In this meta-ethnography, we explore three different angles of Ethical AI design and implementation in a top-down/bottom-up framework, including the philosophical ethical viewpoint, the technical perspective, and framing through a political lens. We will discuss the values and drawbacks of individual and hybrid approaches within this framework. Examples of approaches include ethics either being determined by corporations and governments (coming from the top), or ethics being called for by the people (coming from the bottom), as well as top-down, bottom-up, and hybrid technicalities of how AI is developed within a moral construct, in consideration of its developers and users, with expected and unexpected consequences and long-term impact. This investigation includes real-world case studies, philosophical debate, and theoretical future thought experimentation based on historical fact, current world circumstances, and possible ensuing realities.

Keywords ethics · artificial intelligence · meta-ethnography · reinforcement learning · principles

1 Introduction

As a meta-ethnography, this paper will take an anthropological approach to the culture around AI ethics. This is in no way exhaustive, however, we’ll identify some of the key considerations and tensions in the ethical AI field. We will be using the framework of top-down and bottom-up ethics in AI and examining what this means in three different contexts: theoretical, technical, and political. We define top-down ethics in AI as rule-based systems of ethics. These can come from philosophical moral theories, from top-down programming, or by principles designated by authorities. Alternatively, bottom-up ethics in AI can come from learned experiences, from machine learning and reinforcement learning, or from everyday people and users of technology calling for ethics. Reinforcement learning as an example of applied bottom-up methodology will be examined. We will explore the top-down strategy of principles for AI ethics and discuss their benefits and shortcomings. Hybrid approaches, which blend top-down and bottom-up methodologies, will be discussed. We highlight case studies on data mining in African and indigenous communities, as well as contact tracing for COVID-19 in South Korea and Brazil to demonstrate how ethical AI strategies may apply in different scenarios and cultures to impart a global perspective. There are many areas of concern for AI ethics, and in this paper we create a theoretical account to begin a discussion that contextualizes ethical AI for more advanced research to be continued.

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1.1 Contextualizing Top-Down and Bottom-Up Ethics in AI

Strategies for artificial morality have been discussed in a top-down, bottom-up and hybrid framework in order to create a foundation for philosophical and technical reflections on AI system development. Allen et al. [2005] In a very basic sense, if ethics in AI is programmed based on a system of rules, it is considered top-down. If ethics in AI is learned from observation, such as machine learning and deep learning, without a base set of rules, it is classified as bottom-up. The first perspective to understand is the theoretical moral ethics viewpoint: Ethics can work from the top-down, coming from rules and philosophies, or bottom-up which mirrors the behaviors of people and what is socially acceptable for individuals as well as groups, varying greatly by culture. Next is the technical perspective, interpreted as direct programming from the top and applied machine learning from the bottom: Essentially how to implement algorithmic policies with balanced data that will lead to fair and desirable outcomes. Third, we examine top-down ethics dictated from the powers that be, and bottom-up ethics derived from the demands of the people. We call this the political perspective.

Finally, we connect the three perspectives back together and integrate these concepts into top-down, bottom-up, and hybrid models of how ethics functions for AI. This is an exercise in exploration to reach a deeper understanding. How ethics for AI works in reality is a blend of all of these theories and ideas acting on and in conjunction with one another. The aim of this analysis is to provide a framework to understand and think critically about AI ethics, and our hope is that this will influence the development of ethical AI in the future.

2 Theoretical Ethics Top-Down vs Bottom-Up

The first area to consider is ethics from a theoretical moral perspective. The primary point to mention in this part of the analysis is that ethics has historically been made for people, and people are complex in how they understand and apply ethics, especially top-down ethics. Allen et al. [2005] At an introductory glance, “top-down” ethical theories amount to rule-utilitarianism and deontological ethics, where “bottom-up” refers to case-based reasoning. van Rysewyk and Pontier [2015] Theoretical ethics from a top-down perspective includes examples such as the Golden Rule, the Ten Commandments, consequentialist or utilitarian ethics, Kant’s moral imperative and other duty based theories, Aristotle’s virtues, and Asimov’s laws of robotics. These come from a wide range of perspectives, including literature, philosophy, and religion. Walsh et al. [2016] Most of these collections of top-down ethical principles are made solely for people. The one exception which does not apply to people is Asimov’s laws of robotics, that were developed precisely for AI. However, Asimov himself said the laws were flawed.

