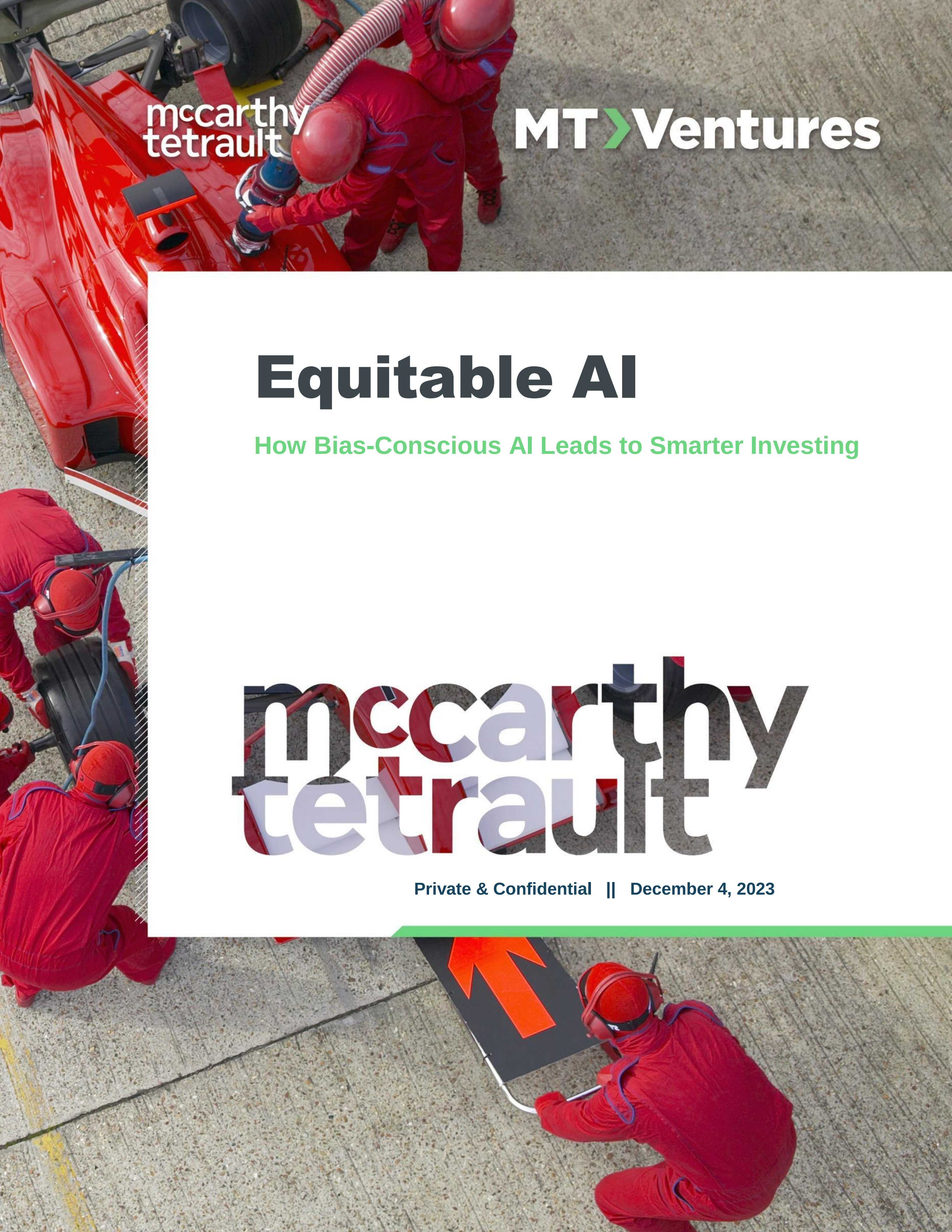
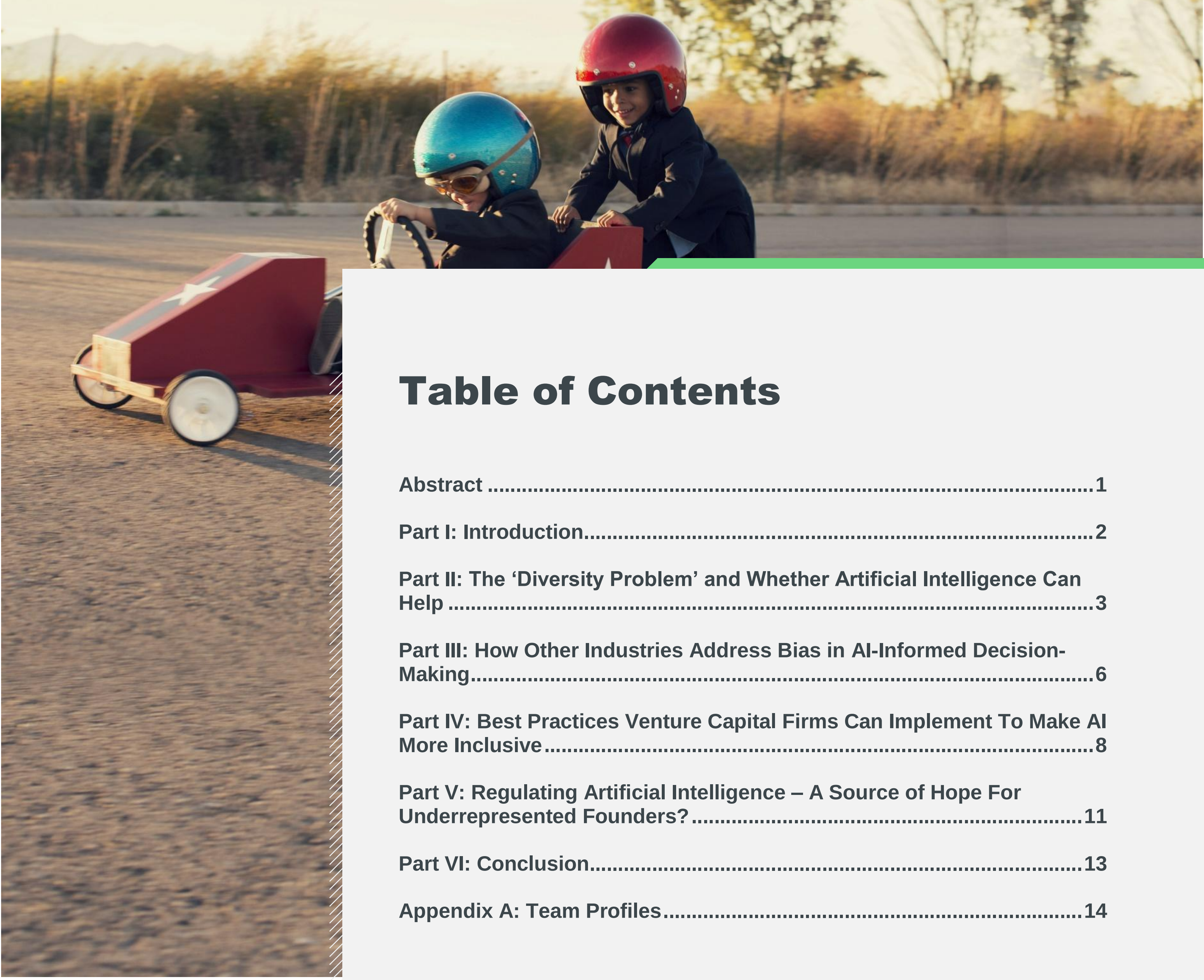


