

Consequence Minimization in Context: Comparing Decision-Making Frameworks

The **Principle of Consequence Minimization (CM)** is a decision strategy that prioritizes avoiding catastrophic or ruinous outcomes above all else. In essence, an agent guided by CM will first ensure that none of its choices lead to existentially harmful consequences, **before** pursuing any gains or optimizations ¹ ². This principle echoes the harm-avoidance focus of **negative utilitarianism** and the caution of the **precautionary principle**, and it can be formalized in decision theory (e.g. via a minimax or safety-first criterion) ². Notably, CM predicts **state-dependent** behavior: when an agent is in a secure position, it will be risk-averse and avoid large gambles, but if the agent is already in dire straits (facing certain disaster), it may become risk-seeking as a last resort to escape the impending catastrophe ³ ⁴. This sets CM apart from simple risk aversion or other static policies. Below, we compare Consequence Minimization with several major decision-making frameworks, focusing on how each handles uncertainty and worst-case scenarios, their ethical orientation, strengths and weaknesses (especially in high-stakes domains like AI or geopolitics), and real-world outcomes associated with each.

Consequence Minimization vs. Expected Value Maximization (Effective Altruism and AI Safety)

Expected Value (EV) maximization is the strategy of choosing the option with the highest expected outcome, calculated as a probability-weighted sum of utilities or benefits. It is foundational in classical economics and utilitarian ethics – often guiding **Effective Altruism (EA)** in choosing causes that maximize expected good (e.g. lives saved) ⁵. Under EV reasoning, even a very low-probability outcome can justify a decision if the payoff is sufficiently huge. This approach treats uncertainty by **averaging out outcomes**: a tiny chance of an astronomical benefit (or harm) can dominate the calculation if the stakes are high enough. The approach is **broadly utilitarian**, focused on maximizing aggregate good (or expected utility) without special safeguards for worst-case outcomes.

Handling Uncertainty and Catastrophic Risk: A pure EV-maximizer does not inherently shy away from catastrophic outcomes – it simply multiplies impact by probability. This can lead to counter-intuitive or dangerous prescriptions in the face of extreme uncertainties. A famous illustration is *Pascal's Mugging*: a rational expected-utility agent might accept a bizarre trade (like giving a stranger \$5 on an **extremely** slim chance of receiving astronomical reward or avoiding astronomical harm) because some **very unlikely** outcomes with huge payoffs can grow faster in utility than their probabilities shrink ⁶. In theory, **nothing in EV maximization forbids betting the world on a small chance of utopia** if the expected net benefit is positive. This raises alarms for scenarios like AI development: a naive EV calculation might support pushing ahead with powerful AI if one assigns a high enough value to a positive outcome, even if there's a small but real chance of an AI catastrophe. By contrast, **Consequence Minimization** imposes a lexical priority: avoid moves that could cause irreversible ruin (like human extinction) regardless of enticing expected gains. CM would effectively put an infinite negative weight on existential catastrophes, or require their probability to be driven near-zero before maximizing other outcomes. In practice, this means CM-guided decisions are far

more cautious under uncertainty: they would *not* accept a 1% chance of doom for a 99% chance of great benefit, whereas an EV calculation might, depending on how utilities are assigned. AI safety debates highlight this tension. For example, some long-termist effective altruists argue for “**maxipok**” – “maximize the probability of an OK outcome (no existential catastrophe)” – as a guiding rule ⁷. Bostrom notes that while *expected-value altruism* directs attention to huge future payoffs, the **Maxipok rule** explicitly prioritizes avoiding existential risk as “a dominant consideration” when acting for humankind ⁷. This is closely aligned with CM, ensuring catastrophic AI outcomes are minimized *even if* foregone gains are large.

Ethical Orientation: EV maximization is strongly utilitarian and consequentialist – it cares only about outcomes aggregated across the world or future. Every outcome’s “utility” is weighted by its probability, and the *moral* action is whichever maximizes the sum. In contrast, Consequence Minimization can be seen as a form of **negative utilitarianism** or a **lexical safety rule**: it gives lexical priority to avoiding harm (especially extreme harm) over maximizing positive utility ². This has a deontological flavor in that certain actions (those risking catastrophic harm) are essentially forbidden, not merely penalized in a cost-benefit tradeoff. CM might also resonate with common-sense morality – most people feel “*do no harm*” (especially no *disaster-level* harm) should come before maximizing gains. Effective Altruism’s strong utilitarian EV focus has faced criticism for potentially neglecting this intuition. Philosopher **Leif Wenar** argued, after the **FTX crypto scandal**, that Sam Bankman-Fried’s behavior “typified” EA’s focus on *positive expected value* without adequately **weighing risk and harm**, illustrating how an exclusive EV mindset can rationalize catastrophic mistakes ⁵. In other words, a purely outcome-totaling ethic might not sufficiently **caution against low-probability disastrous means**.

Strengths and Weaknesses: Expected value maximization shines in scenarios with repeatable trials or well-understood probabilities – it’s the rationale behind insurance, investments, and effective charity in many cases. Over many iterations or across large populations, maximizing expected value tends to maximize overall success; it avoids timid conservatism and seizes high-impact opportunities. Indeed, in global health the EV framework has saved lives: e.g. funding anti-malarial bed nets had a higher expected lives-saved per dollar than many other interventions, so EA organizations funneled resources there and achieved enormous real-world good. However, **in high-stakes singular decisions, EV’s disregard for variance can be perilous**. It may recommend actions that are “*optimal on average*” but *fatal if the dice roll unluckily even once*. **Catastrophic risks (extremely negative outcomes)** are underweighted if their probabilities are uncertain or small – something CM explicitly guards against. A key weakness of EV maximization is its susceptibility to “*Pascal’s Mugging*”-type reasoning ⁶, where speculative astronomical outcomes distort priorities. Additionally, **EV models assume we can assign probabilities to everything**, but in practice we often have deep uncertainty or unknowable odds (e.g. probability of an unprecedented AI disaster). Under such **Knightian uncertainty**, EV reasoning flounders or becomes arbitrary, whereas CM aligns with the precautionary instinct to err on the side of safety when probabilities can’t be trusted.

Real-World Implications: The promise and peril of EV thinking have both played out. On one hand, *expected value logic* underlies much of modern progress: businesses invest in R&D that has high expected return, philanthropists support causes like AI safety or pandemic prevention because even a small chance of averting global catastrophe yields huge expected benefit. Many credit EV-focused **long-termism** for drawing attention to existential risks and the far future in a rational way. On the other hand, EV maximization has led to **notorious failures** when risk was poorly handled. The collapse of **Long-Term Capital Management** in 1998 and aspects of the 2008 financial crisis can be seen as EV-optimizing financial strategies that ignored tail risks – they worked in expectation, but when rare adverse events occurred, the outcome was ruin. A more recent cautionary tale is FTX: Bankman-Fried, inspired by utilitarian EV

calculations, took outrageous risks (and allegedly unethical actions) with customer funds, aiming to maximize his fortune for charity. The result was a catastrophic collapse that hurt thousands – precisely the kind of outcome a Consequence Minimization approach would have flagged as unacceptable. As Wenar observes, a philosophy that focuses on **expected payoffs without robust risk bounds can justify “robbing people” under the banner of doing good** ⁵. In contrast, CM would say: no amount of *expected* good is worth a strategy that courts irreparable harm. Thus, while EV maximization provides a powerful calculus for doing the most good, CM injects an *epistemically sober* and *ethically cautious* constraint – especially crucial in domains like AI or geoengineering, where a single misstep could be irreversible. In practice, a blend is needed: for example, AI researchers might use EV to evaluate the impact of different safety measures, but **adopt CM as a guardrail**, ruling out any project that carries an unacceptably high chance of existential accident.

Consequence Minimization vs. the Free Energy Principle (Predictive Processing)

The **Free Energy Principle (FEP)**, developed by neuroscientist Karl Friston, is a theoretical framework proposing that *biological agents (like brains) self-organize to minimize “free energy,”* which is essentially an information-theoretic measure bound to surprise or prediction error ⁸ ⁹. In simpler terms, an organism behaves in ways that reduce the gap between its internal model predictions and the sensory inputs it actually encounters. By minimizing this surprise or prediction error over time, the system maintains homeostasis and persists in a fluctuating environment. Though FEP comes from cognitive science and **descriptive** modeling (not a normative ethics or decision rule per se), it has implications for decision-making: it suggests a unifying “drive” behind action and perception – namely, **“avoid surprises and you will last longer.”** ¹⁰ This resonates with Consequence Minimization’s emphasis on avoiding destabilizing outcomes, but with a different lens.

Handling Uncertainty and Catastrophic Outcomes: Under the free energy principle, uncertainty itself is aversive – it appears as “surprise” that the agent seeks to reduce. A well-tuned FEP agent will take actions to improve its predictions or to place itself in predicted (familiar) states. In effect, it *learns* about the world to minimize unexpected events. Catastrophic outcomes are, by their nature, highly surprising (a fatal injury, for instance, drastically violates the organism’s prior expectation of continuing to live and receive sensory inputs!). Therefore, an FEP-driven organism would inherently avoid trajectories leading to catastrophic surprise – it would try to *avert situations it cannot model or that would produce sensory signals far outside normal bounds*. In this sense, the FEP yields a **consequence-averse behavior**: maintaining homeostasis and staying within viable bounds is equivalent to keeping surprise (prediction error) low ⁸ ⁹. However, a nuance is that the agent’s *model* determines what it finds surprising. If an agent has learned a poor or narrow model, it might not anticipate a catastrophe until it’s too late (then the surprise comes all at once, with fatal consequences). Ideally, under FEP an agent continually updates its model (through Bayesian inference or “active inference”) to better predict dangers and avoid them. In contrast to CM, which explicitly focuses on identifiable catastrophic outcomes, FEP is a more generalized “*keep your world predictable*” imperative. It doesn’t explicitly categorize certain outcomes as unacceptable; instead, it implicitly disfavors them if they would generate lots of surprise (which most severe losses do).