Azimov used storytelling to demonstrate that his three laws, plus the ‘zeroth’ law added in 1985, had problems of prioritization and potential deadlock. He showed that ultimately, the laws would not work, despite the surface-level appearance of putting humanity’s interest above that of the individual. This theme has been echoed by other theorists on any rule based systems implemented for ethical AI. Asimov’s rules of robotics seemingly encapsulate a wide array of ethical concerns, giving the impression of being intuitive and straightforward. However, in each of his stories, we can see how they fail time after time. Wallach et al. [2008] Science fiction does not predict the future as much as it warns us against its possibilities.

The top-down rule-based approach to ethics presents different challenges for AI than in systems for humans. As humans, we learn ethics as we go, from observation of our families and community, how we react to our environment and how others react to us. Humans first acquire moral values from those who raise them, although it can be argued that individuals make decisions based on their chosen philosophies. As they are exposed to various inputs from new groups, cultures and subcultures, humans modify their core value systems, gradually developing their own personal moral matrix. Etzioni and Etzioni [2017] This personal moral mix could be thought of as a hybrid model of ethics for humans. The question is, how easy and practical is it to take human ethics and apply them to machines?

Some would say it is impossible to teach AI right and wrong, if we could even come to an agreement on how to define those terms in the first place. There is much variety in the details of ethical systems across cultures and between individuals, even though shared values exist that transcend cultural differences. Wallach et al. [2008] There simply is no one set of ethical rules that will be inclusive for everyone.

2.1 The Example of Fairness in AI

Many of the common systems of values that experts agree need to be considered in AI include fairness, or to take it further, justice. Asimov used storytelling to demonstrate that his three laws, plus the ‘zeroth’ law added in 1985, had problems of prioritization and potential deadlock. He showed that ultimately, the laws would not work, despite the surface-level appearance of putting humanity’s interest above that of the individual. This theme has been echoed by other theorists on any rule based systems implemented for ethical AI. Asimov’s rules of robotics seemingly encapsulate a wide array of ethical concerns, giving the impression of being intuitive and straightforward. However, in each of his stories, we can see how they fail time after time. Wallach et al. [2008] Science fiction does not predict the future as much as it warns us against its possibilities.

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Most AI is built to solve problems of convenience and to automate tedious or monotonous tasks in order to free up our time and make more money. Both private and government funding are being used to drive research and development (R&D) in AI for business processes and sales applications. Two of the largest agencies including the European Community Research and Development Information Service (EU CORDIS) and the United States National Science Foundation (US NSF), with 39% and 25% of their funding allocated for applied business R&D, respectively. Galindo-Rueda and Cairns [2021] In 2021 alone, AI startups received $29.5 billion from investors. Williams [2021] This includes a data cloud platform in San Francisco, DataBricks, the highest recipient of US funding, with a $1.6 billion investment, and in China, one of the largest investments went to Aero, a company developing flying vehicles. Mehta et al. [2021]

There is a disconnect between the philosophical worldviews from which much of our ethical understanding originates and the materialistic worldview of computers and robots. Allen et al. [2005] We see it every day in the algorithms that discriminate and codify what retailers think we are most likely to consume. For example, in the ads they show us, we often see elements that don’t align with our values but rather appeal to our habits of consumption. At the core level, these values are twisted to benefit the current capitalistic systems and have little to do with actually improving our lives. We cannot expect AI to jump from corporate materialism to social justice, or reach a level of fairness, simply by tweaking the algorithms.

3 Technical Machine Learning Top-Down vs Bottom-Up

How do we conceptualize top-down AI from the technical perspective? One way is to think of it as a decision tree, often implemented in the form of call centers or chat-bots responding through a series of logic if-then statements. The chat-bot guides the user through a defined set of options depending on the answers inputted. Bottom-up AI is what we typically think of when we hear artificial intelligence: utilizing machine learning and deep learning. As an example, we can think about the AI utilized for diagnostic systems in healthcare and self-driving cars. These bottom-up systems can learn automatically without explicit programming from the start. Eckart [2020]

Top-down systems of learning can be very useful for some tasks that machines can be programmed to do, like the chat-bot example above. However, if they are not monitored, they could make mistakes and it is up to us as people to catch those mistakes and correct them. They may also lack exposure to sufficient data to make a decision or prediction in order to solve a problem, leading to system failure. Here is the value of having a human in the loop. This gets more complicated when we attempt to program the more theoretical concepts of ethics.

