A New Model Exploring Human Financial Risk-Taking Responses to Infection

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Abstract

Signal Detection Theory models how individuals should behave to maximise their expected output for a single, isolated decision. This theory supports the intuition that individuals are more risk-averse as danger increases. State-Dependent Detection Theory builds upon this theory by allowing individuals to make multiple sequential (rather than isolated) decisions. Under certain conditions, this new state-dependent modelling can reverse the original findings of Signal Detection Theory. Applications beyond behavioural ecology, like human risk-taking and decision-making in financial contexts, remain unexplored. Therefore, this report undergoes two phases of model development using financial reserves in an environment at risk of infection. The final model includes an additional option to remain at the current reserve level and new severity factors, such as survival after infection and unlucky infection despite correct choices. Results of the Extended Severity Model align more with Signal Detection Theory than with State-Dependent Detection Theory, and also reveal novel effects of parameters such as background mortality and unlucky infection on risk responses distinct from the initial theories. Future work should extend the model to include autocorrelation and game theory.

Keywords: Signal Detection Theory, State-Dependent Detection Theory, Risk-Taking, Sequential Choices, Decision-Making, Financial Behaviour

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Background

Risk & COVID-19

Risk is a multifaceted concept that generally involves an individual facing a decision with unknown consequences (Aven, 2015). The individual's decision reflects their 'perception of expected utility', shaped by previous experiences and outcomes of risk-taking (Lemos, 2020). However, risk-taking can vary depending on the context and how it is modelled. For example, during the COVID-19 pandemic, governments around the world instated a lockdown requiring the public to remain at home for an unknown period of time as a public health measure aimed at controlling the spread of the virus (Onyeaka et al., 2021). Despite these restrictions, people still chose to leave their homes for essential needs such as work (e.g., Lee et al., 2023) and supplies or due to non-compliance driven by lower perceived vulnerability (e.g., Hills & Eraso, 2021). Each decision to leave the house can be considered risky, as the individual is uncertain whether or not the virus will infect them due to the unknowns about the virus at that particular time.

Modelling Risk-Taking Using an Infection Scenario

Therefore, looking at this infection scenario, two prevalent yet conflicting theories can be used to model this situation. One method of modelling individual risk-taking would be to treat decisions as stand-alone or *isolated* decisions, where the result of the current decision has no impact on future decisions or changes in the environment; this is known as the Signal Detection Theory (McNamara & Trimmer, 2019). However, recent work on foraging decisions has shown that when choices are *sequential*, where multiple decisions are made one after another, with each choice relying on the current state of the individual and the state of the environment, trends opposing classic SDT are found; this alternative is known as the State-Dependent Decision Theory (Trimmer, Ehlman, McNamara & Sih, 2017). These two theories form the foundation of this report, and the following sections will explore each in greater detail.

Signal Detection Theory

Signal Detection Theory (SDT) is a well-known single-decision model that examines decision-making when an individual must differentiate between two events using ambiguous information from a sensory signal. However, this signal does not perfectly discriminate between the two events, so there is still risk of making the wrong decision (Green & Swets, 1966; Trimmer, Ehlman, McNamara & Sih, 2017). Despite its origins in statistics and psychology, this theory has been applied in various fields, including experimental psychology (Pastore & Scheirer, 1974), clinical psychology (Nettle & Bateson, 2012), marketing (Singh & Churchill, 1986), and biology (Nesse, 2005). This broad, multidisciplinary applicability is why the principles of SDT can be effectively illustrated through a simple foraging scenario derived from behavioural ecology (Green & Swets, 1966).

The Foraging Scenario

In this scenario, the goal for prey is to select the best action for what they believe their current environment to be (after receiving an ambiguous stimulus), in order to maximise their payoff values (i.e., expected value) and achieve their reproductive value (i.e., number of reserves needed to reproduce) (Wixted, 2020). Prey can be in one of two environments: *dangerous* (with probability p of predators being present) and *safe* (with probability $1 - p$ of predators *not* being present). Since the probability distributions for each environment overlap, prey are uncertain of which environment they are in. Prey then receive a signal of strength x that provides them with *some* sensory information about their environment (e.g., leaves rustling). However, this signal does not definitively differentiate between the two distributions (e.g., leaves rustling from a gust of wind vs predator stalking), making it an *ambiguous* signal. This uncertainty regarding the environment introduces risk for the prey because the optimal action to take is dependent on the environment; if the environment is *safe*, prey should *forage* (to gather resources, like food), but if the environment is *dangerous*, then the prey should *flee* from predators (to avoid death). Each action also affects the reserve level: foraging *increases* the reserve level, while fleeing *decreases* the reserve level. Hence, the prey has four possible choices with two potential errors - prey could either die from predation from foraging in a dangerous environment or waste reserves by fleeing in a safe environment - but each choice has a fixed payoff (Table 1). As a result of this uncertainty regarding the environment, the prey is forced to make a trade-off between foraging and fleeing.

Table 1

Notation for Payoff Matrix of Classic Signal Detection Theory

		Action	
		Flee or Run Away (R)	Forage (F)
Environment	Dangerous (D)	V_{DR}	V_{DF}
	Not Dangerous (N)	V_{NR}	V_{NF}

An essential assumption of SDT is that individuals have knowledge of the various parameters involved in the model (i.e., probability of the environment being dangerous, payoffs for each environment-action combination, distribution of signals for each environment) and their values (Trimmer, Ehlman & Sih, 2017). This assumed knowledge has been mathematically represented in Equation 1 (taken from McNamara & Trimmer, 2019) below:

$$\frac{P(X \mid D)}{P(X \mid N)} > \frac{1-p}{p}\frac{(V_{NF}-V_{NR})}{(V_{DR}-V_{DF})} \tag{1}$$

Equation 1 indicates that for an individual to maximise their expected payoff they should take evasive action and flee their current environment *if* the signal they receive exceeds a certain *threshold* - determined by the individual based on the relative probability densities of receiving a signal of strength X when danger is present (D) versus absent (N); otherwise, they should remain and forage. Therefore, this equation suggests that when the environment is dangerous, prey are inherently risk-averse and tend to have lower thresholds, making them more sensitive to weaker signals and more likely to flee to avoid predation.

Therefore, the general conclusion of SDT is an intuitive one: *individuals are more likely to engage in evasive action (e.g., run away) as the probability of danger (e.g., through predation) increases* (e.g., Green & Swets, 1966; McNamara & Trimmer, 2019; Nesse, 2005; Trimmer, Ehlman, McNamara & Sih, 2017).

Single-Decision Models: Intuition vs Reality

As a single-decision model, SDT assumes that decision-making is *isolated* - that the present decision does not influence future decisions or the individual's long-term state or goals (Trimmer, Ehlman, McNamara & Sih, 2017). Therefore, given that the prey is only making *one* decision at one time-point, the expected payoffs for each environment-action combination are fixed for all decisions regardless of potential changes to the environment. This isolated decision-making also ignores prey's current state (e.g., of reserves) and the possible effect their current state may have on their future decisions at different time points.

This naive assumption about decision-making counters modern-day research highlighting the importance of current outcomes (or payoffs) in influencing an individual's future decision-making (e.g., Raeva et al., 2011). For example, *prospect theory* is a fundamental theory in behavioural economics which suggests that since losses are valued more than equivalent gains, individuals are likely to alter their future decision-making behaviour after experiencing losses, thus implying outcomes of current decisions to an individual's state (e.g., financial capital) can impact how future decisions are made (Bhesania et al., 2024). Hence, while SDT's general conclusion is intuitive (i.e., individuals are more apprehensive of their environment as the probability of danger increases), it is also based on an oversimplification of decision-making.

State-Dependent Detection Theory

Given this significant limitation of SDT, an updated model known as the State-Dependent Detection Theory (SDDT) was developed (McNamara & Trimmer, 2019; Trimmer, Ehlman, McNamara & Sih, 2017; Trimmer, Ehlman & Sih, 2017). This model integrates the classic SDT model within a framework of state-dependent modelling that also accounts for an individual's present state. SDDT allows for *sequential* rather than isolated decision-making, recognising that individuals regularly make multiple decisions to achieve a goal, and the outcome of one decision in the present time-point can influence subsequent choices at a later time-point (McNamara & Trimmer, 2019).

Sequential versus Isolated Decision-Making

A fundamental aspect of the SDDT model is its representation of time as a sequence of independent discrete time steps (Trimmer, Ehlman, McNamara & Sih, 2017). For instance, classic SDT states that a decision made at one time-point is independent from decisions made at other time-points, past or future, and the outcome of this decision is also independent from the individual's past state. However, SDDT employs a sequential nature to decision-making that allows the model to analyse whether the consequences of a decision made at one time step influence future choices when decision outcomes at different time points are dependent on each other, whilst accounting for the individual's current and future states. For example, in the context of the foraging scenario, if a prey flees at a current time step, while they may reduce the immediate risk of death by predation, they enter decision-making at the next time point with fewer food reserves, thus increasing the risk of death by starvation in future time steps.