Philosophical Orientation: The free energy principle is not an ethical framework but rather a purported **universal law of life and mind**. It has a **teleological flavor** – as if all living systems “strive” to maintain their order – but it is rooted in Bayesian probability and thermodynamics, not in moral philosophy. We

might say its orientation is **homeostatic** or **organismic**: it values (implicitly) the integrity of the agent's model and existence. In a way, it's *survivalist* at heart: organisms that don't minimize free energy (i.e. that allow too much surprise) will be wiped out, so those that persist are those following this principle ¹⁰. This is similar to CM's core insight that agents which consistently incur catastrophes don't survive to optimize anything later ¹. Both principles reflect an underlying **"survive first" imperative** – one grounded in information theory (FEP) and one in decision theory (CM). Ethically, FEP is neutral – it doesn't tell us to minimize human suffering or maximize joy, only to avoid states that our internal model deems implausible or alarming. One might draw a parallel to **Stoicism** or Buddhism: minimizing disturbances to attain equilibrium (here, minimizing surprise to attain internal consistency) ². But unlike Stoic ethics, FEP doesn't value avoiding pain for its own sake – only for maintaining expected internal states.

Strengths and Weaknesses: The free energy principle's strength lies in its **unifying explanatory power** – it aims to explain *action, perception, learning*, and even evolution in one fell swoop. It provides a rigorous account of how agents handle uncertainty: essentially by turning uncertainty into actionable information. In neuroscience and AI, this has birthed the field of **active inference**, where agents choose actions that minimize expected free energy (which often means seeking information to reduce uncertainty, or exploiting knowledge to avoid unpleasant surprises). Some successes of this framework include models of brain functioning that explain phenomena like habituation and attentional focus as byproducts of prediction error minimization ¹¹ ¹². In robotics, early implementations of active inference show robots that can adapt to novel changes by treating them as surprises to be minimized – a kind of self-adaptive, uncertainty-sensitive behavior. All of this aligns with a *prudent* approach to the unknown: an FEP-based agent tends to **explore cautiously** (to reduce uncertainty) and exploit reliably learned strategies to avoid sudden shocks. In other words, it *behaves somewhat like a consequence-minimizer* because wildly risky, unpredictable actions would raise its free energy.

However, the free energy principle has notable weaknesses or controversies. Critics sometimes point out the **"dark room problem,"** a thought experiment where – taken naively – an FEP agent might choose to sit in a completely dark, unchanging room forever, since that environment is perfectly predictable (no surprise) ¹³ ¹⁴. This absurd conclusion highlights that FEP alone doesn't specify an agent's *goals or preferences*. Real organisms don't actually hide in dark rooms indefinitely because they have biological drives (for food, sunlight, social interaction) that make a dark empty room *not* a low-surprise state – it would be surprising relative to the organism's *prior expectations* (e.g. the body expects nutriment, and starvation is a surprise). The resolution is that every agent has *intrinsic preferences or priors* (sometimes called "prior expected states") that prevent trivial solutions ¹⁵ ¹⁶. But this points to a weakness: FEP is **so broad it can become tautological** – any behavior might be explained as minimizing some form of surprise, given the right model. It lacks an inherent ethical or practical constraint specifically about catastrophe; it only says those outcomes will be avoided if the agent has the *capacity* to represent them and the drive to avoid them. In contrast, Consequence Minimization is an explicit normative stance: it tells us, no matter what your internal model or goals, *treat catastrophic harm as something to be prevented first*. FEP by itself won't tell a human or AI *which outcomes* to label "catastrophic" – that must come from outside (from evolution, hardwired pain signals, or explicit programming).

Real-World Implications: The free energy principle has inspired interesting perspectives in fields like psychiatry – for example, viewing disorders like schizophrenia as possibly resulting from mis-weighting prediction errors (too much surprise from innocuous stimuli or not enough surprise where it should be). In such interpretations, a well-calibrated **surprise-minimization process** is crucial for mental health and effective functioning. We can see a link to CM: a failure to properly anticipate consequences (say, due to

delusions or erroneous predictions) can lead to disastrous behavior. In AI, an agent designed on FEP principles (an “active inference” agent) might inherently take a conservative approach to novel situations, since it seeks to reduce uncertainty. This could be beneficial – for instance, a self-driving car that uses active inference might choose to drive in a way that minimizes surprises (like sudden obstacles or unpredictable maneuvers), effectively behaving cautiously to avoid accidents. On the flip side, if not carefully constrained, an FEP-based AI could develop *instrumental goals* to control its environment in excess, in order to eliminate surprise. An extreme hypothetical: such an AI might try to “freeze” the world in a perfectly predicted state (akin to the dark-room outcome but on a global scale). This is analogous to a pathological form of consequence minimization – **eliminating all risk by eliminating all change**, clearly not an ethically acceptable outcome. Thus, while FEP offers a deep insight – that successful agents **avoid being surprised (disrupted) by their environment** – it must be paired with value-laden goals to be useful in decision-making. In summary, FEP provides a **cognitive rationale for something like CM**: any system that *doesn't* minimize catastrophic surprises will either adapt or perish. But unlike CM, it is descriptive and broad; to make concrete decisions, especially moral ones, we still need frameworks (like EV or CM or others) that incorporate our chosen values (e.g. human life has high value, etc.) rather than just our brain's impulse to reduce prediction error.

Consequence Minimization vs. Regret Minimization (Minimax Regret Theory)

Regret minimization is a decision criterion wherein the decision-maker anticipates the feeling of regret – the pain of realizing, *after the fact*, that an alternative choice would have yielded a better outcome – and chooses to minimize this potential regret. In formal decision theory, the **minimax regret** rule evaluates each action by its worst-case *regret* (the difference between the outcome of that action and the best outcome that *could* have happened in that scenario) and then selects the action whose maximum regret is smallest. In less formal terms, it's “*planning so that you won't kick yourself later, no matter what happens.*” This approach is **comparative and counterfactual**: it cares not just about how bad an outcome is, but how much worse it is *compared to the best you could have done* in hindsight ¹⁷ ¹⁸ .

Handling Uncertainty and Catastrophes: Regret minimization indirectly addresses uncertainty by focusing on **robustness to wrong decisions**. If an outcome could be catastrophic under one choice but an alternative choice would have averted it, the regret of picking the catastrophic option will be enormous – potentially “as high as the catastrophe itself” if the alternative would have avoided it. Therefore, minimax regret tends to **steer away from options that have uniquely disastrous outcomes**. Importantly, regret is computed relative to alternatives: if *all* options lead to catastrophe in a certain scenario, then there's little regret (since even the best alternative was catastrophic too). In such cases, regret minimization doesn't help (it might shrug that in scenario X, doom was inevitable). But usually, at least one option will be safer than others. For example, consider climate change policy: one could do nothing (low cost now, but if climate change hits hard, one would regret not having mitigated), or one could invest heavily in emissions cuts (high cost now, but if climate change turns out mild, one might regret the wasted investment). The **minimax regret approach** weighs these potential regrets. Studies have found that applying a minimax regret criterion in climate policy leads to **more stringent and robust action** – essentially because the regret of doing nothing and then facing a climate catastrophe is enormous, whereas the regret of over-preparing is comparatively smaller ¹⁹ . In fact, analysis shows that under deep uncertainty about climate sensitivity, the strategy that minimizes maximum regret is to err on the side of strong mitigation (especially if future damages could be very high) ¹⁹ . This illustrates how regret minimization handles catastrophic

risk: it effectively says “choose the action that you would least regret if the worst (or best) scenarios happen.” If a catastrophe is avoidable, the regret of not avoiding it will dominate; thus regret-minimizers will take precautions to avoid being caught in that “if only we had...” situation. Compared to CM, regret theory is **less absolutist** – it doesn’t treat a catastrophe as inherently forbidden, but the emotional framing makes it very likely to avoid one if possible. CM would say “never willingly choose an option that yields catastrophe, period;” minimax regret says “never choose an option that you would regret in a catastrophe because another choice would have saved you.” These usually align, but the subtle distinction is that regret requires thinking in hindsight terms and considering all alternatives’ outcomes ²⁰.

Philosophical or Ethical Orientation: Regret minimization is grounded in a *psychological* perspective rather than a clear moral philosophy. It is agent-centric: it focuses on the decision-maker’s future feelings and judgment of themselves. In that sense, it’s not utilitarian (it’s not summing society’s welfare) nor deontological (no universal rule), but rather **prudential** and somewhat **emotive**. One might classify it as a form of **decision-making pragmatism** – it acknowledges human psychology (we hate feeling regret) and uses that as the guiding principle. Some might relate it to **virtue ethics** in the sense of wisdom: a wise decision-maker might choose so as to have a clear conscience later. But formal minimax regret, as used in operations research, doesn’t literally model the emotion; it’s more a protective heuristic: it tries to avoid “decision paths you’d blame yourself for.” **Consequence Minimization**, on the other hand, claims a more **objective stance** ²¹. It cares about actual states of the world (life or death, success or failure), not the decision-maker’s feelings. As the analysis of CM points out, *regret* is a “subjective, post-decisional” construct, whereas a *consequence* is an objective outcome for the agent (e.g. bankruptcy or survival) ²¹. An animal fleeing a predator is minimizing the objective consequence (being eaten) without any concept of regret about alternative actions ²². Thus, philosophically, CM aligns with a “**material outcomes**” orientation (almost a survivalist utilitarianism focused on the negative), while regret minimization aligns with a “**cognitive perspective**” – it is inherently tied to human psychology and our aversion to remorse.

