Facial Recognition Technology (FRT) in 2022: What the Data Tells Us

Submitted to: The Standing Committee on Access to Information, Privacy and Ethics

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Introduction

This brief makes use of quantitative data from the 2022 AI Index Report to answer the question: what can data tell us about facial recognition in the year 2022? It answers this question in two parts, first by commenting on FRT capability (what is FRT currently capable of) and second by examining FRT usage (how do public and private actors use FRT)?

This brief was prepared by Nestor Maslej, a research associate at the Stanford Institute for Human-Centered AI (HAI) and one of the co-authors of the 2022 AI Index Report. Although the brief makes use of data from the AI Index, its views are not representative of those of the Stanford Institute for Human-Centered AI (HAI).

The AI Index is an annual report, currently in its fifth edition, that aims to track, distill and visualize key trends in artificial intelligence.[1] The Index aims to be the best and most authoritative single source of information on trends in AI and intends to give policymakers an understanding of AI grounded in empirical data.

[1]To read this year's edition of the AI Index, please visit: https://hai.stanford.edu/research/ai-index-2022

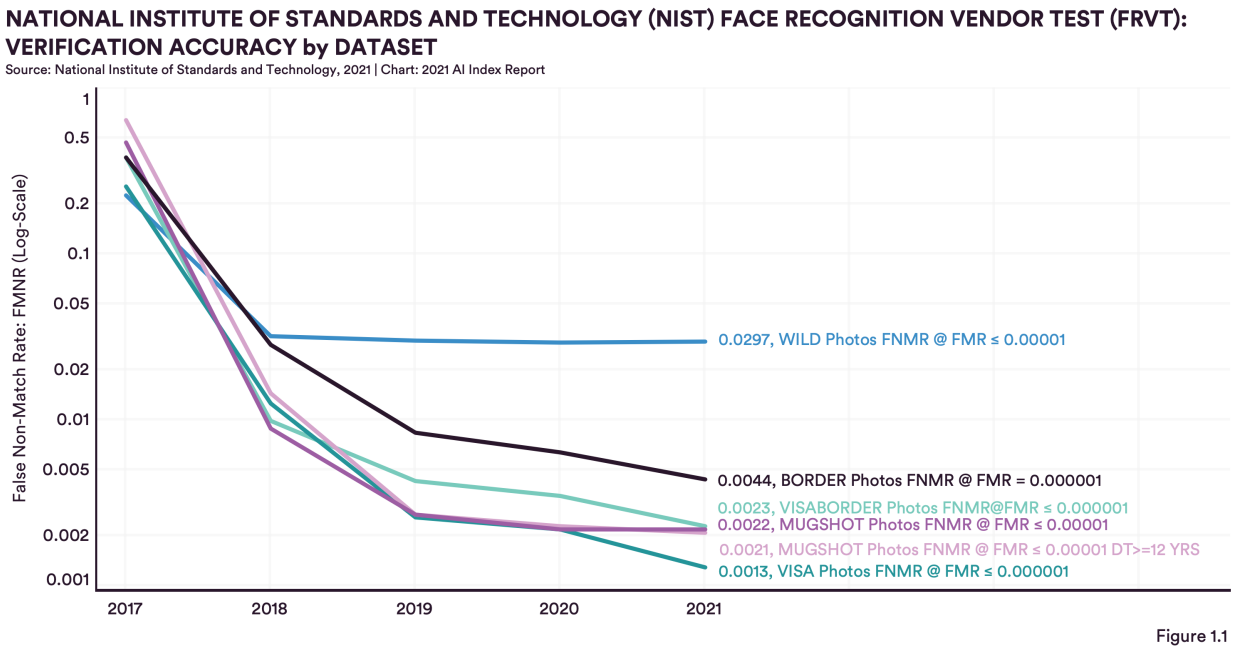

Figure 1.1

1 FRT: Capabilities

1.1 Increasingly more capable

In terms of capability, there has been tremendous progress in the performance of facial recognition algorithms in the last five years. The 2022 AI Index looked at data from the National Institute of Standards and Technology's Face Recognition Vender Test (from the U.S. Department of Commerce) which measures how well FRT performs on a variety of homeland security and law enforcement tasks, such as facial recognition across photojournalism images, identification of child trafficking victims, deduplication of passports and cross-verification of visa images.