Despite sharing the same payoff values for each environment-action combination, the payoffs are another core difference between SDT and SDDT. For example, in the classic SDT model, since decisions are made in isolation, payoff values for each environment-action combination are fixed regardless of the probability of the environment being infected. However, due to the discretion of time, which requires individuals to think about how current choices will affect future states, the payoffs from this state-dependent model will differ depending on the probability of the environment being infected.

Nevertheless, similar to the SDT results, the SDDT variation also makes intuitive sense. For example, when the environment has a higher predation risk, SDT suggests that prey are more likely to run away. However, in SDDT, if the prey believes that this higher predation risk will remain over many time periods (a possibility due to its sequential nature), they may be more likely to continue foraging - findings that directly oppose SDT. This counter finding results from the idea that the more times a prey flees, the lower their reserves will be and the greater the probability of death by starvation; thus, they may be more willing to take on more risk to increase their reserves if they believe the risk of predation to be prolonged over many time steps. Therefore, the state-dependent and sequential nature of SDDT contributes to the variable payoff values in SDDT.

Humanising SDT and SDDT: Financial Reserves

Despite switching from isolated to sequential decision-making and accounting for individual states, SDDT still induces forced outcomes onto its individuals. In the foraging scenario, used for both SDT and SDDT, prey only have the options of either gaining or losing a reserve unit. While this may be appropriate for this scenario with animals, it is less applicable to humans, whose reserves are generally more complex. One potential reserve type that exhibits this complexity is money because of its multi-functional and dynamic nature.

Money is a financial instrument that plays a central role in human life (Gasiorowska & Zaleskiewicz, 2023; Wang et al., 2020). Money is multi-functional, working as a medium of exchange for goods and services, a unit of account (i.e., a common way to measure value) and a store of value (for future use) (Chowdhury, 2024; Cohen et al., 2019; Shirai, 2019). For this report, the latter function of money is of most interest, given that a financial *reserve* is essential for an individual from an economic and psychological perspective. For example, in economics, having a financial reserve as such is viewed as a functional tool that enables individuals to achieve specific life advancements (e.g., starting a family) (Cohen et al., 2019). Although in psychology, it is interpreted more symbolically, providing a sense of security during periods of financial uncertainty (e.g., a pandemic preventing people from going to work) (Cohen et al., 2019; Ryu & Fan, 2023). Nevertheless, the functional and symbolic perspectives on financial reserves further reiterate their importance in a human's everyday life and in supporting human development. As well, money is a dynamic commodity; capital can not only increase (e.g., work) or decrease (e.g., daily expenditure; food, water, housing) but also remain constant (e.g., savings). Therefore, for money to serve its functional and symbolic roles, an individual would need to maximise their financial gain (i.e., earn more than spend) to hold sufficient reserves for the future.

As previously mentioned, since SDT and SDDT models have been applied primarily within behavioural ecology (e.g., Green & Swets, 1966; McNamara & Trimmer, 2019; Sumner & Sumner, 2020; Trimmer, Ehlman, McNamara & Sih, 2017; Trimmer, Ehlman & Sih, 2017), the application of these models to human behaviour remains unexplored. Therefore, this report aims to adapt the model to a more realistic human scenario, focusing on *financial* reserves, rather than a foraging scenario with energy reserves, in an environment where the danger stems from *infection* rather than predation.

Model Development: Fundamental Concepts

Signal Detection Theory intuitively suggests that as the risk of infection increases, people tend to be more risk-averse. More recent research on State-Dependent Detection Theory proposes that when decisions are made sequentially (i.e., one decision per time step), an individual's reserve level acts as a mediating variable, where opposing SDT results are seen as p increases. For the following adapted models, a slightly more elaborate case is posited, one that allows the option of remaining at the same reserve level.

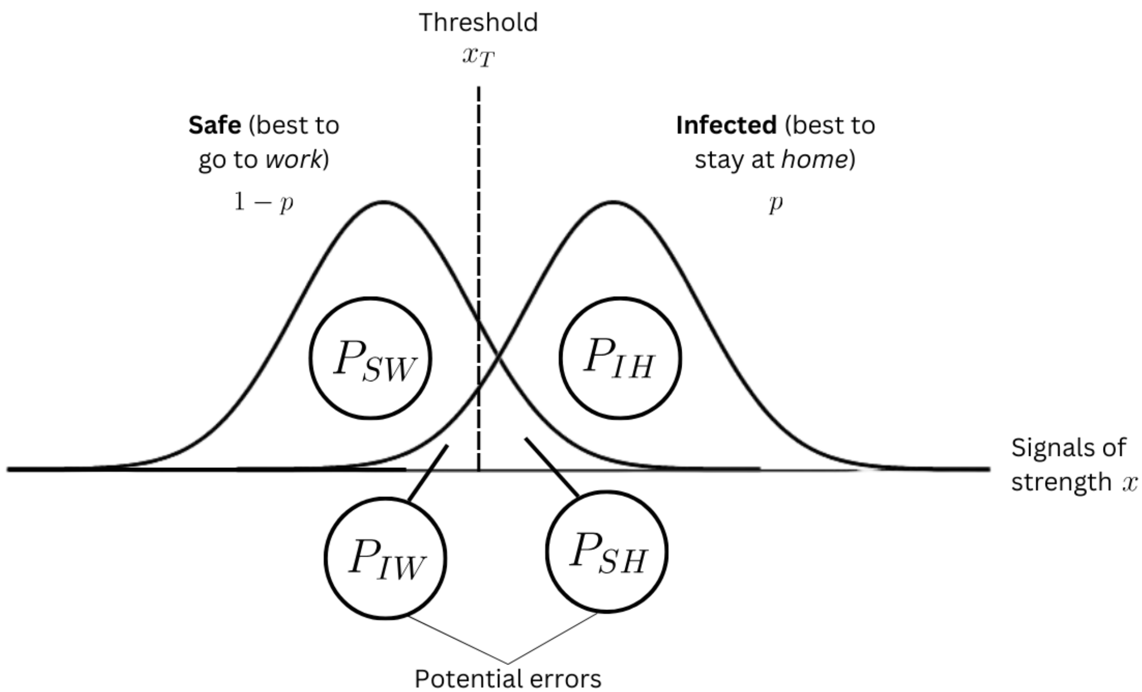
Two models were developed during model development: the severity model and the Extended Severity Model, with the latter used to generate the results. Both models were based on the updated scenario (using financial reserves) shown below and included parameters from the original SDT and SDDT models. However, certain parameters, including payoff values and probabilities, differ due to model-specific calculations. The current section will discuss the parameters shared by both models based on SDT/SDDT, while the following sections will address the calculations specific to each model.

Scenario

The scenario proposes an individual who is in one of two environments, each with a respective probability distribution; the Infected (I) environment has a probability, p, of being infected while the Safe (S) environment has a probability, $1 - p$, of *not* being infected. Similar to previous scenarios, because the two probability distributions for each environment overlap, the individual is unaware of which environment they are in. At each time step, the individual receives a signal (of strength x) that provides some information about the environment. However, this signal information does not clearly differentiate between the two probability distributions to definitively decide which environment it represents. Generally, larger signals suggest the environment is likely to be infected (e.g., empty streets) and smaller signals indicate the environment is expected to be safe (e.g., busy roads). Within each environment, the individual has the option of two actions: staying at home (H) or going to work (W) (Figure 1).

Figure 1

Probability areas for each Environment-Action Combination



Model Assumptions

For the sake of simplification, the model relies on four core assumptions.

1. *There is no limit to how many financial units an individual can gain or lose.* The individual's primary goal is to maximise the probability of the individual increasing their current reserve level (r) by one unit ($r + 1$) and avoid losing a reserve unit ($r - 1$).

2. *Individuals have evolved knowledge about various aspects of the environment and its signal distribution.* Similar to the assumption of SDT, this evolved knowledge includes the understanding that the infected environment has a higher mean signal level than the safe environment, and that both distributions have equal variance.

3. *If the environment is infected, there is a possibility of the individual falling ill,*

regardless of what action they choose.

4. Since the individual acts to maximise their interests, *the outcomes of decisions impact only the decision-maker.*

Payoffs

Each environment-action combination has a certain payoff (i.e., expected value; V). Depending on how the individual evaluates the environment, there is an appropriate action for them to take. For example, when the environment is infected, the individual should stay home, but if the environment is safe, they should go to work. The payoff value for each environment-action combination ($V_{EnvironmentAction}$) for SDDT is shown in Table 2 (where θ is the long-term probability of gaining a reserve unit). The adapted payoff will follow a similar yet distinct pattern.