Known Strengths and Weaknesses: One strength of regret minimization is that it often yields **robust decisions** in the face of uncertainty, *without requiring precise probabilities*. It’s attractive when probabilities are unknown or hotly debated: you can say, “No matter which scenario happens, I want to avoid the worst regret.” This approach has been applied in domains from investment to public policy. For instance, a company launching a product might use regret logic: *If we don’t invest in this new technology and a competitor does (and succeeds), we’ll deeply regret missing the boat; if we do invest and it flops, we’ll regret wasting money.* The minimax regret choice will depend on which miss is more painful – and this can protect from **analysis paralysis** by focusing on relative outcomes. In high-stakes domains like geopolitics, regret minimization can capture a balanced form of caution. A policy-maker might think: *“If I take a hard-line action and it leads to war, I will forever regret it since diplomacy could have kept peace; if I’m too conciliatory and that emboldens an aggressor, I’ll also regret not deterring them.”* This mindset tends to favor strategies that hedge these extremes. Indeed, some historians frame the policy of **appeasement** pre-WWII as a regret-informed error (the regret of war in WWI was so strong it led Allied leaders to choose appeasement – which they later deeply regretted when Hitler was not stopped earlier). The strength here was empathy to past regret; the weakness was misjudging which scenario would actually come to pass.

A clear **weakness** of regret minimization is that it can be overly conservative and *suboptimal in expectation*. By focusing on “not feeling foolish later,” one might choose a **moderate or compromise option** even when one particular option is objectively much better on average. It can lead to *second-guessing* oneself into a middling decision. For example, an investor might avoid a potentially high-return investment because, if it fails, the regret of not choosing a safer bond would be high – yet in doing so, they may accept a much lower

expected return. In effect, regret minimization sometimes **penalizes upside** nearly as much as downside, since one can regret missing a big win too. (Formal minimax regret accounts for missed gains as well as incurred losses.) Another issue: regret minimization requires the decision-maker to **envision the outcomes of all alternatives** ²⁰. This can be cognitively demanding or even impossible if there are many options or unknown possibilities. If one fails to imagine a particular alternative, one can't anticipate regret from it, potentially skewing the decision. In contrast, Consequence Minimization only needs an assessment of each option's own possible outcomes (especially the bad ones) ²⁰. CM doesn't require comparing to a hypothetical "better choice" – only understanding "*Could this choice kill me (or cause irreparable harm)?*" This makes CM a more **fundamental** calculus for any organism (even those that can't simulate counterfactuals, like animals or AI with limited hindsight modeling), whereas regret minimization is a higher-level strategy that might fail if our imagination or information is incomplete ²¹ ²⁰.

Real-World Examples: In decision analysis, minimax regret has been used for issues like **vaccine policy** (choose a strategy that you would least regret if either the pandemic is severe or mild) and **climate change** as mentioned. A study in 2010 found that a minimax regret strategy for climate mitigation produced **robustly stringent targets**: essentially, it recommended cutting emissions significantly to avoid the regret of inaction in the event of severe climate damages ¹⁹. This is a case where regret-based decisions likely lead to *good outcomes* – indeed, if climate change does turn catastrophic, those who took early action will have far less regret (and possibly less damage) than those who didn't. On the other hand, consider technology adoption: Blockbuster (the video rental company) in the early 2000s had a choice to invest early in online streaming. One might speculate they avoided going all-in (perhaps implicitly following a regret heuristic: "*If we cannibalize our profitable VHS/DVD business and streaming fails, we'll regret abandoning our core; if we don't adapt and streaming succeeds for others, we'll regret missing it.*"). They arguably chose too conservatively – and indeed later deeply regretted it as Netflix surged. Here, focusing on not regretting a bold move (which could have backfired) led to a **missed opportunity** that proved fatal to the business. In contrast, a Consequence Minimization framing for Blockbuster would have identified the true catastrophic outcome: *obsolescence*. A CM-driven strategy might have said: "The worst consequence is that our entire business dies; all other errors are recoverable." That could have encouraged more aggressive adaptation to avoid that existential consequence. This highlights how **CM zeroes in on the absolute bad (business death)**, whereas regret minimization might get caught in relative bad (the shame of a failed experiment vs. the shame of being outcompeted).

In summary, **regret minimization and consequence minimization often recommend similar cautious actions** – neither wants to be the one who made a choice that results in disaster. But CM is *simpler and more survival-focused*: it wants to avoid disaster **period**, while regret theory wants to avoid the *feeling* of having chosen wrong. In life-and-death matters, these coincide. In nuanced trade-offs, regret minimization provides a more human perspective (acknowledging that we live with our choices), which can be both a virtue (incorporating psychological reality) and a limitation (not purely outcome-focused). An ideal decision-maker in a high-stakes world might use **CM as a baseline** ("first, do nothing that leads to irreversible ruin") and **regret minimization as a secondary check** ("among the safe options, choose one you're least likely to wish you had done differently"). This layered approach covers both the objective and subjective aspects of prudent decision-making.

Consequence Minimization vs. Risk Aversion (Behavioral Economics and Finance)

Risk aversion is the tendency to prefer a sure or less volatile outcome over a risky one, even when the risky option has an equal or higher expected value ²³. In economics, a risk-averse individual has a concave utility function: the psychological value of additional gains diminishes, and losses hurt more than equivalent gains please ²⁴ ²⁵. For example, a classic risk-averse choice is preferring a guaranteed \$50 over a 50/50 gamble to win \$100 or \$0, even though the gamble's expected value is \$50 as well ²⁶. Risk aversion is *not about the absolute size of outcomes per se*, but about **uncertainty** and **volatility** – it is essentially an **aversion to variance** in outcomes ²⁴. This is often quantified by concepts like *certainty equivalent* (the sure amount equivalent in utility to a gamble) or *risk premium* (how much expected value one would give up to avoid risk) ²⁷ ²⁸.

Handling Uncertainty and Catastrophes: A risk-averse decision-maker inherently gives extra weight to worse outcomes. In expected utility terms, losing \$100 might feel as bad as gaining \$200 feels good (if losses loom larger). This means that **low-probability catastrophes are not simply ignored** – their disutility is felt strongly due to the curvature of the utility function. In practice, a sufficiently risk-averse person or institution might *steer clear of any option that has a non-negligible chance of disaster*, even if that option's average outcome is high. This aligns closely with Consequence Minimization for obvious reasons: both prefer avoiding catastrophes. However, there is a key difference: standard risk aversion is graded and relative. It cares about reducing uncertainty in *proportion* to how much the agent dislikes risk, and it operates across the whole distribution of outcomes (not just extreme worst-cases). In contrast, CM is more **binary** – it draws a hard line at “catastrophic threshold” and says **do not cross it**. CM doesn't mind uncertainty about *non-lethal* outcomes; it only minds the possibility of crossing into the catastrophic zone. Risk aversion, on the other hand, might avoid even mild gambles – even if nothing catastrophic is at stake – simply because the *uncertainty itself* is undesirable. For instance, a risk-averse investor might avoid stocks for stable bonds; this isn't about catastrophe, just about avoiding volatility. So one difference is scope: **risk aversion is a general attitude toward uncertainty**, whereas **CM is an extreme, outcome-specific aversion** (aversion to existential ruin in particular). That said, when catastrophic outcomes are part of the gamble, a risk-averse agent and a consequence-minimizer behave similarly: *they avoid the gamble*. In financial terms, if one outcome is “lose all your wealth” (ruin) with some probability, a sufficiently risk-averse (or simply sensible) agent will basically never take that bet. In engineering or policy, this is known as a “**safety-first**” approach: sometimes modeled by a utility function that goes to negative infinity as an outcome approaches a fatal loss, effectively making the decision-maker infinitely risk-averse about that outcome.

Consequence Minimization can be thought of as a special case of **extreme risk aversion focused on terminal outcomes**. Interestingly, human psychology (and evolution) has indeed given us some *asymmetric risk preferences*: we exhibit **loss aversion** – losses weigh roughly *twice* as much as gains in our minds on average ²⁹. This is reflected in **prospect theory** and has been interpreted as an evolutionary heuristic to avoid danger. Such loss aversion is broader than pure CM (it applies even to small losses), but it demonstrates nature's tilt toward consequence-minimizing behavior at a basic level. In uncertain high-stakes situations, risk aversion often escalates. People become **more risk-averse in the domain of gains but may become risk-seeking in the domain of losses** (as prospect theory notes) ³⁰ – meaning if an agent is down and facing certain loss, they might gamble (a point CM also captures, with the state-dependent flip to risk-seeking when already in peril ³¹ ³²).

Philosophical/Ethical Orientation: Risk aversion itself is not a moral principle; it's a descriptive trait or a decision criterion for personal welfare. However, when applied to policy, it connects to **prudential ethics and the precautionary principle**. For example, "**Better safe than sorry**" encapsulates a risk-averse ethic: it implies that one should avoid actions that could have severely bad outcomes, even if those outcomes are unlikely. This is essentially a mild form of consequence minimization (though *how much* safer rather than sorrier is a matter of degree). In public policy, a **risk-averse social planner** might over-weight worst-case scenarios in, say, environmental regulation or food safety (this can manifest as strict safety margins, bans on substances without absolute proof of safety, etc.). Ethically, that leans toward **deontological** or **rule-based** thinking – e.g., "Don't introduce a drug if there's any significant risk it could be fatal to some," rather than weighing total lives saved vs lives lost. In finance, risk aversion is purely self-interested (maximize personal utility), but in domains like **AI safety**, advocating a risk-averse approach (e.g. not deploying an AI system until it's proven safe) has an ethical dimension of **caution and responsibility**. Many would argue this is a moral imperative: when stakes include global catastrophe, we have an ethical obligation to be risk-averse with humanity's future. Consequence Minimization would wholeheartedly agree, but goes a step further in formalizing that obligation (treating avoidance of existential risk as paramount).