Bottom-up from the technical perspective follows the definition of machine learning. The system is given data to learn from, and it uses that information from the past to predict and make decisions for the future. This can work quite well for many tasks. It can also have a lot of flaws built-in, because the world that it learns from is flawed. We can look at the classic example of harmful biases being learned and propagated through a system, for instance in who gets a job or a loan, because the data from the past reflects biased systems in our society. O’Neil [2016]

Technical top-down and bottom-up ethics in AI primarily concerns how AI learns ethics. Machines do not learn like people do. They learn from the data that is fed to them, and they are very good at certain narrow tasks, such as memorization or data collection. However, AI systems can fall short in areas such as objective reasoning, which is at the core of ethics. Whether coming from the top-down or bottom-up, the underlying concern is that teaching ethics to AI is extremely difficult, both technically and socially.

In order to program ethical AI we need to first evaluate our own ethics. Some specialists predict that AI will not be developed ethically because it is not being used to improve the human condition, rather AI is produced by companies in order to make money. What does a ‘humane’ AI mean, even if it could be developed? Would it extract value from humans in the most ‘humane’ way possible? Raine et al. [2021] One of the biggest questions when considering ethics for AI is how to implement something so complex and unagreed-upon into machines which have contrasting strengths in precision. An ‘ethical algorithm’ is a contradiction in terms: there are no reliable calculations to produce ethics as a rule of thumb. Ethics is no technical enterprise. Vachnadze [2021]

The first hard task is to agree on ethics. We live in a very polarized world. What is fair to some will undoubtedly be unfair to others, presenting several hurdles to overcome. There are three specific challenges to address in this matter Wallach et al. [2008]:

1. Scientists must break down moral decision making into its component parts, which presents an engineering task of building autonomous systems in order to safeguard basic human values.
Here we will introduce the use of a hybrid model of top-down and bottom-up ethics for AI, that has a base of rules or instructions, but then also is fed data to learn from. This method claims to be the best of both worlds, and covers some of the shortcomings of both top-down and bottom-up models. One key example is MIT’s moral machine, which is an online judgement platform geared toward citizens from around the world on the moral dilemmas of unavoidable accidents involving automated vehicles and what choices individuals would assign for them to respond. Examples include whether to spare humans versus pets or pedestrians versus passengers, with many factors such as gender, age, fitness and social status. The Moral Machine collects this data and maps it regionally to compare homogeneous vectors of moral preferences in order to provide data to engineers and policy makers in the development of automated vehicles and to improve trust in AI. It is a hybrid of top-down and bottom up since it collects data from citizens in a bottom-up manner, while also considering top-down morals, principles, and fundamental rules of driving.

4 Political Ethics Top-Down vs Bottom-Up

We use the term political to talk about where the power and decision-making is coming from, which then has an effect that radiates outward and influences systems, programmers, and users alike. Top-down from a political perspective largely concerns principles of ethics in AI which come from corporations, governments, and large organizations. Bottom-up politically concerns the perspectives of individuals and groups who are not in positions of power, yet still need a voice.

The Asilomar AI Principles are an example of a top-down model and have their critiques. This is a comprehensive list of rules developed by attendees of the Future of Life Institute conference, attempting to offer guidelines for developing ethics in AI. Published in 2017, these are one key example of top-down ethics from officials. These principles outline ethics and values that the use of AI should respect, provide guidelines on how research should be conducted, and offer important considerations for thinking about long-term impact. Around the same time, another set of seven principles for Algorithmic Transparency and Accountability were published by the US Association for Computing Machinery (ACM) which addressed a narrower but closely related set of challenges.

Since then we have seen an explosion of lists of principles for AI ethics. The bottom-up side of the political perspective is not as prevalent but could look like crowd-collected considerations about ethics in AI, such as from employees at a company, students on a campus, or online communities. The key feature of bottom-up ethics from a political perspective is determinism by everyday people, mainly, the users of the technology. MIT’s moral machine is one example of this, however, it still has top-down implications such as obeying traffic laws imposed by municipalities. A pure bottom-up community-driven ethics initiative could include guidelines, checklists, and case studies specific to the ethical challenges of crowd-sourced tasks.

Even when utilizing bottom-up “crowd-sourcing” and employing the moral determination of the majority, these systems often fail to serve minority participants. In a roundtable discussion from the Open Data Initiative (ODI), they found that marginalized communities have a unique placement for understanding and identifying the contradictions and tensions of the systems we all operate in. Their unique perspectives could be leveraged to create change. If a system works for the majority, which is often the goal, it may be invisibly dysfunctional for people outside of the majority. This insight is invaluable to alleviate ingrained biases.