Table 2

Generic Payoff Matrix for the Foraging Scenario

		Action	
		Flee or Run Away (R)	Forage (F)
Environment	Dangerous (D)	$V_{DR} = \theta^2$	$V_{DF} = 0$
	Not Dangerous (N)	$V_{NR} = \theta^2$	$V_{NF} = 1$

Environments

Safe Environment

If the individual chooses to go to work, they will gain one financial reserve unit. Alternatively, if the individual decides to stay home, then they will remain at their current reserve level since they would not be earning for one day, and depending on the model, this can result in either a loss of a reserve unit or no change to the reserve level.

Infected Environment

From the assumptions, if the individual chooses to go to work, the model assumes the individual *will* fall ill from infection. If an individual falls sick, they *will* require some time off work, during which they cannot earn income and must rely on their existing financial reserves for some time (e.g., at least a week), leading to a loss of one financial reserve unit. However, if the individual chooses to stay at home, there are two potential outcomes; first, the individual could be safe and remain at their current reserve level (as they would not be earning for one day). Alternatively, the individual could fall into misfortune and lose a reserve unit.

Probabilities

Background Mortality

Background mortality (δ) is a parameter adopted from the previous theories; it introduces additional risk of death unrelated to the choices made by the individual (e.g., illness unrelated to the pandemic infection).

Short-Term Probabilities

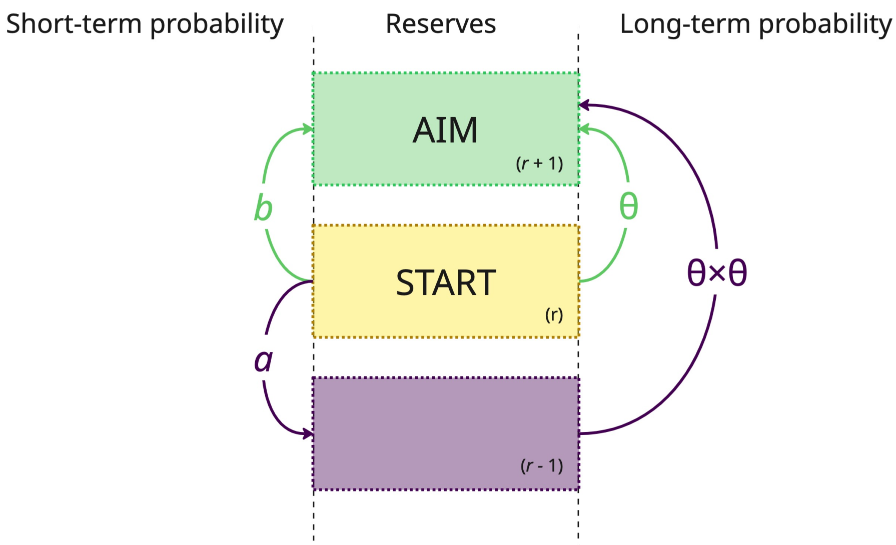
Short-term probabilities capture how an individual's immediate actions affect the reserve level. Each probability is calculated using the probability areas shown in Figure 1, relative to the probability of the environment either being infected (p) or safe (i.e., not infected; $1 - p$), as appropriate. Both models use two short-term probabilities from the original SDT/SDDT model: a is the probability of losing a reserve unit ($r - 1$) and b, which is the probability of gaining a reserve unit ($r + 1$). Additionally, the adapted model introduces c, the probability of remaining at the same reserve level (i.e., neither gaining nor losing a reserve; r).

Long-Term Probability

Long-term probability is the probability of *eventually* gaining a reserve unit, regardless of what reserve level the individual is at, denoted by θ. For example, if an individual is one reserve unit below their initial reserve level, the long-term probability to reach the aim (i.e., one reserve unit above the initial reserve level) would be θ^2 and if they were two reserve units down, their long-term probability would be θ^3 and so on (Figure 2).

Figure 2

Classic SDT/SDDT Probability Ladder



θ is the sum of each short-term probability multiplied by its respective long-term probability of eventually gaining a reserve. The classical θ equation used in SDT/SDDT with parameters a and b is:

$$\theta = a\theta^2 + b$$

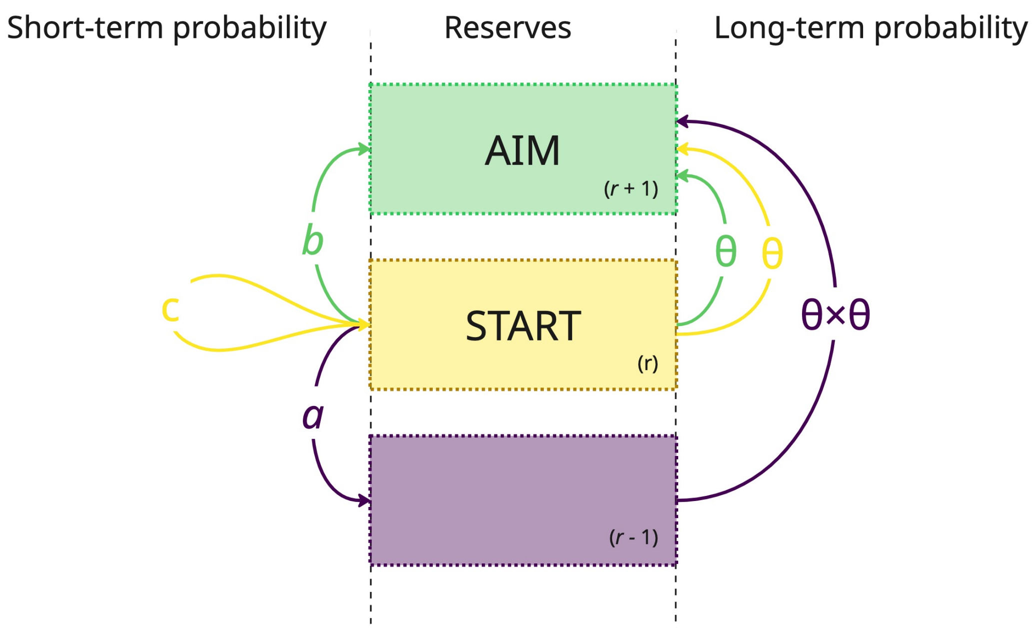
After rearrangement, a quadratic equation of θ terms remains; thus, θ can be solved for by applying the quadratic equation as shown in Equation 2:

$$\theta = \frac{1 + \sqrt{1 - 4ab}}{2a} \tag{2}$$

However, given the introduction of the c parameter, the θ equation was reworked to account for all short-term probabilities. Since θ is the probability of eventually gaining a reserve, this can be achieved by immediately gaining a reserve (b), or gaining a reserve after staying at the current reserve level ($c\theta$) or gaining two reserve levels after initially losing a reserve unit ($a\theta^2$). A figure representation of the updated relationship between short- and long-term probabilities is shown in Figure 3.

Figure 3

Updated Probability Ladder



This updated θ can be mathematically represented as:

$$\theta = a\theta^2 + b + c\theta$$

Again after rearrangement, a quadratic equation of θ terms remains.

$$a\theta^2 + (c-1)\theta + b = 0$$

Therefore, θ can be solved for by applying the quadratic equation as shown in Equation 3:

$$\theta = \frac{-(c-1) + \sqrt{(c-1)^2 - 4ab}}{2a} \tag{3}$$

Signals, Thresholds and θ_{max}

A *threshold* is a critical value used by an individual to make a decision on which action to take when they receive an ambiguous signal. For example, if the signal exceeds the individual's predetermined threshold, they will likely take evasive action and stay home. This predetermined threshold is often referred to as the *optimal level of boldness* (x_T) as it represents the signal strength required for an individual to take an action that often involves some degree of risk (e.g., going to work despite the risk of the environment being infected rather than safe).

x_T is associated with the *largest* long-term probability of eventually gaining a reserve unit (i.e., θ). Therefore, to determine the x_T for a given situation, a θ value is calculated for each possible threshold, and x_T is the threshold with the largest θ, or θ_{max}.

When an individual receives a signal of strength x, this signal is compared against the x_T. Theoretically, a lower x_T infers that the individual is more likely to react at weaker signals of danger (i.e., more likely to stay at home). In comparison, a higher x_T suggests a stronger signal of danger is required for the individual to change behaviour (i.e., more likely to go to work). Overall, the optimal threshold (or level of boldness) is determined by θ_{max} and provides an understanding of how sensitive the individual is towards a signal of strength x.

Model 1: Severity Model

This section will examine initial ideation towards introducing the new short-term probability of remaining at the same reserve level or c and its subsequent integration towards calculating the long-term probability, θ.