Equitable AI

How Bias-Conscious AI Leads to Smarter Investing

Private & Confidential || December 4, 2023



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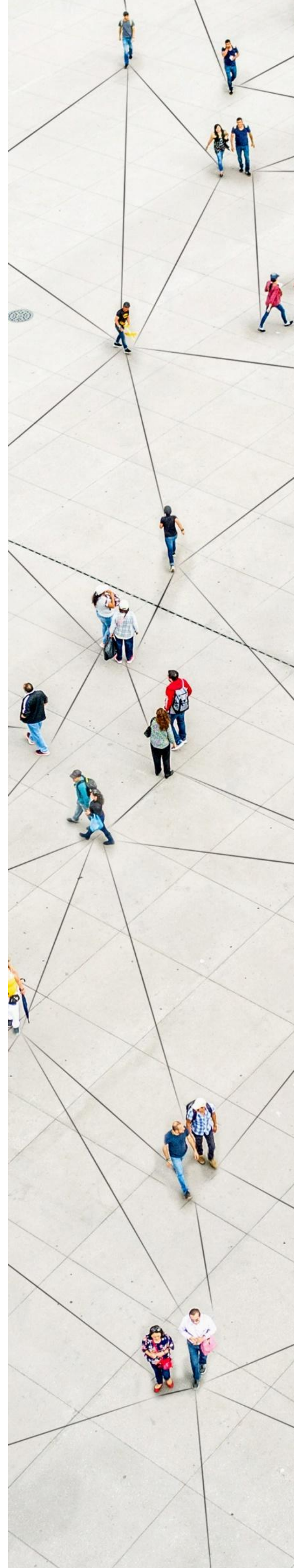
Abstract

The venture capital ("**VC**") industry is fuelled by relationships, networks, and peer comparisons. A function of the limited business and financial track-records of startups, these inputs have unfortunately resulted in a lack of diversity in VC deals and the underfunding of many high potential companies.

Artificial intelligence ("**AI**") is changing the way data is assessed and decisions are made. Increasingly, VC firms, incubators, and accelerators are using AI as a factor in decision-making. Relying on data and objective factors, AI has the potential within the VC industry to shift decision-making towards more informed investment processes that limit unconscious biases. However, AI is only as good as the data it has been given. Since decision-making in the VC industry has historically been influenced by unconscious biases, AI has the potential to produce a similar set of skewed results unless there is a conscious intervention.