In 2017, some of the top-performing facial recognition algorithms had error rates anywhere from roughly 20-50% on certain FRVT datasets.[2] As of 2021, none has posted an error rate greater than 3.0%, and the top-performing model has registered an error rate of 0.1% meaning that for every 1000 faces the model correctly identified 999 (Figure 1.1).

[2]For reference, progress on facial recognition algorithms is measured according to the false non-match rate (FNMR) or the error rate (the frequency with which a model fails to match an image to a person). Moreover, the FRVT tests algorithms on different datasets such as those of border, visa and mugshot photos hence the reference to the differing datasets.

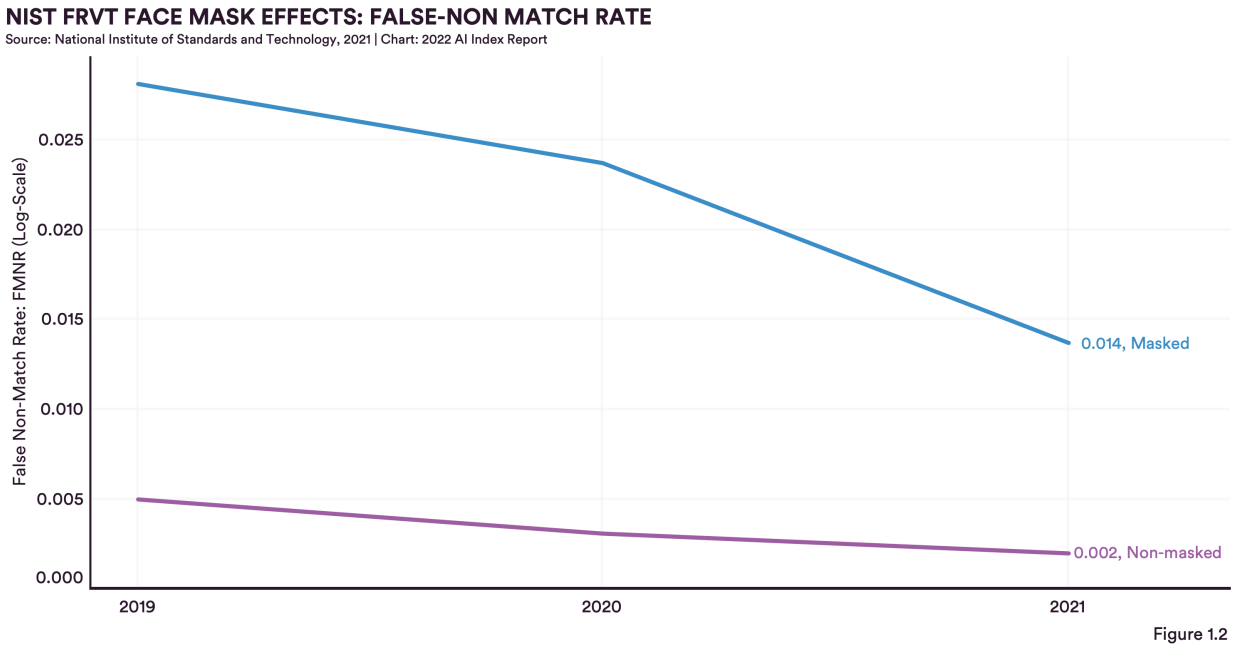

Figure 1.2

1.2 Lower performance on masked faces

Facial recognition has become a tougher challenge for AI systems with the introduction of widespread mask wearing following the onset of the COVID-19 pandemic. As such, researchers have been testing how well their facial recognition systems perform on datasets of masked individuals. At the moment, three significant trends can be observed from the FRVT test as it relates to masked images: (1) facial recognition systems still perform relatively well on masked faces; (2) the performance on masked faces is worse than on non-masked faces; and (3) the gap in performance has narrowed since 2019.