Severity Parameter: z

A new severity parameter, z, quantifies the severity of an individual's situation. The situation is not so severe for low values of z, so reserves remain unchanged when choosing to stay at home and losing a reserve unit when deciding to go to work when the environment is infected (as opposed to dying as with the foraging scenario). For greater values of z, the situation is more serious; there is the potential of death if the individual chooses to go to work while infected or even possibly losing a reserve while staying at home. All probability equations were revised to integrate both the new severity parameter and the short-term probability of maintaining the same reserve level, c.

Probabilities

Short-Term Probabilities: a, b, c

The calculation for each short-term probability is described below. Note that *all* short-term probability equations begin with the probability that the individual does not die due to background mortality (i.e., probability of death unrelated to infection, like a car accident; δ).

a is the sum of the probability densities for environment-action combinations ($P_{EnvironmentAction}$; Figure 1) that result in a potential reserve unit loss scaled by their respective severity (see Equation 4).

$$a = (1 - \delta)\ ((P_{IW} \times p \times (1 - z)) + (P_{IH} \times p \times z) + (P_{SH} \times (1 - p) \times z)) \tag{4}$$

b is the probability that the individual goes to work when the environment is safe, independent of the severity of the situation (see Equation 5).

$$b = (1 - \delta)\ (P_{SW} \times (1 - p)) \tag{5}$$

Similar to a, the new short-term probability c is the sum of the probability densities for environment-action combinations potentially resulting in the individual neither losing nor gaining a reserve unit loss scaled by their respective severity (see Equation 6).

$$c = (1 - \delta)\left((P_{IH} \times p \times (1 - z)) + (P_{SH} \times (1 - p) \times (1 - z))\right) \tag{6}$$

After the short-term parameters are calculated with the equations that include the severity parameter, the long-term probability of *eventually* gaining a reserve (θ) is calculated using Equation 3 noted above. The updated payoff matrix, accounting for the severity parameter, is shown in Table 3 below.

Table 3

Payoff Matrix for the Severity Growth Model

		Action	
		Stay at Home (H)	Go to Work (W)
Environment	Infected (I)	$V_{IH} = (1-z)\theta + z\theta^2$	$V_{IW} = (1-z)\theta^2$
	Safe (S)	$V_{SH} = (1-z)\theta + z\theta^2$	$V_{SW} = 1$

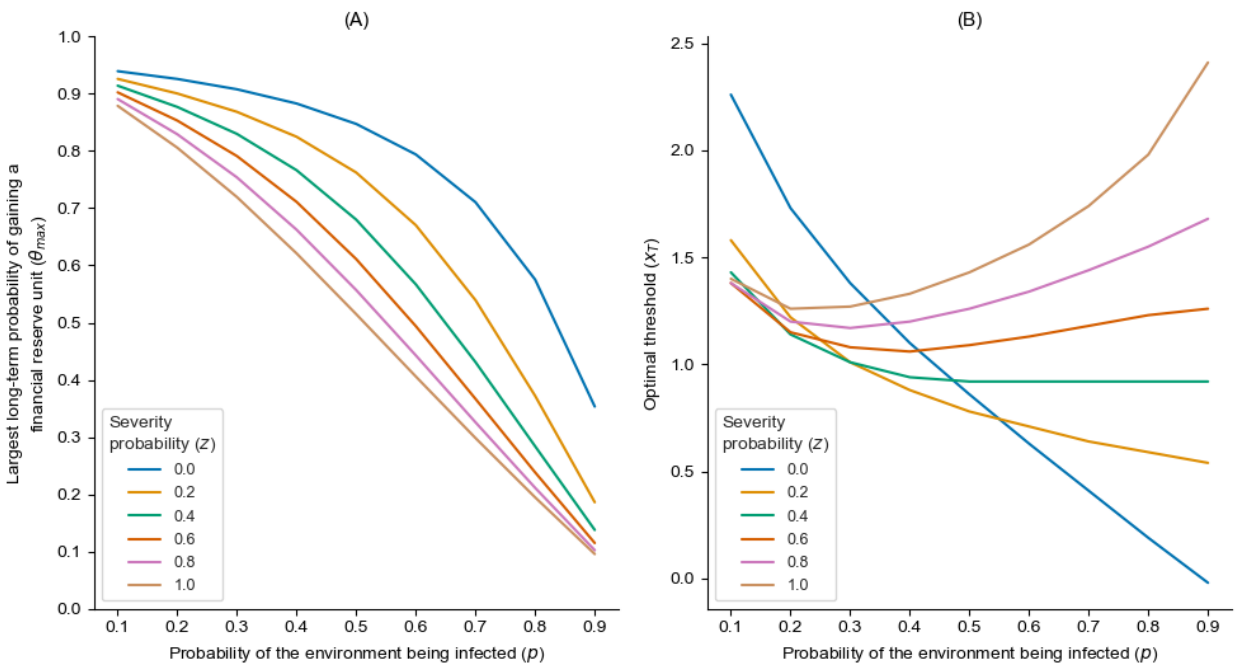
Results

As the probability of infection (p) increases, the largest probability of an individual adding a financial unit to their reserve in the long-term (θ_{max}) decreases for all levels of severity (z). However, the probability of long-term success is greater at lower z values where the situation is less severe (Figure 4A). This result infers that the long-term probability decreases as the risk of infection increases, but the level of seriousness controls the rate of this decrease; the rate is steeper as severity increases.

In contrast, as the probability of infection (p) increases, the influence of severity (z) on the optimal threshold (x_T) becomes more pronounced. When severity is minimal (i.e., $z = 0$), x_T decreases significantly as p increases; however, as the situation gets more severe (i.e., $z > 0$), the pattern of x_T becomes more complex, showing an initial decrease followed by a flattening or slight increase as p rises (Figure 4B). This finding suggests that when the situation is not severe, their thresholds increase as p increases, but as it becomes more serious, the threshold follows a U-curve trend.

Figure 4

(A) *Largest long-term probability of eventually gaining a reserve unit (θ_{max}) across increasing probabilities of environmental infection (p) hued by six unique severity parameters (z).* ***(B)*** *Optimal threshold (x_T) across increasing probabilities of environmental infection (p) hued by six unique severity parameters (z).*



Discussion of Model 1

The above results reflect the patterns observed in SDT and SDDT, albeit in distinct ways. Firstly, when severity is absent, the optimal threshold result resembles SDT's, where the individual is more prone to evasive action as the risk of danger (through infection) increases. Although when severity increases above mid-range, the x_T U-shaped results mimic SDDT's similarly complex finding, where the optimal threshold is weaker at lower probabilities of infection but greater at higher probabilities as individuals account for reserve level changes (McNamara & Trimmer, 2019). These findings suggest that this additional severity parameter z acts as a potential intermediary that switches between SDT and SDDT results.

Whilst this newly discovered intermediary parameter captures the additional short-term probability of remaining at the same reserve level (c), z is an oversimplification of severity. For example, the payoff matrix does not distinguish payoffs between staying at home when the environment is infected, versus when the environment is not infected. This equality in payoffs when evasive action is chosen, regardless of environmental conditions, is not realistic. A possible improvement to this is to focus on the effects of being in an infected environment, such as the risk of infection, even when taking evasive action. Hence, the following section builds upon this model by extracting possible aspects of severity as individual components to obtain distinct payoffs for each environment-action combination.

Model 2: Extended Severity Model

Unlucky Parameter (u)

The *unlucky* parameter (u) is a negative payoff option for V_{IH} - a novel concept not previously seen in either the SDT or the SDDT. This u parameter was included in this model to ensure a clear benefit for staying at home in a safe environment versus an infected environment. This parameter provides some realism to the model; the risk of being infected through everyday behaviours (e.g., getting the mail) still remains, even if necessary precautions are taken (e.g., wearing a mask). u must be between zero and one, and neither extreme. $u = 0$ suggests the individual will not get infected, so the signal would have to absolutely determine the environment as safe for the individual to go to work. The environment certainly conflicts with a key principle of SDT and SDDT of environmental uncertainty. Alternatively, $u = 1$ implies that the individual is certain to get infected, thus making no payoff difference between staying at home and going to work.

Survival Given Infection Parameter (λ)

If an individual is infected, either by going to work or unluckily while staying at home, a *survival* parameter (λ) is introduced to reflect the probability of an infected individual surviving the infection (i.e., $P(\text{Survival} \mid \text{Infected})$). This unique parameter was included to break the fixed payoffs linked to the evasive action. In the original foraging scenario, if the prey runs away, regardless of the environment, it will lose a reserve unit. In contrast, the current scenario introduces variability in the payoff for the evasive action of staying at home, depending on the environment: while staying at home in a safe environment has no change to the reserve level, doing so in an infected environment may result in the loss of a reserve unit (but this is also not guaranteed).