In this problem, there exists an opportunity for VC firms to leverage AI to identify high-potential companies that may otherwise go unnoticed – thus, increasing diversity *and* diversification within their portfolios and outperforming their peers. To mitigate the risk of biased AI systems, VC firms can develop diverse teams, implement training, and develop algorithms that utilize a multi-stakeholder approach as well as sources of seemingly unconnected data.

This whitepaper aims to outline the embedded bias challenge associated with AI implementation for VC decision-making and explores best practices for developing AI that can identify high-potential startups that may otherwise be overlooked.



Part I

Introduction

An enormous market of innovative products and services exists that is powered by women and racially diverse founders.[1] The incredible potential of companies led by underrepresented founders is well-documented – in 2021, 11.4% of unicorns had a female founder and 13% of unicorns with female founders matured to exit, despite receiving less than 3% of VC funds.[2] Moreover, the majority of America's billion-dollar startups were founded by immigrants,[3] with women and BIPOC founders playing a prominent role in developing new enterprises.[4]

Despite the clear potential, a pattern of unbalanced funding across gender and racial lines has persisted for decades.[5] While discrimination in opportunities and outcomes can be seen virtually anywhere, the VC industry is particularly vulnerable to biased decision-making because of its reliance on relationships and networks for early-stage financing and syndication , and market comparables to compensate for limited financial information. Due to unconscious biases, VC firms may not view certain types of companies as favourably as others, despite their immense potential.

Fortunately, rapid advancements in AI present an opportunity for VC firms to mitigate biases and focus time and resources on startups with the highest expected return-on-investment. AI can automate deal-screening and deal-sourcing, ensuring that VCs don't miss out on deals. Moreover, AI facilitates comparative analysis by assessing multiple startups within a particular industry by scraping data from across the web to offer side-by-side assessments of strengths and weaknesses. AI that is trained to use a multi-stakeholder approach can help VC firms find promising startups led by diverse founders that may have been otherwise missed, providing those VC firms with a competitive advantage over others. However, AI presents another unique challenge: AI is only as good as the data it is trained on, and VC deal data reflects the biased decision-making of the industry's past.[6]

As Part I has presented the challenges the VC industry faces with AI, this whitepaper will explore the ways these challenges can be overcome by developing AI models trained on unbiased data. Part II will briefly discuss the current lack of diversity in VC investments and will introduce AI as one piece of the potential solution. Part III will explore pitfalls and best practices from AI applications in healthcare, human resources, and financial services contexts. Part IV will present strategies VC firms can leverage to reduce embedded bias in their AI and improve firm return-on-investment. Finally, Part V will underline the imperative of trained and bias-conscious AI by providing an overview of how Canada, the U.S., and Europe are addressing this issue through legislation.

Part II

The ‘Diversity Problem’ and Whether Artificial Intelligence Can Help

AI implementation in investment decision-making presents both an enormous opportunity and challenge for VCs. By mitigating unconscious biases that may lead investors to undervalue investment opportunities in women- and minority-led startups, AI can help VC firms objectively choose startups with the highest expected return-on-investment. Nevertheless, since decision-making in VC funding has relied on bias-vulnerable criteria in the past – with VC firms often choosing the best startups based on team composition, social cues, and instinct – it will be difficult to develop AI that is not embedded at least to some extent with the unconscious biases of past investment decisions.

Motherbrain, the proprietary AI platform of EQT Ventures in Sweden, married the concept of scrapping data from approximately 40 different sources on the web with different mixes of data and algorithms. EQT recognized that personal networks and word-of-mouth are the dominant tools of the trade, but knew they wanted to take a data-driven approach. This meant mapping connections between data such as app store downloads, website traffic, and founders’ resumes as well as learning the criteria that the investors prioritized and the questions they most commonly ask about a company.[7] It is in these questions (the bias-vulnerable criteria) that one may find the unconscious biases of past investment decisions.

Part II will begin by outlining the diversity problem in VC funding allocation, and then introduce AI as a part of the potential solution, while paying particular attention to the risks and limitations of imperfect data. Although AI holds incredible potential, it is imperative that technologists, thought leaders, and policy teams consider the ramifications of building AI without attention to equity[8] – especially in the VC industry, where failing to do so could serve to amplify group-think. If improperly used, AI technologies for evaluating and selecting startups to fund may perpetuate tech’s diversity problem and fail to identify the best investments based on objective metrics.

