what it claims to be,[40] and that its condition is substantially unchanged.[41] It follows that the authenticity of evidence is a condition precedent to its admissibility.[42]

6. MANIPULATED DATA IN THE DIGITAL REALM

The issue of digitally manipulated electronic records has been present since the early days of computers. Digital signature technologies were developed to combat concerns about forged electronic records, ensuring their integrity. However, a new type of manipulation, known as "deep fakes," has emerged as a significant concern. Deep fakes involve altering images or videos by replacing a person's likeness with another's using ML and AI techniques like autoencoders and generative adversarial networks. These alterations are highly deceptive, capable of replicating subtle gestures and movements, even altering audio streams to mimic well-known voices[43]. This development poses serious threats, allowing for the misrepresentation of leaders thereby fomenting mistrust and compromise national security[44] and the spread of misinformation, including the creation of non-consensual pornography[45].

Detecting a manipulated image requires time, expertise, and specialized tools. When questioning the authenticity of a digital image[46], a digital evidence professional conducts a thorough investigation. This involves a reverse image search[47], analyzing image metadata for

[39]*Supra* note 2 at 2.
[40]*Supra* note 2 at 2.
[41]McCormick,*Evidence* 686 (West Publishing Co., 3rd edn., 1984)
[42]Daniel Seng, "Computer Output as Evidence" 130 *Sing JLS* 161 (1997).
[43]Catherine Stupp, "Fraudsters Used AI to Mimic CEO's Voice in Unusual Cybercrime Case"WALL ST. J. (2019).
[44]Britts Paris &Joan Donovan, Deepfakes and Cheap Fakes: The Manipulation of Audio and Visual Evidence *available at*<https://datasociety.net/wp-content/uploads/2019/09/DS_Deepfakes_Cheap_FakesFinal-1.pdf>(last visited on 15 March 2024).
[45]Janko Roettgers, "Porn Producers Offer to Help Hollywood Take Down Deepfake Videos"*available at*<https://variety.com/2018/digital/news/deepfakes-porn-adult-industry-1202705749/>(last visited on 3 March 2024)

[46]Hany Farid, "Fake Photos"*The MIT Press*, 2019.
[47]Andreas Rossler *et. al*., "Face Forensics: A Large-scale VideoDataset for Forgery Detection in Human Faces" *available at*<https://arxiv.org/pdf/1803.09179.pdf> (last visited on 27 February 2024)

inconsistencies[48], computing image exposure and adjustments made by software[49] and cameras, determining flash usage, and scrutinizing light patterns, shadows, and reflections[50]. Additionally, analysis of vanishing lines, shadow geometry, reflection patterns, and lens flare is conducted. It's important to acknowledge that an incredible image may still be credible[51]. With advancements in ML technologies, it's challenging for systems to ascertain if an image is entirely real or computer-generated, as AI can generate convincing "natural" artifacts that can deceive both automated analysis systems and human perception.

Hence, addressing the evidential treatment of manipulated digital data mirrors that of other electronic evidence, necessitating authentication. In essence, authentication issues, including those related to manipulated digital data, demand courts to establish clear procedures, understand the limitations of the presumption of reliability, and adopt a robust approach to disclosure or discovery. This comprehensive approach is essential for effectively addressing these issues.

7. LIABILITY OF ARTIFICIAL INTELLIGENCE

The scientific community acknowledges that AI surpasses human intellectual capacity and holds potential beyond current comprehension. Employed across various sectors like law, banking, and medicine, AI relies on machine learning. Questions arise regarding AI's accountability under criminal law and liability for damages resulting from errors or negligence. With no specific regulations, Article 12 of the United Nations Convention is applicable, suggesting that individuals who program computers to perform tasks may be held responsible for resulting damages.

From a legal standpoint, AI is often viewed as a tool, prompting consideration of liability through the lens of vicarious liability[52]. This principle holds the master responsible for the actions of their servant. The question arises whether this also applies to AI, with the maker or creator serving as the master. Given AI's resemblance to a servant, it falls under vicarious liability. Despite nuances in legal systems, liability ultimately stems from the master-servant

[48]Metadata would include data about the camera (make, model), shutter speed, aperture size, focal length,image format, compression, compatibility, geo-location information, date, time and location tags. The metadatacan be used to match an image to a particular device. In addition, when an image is saved and manipulated, themetadata might be modified, augmented or removed.