Probabilities

Short-term Probabilities: a, b, c

a includes either staying alive after infection (λ) resulting from going to work when the environment is infected *or* staying alive after infection as a result of being unlucky and infected while staying at home when the environment is infected (see Equation 7).

$$a = (1 - \delta)\left((P_{IW} \times p \times \lambda) + (P_{IH} \times p \times u \times \lambda)\right) \tag{7}$$

b is the probability that the individual goes to work when the environment is safe relative to the probability of the environment being safe (see Equation 8).

$$b = (1 - \delta)\left(P_{SW} \times (1 - p)\right) \tag{8}$$

c is a new probability parameter novel to both SDT and SDDT scenarios. This parameter denotes the probability of the individual staying at the current reserve level as a result of either staying at home when the environment is safe *or* remaining uninfected when staying home in an infected environment (see Equation 9).

$$c = (1 - \delta)\left((P_{SH} \times (1 - p)) + (P_{IH} \times p \times (1 - u))\right) \tag{9}$$

Finally, *residual death* (d) is the short-term probability of an individual dying from infection as they try to gain a reserve unit. d is the remaining probability after subtracting each key probability parameter from 1 (shown in Equation 10).

$$d = P_{IW} \times \lambda = 1 - a - b - c \tag{10}$$

Long-term Probability: θ

Similar to the preliminary model, the long-term probability (θ) is calculated using Equation 3. The updated payoff matrix for this Extended Severity Model (ESM), accounting for the severity parameter, is shown in Table 4 below.

Table 4

Payoff Matrix of the ESM with Payoff Values

		Action	
		Stay at Home (H)	Go to Work (W)
Environment	Infected (I)	$V_{IH} = (1-u)\theta + \lambda u\theta^2$	$V_{IW} = \lambda\theta^2$
	Safe (S)	$V_{SH} = \theta$	$V_{SW} = 1$

Results

For this set of results, the fixed parameters used in the model are shown in Table 5 below, unless explicitly stated otherwise. The code for the simulation and the figures are available on GitHub noted in Appendix A.

Table 5

Fixed parameters for the ESM results.

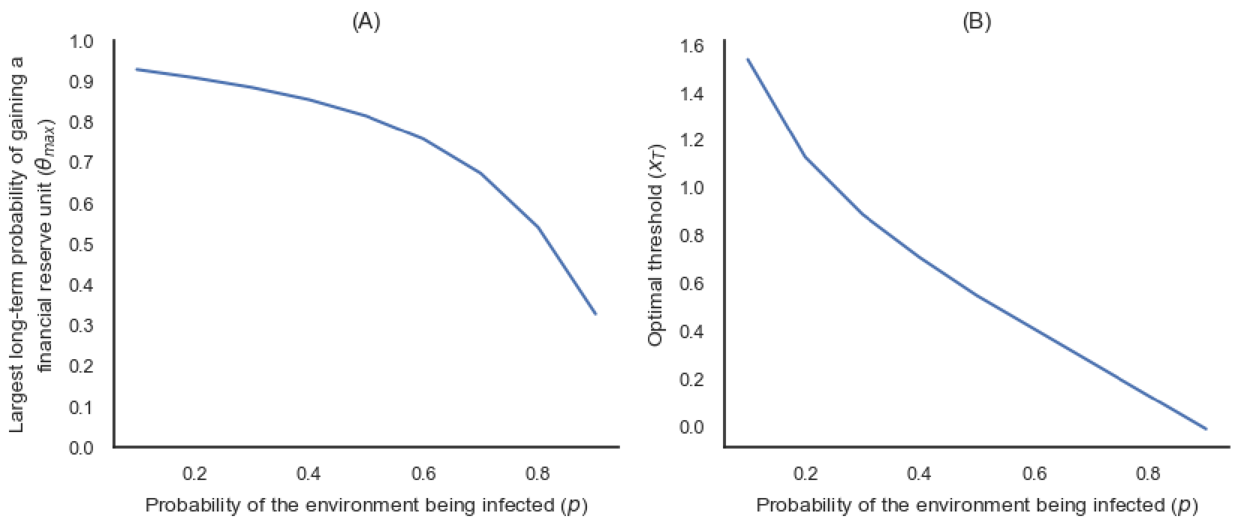
Parameter	**Value(s)**
Safe environment	Mean = 0; Variance = 1
Infected environment	Mean = 1.5; Variance = 1
Background mortality (δ)	0.05
Probability of surviving infection (λ)	0.85
Probability of getting infected while at home (unlucky probability; u)	0.01
Probability of infection (p)	0.1 to 0.9 (inclusive) in steps of 0.1
Thresholds	-3.0 to 4.5 (inclusive) in steps of 0.01

Long-Term Probability and Optimal Thresholds

The largest probability of gaining a reserve unit in the long-term (θ_{max}) and the associated optimal threshold (x_T) both show a negative relationship as the probability of environmental infection (p) increases; however, the magnitude of each relationship varies. For example, there is a steady decline of θ_{max} at low to mid-range p values, which becomes much sharper at higher values of p (Figure 5A). Similarly, (x_T) also falls as p increases with an initially sharp decline that becomes less steep but remains consistently downward across all subsequent values of p (Figure 5B). These particular relationships suggest that as the risk of potential infection increases, individuals are less likely to gain a reserve unit in the long-term (θ_{max}), which is associated with a lower optimal threshold (x_T).

Figure 5

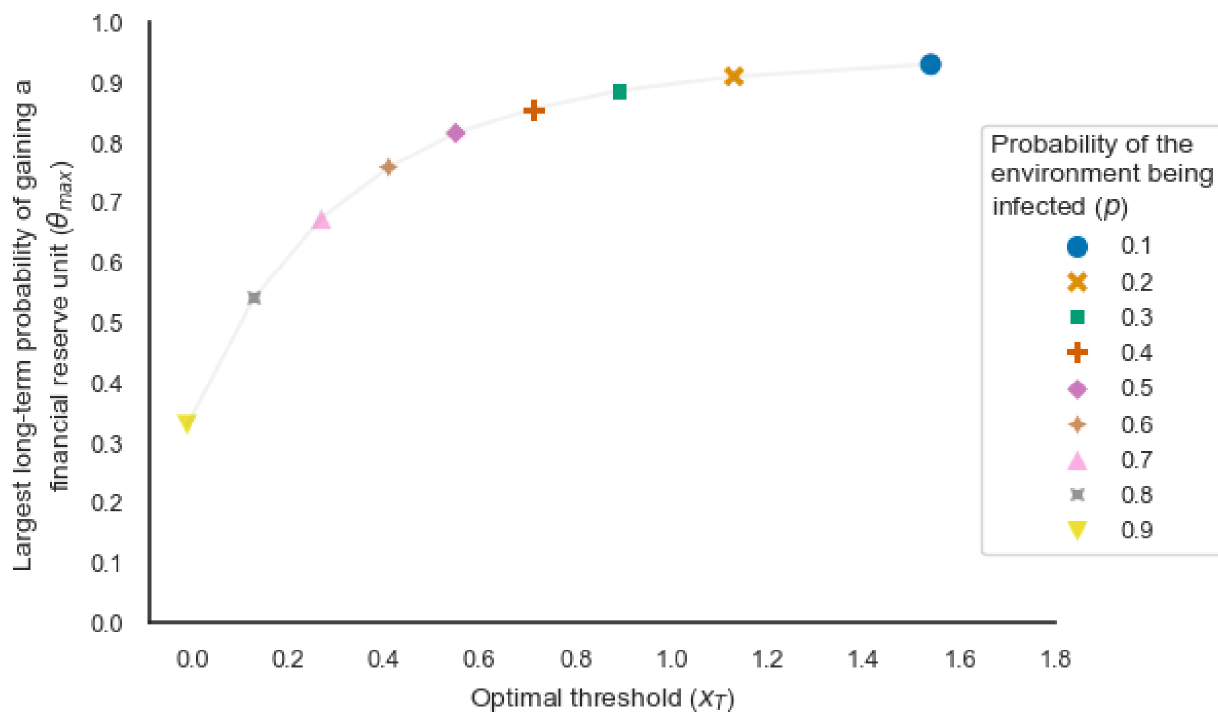
(A) *Largest long-term probability of eventually gaining a reserve unit (θ_{max}) across increasing probabilities of environmental infection (p).* ***(B)*** *Optimal threshold (x_T) across increasing probabilities of environmental infection (p).*



When comparing the relationship between θ_{max} and x_T across values of p, a positive relationship is observed between the best long-term probability and the threshold (Figure 6); however, this relationship is inverted when accounting for p. Therefore, individuals with a greater threshold are more likely to gain a reserve level over time, but this relationship depends on the low risk of infection.