THE ‘DIVERSITY PROBLEM’ – WE ASK MEN TO WIN AND WOMEN NOT TO LOSE

The network-driven VC industry often lacks diversity and, consequently, exposure to diverse startups. It is estimated that Caucasian men control 93% of VC funds, with most VC funds not having any women on their investment team[9] and only 0.2% of VC partners (the ultimate decision-makers) being Black or Latina women.[10] As a result, founders who are minorities face numerous obstacles to obtaining funding. Female founders, for instance, “are *significantly* less successful garnering interest and raising capital from male investors compared to observably similar male founders,”[11] especially female BIPOC founders, who receive only 2% of VC funding.[12] Moreover, one study found that gender bias exists within the questions asked to founders by both male *and* female VCs – that is, a tendency toward asking ‘promotion questions’ to male founders compared to a tendency toward asking ‘prevention questions’ to female founders.[13] The VC industry’s diversity problem also affects funding for startups with LGBTQ+ founders, who receive less than 1% of VC funding.[14]

As a field generally predominated by individuals of a similar gender, race, and background, VC firms are prone to investing in founders that are *like them*.[15] Put another way, ‘what you *are* is what you *like*.’[16] Humans naturally have unconscious biases in their decision-making, but these can be overcome by deliberate action. This is especially important in the VC industry, since many decisions are based on group behaviour and subjective cues like “fit”, “likeability”, or “gut instinct”.[17] When investment decisions are made using subjective criteria, unconscious predispositions implicitly lead investors to hesitate from stepping outside their comfort zone.[18] As a result, startups with founders that do not fit within the ‘comfort zone’ of VC investors – that is, founders that do not fit a similar demographic or ethnic profile as the investors – may be overlooked.

Several empirical studies have demonstrated this diversity problem. For instance, one study found that when women entrepreneurs fabricated an imaginary male co-founder on their team, they received more interest in their venture than when using solely female names.[19] Another study found that male and female founders are implicitly held to different standards in the pitching process, such that “[f]emale entrepreneurs are implicitly expected to prove they can execute a safe return of capital to the investor, whereas male entrepreneurs are instead expected to show the opportunity can grow.”[20] In other words, “we ask men to *win* and women *not to lose*.”[21] When we hold founders to these different standards and don’t overcome the implicit biases present, the result is imperfect decision-making. VC firms may be missing out on big winners as their ability to recognize successful teams is potentially clouded by unconscious biases. Access to capital considerations may also prevent certain founders from getting the same attention as others, given the VC industry’s heavy reliance on syndication and follow-on financing. A conscious or unconscious worry over the availability of upstream financing may cause male and female investors to prefer male-led startups.[22]

CAN ARTIFICIAL INTELLIGENCE SOLVE THE DIVERSITY PROBLEM?

Unbiased data driven decision-making through AI will play a role in more objective capital allocation. Bias-conscious AI can ameliorate VC decision-making toward more objective processes that are not subject to unconscious biases. While subjective factors such as team dynamics, grit, and extreme obsession with the problem and customer outcomes will always be essential in capital deployment, bias-conscious AI can provide objective feedback on inputs and improve the ability of VC firms to evaluate a business against factors such as traction, customer acquisition cost, and financial performance.

To do so, however, AI must be trained from historical data on startups that have succeeded *and* those that have failed.[23] The failure to do so results in a tendency toward “backward-similar” investments – that is, an AI algorithmic bias that expresses a preference for startups that are similar to previously VC-funded ‘successful’ businesses.[24] Algorithm bias occurs when an algorithm produces results that are systemically prejudiced due to a certain set of assumptions in the machine learning process. Put differently, the concern is that simply having access to VC funding will be overinflated as an indicator of quality. As a simple example, consider two industries: forestry and tech. If the majority of historically successful startups were in the tech sector, AI might favour startups within the tech sector as the best future investment simply because of their past prevalence, even where a forestry startup is clearly more destined for success based on performance-driven factors.

Research has shown that VC firms that “adopt AI become better at identifying good quality startups, i.e., those that survive and receive follow-on funding, *but only within the pool of startups whose business is similar to that developed by past companies*.”[25] Consequently, AI adoption by VC firms can be associated with an increase of investment into startups that are similar to previously successful startups.[26] This is expected, given the training datasets, but is exclusionary and prioritizes proximity over quality. “When the initial dataset over- or under-samples marginalized groups it can skew conclusions that are drawn by the algorithmic models during the data mining process. Those skewed conclusions, when deployed in an AI system, may very well discriminate against these marginalized groups.”[27]

Consider again the example of tech startups compared to forestry startups. Now, replace “tech” with Caucasian male founders and “forestry” with female BIPOC founders. Since it is estimated that female BIPOC founders currently receive only 2% of VC funding,[28] it is unlikely that an algorithm would suggest a startup with a female

BIPOC founder as the best company to invest in – the model just hasn't seen a lot of successful companies with those individuals as founders. Thus, by using AI to choose future investments based on historically funded startups, VC firms remain subject to unconscious biases, and worse, these biases will likely be amplified in future investments.