The NIST FRVT face mark effects test suggests that FRT algorithms perform 1.2 percentage points lower on masked compared to unmasked VISA photos of faces (Figure 1.2). In 2019, the performance difference stood at 2.3 percentage points.

In 2021, researchers from the Beijing University of Posts and Telecommunications released a new dataset of 6,000 masked faces for FRT researchers (Masked Labeled Faces in the Wild). Their estimate shows that top FRT algorithms perform 5 to 16 percentage points worse on masked faces compared to unmasked ones (Figure 1.3).

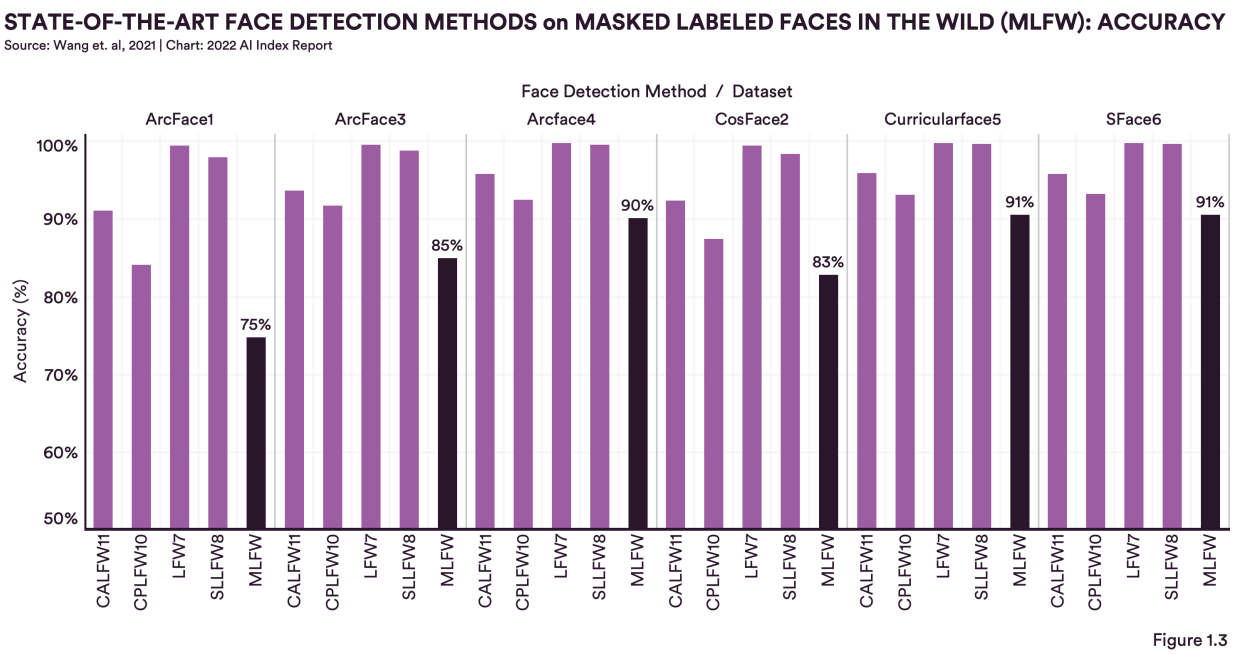

Figure 1.3

2 FRT: Usage

Data from the AI Index also demonstrates that FRTs are becoming more prevalent in both public and private spheres.

2.1 Increased usage by U.S. government agencies

In 2021, 18 of 24 US government agencies used FRT technologies (Figure 2.1). The specific use cases of FRT varied by department: 16 departments used the technology for digital access or cybersecurity, 6 for creating leads in criminal investigations, and 5 for physical security.[3] Moreover, 10 departments noted that they had hoped to use FRT more extensively in the future. These figures are admittedly U.S.-centric, but they illustrate the nature and extent to which FRTs are used by certain government agencies.