There is an assumption that bottom-up data institutions will represent everyone in society and always be benign. Alternatively, here is a counter-argument that their narrow focus leads to niche datasets and lacks applicability to societal values. In the best light, Bottom-up data institutions are viewed as revolutionary mechanisms that could rebalance power between big tech companies and communities. An important point to keep in mind when thinking about bottom-up ethics is that there will always be different ideals coming from different groups of people, and the details of the applications are where the disagreements abound.

5 The Bottom-up Method of AI Being Taught Ethics

Here we recombine the perspectives of theoretical, technical, and political bottom-up ethics for AI as an analytical thought experiment. Bottom-up approaches to ethics in AI are those which learn through experience and strive to create environments where appropriate behavior is selected or rewarded, instead of functioning under a specific moral theory. These approaches learn either by unconscious mechanistic trial and failure of evolution, by engineers or programmers adjusting to new challenges they encounter, or by the learning machine’s own educational development.
Many difficulties arise when evolving and developing strategies that hold the promise of a rise in skills and standards, which are integral to the overall design of the system. Trial and error are the fundamental tenets of evolution and learning, which rely heavily on learning from unsuccessful strategies and mistakes. Even in the fast-paced world of computer processing and evolutionary algorithms, this is an extremely time-consuming process. Additionally, we need safe spaces for these mistakes to be made and learned from, where ethics can be developed without consequences.

5.1 Reinforcement Learning as a Methodology for Teaching AIEthics

Reinforcement learning (RL) is a technique of machine learning where an agent learns by trial and error in an interactive environment, utilizing feedback from its own actions and experiences. Reinforcement learning is different from other forms of learning that rely on top-down rules. Rather, this system learns as it goes, making many mistakes but learning from them, as it adapts through sensing the environment. RL is commonly used in training algorithms to play games, such as Alpha Go and chess. When it originated, RL was studied in animals, as well as early computers. The trial and error nature of this technique began in the psychology of animal learning in the early 1900s (Pavlov), as well as in some of the earliest work in AI. This all came together in the 1980s to form the modern field of reinforcement learning.

RL utilizes a goal-oriented approach, as opposed to having explicit rules of operation. A ‘rule’ in RL can come about as a temporary side-effect as it attempts to solve the problem, however if the rule proves ineffective later on, it can be discarded. The function of RL is to compensate for machine learning drawbacks by mimicking a living organism as much as possible. This style of learning that throws the rule book out the window could be promising for training something like ethics, where the rules are not overly consistent or even agreed upon. Ethics is more situation-dependent, therefore teaching a broad rule is not always sufficient. Could RL be the answer?

The problems addressed by RL consist of learning what to do and how to navigate situations into actions in order to maximize a numerical reward signal. The three most important distinguishing features of RL are:

1. the environment is a closed-loop
2. the agent is not given direct instructions on what actions to take
3. there are consequences (reward signals) playing out over epochs

Turning ethics into numerical rewards can pose many challenges but may be a hopeful consideration for programming ethics into AI systems. Critically, the agent must be able to sense its environment to some degree and it must be able to take actions that affect the state.

5.1.1 Can reinforcement learning be methodized in ethics for AI?

One of the ways that RL can work in an ethical sense, and to avoid pitfalls, is by utilizing systems that keep a human in the loop. In order to overcome limitations of interactive learning, a complementary approach can involve a human teacher in the learning process. Keeping a human in the loop is critical for many issues, including those around transparency. Moral uncertainty needs to be considered, purely because ethics is an area of vast uncertainty, and is not an answerable math problem with predictable results. Could an RL program eventually learn how to compute all the different ethical possibilities?

To take it one step further from relying on a human in the loop, we can adopt a society-in-the-loop framework for thinking about AI systems, which is a new kind of social contract that extends to oversight conducted by society as a whole. This may take a lot of experimentation. It is important to know the limitations, while also remaining open to being surprised. We worry a lot about the unknowns of AI: Will it truly align with our values? Only through experimentation can we find out.

RL systems need a ‘safe learning environment’ such as in MIT’s moral machine, where they can learn without any harm being caused to humans, assets, or the real world. The gap between simulated and actual environments, however, complicates this issue, particularly related to differentiating societal and human values.