Headline, a San Francisco based VC firm managing $4B in assets, has been using AI and machine learning for almost two decades. They have several proprietary platforms, including Searchlight. Searchlight allows Headline to search millions of websites to find little known technologies by analyzing growth and performance of early-stage companies across multiple sectors. Using Searchlight, Headline found an open-source password manager, Bitwarden, in Florida that was previously unknown to any investors, as they weren't in an investor network. Headline invested in the company in 2019 and in 2022 Bitwarden secured a $100 million growth round. Thomas Gieselmann, founding partner of Headline, explains that data "truly does remove bias in that it allows us to talk to companies that have traction but otherwise don't have access to [traditional VC] networks.'[29]

The primary challenge facing AI implementation within the VC industry is the imperfect data upon which it relies. When the data we give AI is the result of inherently biased decision-making, we cannot expect anything different, as AI in itself is not biased or irrational and only adopts the biases of its underlying data. The remainder of this whitepaper will discuss potential solutions to the bias challenge and provide suggestions to limit its impact on the VC industry.

Part III

How Other Industries Address Bias In AI-Informed Decision-Making

AI technology has the potential to reduce costs and improve efficiency across industries. Generative AI, capable of creating content, is predicted to add trillions of dollars in value to the global economy annually.[30] However, as discussed throughout this whitepaper, there are significant risks in terms of bias and discrimination in AI-based decision-making applications. Particularly susceptible to bias are industries that impact livelihood and welfare including healthcare, human resources, and financial services. Part III will investigate AI applications in these industries, key lessons from these applications, and relevant considerations for VC investment decisions.

DECISION-MAKING WITH ARTIFICIAL INTELLIGENCE IN OTHER INDUSTRIES

AI technology is being developed to improve healthcare outcomes. Google and Mayo Clinic Research Hospital are collaborating to develop a healthcare AI tool that demonstrates drastically more accurate health care outcomes through targeted training and expert input.[31] However, development efforts have been plagued by embedded bias, with Google acknowledging the need for further work on validation, safety, and ethics.[32] Like AI developed for the VC industry, the risk with these applications is non-diverse, biased datasets.

Credit lenders have also recently started implementing AI to streamline decision-making. However, their use of AI may, if historic biases are not accounted for, similarly exacerbate discrimination against historically marginalized groups. Evidence indicates that access to mortgage credit differs sharply by race and ethnicity and contributes to gaps in homeownership and wealth.[33] This systemic discrimination, if not addressed, may be built into automated decision-making tools.

AI is also used increasingly at various stages of staffing and recruitment, including creating job descriptions, screening applicants, and evaluating candidates.[34] The use of AI to inform recruitment decisions has the significant risk of exacerbating patterns of discrimination that have existed in the workplace for decades. The reliance on subjective criteria to choose candidates rather than objective and measurable criteria, similar to the decision-making process in the VC industry, contributes to these patterns of discrimination. The historical reliance on subjective factors and resulting homogeneity in selections has created a biased dataset which, in turn, leads to biased algorithms when used in AI systems.[35]

An early example of bias in automated decision-making in the human resource context is Amazon's 'secret' AI recruiting tool that contained an embedded bias against female candidates.[36] Although "the tool was intended to make the hiring process quicker by assigning applicants scores . . . it was later removed from use because it was not producing gender-neutral results. The tool had taught itself, based upon historical data, that male candidates were preferred."[37] Like our above example of tech and forestry companies, prevalence was ranked above quality and the bias towards male hires was amplified.

KEY LESSONS FOR ENHANCING DIVERSITY

There are three lessons that emerge from these industry applications of AI to inform decisions: (i) representative data is important to inform accurate decisions; (ii) implicit bias in data perpetuates and amplifies existing patterns of discrimination; and (iii) intervention and accountability for mitigating bias require transparency.

First, representative data is necessary to inform accurate decisions for diverse populations. For example, bias in healthcare AI technology resulting from a lack of diverse historical data can lead to missed or inaccurate diagnoses and decisions, causing preventable risks to patient dignity, access, and quality of care.[38] Studies have found that AI quality has suffered as a result of smaller datasets for racially diverse and female patients, a result, in part, of their unequal access to healthcare.[39]

Incorporation of representative data, including personal characteristics and social determinants of health, is essential for healthcare-related AI to serve all patients.[40] Interdisciplinary input and representative data are needed to teach AI to track sensitive characteristics where it is warranted and to thwart attempts where it is not.[41]

Across other industries, a lack of representative data remains at the core of the issue. Quality data matters, and when it comes to training AI models, ‘garbage in means garbage out.’ Without diverse data and large data sets that represent the subject of the decision, AI applications will continue to have built-in bias resulting in the perpetuation and amplification of discriminatory practices.

Second, and unsurprisingly, AI trained on biased data leads to the amplification of discriminatory outcomes and inequality.[42] A study done on credit scores for minority and low-income groups demonstrated two challenges: 1) limited data to start with, and 2) embedded bias in the data that is available.[43] Less data leads to less accurate assessment results, which further multiplies into biased datasets being used for automated decision-making. In the credit industry, this leads to “disparities in credit access and credit misallocation across social groups.”[44] The solution requires improvement of the data itself, rather than solely addressing AI algorithms. By identifying additional factors that may provide a more precise metric of success, organizations can reduce the reliance on subjective criteria and increasingly rely on accurate, measurable data.