2.2 Heightened private investment

Since 2017 there has been a total of 7.49 billion U.S. dollars globally invested in funding facial recognition startups (Figure 2.2). However, only a small 1.6 million dollars of that investment has

[3]For more information, consult the following source: https://www.gao.gov/products/gao-21-526

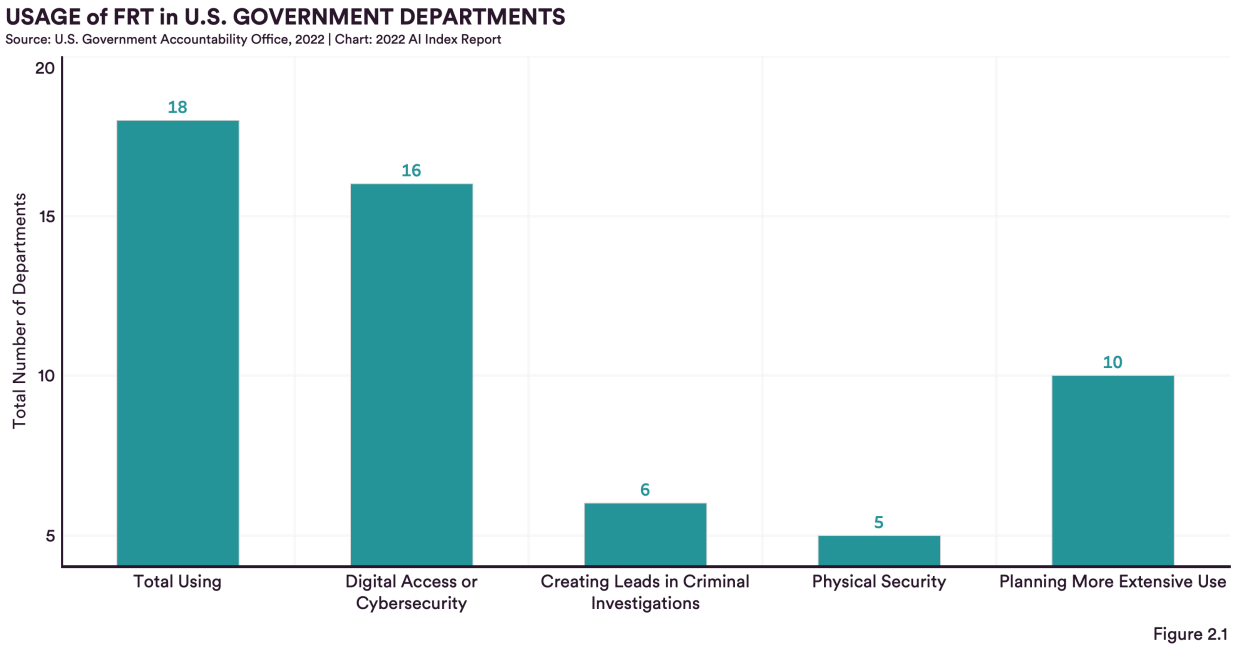

Figure 2.1

gone towards Canadian FRT companies (Figure 2.3). Of 24 countries that have had investment in FRT since 2017, Canada is 24th in terms of total investment.

In the last five years, the overall amount of private investment in FRT technologies has increased 105% suggesting that business interest in FRT is growing (Figure 2.4). AI Index estimates also illustrate that in the same period FRT has been the 12th most funded out of 25 AI focus areas.

2.3 Relatively low business embedding

The results of a McKinsey survey included in the 2022 AI Index Report suggest that compared to other AI technologies, facial recognition has not been as widely embedded in business processes (Figure 2.5). The survey, which polled leading business executives, shows that across all surveyed industries, only 11% of businesses had embedded facial recognition technologies in their standard business processes which trailed robotic process automation (26%) and natural language speech understanding (14%) as the most embedded technologies.