6 The Top-Down Method of AI Being Taught Ethics

Summarizing top-down ethics for AI brings together the philosophical principles, programming rules, and authoritative control. A common thread among all sets of top-down principles is ensuring AI is used for “social good” or “the benefit
Table 1: Principles and their commitments for technologists to develop machine learning systems responsibly as described in the practical framework to develop AI responsibly by The Institute for Ethical AI & Machine Learning [2021].

| Principle                          | Commitment of Technologists                                      |
|------------------------------------|------------------------------------------------------------------|
| Human Augmentation                 | to keep a human in the loop                                      |
| Bias Evaluation                    | to continually monitor bias                                      |
| Explainability and Justification   | to improve transparency                                          |
| Reproducibility                    | to ensure infrastructure that is reasonably reproducible         |
| Displacement strategy              | to mitigate impact on workers due to automation                  |
| Practical accuracy                 | to align with domain-specific applications                       |
| Trust by privacy                   | to protect and handle data                                      |
| Data risk awareness                | to consider data and model security                              |

Table 2: Principles and their commitments for responsible machine learning and AI systems by (Marengo, 2021) [Phillips et al. [2021]]

| Principle                          | Commitment of AI system                                          |
|------------------------------------|------------------------------------------------------------------|
| Explanation                        | to provide evidence and reasons for its processes and outputs, be readable by a human, and explain its algorithms |
| Meaningful and Understandable      | to have methods to evaluate meaninglessness                       |
| Explanation accuracy               | to correctly reflect the reason(s) for its generated output       |
| Knowledge limits                   | to only operate under conditions for which it was designed and not give overly confident answers in areas it has limited knowledge of |

6.1 Practical Principles for AI Ethics

Principles of AI are a top-down approach to ethics for artificial intelligence. Lists of principles are very useful, not only for AI and its impact, but also on a macro social level. Because of AI, people are thinking about ethics in a whole new way, specifically, how do we define and digest ethics in order to codify it? Principles can be broken into two categories, principles for people who program AI systems to follow, and principles for the AI itself. Some of the principles for people, mainly programmers and data scientists, read like commandments. One example from the Institute of Electrical and Electronics Engineers (IEEE), whose global initiative on Ethics of Autonomous and Intelligent Systems developed the IEEE P7000 series including frameworks and certifications for ethical AI design [2021] [2022b]. Another example from The Institute for Ethical AI & ML whose framework lists eight principles geared toward technologists committing to ethical AI development. Table I [The Institute for Ethical AI & Machine Learning [2021]]

Other lists of principles apply to the ethics of AI systems themselves and what they should adhere to. One such list consists of four principles, published by the National Institute of Standards and Technology (NIST) and are intended to promote explainability. Table II [Phillips et al. [2021]]

These principles overlap across corporations and agencies. The Berkman Klein Center for Internet and Society at Harvard, published a detailed overview of forty seven principles that various organizations, corporations, and other entities are adopting, where they overlap, and their definitions. Field et al. [2020] The authors provide many lists and descriptions of ethical principles for AI, and categorize them into eight thematic trends:
One particular principle that is missing from these lists regards taking responsibility for the non-human world, as briefly mentioned by Paula Boddington in her book, Toward a Code of Ethics for Artificial Intelligence (p.14, 2018). Boddington [2017]. AI will hasten the already rapid changes we are implementing in the world, and it is up to us to determine which changes count as good and which count as bad, especially for non-human life. Boddington [2017]. We will all have different opinions on this, but the environmental impact of AI needs to be part of the discussion.

Principles are often theoretically sound, yet act as a veil that presents the illusion of ethics. This can be dangerous because it makes us feel like we are practicing ethics while business carries on as usual. Part of the reason for this is because the field of ethical AI development is so new and more research must be done to ensure the overall impact is a benefit to society. So far, little scholarly focus or understanding of the efforts of AI principles, either individually or within the larger context, considers discernible trends. Fjeld et al. [2020].

Principles are a double sided coin. On one hand, making the stated effort to follow a set of ethical principles is good. It is beneficial for people to be thinking about doing what is right and ethical, and not just blindly entering code that could be detrimental in unforeseen ways. Some principles are simple in appearance yet incredibly challenging in practice. For example, if we look at the commonly adopted principle of transparency, there is quite a difference between saying that algorithms and machine learning should be explainable and actually developing ways to see inside of the black box. As datasets get bigger, this presents more and more technical challenges. Boddington [2017]. Furthermore, some of the principles can conflict with each other, which can land us in a less ethical place than where we started. For example, transparency can conflict with privacy. We can run into a lot of complex problems around this, which needs to be addressed quickly and thoroughly as we move into the future.