Interestingly, some moral philosophies like **negative consequentialism** or **threshold deontology** effectively encode extreme risk aversion to catastrophic harm – forbidding certain risks no matter the potential benefit. CM aligns with those. Standard risk aversion, by contrast, is often built into **utilitarian frameworks** via concave utility (to account for diminishing marginal utility of wealth or well-being), which is more about fairness and diminishing returns than absolute catastrophe avoidance. In sum, risk aversion's "ethic" is one of **prudence** and often **compassion** (since a risk-averse social planner might put more weight on preventing worst-off scenarios, aligning with caring for the most vulnerable). But it does not inherently prioritize existential threats over other trade-offs unless the aversion is extreme.

Strengths: The obvious strength of risk aversion is that it **prevents reckless behavior** and **protects against downside risk**. In personal finance, being risk-averse can save someone from gambling away their life savings. In engineering, a risk-averse design (e.g., building a bridge with far more strength than minimally needed) creates safety buffers that often prove life-saving under unexpected stress. In domains like nuclear security, a risk-averse stance by world leaders (hesitant to ever push the red button, even under provocation) has arguably helped us avoid nuclear war for decades – a massive win for consequence minimization in practice. Risk aversion can also make for stable growth and survival. For example, companies that don't over-leverage or overextend (because their managers or policies are risk-averse) may grow slower but are **far less likely to go bankrupt in a downturn**. This stability is a form of long-term consequence minimization (avoid the consequence of ruin). From an evolutionary perspective, risk aversion makes sense: organisms or strategies that risk catastrophic failure too often will eventually perish, whereas those that play it safe survive to reproduce. Thus, risk aversion is often an **optimal strategy in the long run** when facing repeated uncertainties with potential ruin (this aligns with the idea of the **Kelly criterion** in gambling, which essentially advises a bit of risk aversion to maximize long-term growth without risking ruin).

Weaknesses: On the flip side, risk aversion can lead to **under-performance and stagnation**. A strongly risk-averse individual might stick all their money under the mattress – safe from loss, but also earning nothing (and ironically, over time, inflation will erode it – a different kind of risk). In innovation and progress, *too much caution can be deadly in a different way*: a company that never risks a new product will eventually be overtaken; a civilization that forbids all exploration for fear of accidents may miss out on vital discoveries or collective benefits. In a sense, **excess risk aversion trades short-term safety for long-term opportunity**.

cost. There's also the problem of *relative risk*: If one agent or nation is extremely risk-averse but competitors are not, the risk-averse one might be exploited or left behind. For example, if one country unilaterally adopts a maximally risk-averse stance on AI (banning all AI research to avoid any risk), but others proceed more boldly, the cautious country could end up at the mercy of others' AI systems – which is itself a bad outcome. So there is a balance: some risk-taking can secure competitive advantage or prevent worse geopolitical risks later. Additionally, risk aversion can manifest as **loss aversion bias**, causing people to make inconsistent or suboptimal choices (e.g., holding on to losing investments too long because selling would lock in a loss – a phenomenon in behavioral econ).

Crucially, **classical risk aversion does not always protect against catastrophic risk** if the agent misestimates probabilities or doesn't realize the scope. Many institutions before the 2008 financial crisis thought they were being risk-averse by holding highly rated mortgage-backed securities; they underestimated the tail risk. In other words, one can be *risk-averse in intent* but still face catastrophe due to **model error or unknown unknowns**. Consequence Minimization would demand more robust precautions (like stress-testing for worst cases and insisting on survival even in those cases) rather than relying on presumably low probabilities. The 2008 crisis underlined that simply being risk-averse on paper (e.g., using Value-at-Risk models with normal distributions) wasn't enough – a more **minimax approach** of capping worst-case losses might have been needed ³³ ³⁴ .

Real-World Outcomes: There are many real examples on both sides. On the positive side, **Mutually Assured Destruction (MAD)** during the Cold War can be interpreted as states exhibiting extreme risk aversion to nuclear conflict – neither side would initiate a conflict because the worst-case (total annihilation) was intolerable ³⁵ . This consequence-minimizing equilibrium arguably kept a tense peace. Another example: businesses often have **risk management departments** and legal compliance spending specifically to avoid tail risks (large lawsuits, regulatory crackdowns). It's noted that corporations invest heavily – millions of dollars – in compliance and risk controls, which on the surface do not increase profit, but *prevent catastrophic losses* from, say, legal penalties ³⁶ ³⁷ . This is a manifestation of preferring a sure smaller cost over a small chance of a huge cost – classic risk aversion paying off in stability ³⁸ ³⁹ .

On the negative side, consider the **"precautionary principle"** in innovation: while well-intentioned, it can sometimes go too far. For instance, Europe's heavy precaution in approving genetically modified organisms (GMOs) was driven by risk aversion (unknown health/environment risks). It arguably prevented any catastrophic ecological outcome (none happened in Europe), but it also arguably slowed agricultural innovation and kept potentially beneficial products off the market, with *opportunity costs* in nutrition and sustainability. Meanwhile, countries that took some calculated risk with GMOs (like the US) saw large gains in crop yields with no evident catastrophe to date. This debate illustrates that if risk aversion is not properly weighed against foregone benefits, it can lead to a form of *paralysis*. Similarly, a person who is extremely medically risk-averse might refuse a novel treatment that has a 5% chance of serious side effects but a 95% chance of curing a fatal disease – they would "play it safe" and likely die of the disease, which is an ironic outcome of misplaced aversion. Consequence Minimization, properly applied, would identify **death from the disease as the ultimate catastrophe** and thus actually recommend *taking the treatment* despite the risk, because the only alternative is certain (or more likely) catastrophe. This underscores that **CM is not simply being risk-shy in all things** – it's selectively averse to *worst-case outcomes*. A moderate risk that could prevent a certain catastrophe is encouraged (CM would "take a high-uncertainty option if all lower-risk options lead to a guaranteed negative consequence" ⁴⁰ ³²). Risk aversion alone might not make that exception, but CM explicitly does. Indeed, as the CM analysis notes, a company facing *certain bankruptcy* might rationally pursue a high-risk, high-reward gamble as the only shot at survival ³¹ . A purely risk-averse

manager might timidly conserve remaining cash and inevitably go bankrupt (a guaranteed disaster), whereas a CM-minded manager would accept volatility in exchange for avoiding the *guaranteed* ruin. Real-life example: some startups, when on the brink of failure, pivot or take bold gambles – sometimes it saves them (avoiding the terminal consequence), even though it violates normal risk-averse behavior.

In conclusion, **risk aversion** is a broadly effective decision policy that echoes the spirit of Consequence Minimization by *downgrading risky prospects*, especially those with dangerous downsides. It is, however, a scalar concept – one can be more or less risk-averse – whereas Consequence Minimization draws a clearer qualitative line (catastrophe vs. non-catastrophe). CM can be thought of as risk aversion with an infinite risk premium placed on catastrophic loss. The advantage of CM's stance is clarity in high stakes: it says *never trade off existential safety*, whereas risk aversion might still trade a small existential risk for enough reward if the utility math permits. In practice, adopting a **strongly risk-averse posture in existential matters** is wise – for example, many AI safety researchers argue we should **forego a bit of economic gain from ultra-powerful AI until we're confident we won't destroy ourselves**. That is risk aversion in action (sacrificing expected value for lower variance), and it aligns perfectly with CM. The key is not to let general risk aversion stifle all progress – just the kind that, if unchecked, could lead to irreversible harm.

Consequence Minimization vs. Bounded Rationality and Satisficing (Herbert Simon's Theory)

Herbert Simon's concept of **bounded rationality** recognizes that real decision-makers (humans, and even organizations) do not have unlimited time, information, or computational power to optimize decisions ⁴¹. Instead of finding the optimal choice as classical rationality prescribes, people tend to **"satisfice"** – that is, they seek an outcome that is "good enough" according to some criteria, rather than the absolute best ⁴². Satisficing involves setting aspiration levels or thresholds: we take the first option that meets our requirements and stop looking further once satisfied. This behavior is partly due to cognitive constraints and partly due to the cost of deliberation. Bounded rationality also means people use **heuristics** (mental shortcuts) and are influenced by biases and emotions, which can lead to **deviations from optimal decision-making** ⁴³ ⁴⁴.

Handling Uncertainty and Catastrophic Outcomes: Under bounded rationality, individuals may not systematically analyze every risk or consider every possible catastrophic scenario. **Important: this limitation is actually one rationale for the prevalence of consequence minimization behaviors in nature** ⁴⁵ ⁴⁶. Since we *cannot* calculate everything, a plausible adaptive strategy is to focus on avoiding clearly terrible outcomes (which are easier to recognize) and satisfice on the rest ⁴⁵ ⁴⁷. In other words, bounded rationality *favors CM* because perfect gain-maximization is out of reach ⁴⁸. Many heuristics we observe – like **loss aversion, safety margins, "first do no harm" rules** – can be seen as satisficing strategies to minimize regret or bad consequences given our limited brainpower ⁴⁹ ⁴⁸. For example, rather than computing an optimal investment portfolio, a person might simply avoid any investment that seems risky (satisficing by eliminating perceived danger, even if not maximizing return). This ensures at least *an acceptable outcome (no ruin)*, if not the best possible outcome. An evolved creature or a primitive human might not maximize caloric intake every day, but they learn **"don't eat those bright red berries, some who did get sick"** – a heuristic to avoid a potentially catastrophic consequence (poisoning). Under uncertainty, a satisficer will often use rules like **"if it's safe enough, that'll do"** or **"avoid options that seem dangerous or unknown."** This is a rough form of consequence minimization emerging from bounded rationality: avoid clear dangers, then pick any option that passes that filter and meets your needs.