Finally, the third lesson is that without transparency around the inputs and processes used to develop automated decision-making tools, it is difficult to prevent discrimination.[45] Human intervention, accountability, and measuring potential bias are essential but challenging due to the complexity of AI technology. Increased transparency about the data and inputs that are used to train decision-making algorithms allows for internal and external analysis for potential biases that may be affecting outcomes. While human intervention will continue to be required to grow datasets for historically marginalized social groups, we must note that human intervention may also lead to new biases, as we cannot always predict or determine who will intervene and what that impact will be.

CONSIDERATIONS FOR VENTURE CAPITAL FIRMS

VC firms can learn from other industries to understand how best to approach data and algorithm design, as the quality of input data plays an important role in the accuracy and precision of decisions. Considerations for improving data quality include assessing the relevancy of characteristics deemed to indicate success and ensuring diversity is a focus in data collection. Determining the historical factors that indicate a greater likelihood of startup survival, and ultimately success, is essential for accurate decision-making in VC firms.[46] Once the factors are determined, the data must then be collected with equitable precision. Diverse data that represents the large and growing community of startup companies is essential for these factors to be identified without perpetuating historical patterns of discrimination.

Beyond technical solutions, consideration should also be given to implementing transparency and accountability processes to monitor and remove discrimination and course-correct AI models over time. The long investment periods of VC firms make immediate validation a challenge because returns-on-investment can take years to materialize.[47] That being said, internal transparency and assessment of key milestones may provide early insight into the accuracy of automated decision-making systems.

Part IV

Best Practices Venture Capital Firms Can Implement To Make AI More Inclusive

Several best practices have been documented that help create more inclusive AI. These practices span the entirety of the AI value chain, namely during development, pre-deployment, and post-deployment, and focus on diverse teams, diverse data, and ongoing monitoring and improvement.[48]

DIVERSE TEAMS, BETTER OUTCOMES

Diverse founder teams demonstrably create more innovation and deliver better business outcomes, with superior performance over the long-term.[49] In line with the prevalence of relationships and networks within the VC industry, more diverse venture investing teams are more likely to fund diverse founders. Gender diverse teams are three times more likely to invest in a female CEO and nearly three times more likely to invest in female-led entrepreneur teams.[50] Notably, and as readers should by now expect, diverse investing teams are correlated with better returns for investors, with multiple studies directly noting the negative effects of homogeneity on individual investment exits and overall fund returns.[51] Coined the *diversity dividend*, diversity significantly improves financial performance on measures such as profitable investments at the individual portfolio-company level and overall fund returns.[52] Increasing diversity in VC is important not only to advance equality, but to increase returns – and is especially important during the implementation of AI used to inform the next portfolio of investments.

Algorithms can be designed to avoid potential discrimination and objectively pinpoint unconscious factors.[53] Hiring inclusively and building teams across various genders, races, and ethnicities will open the door to inclusive AI that enables AI-conscious VC firms to outperform others. Among the many benefits derived from diverse teams, the ability to spot bias, increase creative thinking, and the ability to anticipate future problems are particularly important in the development of AI.[54]

Diversifying the VC industry needs a top-down approach. Promoting gender and racial diversity at the partner level provides benefits for stakeholders. Female and racialized VCs are more likely to invest in female-led and racialized startups as they are more likely to detect and correct bias.[55] Further, gender and racially diverse leadership is crucial to lasting change, since the greater the exposure to a new idea (i.e., female and minority leadership in a VC firm), the more acceptable it becomes.[56] Diverse development teams are an important factor to ensure that female and racialized founders receive the attention they deserve. Ultimately, AI reflects the people who build it – thus, it is up to each VC firm using AI to put together the ideal workforce it needs to meet its business and diversity goals.

DATA DIVERSITY

Data management is crucial to developing inclusive AI because the training data serves as the foundation of the model. The AI system learns from the training data to generate its own rules.[57] Naturally, if the input data is tainted with bias, the algorithms developed by the AI will reflect this same bias. As such, the quality, diversity, and representativeness of the data will directly impact the types of funding decisions AI will make. VCs need to begin by casting a wide net to avoid a lack of coverage.[58] Given that AI learns by finding patterns in data, the data curated by humans must include both a large quantity of data and a breadth of data to enable AI to come to the right conclusions from the patterns it observes.[59] One way to ensure the breadth of the collected data is to connect with representatives of impacted stakeholder groups that are often omitted from datasets.[60] VCs looking to expand their datasets may want to consider partnering with stakeholders who predominantly work with female or racialized founders.

Diverse teams can help increase data diversity. Teams with various educational backgrounds, political affiliations, and risk tolerances are more likely to detect and correct bias.[61] AI is far more likely to perform better pattern recognition if it goes through a vetting process designed and implemented by a team of diverse individuals rather than a homogenous team.