Figure 6

Relationship between optimal threshold (x_T) and the largest long-term probability of eventually gaining a reserve unit (θ_{max}) styled by the probability of the environment being infected (p)



Short-Term Probabilities

As the probability of the environment being infected increases, the short-term probabilities of gaining a reserve unit (b; green) and experiencing no change in reserves (c; blue) exhibit clear negative and positive trends, respectively (Figure 7). However, the probability of losing a reserve (a; red) remains relatively low, following an inverted U-shape after zooming in (Figure 8).

Despite the differing trends, both b and c appear to follow the same rate of decline and incline, respectively. As p increases, the downward trend of immediately increasing an individual's reserve level intersects with the upward trend of no change to reserve levels around the central range of p. Both b and c have larger probabilities than a for all probabilities of environmental infection. As previously mentioned, the probability of immediately losing a reserve unit exhibits an inverted U-shape - a steep increase at lower values of p, peaking around the mid-range, followed by a gradual decline at higher values of p. Even though the probability of losing reserves shows a unique trend from the other two immediate probabilities, a values remain comparatively small when viewed against the other two.

Figure 7

Short-term probabilities of gaining a reserve unit (green), losing a reserve unit (red), and no change to reserves (blue) across infection probabilities (p).

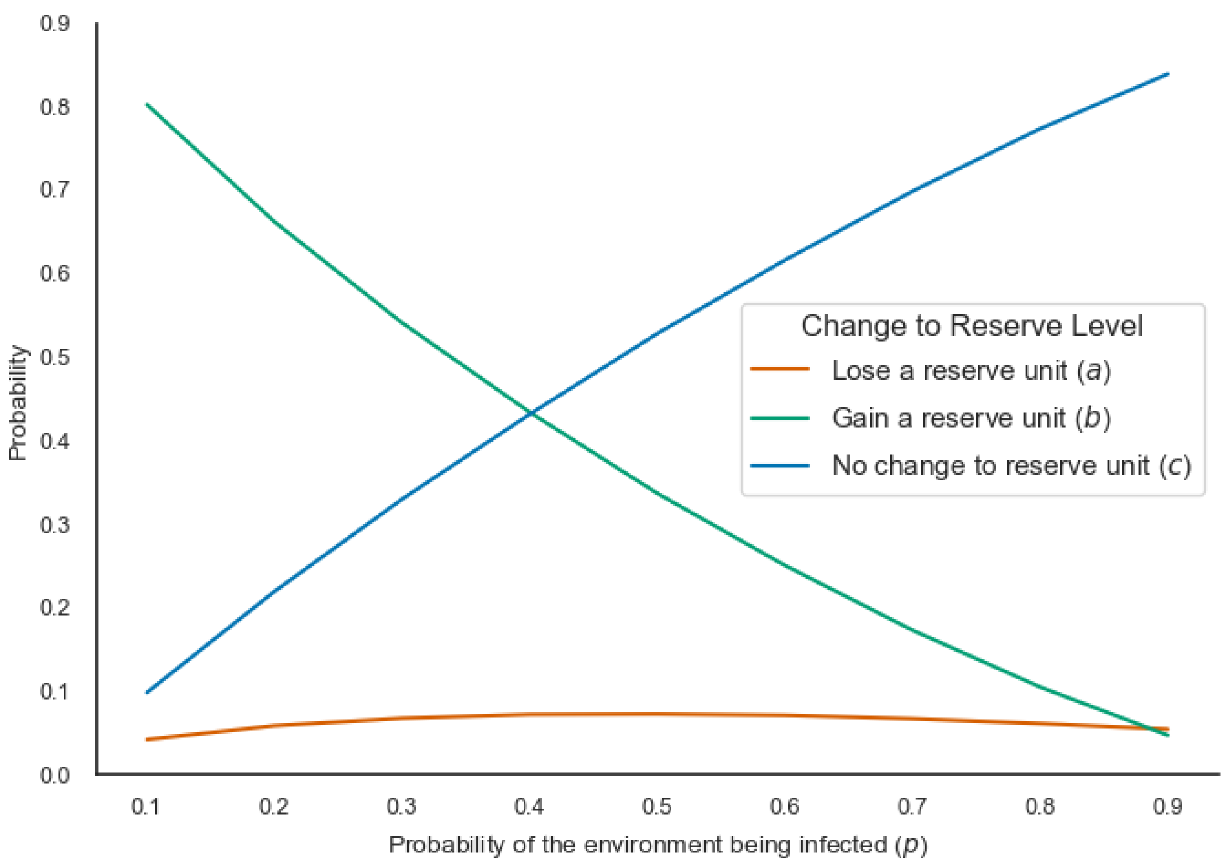
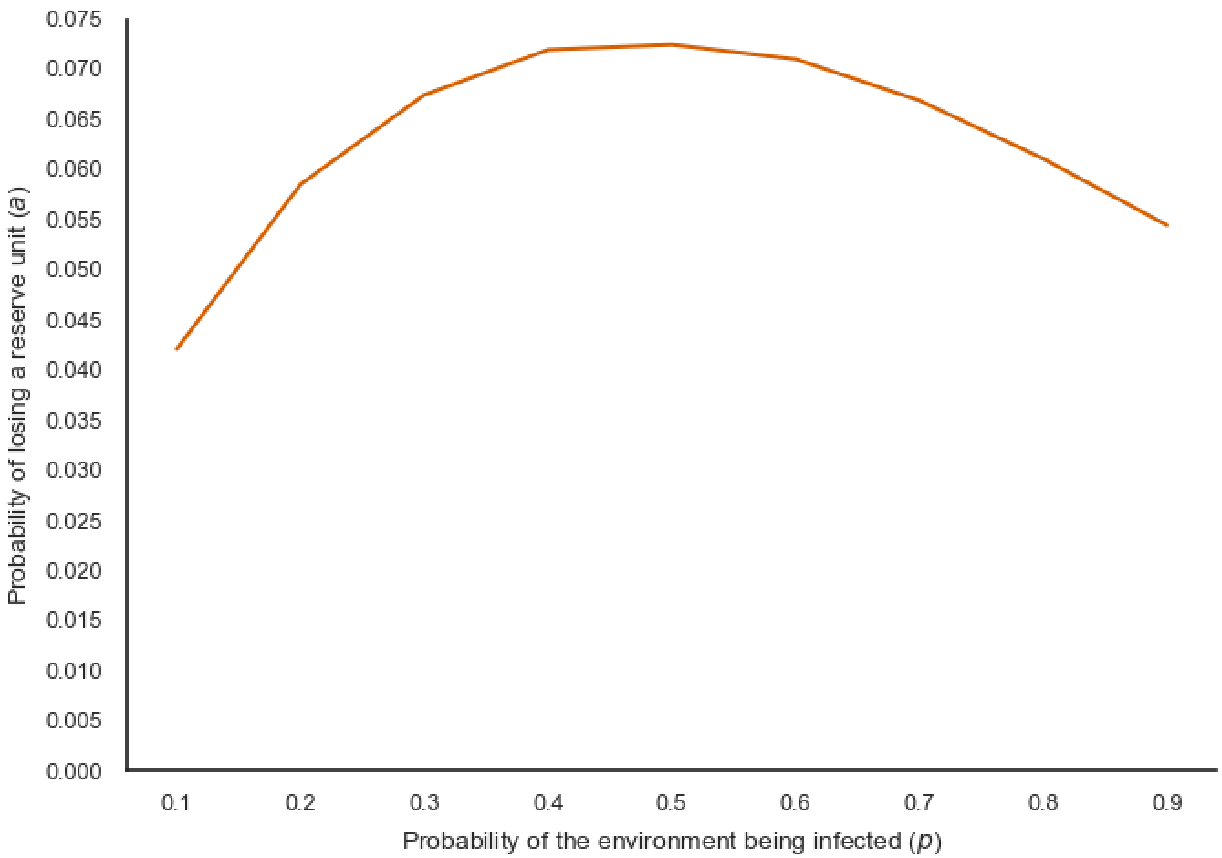


Figure 8

Magnified view of the short-term probability of losing a reserve unit (red) across infection probabilities (p)