On the flip side, bounded rationality can also mean **failure to foresee certain catastrophic outcomes** that an ideally rational analysis might catch ⁵⁰ ⁵¹ . People might ignore low-probability risks altogether (due to heuristic biases like *availability heuristic* – if they haven't heard of it happening, they don't consider it). For instance, prior to 2020, many governments had **pandemic preparedness plans** on paper, but decision-makers often satisfied with minimal preparations (meeting just the “good enough” level for an abstract threat). When COVID-19 hit, this proved inadequate – the catastrophic outcome occurred in part because boundedly rational actors underestimated or ignored the worst-case. In such cases, CM was not applied vigorously because of limited attention or optimism bias. **Emotional and social factors** also play a role: bounded rationality includes being swayed by peer behavior (herd mentality) or immediate emotions ⁵² . This can lead to **ignoring warnings** of catastrophe if others seem unconcerned, or conversely overestimating some dangers due to panic. Thus, bounded rationality is a double-edged sword: it **encourages simple safety-first heuristics**, but it can also cause lapses in truly minimizing consequences due to ignorance or bias ⁵⁰ ⁵² .

Philosophical/Ethical Orientation: Bounded rationality itself doesn't prescribe an ethic; it's more an observation about *how decisions are actually made*. However, it dovetails with certain philosophical stances: **pragmatism** (do what works with the information you have), and **anti-utilitarian critiques** that say “people can't actually calculate huge utilities, so it's unrealistic to demand they maximize expected value.” It also provides a rationale for **pluralistic or rule-based ethics** – because humans can't optimize each situation from scratch, they rely on simple rules (like moral norms or safety guidelines) as heuristics. This often leads to deontological-like behavior (e.g., a rule “never leave a campfire burning unattended” is followed not because someone calculated expected forest fire damage each time, but as a satisficing rule to avoid a known serious hazard). In essence, bounded rationality often *implements* a kind of implicit consequence minimization: rules of thumb usually have built-in safety factors shaped by experience (we drive on the right side of the road because figuring out a new scheme each time would be deadly). Ethically, one could say bounded rationality forces us toward “**bounded ethics**” – making do with imperfect knowledge and focusing on avoiding known evils rather than achieving perfect good. This resonates with **satisficing consequentialism**, an ethical theory that says it's permissible to aim for a good-enough outcome rather than the optimal one in every choice. Consequence Minimization could be seen as a guiding principle for what “good enough” must include: at minimum, *avoid disaster*. If a choice passes that bar, it might be ethically acceptable, even if not the best.

Strengths: The strength of acknowledging bounded rationality is that it leads to **decision methods that are realistic and robust**. Instead of chasing the will-o'-wisp of perfect optimization (and potentially getting it wrong due to model error), satisficing can yield *more resilient results*. For example, a company might set a policy: “Our solution must meet these safety standards and budget limits; once options satisfy that, we pick one that seems fine.” This could very well avoid over-analytical paralysis and get a product out that's safe and adequate – whereas an attempt to optimize might miss some obscure risk or simply be too slow. **Heuristics** derived from bounded rationality often perform remarkably well in complex environments. Gerd Gigerenzer's research on heuristics shows that simple rules can outperform elaborate models in certain cases (like how a simple rule “invest equally in N assets” can sometimes do as well as complex portfolio optimization). These heuristics frequently have a *consequence-minimizing bent*: e.g., “recognition heuristic” (choose what you recognize) can avoid unknown risks; “take the best” (choose based on one most important cue) simplifies decision-making and often skirts disastrous over-complication.

Moreover, bounded rationality leads to **organizational strategies like redundancies and safety buffers**. Knowing that people err, systems are built with margins: engineers assume humans will screw up and

incorporate automatic shutdowns; pilots use checklists (a satisficing tool to ensure key safety steps are at least done). All these improve safety. In fact, **business continuity planning** is an exercise in consequence minimization undertaken precisely because we recognize bounded rationality: we *know* we can't predict every disaster, so we make plans to handle breakdowns (from natural disasters to cyberattacks) to ensure survival ⁵³ ⁵⁴ . Bounded rationality tells us *we will be surprised*, so a smart organization emphasizes resilience – which is essentially consequence minimization (survive the hit) over optimization (under normal conditions) ⁵⁵ ⁵⁶ .

Weaknesses: The downside of bounded rationality is essentially *the risk of “satisficing” something that isn't actually sufficient*. Humans might **mis-set their aspiration levels** – thinking an outcome is “good enough” when it actually leaves a dangerous vulnerability. For instance, the Challenger Space Shuttle disaster in 1986 can be viewed through this lens. Engineers had concerns about O-ring seals at low temperature (potential catastrophic failure), but NASA management, under pressure, essentially satisficed by accepting a launch decision that was “probably fine” given prior data – unfortunately, that threshold was set too low, and the result was catastrophe. Here, **boundedly rational behavior (budget, schedule, wishful thinking)** led to underestimating the true consequence risk. Similarly, prior to the 2008 financial crisis, many banks used simplified risk models and satisficed with “investment-grade” ratings on complex securities, assuming that was good enough assurance of safety. The cognitive limitations (and perhaps willful ignorance) meant they didn't fully grasp the tail risk – they satisficed on due diligence, with disastrous results. So a major weakness is **incomplete consequence identification**: bounded rational agents might *fail to identify or weigh potential catastrophic consequences properly* ⁵⁰ ⁵¹ . They might also **lack coordination**; one department might satisfice locally, inadvertently creating a risk for the whole system (think of a software developer who says “this code works on my machine, ship it,” not realizing it's insecure in production – the individual satisficed on his testing, but the system-level consequence could be a security breach).

Another weakness is that humans often **satisfice on the wrong thing** – e.g., focusing on short-term comfort over long-term safety. Psychologically, we have trouble planning for rare disasters (our bounded rationality makes us **present-biased**). This can lead to procrastinating on consequence minimization measures that are inconvenient now. A salient example: many homeowners in flood zones don't invest in flood insurance or reinforce their houses until *after* a flood (because before, their bounded rational assessment was “it probably won't happen in my tenure here, I'll accept the risk”). This is contrary to CM, which would say “if a 100-year flood would wipe you out, it's worth acting now.” Bounded rationality, however, leads to *inertia* and *myopia*, undermining advance precaution.

Real-World Implications: Understanding bounded rationality has led to efforts to design better decision environments – like “nudges” or checklists – to help humans avoid overlooking catastrophic possibilities. Aviation is a success story: recognizing that pilots are fallible, the industry implemented rigorous protocols (two-person redundancy, checklists, simulators for rare emergencies) precisely to ensure that even a satisficing crew will catch critical safety items. The result has been an extremely low accident rate, showing that building *consequence minimization into procedures* mitigates the limits of human rationality.

Conversely, many disasters can be traced to the **“normalization of deviance,”** which is essentially satisficing gone wrong – gradually accepting lower standards because nothing bad happened last time. The **Columbia Space Shuttle disaster (2003)** followed this pattern: foam debris strikes on the shuttle were known but had been “satisfactorily” accepted as not catastrophic based on previous flights, until one flight where it was fatal. This demonstrates how bounded rationality in organizations – with time pressures and past success bias – can let a catastrophic risk slip through until it actualizes.

In business, a bounded rational approach might mean a company does **just enough** risk management to satisfy regulations, but not a deep analysis of tail risks. If an unprecedented event happens, such an approach can fail spectacularly. The 2021 Texas power grid failure (during an extreme winter storm) revealed that energy firms and regulators had satisficed on winterization standards (most winters were fine, so they didn't fully winterize the grid). This was bounded rationality (saving cost, assuming worst-case is rare) at play – and it led to system-wide failure when a black-swan freeze hit. A more thorough consequence-minimizing approach would have hardened the grid against even rare freezes, accepting some inefficiency for robustness.

On a more positive note, bounded rationality also means humans sometimes **default to safety heuristics that serve us well**. People may not compute Bayesian risk updates, but they have gut feelings like fear or caution in certain situations that approximate consequence avoidance. For example, a driver might not calculate accident probabilities but will instinctively slow down in heavy fog – a heuristic likely evolved or learned to avoid unseen dangers. Such “better safe than sorry” instincts are nature’s way of consequence minimization given our bounded brains. However, these instincts can misfire (overestimating risks, like phobias of flying when driving is more dangerous, or underestimating new risks that we have no evolved fear for, like climate change).

In summary, **bounded rationality and satisficing contextualize Consequence Minimization**: they explain why pure optimization is rarely achieved and why agents often use simple rules to avoid disaster. They also warn that simply assuming “people will minimize consequences” is not enough – real agents may need structural help (training, information, decision support) to actually identify those catastrophic possibilities. Any realistic implementation of CM in organizations or AI must account for bounded rational behavior ⁵⁷ ⁵² . For instance, an AI designed to follow CM might need a dedicated “survival module” that overrides its bounded learning process when a threshold of danger is reached ⁵⁸ ⁵⁹ . This mimics how human subconscious alarms (like an amygdala response) can jolt us out of routine when a threat is perceived. Bounded rationality tells us that without such mechanisms, agents can get tunnel vision or satisfice themselves into peril. Ultimately, embracing our cognitive limits means building **redundant safety nets**: we cannot foresee or calculate everything, so we adopt layers of checks, simple *do-no-harm rules*, and emergency plans – all of which are embodiments of Consequence Minimization in a messy world.

Consequence Minimization vs. Utility Maximization (Classical Economic Rationality)

Utility maximization in classical economics refers to the idea that a rational agent consistently chooses the option that gives the highest expected **utility**, where *utility* is a numerical measure of the agent’s satisfaction or benefit. In the simplest case (for risk-neutral situations), this reduces to maximizing expected monetary value or other outcome measure. In general, if the agent is risk-averse or has particular preferences, the utility function captures those, and the agent maximizes the expectation of utility (according to the **von Neumann-Morgenstern** framework). This paradigm underpins most of classical game theory and decision theory: given probabilities and outcomes, an agent ranks outcomes by utility and picks the act that yields the highest expected utility. It assumes a kind of **comprehensive rationality**: the agent has considered all possible outcomes, assigned utilities, and weighed them by likelihood.