Overall, we want these concepts in people’s minds: such as Fairness, Accountability, and Transparency. These are the core tenets and namesake of the FAAcT conference that addresses these principles in depth. [202] [2022c]. It is incredibly important for corporations and programmers to be concerned about the commonly addressed themes of bias, discrimination, oppression, and systemic violence. Yet, what can happen is that these principles make us feel like we are doing the right thing, however, how much does writing out these ideals actually change things?

In order for AI to be ethical, A LOT has to change, and not just in the tech world. There seems to be an omission of the unspoken principles: the value of money for corporations and those in power and convenience for those who can afford it. If we are trying to create fairness, accountability, and transparency in AI, we need to do some serious work on society to adjust our core principles away from money and convenience and towards taking care of everyone’s basic needs and the Earth.

**Could AI be a tool that has a side effect of starting an ethics revolution?** How do we accomplish this? The language that we use is important, especially when it comes to principles. It is important to use market-friendly terms. If we want morality to win out, we need to justify the organizational resources necessary, when more times than not, companies will choose profit over social good. Moss and Metcalff [2019]. There is a need to focus on areas of tension in ethics in AI, and investigate the ambiguity of terms like ‘fairness’, ‘justice’, and ‘autonomy’. We need to question how these terms might be interpreted differently across various groups and contexts. Whittlestone et al. [2019].

Principles need to be formalized into standards, codes and ultimately regulation in order to be useful in practice. It is important to acknowledge tensions between high-level goals of ethics, which can differ and even contradict each other. In order to be effective, it is vital to include a measure of guidance on how to resolve different scenarios. In order to reflect genuine agreement, there must be acknowledgement and accommodation of different perspectives and values as much as possible. Wallach et al. [2008].

Four reasons which point to the benefits and importance of discussing tensions for AI ethics are:

1. bridging the gap between principles and practice
2. acknowledging differences in values
3. highlighting areas where new solutions are needed
4. identifying ambiguities and knowledge gaps

Each of these needs to be considered ongoing, as these tensions will not be solved overnight. Particularly, creating a bridge between principles and practice is important. There must be thought put in when drawing up codes of ethics and attempting to implement ethical reasoning in machines. There must be a balance between the demand for a robust moral reasoning and rejecting anything we can’t immediately understand by safeguarding against making anything too rigid to allow for growth, essentially “throwing the moral baby out with the bathwater” Boddington [2017].

Codes of ethics, or ethical principles for AI are imperative to starting important conversations. However, it can’t stop there. The future will see more and more ways that these principles are put into action, and see technologists and theorists working together to investigate ways to make them work. We must open minds to ideas beyond making money for corporations and creating conveniences, and rather toward addressing tensions and truly creating a world that works for everyone.

7 The Hybrid of Bottom-Up and Top-Down Ethics for AI

We have reviewed the benefits and flaws of a bottom-up approach to ethics in AI, and visited the upsides and pitfalls of the top-down approach as well. Could the solution lie somewhere in between, in a hybrid model? Additional problems are posed by hybrid approaches when meshing a combination of diverse philosophies and dissimilar architectures. Allen et al. [2005] However, many agree that a hybrid of top-down and bottom-up would be the most effective model for ethical AI. Simultaneously, we need to question the ethics of people, both as the producers and consumers of technology, whilst we assess fairness in AI.

Hybrid AI combines the most desirable aspects of bottom-up, such as neural networks, and top-down, also referred to as symbiotic AI. When huge data sets are combined, neural networks are allowed to extract patterns. Then, information can be manipulated and retrieved by rule-based systems utilizing algorithms to manipulate symbols. SAGAR [2021] Further research has observed the complementary strengths and weaknesses of bottom-up and top-down strategies. A hybrid program synthesis approach has been developed, improving top-down interference by utilizing bottom-up analysis. Raza and Gulwani [2020] When we apply this to ethics and values, ethical concerns that arise from outside of the entity are emphasized by top-down approaches, and the cultivation of implicit values arising from within the entity are addressed by bottom-up approaches. While hybrid systems lacking effective or advanced cognitive faculties will be functional across many domains, it is essential to recognize times when additional capabilities will be required. Allen et al. [2005]

Next we will explore case studies, which reflect some ethical AI concerns in real-world examples.

7.1 Case Study 1: Data Mining

Data sharing is a great example of conflicting principles of AI ethics. On one hand, it is the epitome of transparency and a crucial element to scientific and economic growth. On the other hand, it propagates serious concerns about privacy, intellectual property rights, organizational and structural challenges, cultural and social contexts, unjust historical pasts, and potential harms to marginalized communities. Abebe et al. [2021] We can reflect on this as a hybrid of top-down and bottom-up ethics in AI, since it utilizes top-down politics, bottom-up data collection, and is theoretically a conflict between the principles of the researchers and the researched communities.