[49]This explores the quantitative relationship between the camera settings and the properties of the image:exposure, depth of field, motion blur, ISO (International Organization for Standardization) settings.

[50]For deep fakes, this includes reviewing light patterns on the surfaces of eyes and ears.

[51]Hany Farid illustrates this in Fake Photos (The MIT Press, 2019) at pp 38-45 and points out that it can beimportant to establish whether a gruesome image of a beheading was plausible.

[52]PauliusCerka *et. al.*, "Liability for damages caused by artificial intelligence" 31(3) *CLSR* 376 (2015)

relationship rather than the wrongful act itself. The "deep pocket theory" supports compensating damaged parties for AI actions conducted in good faith, acknowledging inevitable harm and the need for redress.[53]

8. ANTI COMPETITIVE CONCERNS DUE TO THE USE OF AI

An arrangement is considered collusive when involved parties engage in conduct that stems from either direct or indirect communication between them[54]. Deciding or manipulating prices in the bidding process affects other credible players[55]. Further, bid rigging or fixing of bids acts as a barrier to new entrants in the market, thus making it anticompetitive.

Tacit collusion called the Hub and Spoke scenario, occurs when sellers do not communicate directly. This situation often arises when online retailers utilise identical or similar pricing algorithms, potentially leading to price-fixing[56]. The use of a common intermediary to determine the prices increases the possibility of the existence of a hub-and-spoke structure[57]. The rulings issued by the CCI in the *Hyundai Motors*[58] and *Uber*[59] cases suggested not considering the elements of having 'known' or 'intention' for hub-and-spoke agreements. The 2019 review committee[60] also felt that owing to the overall deleterious effects of cartels, the requirement of knowledge or intent should not be imposed, but such hubs may be presumed to cause AAEC in terms of § 3(3) of the Competition Act.

By providing companies with powerful automated mechanisms "to monitor prices, implement common policies, send market signals or optimise joint profits with deep learning techniques, algorithms might enable firms to achieve the same outcomes of traditional hardcore cartels through tacit collusion"[61]. The 2019 Committee concluded that the existing framework under § 3 is sufficient to cover 'algorithmic collusion' scenarios. The Committee

[53]Jack G. Conrad, "E-Discovery revisited: The need for artificial intelligence beyond information retrieval" *available at* https://www.researchgate.net/publication/220539249_E-Discovery_revisited_The_need_for_artificial_intelligence_beyond_information_retrieval (last visited on 18 March 2024)

[54]*Suiker Unie* v. *Commission*, 1975 ECR 1663.

[55]*Rajasthan Cylinders & Containers Ltd.* v. *UOI*, C. No. 3546 of 2014 (SC).

[56] Grant Murray and Keith Jones, 'Latest (economic) thinking on competitive impact of pricing algorithms - paper by UK's Competition and Markets Authority' (Kluwer Competition Blog, 3 September, 2021)

[57] Peter Picht & Benedikt Freund, "Competition Law in the Era of Algorithms" 39 *Eur. Comp. L. Rev.* 403 (2018).

[58]Fx Enterprise Solutions (India) (P) Ltd. v. Hyudai Motor (India) Ltd. 2017 SCC OnLine CCI 26.

[59]*Samir Agrawal* v. *ANI Technologies Pvt. Ltd*., 2018 SCC OnLine CCI 86.

[60]Competition Law Review Committee Report to review and recommend a robust competition regime(Ministry of Corporate Affairs, 2019)

[61]OECD, 'Algorithms and Collusion: Competition policy in the digital policy',*available at* <http://www.oecd.org/daf/competition/Algorithms-and-colllusion-competition-policy-in-thedigital-age.pdf>*(*Accessed on 11 March, 2024)

further agreed that the proposed amendments to clarify the inclusion of 'hub and spoke' cartels in § 3(3) by way of adding an explanation to § 3(3) and to make § 3(4) inclusive will further strengthen the framework for regulating anti-competitive arrangements by expanding the scope of § 3.Therefore, even the argument that prices determined by the algorithm merely reflect natural market changes does not absolve liability. This is because these fluctuations were not discerned and assessed by fallible human perception and cognition but by a sophisticated AI algorithm.