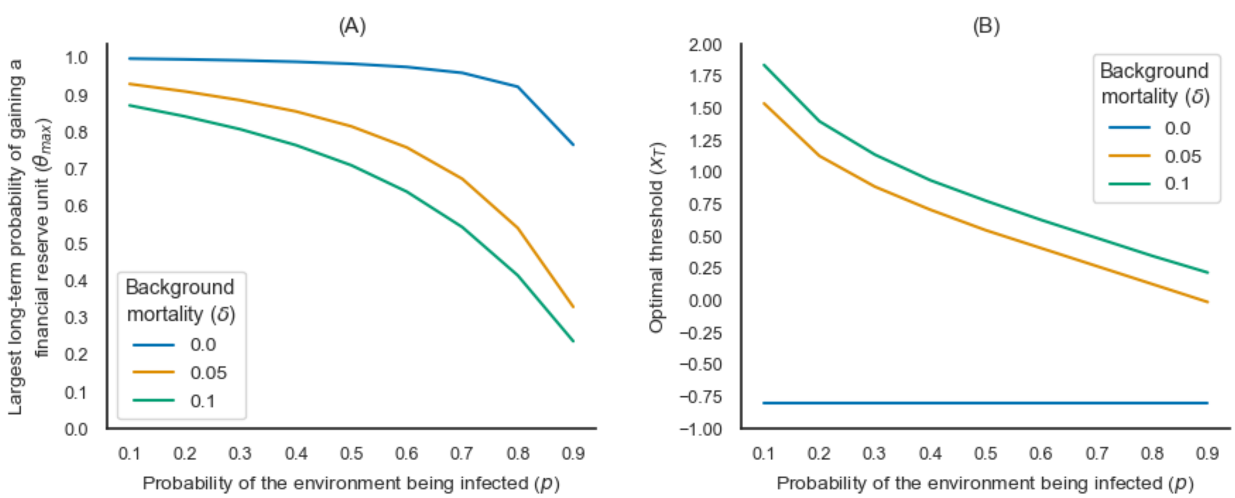
Background Mortality (δ)

Figure 9 shows that *both* long-term probability and optimal threshold generally decrease as the risk of the environment being infected grows. However, this negative trend relies on the presence of background mortality being present, even more so, with x_T than $theta_{max}$. For example, when $\delta = 0$ (so death can *only* result from infection), θ_{max} remains relatively constant at a high probability, only showing a slight decline at the extreme high values of p (Figure 9A); similarly, the x_T remains constant at a relatively low threshold compared to when $\delta > 0$ for all probability values of infection (Figure 9B). These results suggest that, given background mortality is absent, a low threshold can be used to maintain high probabilities for long-term success even under substantial infection risk.

Moreover, as δ increases, θ_{max} shows a gradual rate of decrease from low to mid-range values of p, but sharply steepens at higher values of p. Additionally, increasing δ consistently *lowers* overall θ_{max} for all values of p. Therefore, the long-term probability for $\delta = 0.1$ is lower than that for $\delta = 0.05$, which in turn is lower for $\delta = 0$. In contrast, when considering x_T, as δ increases, θ_{max} shows an initial sharp steep decline at low p followed by a not as sharp but still steep decline that is constant for the remaining range of p. Also differing from θ_{max}, increasing δ is associated with consistently *higher* values of x_T for all values of p. From these findings, when background mortality is present, a growing δ coupled with a rising risk of the environment being infected substantially reduces the individual's probability of gaining a reserve unit long-term while increasing the individual's optimal threshold to react.

Figure 9

(A) *Largest long-term probability of eventually gaining a reserve unit (θ_{max}) across infection probabilities (p) when background mortality (δ) is* 0 *(blue),* 0.05 *(orange) and* 0.1 *(green).*
(B) *Optimal threshold (x_T) across infection probabilities (p) when background mortality (δ) is* 0 *(blue),* 0.05 *(orange) and* 0.1 *(green).*



***Unlucky Probability* (u)**

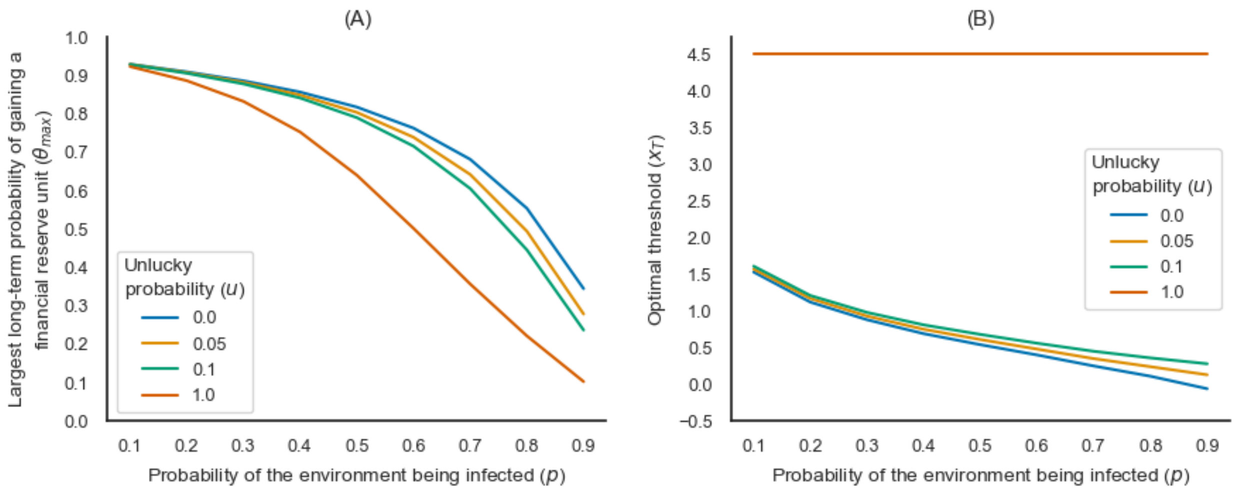
A unique parameter is the probability of still getting infected despite choosing to stay home in an infected environment (V_{IH}), noted as the *unlucky* probability and denoted as u. This unlucky parameter controls the rate of decline between both long-term probability and optimal threshold across all values of p, with a notable exception when $u = 1$ (Figure 10).

The largest probability of eventually gaining a reserve unit decreases non-linearly for all levels of u as p increases. When $u < 1$, the long-term probability is approximately equal for lower values of p, but the rate of decrease varies as u increases. As u increases, θ_{max} is consistently lowered across all values of p; θ_{max} is consistently greater when $u = 0.0$ (blue) than when $u = 0.05$ (yellow) or $u = 0.1$ (green); however, when $u = 1.0$ (orange), θ_{max} is significantly lower than for other u values, and the magnitude of decline is more prominent with increasing p (Figure 10A). These finding suggests that increasing the unlucky probability diminishes an individual's best probability of *eventually* gaining a reserve unit. Still, when u is absolute, this severely impacts the ability to maintain a high long-term chance of success or safety, especially as the risk of infection rises.

Alternatively, when $u < 1$, the optimal threshold decreases as the probability of infection increases (Figure 10B). For these values of u, the optimal thresholds follow a declining trend with $u = 0.1$ (green) generally higher and $u = 0.0$ (blue) usually lower than their counter u values at any given p. This result suggests that this increased risk of infection while at home in a potentially infected environment consistently produces a slightly higher optimal threshold. Although in notable contrast to the other curves, when $u = 1.0$ (orange), x_T remains constant and at the highest possible threshold value across all p values. This anomalous finding suggests that the optimal threshold becomes independent of the infection probability when the unlucky probability is certain.

Figure 10

(A) *Largest long-term probability of eventually gaining a reserve unit (θ_{max}) across infection probabilities (p) when the unlucky probability (u) is* 0 *(blue),* 0.05 *(yellow),* 0.1 *(green) and 1.0 (orange).* ***(B)*** *Optimal threshold (x_T) across infection probabilities (p) when the unlucky probability (u) is* 0 *(blue),* 0.05 *(yellow),* 0.1 *(green) and 1.0 (orange).*



Comparison with SDT and SDDT: Using the SDT Equation

The Signal Detection Theory equation calculates the optimal threshold resulting from evasive action (e.g., fleeing, staying at home). McNamara and Trimmer (2019) reworked Equation 1 to gain additional insight into how the payoffs may vary as p increases, within the foraging scenario. For instance, since V_{DF} results in death, the payoff value is 0. As well, given an individual is one unit from their aim, $V_{NF} = \alpha$ where α is the probability of immediately gaining one reserve unit. The long-term probability of acquiring a reserve unit is θ after losing a reserve unit, so $V_{NR} = V_{DR} = \alpha\theta^2$. These mathematical interpretations are represented in Equation 11 below.