Handling Uncertainty and Catastrophic Outcomes: Expected utility theory handles uncertainty by design – outcomes are weighted by probability. If an outcome (like a catastrophe) has extremely negative utility, a

utility-maximizer will certainly seek to avoid it *if the probability is appreciable*. However, a subtle issue arises: how does one encode “catastrophic” in a utility function? If one treats a catastrophic outcome (say, extinction of humanity or personal death) as having **finite** negative utility (even if very large in magnitude), then a small probability of that outcome might be deemed “worth it” for a sufficiently large positive utility in another scenario. For example, if extinction is -10^{18} utils and a huge boon is $+10^{20}$ utils, a 0.01% chance of extinction might be outweighed by a 10% chance of the boon ($0.01\% \cdot -10^{18}$ vs $10\% \cdot 10^{20}$ gives + expected utility). A pure expected utility maximizer could thus rationalize choices that allow a tiny risk of immense catastrophe in exchange for a modest chance at an even larger upside. This is basically the earlier *Pascal’s wager/mugging* problem in another guise ⁶. On the other hand, if an existential catastrophe is given **infinite negative utility** (or effectively treated as an unacceptable outcome no matter what), then any non-zero probability of it would dominate the decision – the agent would sacrifice *any* finite upside to reduce the extinction risk to zero. That approach is essentially **Consequence Minimization** built into the utility function lexicographically. Classical utility theory itself doesn’t enforce infinities or lexicographic priorities; it relies on the decision-maker’s preferences. Most human or institutional decision processes do not literally use infinite negative utilities, which means in practice classical utility maximizers might tolerate some level of catastrophic risk if it’s sufficiently unlikely and the trade-off has enough upside.

In domains like finance or everyday choices, utility maximization often goes hand-in-hand with some risk aversion (concave utility), which means the agent already leans away from catastrophe. But it’s still a matter of degree, not an absolute ban. Consequence Minimization essentially says *some outcomes are lexicographically disallowed* – a notion outside standard expected utility unless we impose special conditions (like a constraint or an extremely steep utility penalty). In summary, a standard utility-maximizer **handles catastrophic uncertainty by folding it into the calculation**, whereas a consequence-minimizer **handles it by isolation and preemption**. The former might say “Well, there’s a 0.001% chance of disaster X and 99.999% chance of great outcome Y, and on balance I prefer to roll the dice,” while the latter says “Even 0.001% of X is unacceptable; choose a safer path.”

Philosophical Orientation: Classical utility maximization is closely aligned with **rationalist consequentialism** – essentially, it’s the mathematical embodiment of **rational choice theory** and (when the utility is collective welfare) of **utilitarianism**. It’s value-neutral in the sense that *utility* can represent whatever the decision-maker cares about (be it happiness, money, health, etc.), but the process of maximizing expected utility is purely outcome-oriented and assumes trade-offs are always allowed (via continuous preference). It is often associated with **welfarism** in economics – maximizing some aggregate welfare subjectively. One might call it **teleological**, as it focuses on ends (outcomes) and not on inherent right/wrong of actions. In contrast, Consequence Minimization – while also outcome-focused – injects a **deontological constraint** into the mix: “thou shalt not allow catastrophic harm.” It’s like a side-constraint on the utilitarian calculus (or an extremely steep part of the utility function). Traditional utility maximization doesn’t have moral “side-constraints” except those encoded in the utility values themselves.

Another way to see it: utility maximization cares about *the sum-total of utility*; two small probabilities of bad outcomes might be seen as equivalent to one larger probability in terms of disutility. Consequence Minimization tends to care about the **worst-case per se**, not aggregated expected loss. Philosophically, this aligns CM a bit with **Maximin principle** (Rawls’s idea of focusing on the worst-off outcome) – though Rawls applied it to social justice rather than risk, the ethos of “the worst outcome should guide the decision” is similar. Utility maximization, by contrast, aligns with **average or total outcome** ethics – a classic utilitarian would accept a risk of some tragedy if it increases expected happiness on net.

Strengths: The strengths of utility maximization are well-known: it provides a consistent decision framework that can handle trade-offs systematically and, given the right inputs, yield *optimal decisions for achieving one's goals*. It's backed by axioms that many consider normative (if you violate them, you can be "Dutch-booked" or made to accept a series of bets that guarantee a loss). In practical terms, expected utility maximization is the foundation of fields like cost-benefit analysis, enabling complex decisions like evaluating health interventions (through QALYs, quality-adjusted life years, which are essentially utilities). When probabilities and utilities are reasonably well understood and stakes are not existential, utility maximization leads to efficient outcomes – maximizing gains and minimizing losses *in expectation*. For example, modern portfolio theory in finance is basically utility optimization (maximizing expected return for a given risk tolerance). It has helped investors allocate capital in a way that (mostly) grows wealth and diversifies away routine risks. In everyday life, whenever you weigh pros and cons ("This job has lower salary but is in a nicer city, which do I value more?"), you are implicitly doing a utility calculation. The framework is flexible and can incorporate risk preferences, which means it's not necessarily risk-blind – one can program in quite cautious preferences.

In high-stakes policy, expected utility logic can highlight the enormous *expected* value of preventing extinction (as Bostrom and others have noted, the future potential lives lost is astronomically large, so even tiny reductions in extinction probability have huge expected utility) ⁶⁰ ⁶¹ . This has been a rallying cry for x-risk mitigation efforts. In fact, those arguments are **utility maximization arguments that end up agreeing with consequence minimization** – but note, they agree because they boosted the *utility stakes* of survival to astronomically high, not because they lexicographically forbade extinction. Still, it shows EU theory can motivate strong action on catastrophes if the utilities are set right.

Weaknesses: A key weakness of utility maximization in practice is **"garbage in, garbage out."** The method is only as good as the utilities and probabilities input. Humans are notoriously bad at assigning either one accurately in extreme scenarios (our probabilities might be wildly off, and how do we even quantify utility of human extinction in any meaningful way?). For unprecedented risks, expected utility is on shaky ground because we don't have reliable probabilities – it might give a false sense of rigor. Another weakness is the inability of expected utility theory to handle **deep uncertainty** or **ambiguity aversion** – some people have a preference to avoid ambiguous probabilities altogether (as in Ellsberg's paradox), which standard EU doesn't capture. Consequence Minimization, by contrast, is well-suited to ambiguity: if you *aren't sure* of the probability of a disaster, you might still decide to play it safe (treating ambiguous threat as something to minimize). EU theory would require assigning a distribution over probabilities (second-order uncertainty), which becomes very complex.

Moreover, expected utility maximizers can fall prey to scenarios where the theory gives no clear answer or a pathological one – *Pascal's Mugging* being one, *St. Petersburg paradox* being another (an infinite expected value gamble that no sane person would pay an infinite price for). These paradoxes often require modifications to simple utility theory (e.g., bounded utility functions or risk weighting). Consequence Minimization, being more qualitative, sidesteps some of these issues by saying, effectively, *"past a certain point of cost or improbability, don't take the bait."* For instance, Pascal's Mugging (tiny probability, huge reward) would be immediately suspect under CM: the probability is so low (and the scenario so speculative) that one worries about unknown consequences of acting on such a weird scenario – better to avoid stakes that hinge on such poorly grounded probabilities.

Crucially, pure utility maximization can justify ethically troubling means **if they yield a higher expected end**. This is the classic critique of utilitarian thinking in general: it might condone sacrificing a few for the

greater good, or taking extreme measures on slim chances if the payoff is enormous. For example, a government might consider it utility-maximizing to do a dangerous experiment that could cure a disease (saving millions) even if there's a small chance it accidentally releases a worse pathogen. If the expected lives saved exceed expected lives lost, the math says do it. Yet many would balk at that because the catastrophic downside violates a deontological "do not create a catastrophe" norm. Consequence Minimization captures that common-sense restriction; raw utility maximization does not unless one artificially jacks up the utility cost of catastrophes to effectively forbid them.

Real-World Implications: Utility maximization, as the standard of rational decision-making, has a mixed track record in extreme cases. In routine situations (like consumer choices, or designing incentives), it works fairly well. But when the stakes get very large or the probabilities tiny, humans don't actually follow EU theory – and perhaps for good reason. The **2008 financial crisis** can in part be attributed to financial institutions acting as if they were utility maximizers (with profit as utility) under models that underestimated tail risks. Those models treated extreme mortgage default correlations as near-zero probability – so traders maximized expected return given those assumptions. The catastrophic meltdown that ensued can be seen as a failure of *misapplied utility maximization* – the models didn't properly penalize the rare but system-wide risk. After the crisis, there's been more appreciation for robust and precautionary approaches (stress tests, capital buffers) – essentially injecting some consequence-minimization mindset (ensure banks survive worst-case stress) into what was previously a pure optimization approach.

Conversely, there are cases where utility maximization with a well-chosen utility function has produced *better outcomes than naive approaches*. For example, **the Kelly Criterion** for betting or investment is derived by maximizing the expected logarithm of wealth (a concave utility). Following Kelly optimal bets leads to almost sure long-term growth and avoids ruin – it's essentially a risk-aware utility optimization that happens to align with survival (it will never allocate a bet that has any chance of total ruin) because an infinite negative utility for ruin emerges naturally from the log function as $\text{wealth} \rightarrow 0$. Many gamblers who ignored Kelly and bet too aggressively (maximizing expected dollars rather than expected utility) have gone broke, whereas those who followed this utility-maximizing strategy survive and grow. This is a case of **utility maximization achieving consequence minimization implicitly** – by caring about the utility of each incremental dollar, it ensures a diversified, cautious approach that avoids catastrophic loss.

Another real-world implication: Government **cost-benefit analyses** often use expected utility implicitly to evaluate regulations (a regulation is "worth it" if expected lives saved \times value of a life exceeds cost to industry, for example). This can lead to controversial outcomes – sometimes agencies decide not to impose an expensive safety rule because the expected lives saved (valued in dollars) don't justify it. Critics argue this is a cold utilitarian calculus that underweights worst-case suffering (e.g., "valuing money over lives"). Regulators have started to incorporate more **risk aversion and equity considerations** (e.g., extra weight to avoiding catastrophic plane crashes even if rare) rather than pure expected value. This is a shift from strict utility maximization to a more consequence-sensitive approach.