DISSENTING VIEW

There are some instances that suggest that the use of simillar or same algorithm shouldn't be made punishable like in the case of the Amazon case *(US v Topkins)*[62] U.S. Department of Justice (DOJ) made the observation that the algorithms' usage per se and algorithmic pricing were not inherently illegal or anti-competitive. However, it was the agreement to implement the algorithms jointly that made the conduct anti-competitive. To find the existence of a cartel, there has to be the existence of an agreement. An agreement refers to a 'meeting of minds'[63] or a consensus between the parties concerned, gathered from a common motive[64]. Merely following a price leader and adopting the price he announced would not imply an arrangement as it lacks mutuality[65].

Industry-wide use of a similar algorithm by a third-party vendor IPSO facto cannot result in a hub-and-spoke conspiracy leading to the horizontal cartel. As the U.S. Supreme court noted *"there must be overall awareness about the conspiracy and that each defendant knew or had the reason to believe that their own profits were dependent upon the success of the entire venture"*[66].The Competition Commission of India (CCI) has recently took a different approach in the Uber case while CCI rejected the similar price-fixing allegation against Uber[67]. The commission held that unilateral decision of individual driver to adopt algorithmic pricing determined by Uber does not raises anticompetitive concern without collusion among the drivers.And in the Airline case, the CCI noted that the involvement of a "human" element to decide the final prices indicated that the use of algorithms was only to facilitate genuine price determination in an industry that required dynamic pricing and was not done with a

[62]*United States of America* v. *Topkins*, No. 15-00201 WHO N.D. Cal. 2015
[63]*Commission* v. *BayerAG*, 2004 4 CMLR 15.
[64]*Volkswagen AG* v. *Commission of the EC*, 2002 2 ECR 2707.
[65]All India Motor Transport Congress v. Indian Foundation of Transport Research & Training (IFTRT), 2016 SCC OnLine Comp AT 292
[66]*Interstate Circuit* v. *United States*, 306 US 208 (1939), 227.
[67]Id at 22

view of implementing price cartel[68].

9. CONCLUSION

It becomes evident that addressing reliability in AI evidence, understanding the limitations of machine learning, grappling with admissibility challenges, and clarifying liability concerns would require holistic approaches when one navigates the complex terrain of AI governance and enforcement. Ensuring the reliability of AI evidence requires rigorous validation processes and careful examination of ML algorithms to mitigate biases and errors. The legal framework that would regulate the AI evidence, from authentication procedures to differentiating between real evidence and hearsay, should also be clear and uniform.

Liability frameworks must be flexible enough to hold the creators of AI responsible for damages resulting from AI actions while keeping the needs of innovation in check. Concepts like vicarious liability and the "deep pocket theory" offer avenues for compensating parties harmed by AI shortcomings.

Lastly, addressing anti-competitive concerns from AI adoption entails regulatory adjustments to cover the algorithmic collusion scenario and bolster enforcement of the anti-competitive regulations.

10. SUGGESTIONS

1. Regulatory Reforms: Lawmakers need to create regulations that specifically address the unique challenges presented by AI, including how to handle AI-generated evidence, establish liability frameworks, and manage the role of algorithms in anti-competitive behavior.
2. Interdisciplinary Collaboration: It's crucial for legal experts, technologists, and ethicists to work together to create thorough guidelines for AI governance. By combining different fields, we can gain a deeper understanding of how AI affects legal processes and society as a whole.
3. Transparency and Accountability: Developers of AI must focus on being transparent in their algorithmic decision-making and take responsibility for the ethical consequences of their work. There should be auditing processes in place to ensure they meet legal standards.
4. Continuous Education and Training: Ongoing education about AI technologies and their effects on the legal system is essential for legal professionals and judges. This training should

[68] In re,Alleged Cartelisation in the Airlines Industry, 2021 SCC OnLine CCI 3

cover the intricacies of machine learning, the biases that may arise, and how to assess AI-generated evidence.

5. International Collaboration: Since AI operates on a global scale, it's important for countries to work together and align their regulations. Collaborative international efforts can help create consistency in AI governance, improve legal certainty, and support cooperation across borders.

In conclusion, tackling the complexities of AI governance and enforcement demands proactive strategies, collaborative efforts across disciplines, and flexible regulatory frameworks to ensure accountability, fairness, and transparency in the age of AI.