PRIVATE INVESTMENT in AI by FOCUS AREA, 2017–21 (SUM)

Source: NetBase Quid, 2021 | Chart: 2022 AI Index Report

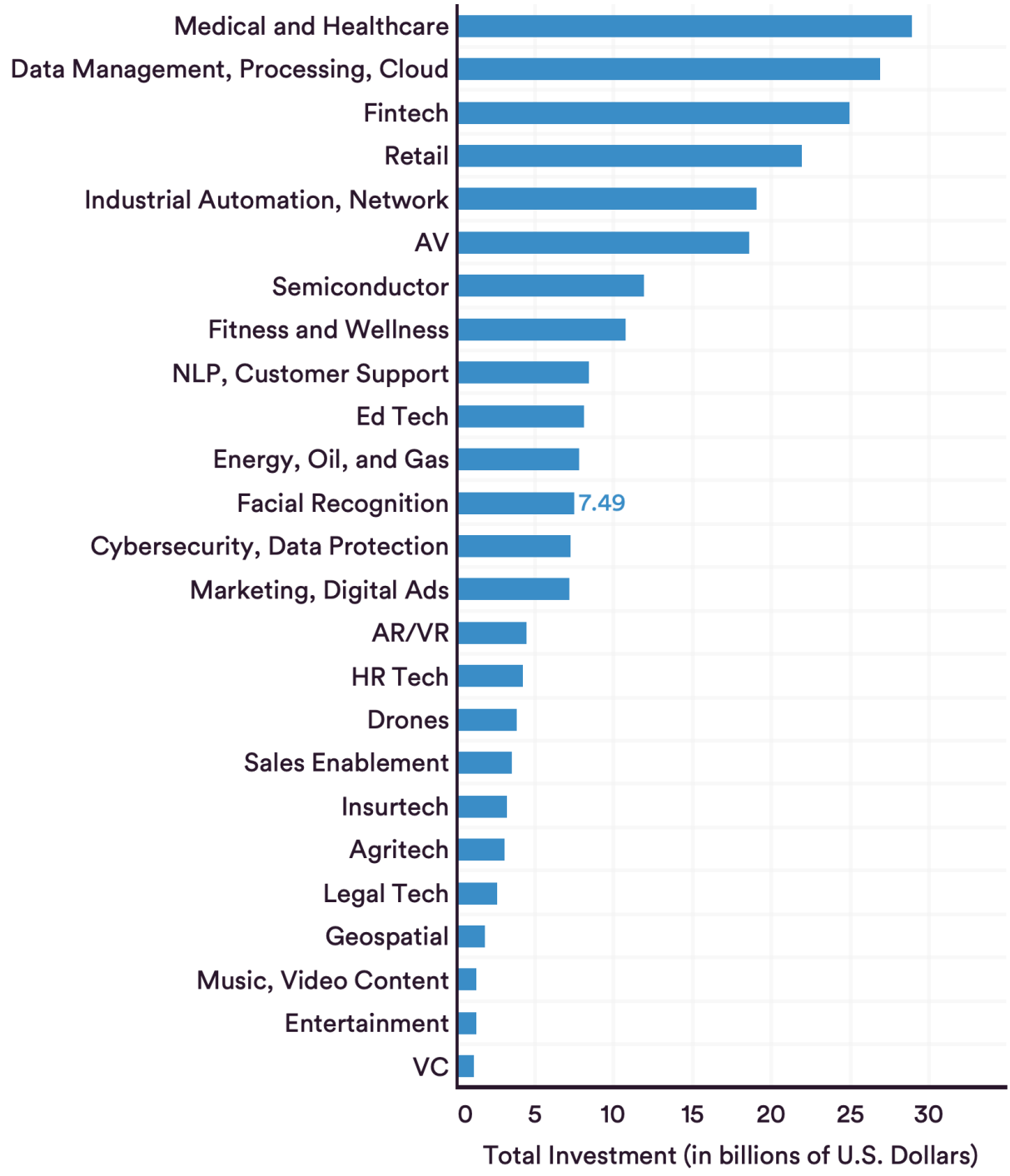

Figure 2.2

PRIVATE INVESTMENT in FACIAL RECOGNITION by GEOGRAPHIC AREA, 2017-2021 (SUM)