The term data colonialism can be used to describe some of the challenges of data sharing, or data mining, which reflect the historical and present-day colonial practices imposed in African and Indigenous contexts. Couldry and Mejias [2019] When we use terms such as ‘mining’ to discuss how data is collected from people, the question remains, who benefits from the data collection? The use of data can paradoxically be harmful to communities it is collected from. Trust is challenging due to the historical actions taken by data collectors while mining data from indigenous populations. We must address the entrenched legacies of power disparities concerning what challenges they present for modern data sharing. Abebe et al. [2021]

One problematic example is non-government organizations (NGOs) that try to ‘fix’ problems for marginalized ethnic groups, often referred to having the ‘white savior complex’, and can end up causing more harm than good. For instance, the problem of access to clean potable water, which a Europe-based NGO planned to address in Buranda, while testing new water accessibility technology and online monitoring of resources. Abebe et al. [2021]. The NGO failed to understand the perspective of the community on the true central issues and potential harms. Sharing the data
publicly, including geographic locations, put the community at risk, as collective privacy was violated. In the West we often think of privacy as a personal concern, however collective identity serves as a great importance to a multitude of African and Indigenous communities. This introduced trust issues due to the disempowerment of local communities in the decision-making process.

Of consideration is that the implementation of data mining for digitization and AI technology is not always introduced for the benefit of those countries citizens. Governments representing countries in the Global South need to account for many factors prior to implementing these processes humbly including economic conditions that might affect standards of living including unemployment rate. Gross Domestic Product per Capita Purchasing Power Parity (GDP-PPP), and access to advanced education. Montoya and Rivas [2019] Balancing these considerations against the need to compete in the global race for AI advancement in order to protect their most vulnerable populations is key.

Another case study in Zambia observed that up to 90% of health research funding comes from external funders, meaning the bargaining power gives little room for negotiations for Zamban scholars. In the study, power imbalances were reported in everything from funding to agenda setting, data collection, analysis, interpretation, and reporting of results. Vachnadze [2021] This example exhibits further the understanding that trust cannot be formed on the foundation of these imbalances of power.

Due to this lack of trust, many researchers have run into hurdles with collecting data from marginalized communities. Many of these research projects lead with good intentions, yet there is a lack of forethought into the ethical use of data, during and after the project, which can create unforeseen and irreparable harms to the well-being of communities. This creates a hostile environment to build relationships of respect and trust. [Abebe et al. 2021]

To conclude this case study in data mining, we can pose the ethical question, “is data sharing good/beneficial?” First and foremost, local communities must be the primary beneficiaries of responsible data sharing practices. Abebe et al. [2021] Can citizens benefit if they are part of the AI implementation process? In a comparison of salaries vs experience for Latin American and Caribbean engineers produced by LatinX in AI™, they demonstrated for roles involving data and machine learning, the average salary is higher for similar years of experience than for engineering roles not involving data. Montoya and Rivas [2019] It is important to specify who benefits from data sharing, and to make sure that it is not doing any harm to the people behind the data.

7.2 Case Study 2: Contact Tracing during the Covid 19 Pandemic

Contact tracing can be centralized or non-centralized, which directly relates to top-down and bottom-up methods. Depending on the country and government, some have taken a more centralized top-down approach, and some have utilized a hybrid approach of government recommendations and bottom-up implementation via self-reporting. The centralized approach is what was deployed in South Korea, where by law, and for the purposes of infectious disease control, the national authority is permitted to collect and use the information on all COVID-19 patients and their contacts. In 2020, Germany and Israel tried and failed at adopting centralized approaches, due to a lack of exceptions for public health emergencies in their privacy laws. Getting past the legal barriers can be a lengthy and complex process and not conducive to applying a centralized contact tracing system for the outbreak. SAGAR [2021]

Justin Fendos, a professor of cell biology from South Korea, wrote that in supporting the public health response to COVID-19, Korea had the political willingness to use technological tools to their full potential. The Korean government had collected massive amounts of transaction data to investigate tax fraud even before the COVID-19 outbreak. Korea’s government databases hold records of literally every credit card and bank transaction, and this information was repurposed during the outbreak to retroactively track individuals. In Korea, 95% of adults own a smartphone and many use cashless tools everywhere they go, including on buses and subways. Fendos [2020] Hence, contact tracing in Korea was extremely effective.