For VC firms implementing AI into their investment decision-making, it is important to ensure that dataset bias is mitigated. A stress test developed by Microsoft asks AI users to ask the following questions as they develop AI:

1. If you're using a training dataset, does that sample include everyone in your customer base?
2. If not, have you tested your results with people who weren't part of your sample?
3. What about the people on your AI teams — are they inclusive, diverse, and sensitive to recognizing bias?[62]

Stakeholders and community members (e.g., upstream VC firms, exited founders, and ecosystem partners) can also play an important role in training AI. An uptick in conversations about AI ethics has led to a rise in open-source projects.[63] For smaller VC firms, ecosystem partners in the early stages of AI development can help curb the possibility of unwanted bias or unpredictable outcomes. Another way to mitigate unpredictable outcomes is to incorporate a large, representative set of end users during early stages of testing.[64] This could be an approach that small VC firms might take where they partner with multiple VC firms to increase the size of the data set. This practice can help identify and fill gaps and potential users that were not accounted for in the first place. Adopting a multi-stakeholder approach, where exited founders and ecosystem partners are educated on the purpose of the AI can help identify biases and anticipate problems that may only be relevant to their demographic but will likely be missed by others. Repeated testing with stakeholders and beta groups can help gain new viewpoints and assess inclusivity.[65] Furthermore, redefining bias as a natural predisposition, rather than an intentional maliciousness, will incentivize stakeholders to identify and spot biases.

MY ARTIFICIAL INTELLIGENCE IS BIASED – WHAT NOW?

No matter the measures taken during development and pre-deployment, the risk that bias is "baked in and scaled" by AI systems remains.[66] As such, it is important that any AI system goes through post-deployment evaluation. VC firms should consider appointing an individual or a team to monitor the model post-deployment to determine if the AI is working as intended and if it is indeed identifying underrepresented founders. Moreover, the definition of underrepresented founders will change over time, as the AI model improves. As such, a constant feedback loop will be necessary to confirm the model is actually performing as intended.

AI is typically evaluated through benchmarking – the process of measuring and comparing model performance on a specific task or set of tasks.[67] However, performance on a benchmark dataset is usually measured by one single performance metric to enable quick comparisons between different models. In VC, this performance metric might be an exit multiple. This practice has proven risky since compiling the performance characteristics of a model into one single performance metric can provide a skewed image of the model's performance abilities. Moreover, in VC, long investment periods will result in the inability to immediately validate a model's performance. To ensure that this is not the case, VC firms should develop clear performance metrics over time, to assess a model's intended purpose. Furthermore, VC firms should consider creating an "open feedback loop" to collect feedback on their particular AI platform/model.[68] Developing a protocol and implementing the infrastructure necessary to collect feedback will go a long way in providing insight on user experience.[69]

Part V

Regulating Artificial Intelligence – A Source Of Hope For Underrepresented Founders?

Managed mindfully, AI is a friend, not a foe. Leveraging AI can be extremely beneficial to the VC industry, as it provides a more objective way for VC firms to identify and evaluate early-stage startups and determine if they are worthy of VC funding. Used correctly, AI has the potential to initiate a paradigm shift. VC firms may be able to allocate funding more effectively without the limitations of their networks, word-of-mouth referrals, and the unconscious biases that may impair performance and perpetuate inequality.[70]

To facilitate the adoption of AI while addressing the concern of embedded bias, international leaders in AI, including Canada, Europe, and the U.S., are in the process of adopting AI regulations. For industry participants, as McCarthy Tétrault partner Charles Morgan has remarked, it is "critical that companies proactively address the associated risks" before new AI regulations take effect.[71]

In Canada, the federal government has introduced Bill C-27, the *Artificial Intelligence and Data Act (AIDA)*, to set the foundation for the responsible design, development, and deployment of AI systems. Bill C-27 requires "Persons responsible" for AI systems to undertake assessments to determine whether they are "high-impact".[72] High-impact systems will require mitigation and ongoing monitoring for compliance.[73] Recently, the Minister of Innovation, Science and Industry defined what it means to be "high-impact" and it appears that AI in the VC world does not readily fall under the definition of high-impact. The government does recognize that this list could change. Furthermore, Section 8 of AIDA proposes specific obligations on anyone who is responsible for "high-impact" systems to "establish measures to identify, assess and mitigate the risks of harm or biased output that could result from the use of the system."[74] Given that we know remedying data bias is of key concern, VC firms will want to proactively mitigate these risks, as the regulatory penalties will be severe.

Due to the rising concerns that AI is perpetuating and amplifying discrimination, the White House has published the Blueprint for an *AI Bill of Rights*. While recognizing that there is a lot of good to come from the advent of AI, the White House cautions against using the technology in a way that compromises American civil rights.[75] The White House Office of Science and Technology Policy identifies five principles to guide the design, use and deployment of automated systems. Principle 2, *Algorithmic Discrimination Protections*, requires AI designers, developers, and deployers to take proactive and continuous measures to protect individuals from algorithmic discrimination, and to design AI in an equitable way. Measures include equity assessments, use of representative data, protection against proxies for demographic features, ongoing disparity testing, and mitigation.[76] While the Blueprint does not have the teeth and legislative protections of an actual Bill of Rights, it is a stepping stone to building responsible AI across industries.