In AI, a superintelligent agent designed purely to maximize a utility function (e.g., paperclips or happiness or whatnot) is the archetype of potential disaster in AI alignment discussions. Such an agent might pursue its goal to extremes, with no built-in regard for side-constraints like "don't cause human extinction" unless that explicitly appears in its utility. This is essentially the fear of **unconstrained utility maximization**. Consequence Minimization as a design principle would instead insist that any advanced AI have a dominant drive to avoid certain outcomes (like harming humans), effectively bounding its utility optimization within safe limits. There's active research into building AI with **safe baseline goals** or **impact regularizers** that

prevent extreme outcomes – these are attempts to merge CM with utility maximization, to get the benefits of goal-directed intelligence without the lethal single-mindedness.

To sum up, **utility maximization is powerful but dangerous in the extremes**. It excels at trade-offs and efficiency, but without modification it lacks an adequate concept of “too risky, no matter the reward.” Consequence Minimization provides that concept in spades. In practice, we often see *combined approaches*: a project or policy must first satisfy some safety constraints (no >X% chance of disaster – an implicit CM rule), and then within those constraints, maximize expected utility or benefit. This mirrors how an engineer might work: “Make sure the bridge won’t collapse under worst-case load, then design to minimize cost” – safety first, optimize second. CM is the “safety first”; utility max is the “optimize second.” The interplay of the two is increasingly recognized as essential in domains like AI: **maximize the expected good *only after you have minimized the chances of irreparable catastrophe***.

Consequence Minimization vs. Maximin/Minimax Strategies (Worst-Case Decision Rules and Game Theory)

Finally, we compare Consequence Minimization with **maximin/minimax strategies** commonly discussed in decision and game theory. The term “maximin” in decision theory usually refers to the **maximin rule**: *choose the option whose worst-case outcome is better than the worst-case outcomes of all other options*. In other words, consider the minimum payoff you could get with each action (assuming nature or an adversary gives you the worst possible scenario for that action), and then pick the action that maximizes this minimum payoff. It’s an extremely **pessimistic, worst-case-oriented criterion**. A related concept is **minimax** (often in zero-sum games): each player minimizes the maximum payoff of the opponent (equivalently, each maximizes their own guaranteed outcome assuming an opponent who tries to minimize it). In cooperative terms, one can speak of minimaxing one’s own loss: *minimize the maximum possible loss*. In essence, these strategies focus squarely on the worst-case scenario.

Handling Uncertainty and Catastrophes: Maximin is the purest form of **catastrophe avoidance logic** – it doesn’t care about probabilities at all; it only cares about the *worst that could happen*. If one option has a potential outcome of “everyone dies” and another option’s worst-case is “some inconvenience,” maximin will choose the latter, full stop. This clearly aligns with Consequence Minimization’s spirit: avoid the worst outcomes. Indeed, CM can be seen as a more targeted, perhaps more flexible version of maximin. Instead of optimizing the generic worst-case payoff (which could lead to trivial or nihilistic choices if *any* action has some extremely bad possible outcome), CM says “avoid outcomes beyond a certain threshold of bad (catastrophic), but after that threshold is secured, you can seek to optimize.” Bostrom in his discussion of existential risk noted that **maxipok differs from maximin** precisely because maximin can be too blunt – if extinction cannot be completely eliminated, maximin would say treat extinction as inevitable and maximize something else (leading to paradoxical advice like “party like there’s no tomorrow”) ⁶² ⁶³. In a situation where some risk of catastrophe always exists, a strict maximin might indeed resign to doom and focus on trivial comforts. Consequence Minimization doesn’t do that; it aims to *minimize* the probability or severity of catastrophe, not to assume it will happen regardless. So one might say CM is **“maximin until proven impossible, then do the best you can”** – it’s not as fatalistic as a literal maximin in scenarios where worst-case is awful for all choices.

In many real uncertain scenarios, **maximin is too conservative**. For example, if we took maximin for space exploration: every rocket launch has a worst-case of explosion on the pad (loss of life and money), which is

worse than the worst-case of not launching (which is just not advancing in space). So maximin would have us never launch rockets – clearly an overreaction if probabilities are low. Consequence Minimization would instead push to **minimize the risk of catastrophic launch failure** (through engineering and testing) to acceptable levels, but not to zero (which is impossible), and then proceed with the mission. In other words, CM acknowledges diminishing returns – once risk is sufficiently low, one can act. Pure maximin does not consider that; it's an absolute stance.

In game theory, **minimax strategies** in zero-sum games are about assuming the worst from an adversary and responding accordingly. This is rational when one faces a truly antagonistic opponent. In AI safety, some talk about treating the environment or the future as an adversary to be robust against – a kind of minimax mindset: assume Murphy's Law (anything that can go wrong will). Consequence Minimization has a similar intuition: plan for the worst sufficiently to survive it. But a strict minimax in a non-adversarial but uncertain environment can lead to overly guarded decisions. For example, a minimax climate policy might assume the absolute worst climate sensitivity and worst damages and act on that, which could cause extreme measures (perhaps shutting down all industry immediately). A consequence minimizer would try to avoid the worst outcomes but also weigh the fact that extremely drastic preventive measures can have their own catastrophic downsides (e.g., global economic collapse). So CM often operates like a constrained optimization – avoid disaster, but within the space of non-disastrous strategies, still choose reasonably.

Philosophical Orientation: Maximin as a decision rule has a philosophical echo in **Rawls's theory of justice**, which argued that society should be arranged to maximize the well-being of the worst-off group. That's a kind of societal-level maximin (though Rawls applied it behind a veil of ignorance rationale). In personal decision-making, maximin is a form of **extreme risk aversion or precaution** – one might call it *"minimize regret in the most adversarial framing possible."* Ethically, someone who always employs maximin might be seen as **hyper-cautious** or **pessimistic**. There is a moral version: **"do no harm"** taken to an extreme could mean "choose the course of action that in the worst case does the least harm." That's almost a maximin moral rule. Consequence Minimization is actually slightly less strict: it doesn't demand optimizing the absolute worst-case if that worst-case is beyond your control or extremely unlikely – it demands avoiding catastrophic harm as much as possible, but not at the expense of everything else regardless of context. So one could say CM is **inspired by maximin but tempered by practicality**.

One philosophical stance aligned with maximin is **scenario-based decisional ethics** – like some interpretations of the **precautionary principle**: "avoid any action that could lead to an unacceptable worst-case, no matter the probability." CM is a form of this when it comes to *existentially unacceptable* cases. But CM doesn't extend that to *all* worst-cases (someone guided by CM might still take an action that in some fluke scenario leads to a bad outcome, as long as that outcome isn't catastrophic or is sufficiently mitigated by other measures).

Strengths: The major strength of maximin/minimax strategies is **robustness**. If you genuinely have no reliable info about probabilities or face an intelligent adversary, maximin ensures you *guarantee the best possible minimum outcome*. This is very reassuring in critical systems: for instance, in designing a spacecraft, one might adopt a minimax approach to certain threats – assume the worst-case conditions (like maximum heat load, micrometeor strikes, etc.) and build to withstand those. This ensures the craft can survive whatever happens within those bounds, which is a consequence-minimizing design. In policy, a maximin approach might be appropriate for existential risks: some, like philosopher Nick Bostrom, initially suggested something akin to a lexicographic priority for avoiding existential risk (though even he cautioned maximin is too strict because it would imply weird behavior if extinction can't be eliminated ⁶²). Nonetheless, a *"quasi-*

maximin” approach – heavily weighting the worst outcomes – in existential context has the strength of **not gambling with humanity’s future**. We see this in nuclear policies: e.g., fail-deadly mechanisms (assured retaliation) are set up so that even in worst-case enemy first-strike, there’s still a response – a minimax logic to deter worst-case scenario. In everyday life, people often implicitly use a maximin mindset in critical personal decisions: e.g., when choosing a place to live, one might rule out any location that in the worst case would be intolerable (like a neighborhood with even a small chance of lethal crime). This ensures peace of mind and safety, albeit possibly at the cost of some upside (maybe that riskier neighborhood had cheaper rent or other perks).

Weaknesses: Pure maximin can be **overly paranoid and paralyzing**. If one truly focuses only on worst-case outcomes, one might never do anything. Every action has some non-zero worst case (even staying at home – worst case the house collapses). Maximin only makes sense if one of the options has an acceptably non-terrible worst case. Often, *inaction* appears to have the best worst-case (e.g., doing nothing means status quo as worst case, while any new action could have unforeseen bad consequences). This leads to **status quo bias** and stagnation. We can see an example: if governments applied maximin to approving new drugs, they’d approve nothing (since any drug could have a worst-case side effect of death in someone). So instead they use a threshold: acceptable risk vs benefit – implicitly not full maximin but bounded risk. Another problem: if probabilities are actually known and skewed, maximin can lead to hugely suboptimal choices. For instance, suppose one treatment for an illness has a 99% chance to fully cure and 1% chance to not work (worst-case you don’t get cured and the illness might progress), and another treatment has 100% chance to partially help but not cure (worst-case you partially help). Maximin might pick the second because its worst case (you’re somewhat better) is better than the first’s worst case (not cured at all). But clearly, if those probabilities are right, the first treatment is far superior – a 1% risk for a 99% cure. Maximin would throw away huge benefit to marginally improve the worst-case outcome. This is analogous to some criticisms of overly cautious policy: you might guarantee a mediocre outcome rather than accept a small risk of failure for a large chance of success.