Public opinion about surveillance in Korea has been stated to be overwhelmingly positive. Fatalities in Korea due to COVID-19 were a third of the global average as of April 2020, when it was also said that they were one of the few countries to have successfully flattened the curve. There have been concerns, despite the success, regarding the level of personal details released by health authorities, which have motivated updated surveillance guidelines for sensitive information. Fendos [2020]

Non-centralized approaches to contact tracing are essentially smartphone apps which track proximal coincidence with less invasive data collection methods. These approaches have thus been adopted by many countries, and don’t have the same cultural and political obstacles as centralized approaches, avoiding legal pitfalls and legislative reform. SAGAR [2021]

One study focused on three heavily impacted cities in Brazil which had the most deaths from COVID-19 until the first half of 2021. A methodology for applying data mining as a public health management tool included identifying
variables of climate and air quality in relation to the number of COVID-19 cases and deaths. They used rules-based forecasting models and provided forecasting models of new COVID-19 cases and daily deaths in the three Brazilian cities studied. However, the researchers noted that counting of cases in Brazil was affected by high under-reporting due to low testing, as well as technical and political problems, hence the study stated that cases may have been up to 12 times greater than investigations indicated. [Barcellos et al. 2021]

We can see from these examples that contact tracing works very differently in countries which have contrasting systems of government, and the same approach would not work for all countries. Different models across the spectrum of top-down, hybrid, and bottom-up need to be considered with all factors involved, and consistently monitored for effectiveness.

8 Conclusion

We have taken apart top-down and bottom-up ethics in AI in three ways: theoretically, technically, and politically. Then we took a step back and looked at bottom-up, top-down, and hybrid models of ethics for AI in more detail. Within this, we reviewed reinforcement learning as a bottom-up example, and principles as a top-down example. Then we reviewed case studies to show just how complex and variant ethics in AI can be in different cultures and regions. Ethics in AI needs more research and consideration from multiple fronts while being continuously monitored for unforeseen side effects and consequences. In a paper titled Artificial Morality: Top-down, Bottom-up, and Hybrid Approaches, the authors lead by stating that the burden of ethical behavior in artificial morality shifts to the computer systems themselves and away from designers and users. [Allen et al. 2005] This is a questionable claim. Machines cannot be held responsible for what they learn from people, ever. Machines do not have an inherent conscience or morality as humans do. They don’t work in the same way, and cannot be held to the same standards. However, AI can act as a mirror, and the problems that arise in AI often reflect the problems we have in society. People need to assume responsibility, both as individuals and as a society at large. Corporations and governments need to cooperate, and individual programmers and technologists should continually question and evaluate these systems. In this way, we can use AI technology in an effort to improve society, and create a more sustainable world for everyone.

The approach of moral uncertainty is intriguing because there isn’t ever one answer or solution to an ethical question. To admit uncertainty leaves ethical AI development open to continued questioning that can lead us to the answers that may be complex and decentralized. There is not one ethical proposition that will work for everyone everywhere.

This path could possibly create a system that can adapt to meet the ethical considerations of everyone involved. [Allen et al. 2005] Ultimately, societal ethics need to be considered, as AI does not exist in a vacuum. A large consideration is technology in service of making money, primarily for big corporations, and not for improving lives and the world. As long as this is the backbone driving AI and other new technology, we cannot reach true ethics in this field. Given our tendency for individualism over collectivism, who gets to decide what codes of ethics AI follows? If it is influenced by big tech, which is often the case, it will serve to support the ethics of a company, which generally has the primary goal of making money. The value of profit over all else needs to shift.

Ethics has been transformed into a form of capital by big tech. It has become one of the many ‘things’ that must be tamed by contemporary capitalists as an external transactional object. Ethics has become more corporatized, rather than corporations becoming more ethical. To maintain a system of production which centers on profit making, ethics has been reduced to a form of capital. [Phan et al. 2021] This reflects the case study of data mining in African and Indigenous communities, which set out to do good, however were still working in old frameworks around mining resources for personal gain, regurgitating colonialism. Until we can break free from these harmful systems, building an ethical AI is either going to continue to get co-opted and re-capitalized, or it will find a way to create brand new systems where it can truly be ethical, creating a world where other worlds are possible.

To leave us with a final thought: “Ethical issues are never solved, they are navigated and negotiated as part of the work of ethics owners.” [Moss and Metcalf 2019]

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