The EU's *Artificial Intelligence Act* aims to address the potential dangers involved with using AI by ensuring that it is safe and respects fundamental rights and values.[77] The legislation takes a risk-based approach where different types of regulations apply depending on if the AI is unacceptable risk, high risk, or low/minimal risk. Failure to comply with the regulations can lead to severe penalties of up to $30 million for certain offences if the offender is a company.[78] The level of risk is not clearly defined, however, and it is yet to be seen whether VC firm AI models will be captured.

Furthermore, there are also international frameworks that provide ethical guideposts for AI development. For instance, *Responsible AI: A Global Policy Framework*, calls upon stakeholders to develop AI that considers principles such as “ethical purpose and societal benefit” and “fairness and non-discrimination.” Among other things, the framework states that “[o]rganizations that develop, deploy or use AI systems and any national laws that regulate such use shall ensure the non-discrimination of AI outcomes, and shall promote appropriate and effective measures to safeguard fairness in AI use.”[79]

While the VC industry generally favors less regulation, it is in the best interest of VC firms, both from a business and a legal perspective, to get behind creating more inclusive AI. Although the private sector currently has a substantial amount of discretion regarding the use of AI technology, the new wave of regulations and global frameworks are going to create many new obligations for anyone using AI. Accordingly, responsible AI development will be imperative and VC firms ought to start thinking now about the most effective way to comply with upcoming policy frameworks.

Part VI

Conclusion

AI will become an essential tool VC firms use when filling the top of the funnel and assessing startups for capital deployment. AI can provide objective feedback on inputs and improve the ability of VC firms to evaluate a business against factors such as traction, customer acquisition cost, and financial performance. If properly debiased, AI will increase the number of high potential companies founded by historically marginalized groups at the bottom of the funnel and lead to higher returns-on-investment for VC firms.

Of course, unconscious bias in historical decision making by VCs may result in further amplification of discriminatory outcomes when decision-making is automated. Careful consideration of how other industries have come up against these issues can inform best practices. To mitigate the risk of biased AI systems, firms should develop diverse teams, implement training, and leverage a multi-stakeholder approach. AI implementation is changing the way data is assessed, factors are weighted, and decisions are made. By leveraging AI with diversity as a priority, VC firms can optimize investment outcomes. Ultimately, AI implementation by VC firms can allow them to identify and discover startups that may otherwise be missed, and achieve a higher return-on-investment.

McCarthy Tétrault lawyers, such as the leading expert on responsible AI, Charles Morgan, or the team at MT>Ventures, can help VC firms implement responsible AI governance and navigate vendor management by advising on how to set up an AI committee, developing and implementing policies and responsible AI impact assessments, and assisting companies in negotiating contracts with vendors of AI-enhanced solutions.

Appendix A: Team Profiles

Aliya Ramji, Co-founder

Expertise: Venture Capital|| Office: Toronto || Partner

Aliya Ramji is a partner of McCarthy Tétrault and co-founder of MT>Ventures, a wholly-owned division of the firm. Based in Toronto, Aliya is focused exclusively on startups, scaleups and other fast-growth businesses. In addition to delivering tailored legal advice and other strategic value to high-potential businesses in the startup or scale-up phase, Aliya regularly advises venture capital, angel and strategic investors, as well as parties looking to create strategic alliances or partnerships with founders or start-ups.

Charles Morgan, Partner

Expertise: Technology || Office: Montréal || Partner

Charles Morgan is a partner of McCarthy Tétrault in the Montréal office. Charles is a nationally recognized leader in cybersecurity, data protection, and technology law and has co-authored several books on the topic. He frequently advises clients on complex matters involving artificial intelligence, privacy, and data security, among other things.

Charlene Theodore, Chief Inclusion Officer

Charlene Theodore is Chief Inclusion Officer at McCarthy Tétrault. Charlene is committed to advancing the Firm's core mission to accelerate diversity, inclusion, and corporate social responsibility and oversees the Firm's award-winning Inclusion Now program.

Eashan Karnik, Associate

Expertise: Venture Capital || Office: Toronto || Associate

Eashan Karnik is an associate in the MT>Ventures division of McCarthy Tétrault in Toronto. Eashan is focused purely on high-growth startups and delivers tailored legal advice for managing growth. He regularly advises clients on a broad range of issues in venture financing, compliance with regulatory authorities, labour & employment, and corporate governance.

John Durland, Associate

Expertise: Venture Capital || Office: Toronto || Associate

John Durland is an associate in the MT>Ventures division of McCarthy Tétrault in Toronto. John is entirely focused on high-growth emerging companies and regularly advises clients on a broad range of issues including corporate formation and governance, financings, and other corporate and commercial transactions.

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