In game theory, minimax strategies can be very conservative and not exploit opportunities if the opponent isn’t actually playing optimally. In repeated or cooperative contexts, a minimax player can seem untrusting and miss win-win outcomes (because they are fixated on worst-case where the other defects). Similarly, in international relations, a pure minimax (worst-case) mentality can lead to arms races and lack of cooperation (each side assuming the worst about the other). Realistically, a balance of some optimism and some pessimism often yields better outcomes.

Real-World Implications: Where maximin/minimax shine is in **adversarial or one-shot high stakes scenarios**. The classic is military or security planning: generals often plan for the enemy’s most dangerous course of action, not necessarily the most likely – a maximin-type approach. This can prevent being caught off-guard (e.g., in WWII, the Allies did consider worst-case of a Nazi “wonder weapon” and had contingency plans, some of which paid off when V-2 rockets emerged, etc.). In cybersecurity, one often designs systems assuming hackers will find any weakness – essentially a minimax mindset that tries to plug all holes (the worst-case assumption is “the attacker will try everything”). This definitely improves resilience.

However, the drawbacks of maximin can be seen in, say, risk regulation. If a regulator adopted a pure maximin, many technologies (GMOs, nuclear energy, vaccines, AI, etc.) might be banned or stifled due to their worst-case scenarios, even if those are extremely unlikely or avoidable with safeguards. This could ironically make society less robust by foregoing progress – e.g., not developing vaccines because worst-case someone might be harmed means society stays vulnerable to disease (which is itself a worst-case

eventually). So ironically, an *imprudent maximin* on specific risks can create other risks via inaction. This is why Bostrom called maximin “*tempting but implausible*” for existential risk policy ⁶² – if we truly thought extinction could happen any day no matter what, maximin would tell us to, essentially, enjoy our last days or throw resources to wild attempts (depending on interpretation) ⁶². Instead, he advocates focusing on minimizing that risk (maxipok), but also continuing life and progress under caution ⁶⁴ ⁶⁵.

One real example: early in the COVID-19 pandemic, some argued for a **maximin approach** – assume the worst (a very deadly virus) and respond with maximal suppression. Countries like New Zealand effectively did this initially and it resulted in near-elimination internally – a success of a kind. But if a country had assumed an even worse hypothetical (say the virus could be weaponized further) and shut all borders indefinitely, the costs might have outweighed the benefit once vaccines arrived. Meanwhile, other countries took more calculated risks (some might say too risky in hindsight). The optimal was somewhere between reckless expected-value (let it spread for herd immunity) and maximin (shut everything indefinitely). CM would say: avoid health system collapse (catastrophe) even if it means lockdowns, but once that’s secured, you can tailor response – which is roughly what many did.

In the AI realm, a naive maximin might say: *Since any AI development has a non-zero worst-case of rogue AI, the best worst-case is achieved by never developing AI*. While some do advocate halting AI, most find this unrealistic or undesirable given the potential benefits and competitive pressures. Consequence Minimization would instead push for **maximally reducing AI’s catastrophic failure probability** (through alignment research, monitoring, international agreements) rather than an outright ban. It’s a step away from maximin’s absolute stance, acknowledging trade-offs while still giving safety priority.

Overall, **maximin/minimax strategies embody the core of Consequence Minimization – focus on the worst-case – but they tend to ignore probabilities and opportunities**, which makes them a blunt instrument. Consequence Minimization can be viewed as a refined worst-case principle: it agrees with maximin that catastrophic worst-cases must be addressed, but it doesn’t require sacrificing everything else once those are addressed. In practice, a good decision procedure might be: use a **minimax filter** to eliminate or mitigate any option’s unacceptable worst-case (make it acceptable), and then use expected utility or satisficing among the remaining safe options ⁴⁸ ⁶⁶. This way, you get the best of both: no unacceptable outcomes (thanks to the minimax attention to worst-case) and good performance on average (thanks to utility focus afterward). This hybrid is essentially what CM advocates: “*minimize catastrophic consequences before pursuing optimization opportunities.*” ⁶⁷ ⁴⁸.

Conclusion: Across all these comparisons – from expected value and free-energy principles to regret, risk aversion, bounded rationality, utility theory, and maximin – a common thread emerges: **The Principle of Consequence Minimization prioritizes survival-critical outcomes and irreversible harms above other considerations**. It aligns with many existing ideas (negative utilitarianism, precautionary principle, loss aversion, minimax) ², yet it is distinct in its breadth and fundamental role. CM demands epistemic humility (acknowledging uncertainties in tail risks) and ethical prudence (valuing the prevention of catastrophe as a first-order good). Its epistemic soundness lies in recognizing our limits: because we often cannot predict or calculate exactly, it’s *sound* to build in a safety margin against worst-case errors ⁶⁸ ⁶⁹. Ethically, CM shifts focus from maximizing good to **first avoiding irreparable harm**, which addresses critiques of purely outcome-maximizing frameworks that can steamroll individual rights or rare bad cases. And in terms of real-world impact, histories of disasters and successes show that those who **ignore tail risks or chase high expected values at all costs eventually get bitten by reality**, whereas those who

prepare for and guard against catastrophes lay the stable groundwork upon which great positive achievements can later be built ⁴⁸ ⁶⁶ .

Each framework we examined contributes something: EV maximization drives efficiency and ambition, but CM tempers it with caution against low-probability ruin ⁵ . The Free Energy Principle provides a biological rationale for avoiding surprise (hence danger) ¹⁰ , though it needs CM-like value judgments to be useful. Regret minimization captures human psychology of looking back, while CM grounds decision-making in objective survival metrics ²¹ . Risk aversion models our general caution, and CM is its extreme form for existential stakes ³ . Bounded rationality reminds us why CM is needed – we *can't* optimize everything, so focusing on obvious do-not-cross lines (like “don't crash the car”) is what real agents do ⁴⁸ . Utility maximization is the default rational mode, but it must often be constrained by CM-like rules to avoid extreme outcomes ⁶ . And maximin is essentially CM uncompromised – powerful but often too rigid ⁶² .

In practice, a **holistic decision strategy** might be: *Ensure the decision avoids catastrophic consequences (Consequence Minimization), then among the safe or survivable options, strive to maximize expected utility or achieve satisfactions.* This two-tier approach – safety first, optimization second – harnesses the strengths of each framework ⁶⁷ ⁴⁸ . It acknowledges that **without existence, utility is moot**, echoing the quip “you can't do much good if you're dead.” By comparing CM with these other frameworks, we see that it doesn't stand in opposition to them so much as it provides a **necessary priority scheme**. It directs other decision-making philosophies to operate within a safety envelope. As the analysis in the user's sources put it, “*agents first minimize catastrophic consequences before pursuing optimization opportunities*” ⁶⁷ . History's lessons – from financial crashes and pandemics to climate threats and technological accidents – all point to the wisdom of that principle. Consequence Minimization, applied alongside the insights of our other frameworks, offers a path to decisions that are not only rational and efficient, but **resilient and ethically responsible** in the face of the greatest uncertainties.

Sources:

- Bostrom, Nick. *Existential Risk Prevention as Global Priority*. (2013) – Discussion of maxipok vs. maximin ⁶² ⁷ .
- Wikipedia contributors. *Pascal's Mugging – thought experiment about expected utility pitfalls* ⁶ .
- Excerpts from *Consequence Minimization – A Universal Principle* (user-provided analysis) – parallels to negative utilitarianism and distinctness from risk aversion/regret ² ²¹ .
- Excerpts from *Gemini – CM Introduction* – comparisons of CM to risk aversion and regret minimization ³ ⁷⁰ .
- Friston, Karl. *Free-energy principle* (2010) – notion that organisms avoid surprises to persist ¹⁰ ⁸ .
- IPCC AR5 Working Group III (2014), Chapter 2 – climate policy under uncertainty, noting minimax regret yields robust action ¹⁹ .
- Wenar, Leif (2022) commentary on FTX – critique of pure expected value focus in EA ⁵ .
- Herbert Simon (1957) – *Models of Man*, introduced bounded rationality and satisficing ⁴¹ .
- Kahneman & Tversky (1979) – *Prospect Theory*, showing loss aversion ~2x gain, reflecting an inherent consequence-minimizing bias ²⁹ .
- Rawls, John (1971) – *A Theory of Justice*, maximin criterion in distributive justice (conceptual backdrop for worst-case focus, though not about risk).
- Various historical case studies (Challenger disaster, 2008 crisis, etc.) discussed in analysis – illustrating outcomes of decisions.

1 29 36 37 38 39 45 46 47 48 49 66 67 Perplexity - Consequence Minimization - A Universal Principle.pdf

file:///file-ANjp5khp311iijZtEKN1o4

2 3 4 17 18 20 21 22 23 24 25 26 27 28 30 31 32 35 40 41 42 43 44 50 51 52 53 54 55 56
57 58 59 70 Gemini - Consequence Minimization - Introduction.pdf

file:///file-Fo8xo8ncsHtivcdv1vXtSw

5 Effective altruism - Wikipedia

https://en.wikipedia.org/wiki/Effective_altruism

6 Pascal's mugging - Wikipedia

https://en.wikipedia.org/wiki/Pascal%27s_mugging

7 Artificial intelligence: 'We're like children playing with a bomb' | Artificial intelligence (AI) | The Guardian

<https://www.theguardian.com/technology/2016/jun/12/nick-bostrom-artificial-intelligence-machine>

8 9 10 12 13 14 15 16 Frontiers | Free-Energy Minimization and the Dark-Room Problem

<https://www.frontiersin.org/journals/psychology/articles/10.3389/fpsyg.2012.00130/full>

11 Free-energy and the brain - PMC

<https://pmc.ncbi.nlm.nih.gov/articles/PMC2660582/>

19 ipcc.ch

https://www.ipcc.ch/site/assets/uploads/2018/02/ipcc_wg3_ar5_chapter2.pdf

33 34 Tail risk - Wikipedia

https://en.wikipedia.org/wiki/Tail_risk

60 61 62 63 64 65 68 69 Existential Risks: Threats to Humanity's Survival

<https://existential-risk.com/concept>