Source: NetBase Quid, 2021 | Chart: 2022 AI Index Report

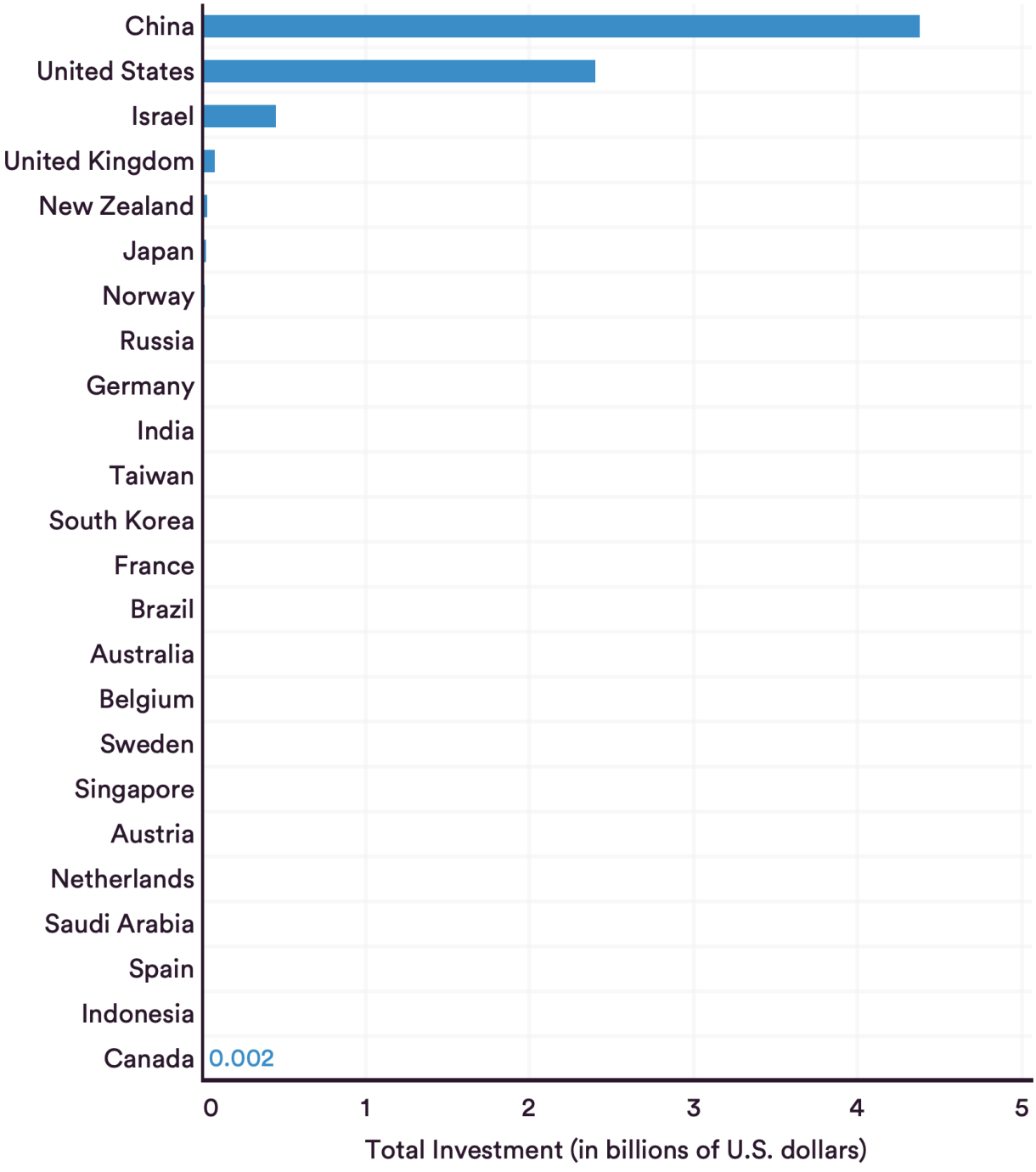

Figure 2.3

PRIVATE INVESTMENT in FACIAL RECOGNITION, 2017-2021

Source: NetBase Quid, 2021 | Chart: 2022 AI Index Report

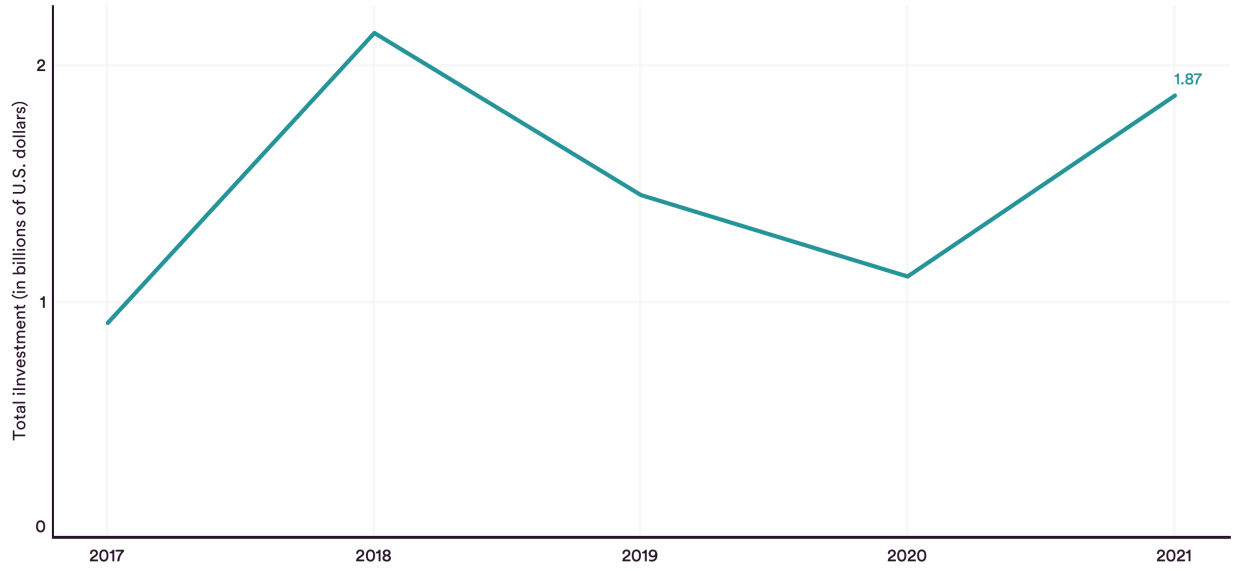

Figure 2.4

AI CAPABILITIES EMBEDDED in STANDARD BUSINESS PROCESSES, 2021

Source: McKinsey & Company, 2021 | Chart: 2022 AI Index Report

Industry	Computer Vision	Deep Learning	Facial Regonition	Knowledge Graphs	NL Generation	NL Speech Un-derstanding	NL Text Un-derstanding	Physical Robotics	Recom-mender Systems	Reinforce-ment Learning	Robotic Process Automation	Simulations	Transfer Learning	Virtual Agents
All Industries	23%	19%	11%	17%	12%	14%	24%	12%	17%	16%	26%	17%	12%	23%
Automotive and Assembly	15%	14%	9%	16%	3%	11%	12%	24%	12%	5%	33%	27%	6%	12%
Business, Legal, and Professional Services	29%	24%	15%	20%	23%	18%	19%	13%	22%	27%	31%	18%	21%	19%
Consumer Goods/Retail	23%	12%	14%	17%	11%	13%	14%	4%	8%	8%	16%	9%	1%	15%
Financial Services	17%	16%	11%	16%	12%	18%	32%	4%	13%	16%	33%	12%	12%	28%
Healthcare Systems/Pharma and Medical Products	30%	25%	12%	19%	10%	8%	26%	28%	22%	13%	28%	22%	19%	31%
High Tech/Telecom	28%	22%	6%	17%	17%	18%	34%	5%	19%	15%	23%	14%	11%	25%

% of Respondents (AI Capability)

Figure 2.5

Conclusion

In conclusion, this brief has presented the AI Index's key findings on the current capabilities and usage of FRT. This data is shared with the intention of productively informing the committee's deliberations on the regulation of facial recognition technologies in Canada.