$$\frac{(V_{NF} - V_{NR})}{(V_{DR} - V_{DF})} = \frac{\alpha - \alpha\theta^2}{\alpha\theta^2 - 0}$$

$$= \frac{\alpha(1 - \theta^2)}{\alpha\theta^2}$$

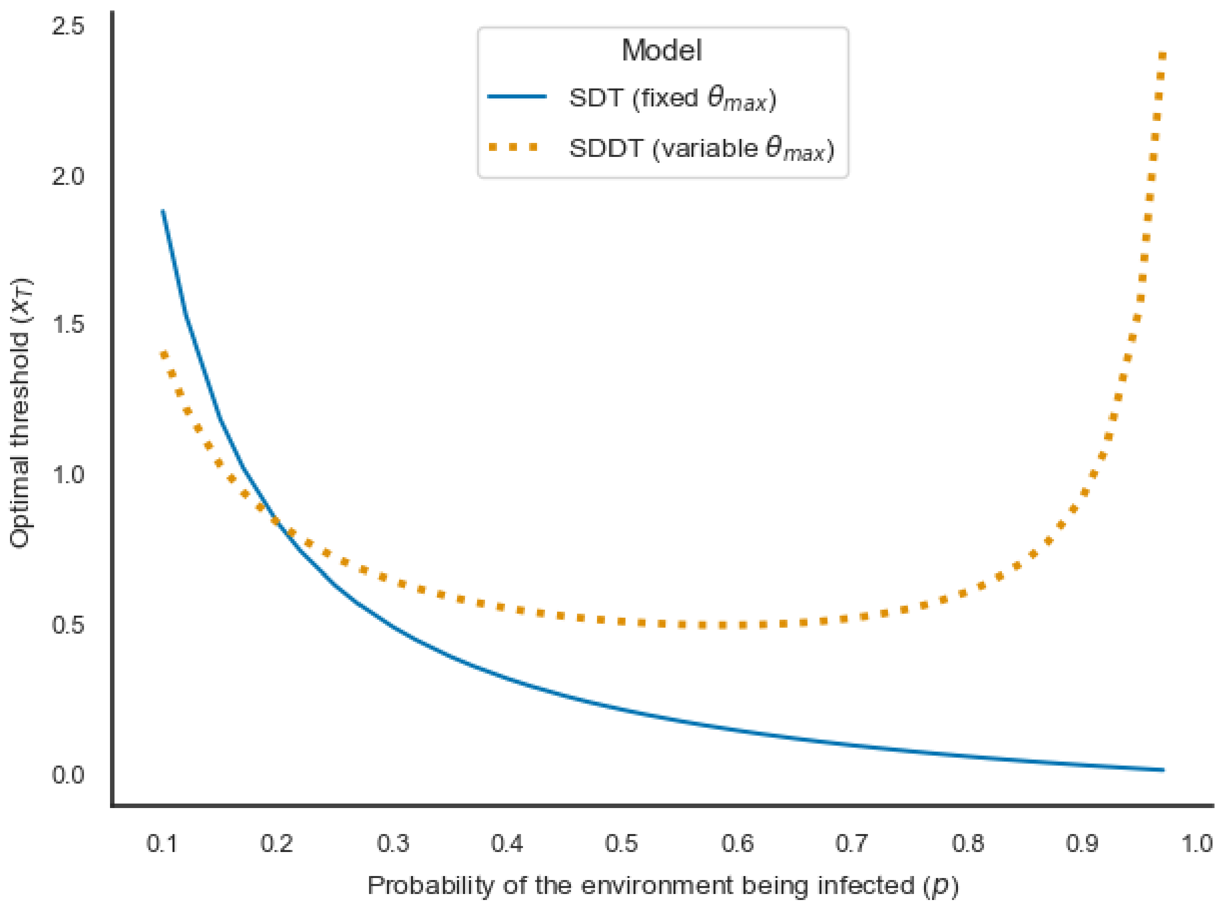
$$= \frac{(1 - \theta^2)}{\theta^2}$$

$$x_T = \frac{(1 - p)}{p} \times \frac{(1 - \theta^2)}{\theta^2} \tag{11}$$

Using Equation 11, the optimal thresholds under SDT, SDDT and the current ESM are visualised in Figure 11. For the SDT curve (blue, solid), a monotonic downward trend for the optimal threshold is present as the probability of danger (p) increases. In contrast, the SDDT curve (orange, dotted) exhibits a U-shaped pattern, with a steady decline when the risk of infection is low, a less gradual decline at mid-range values, and a steep increase at higher p values. This finding matches those in past literature (e.g., McNamara & Trimmer, 2019; Trimmer et al., 2017).

Figure 11

Comparing optimal thresholds (x_T) resulting from the Signal Detection Theory (SDT; blue, solid) and the State-Dependent Detection Theory (SDDT; orange, dotted) across increasing probabilities of the environment being infected.

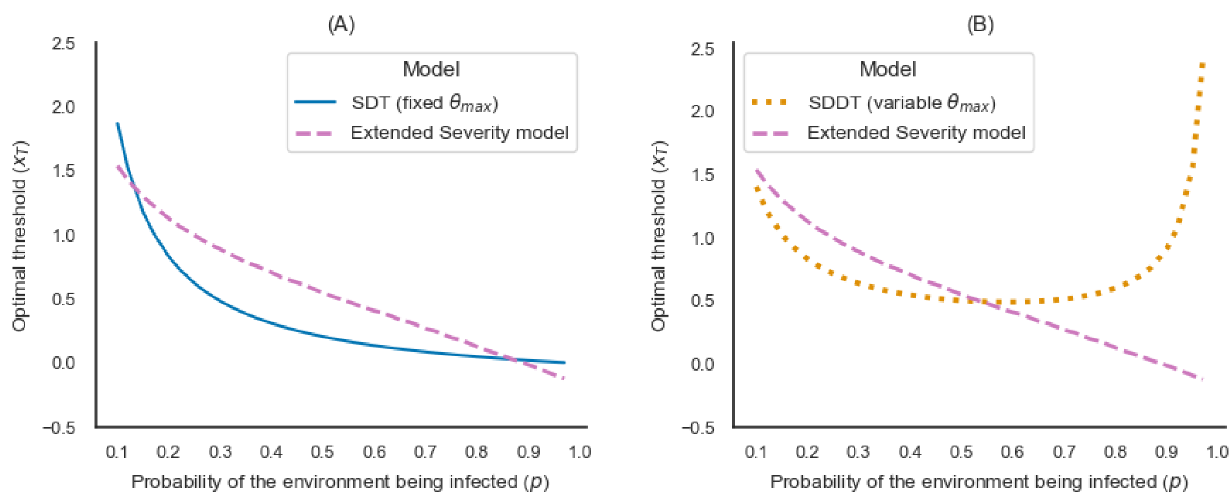


However, when the optimal threshold calculated for the current ESM is compared with the two established results, it reveals considerable patterns. Firstly, a similar downward trend is present when compared against classical SDT (Figure 12A) but not SDDT (Figure 12B). Compared with SDT (blue, solid), the rate of decline varies; the current ESM is more linear than SDT's monotonic decline. Despite having a comparable optimal threshold at extreme p values, SDT typically has a greater x_T than the ESM for lower ranges of p, which reverses when p increases between mid to high ranges. Alternatively, when compared with

SDDT, the current ESM has larger threshold values for low to mid-range probabilities of infection; this reverses with x_T values being lower than those of SDDT from mid to high p values.

Figure 12

*Comparing optimal thresholds (x_T) resulting from the Extended Severity Model (pink, dashed) with **(A)** the Signal Detection Theory (SDT; blue, solid) and **(B)** the State-Dependent Detection Theory (SDDT; orange, dotted).*



General Discussion

Results Overview

The Extended Severity Model (ESM) produces results that more closely resemble SDT than SDDT, though important differences remain. For example, ESM shows that as the probability of environmental infection increases, the individual tends to adopt a lower optimal threshold, making them more sensitive to weaker infection signals. However, this relationship is more linear in ESM than in SDT.

Moreover, when examining the short-term probabilities, as the risk of the environment being infected increases, the immediate probability of losing a financial reserve remains relatively constant at a very low probability, while the immediate probability of gaining a reserve declines and the probability of remaining at the current reserve level increases.

Alternatively, when background mortality is considered, ESM diverges from both SDT and SDDT (as presented in McNamara & Trimmer, 2019), showing a negative linear relationship between the optimal threshold and the probability of the environment being infected. However, ESM also reveals distinct internal patterns; higher background mortality results in a consistently higher optimal threshold across all probabilities of environmental infection, whereas in the absence of background mortality, the threshold remains constant at a significantly lower level.

Furthermore, the unlucky parameter produced unique results: at absolute certainty (i.e., individual becomes infected even while staying home in an infected environment), the optimal threshold remains fixed at its maximum value. With a more realistic probability value, the results align more closely with SDT than with SDDT, as there is greater risk-aversion when the probability of environmental infection rises; although, the optimal threshold generally increases as the unlucky probability rises.

Interpretation of Results

Increased sensitivity to infection signals as the probability of environmental infection rises is consistent with classic SDT results (Trimmer, Ehlman & Sih, 2017). However, the linearity in this relationship between infection risk and the optimal threshold means that thresholds at most probabilities are higher than in SDT. This heightened risk-seeking may reflect the relationship between the uncertainty individuals face and their financial context. Increased uncertainty in situations with financial reserves may encourage bolder action, a finding that aligns with prior research (e.g., Mattos, 2022; Oliver, 2013), though not a consensus finding (e.g., Aufenanger & Wrede, 2017).

Additionally, some aspects of loss aversion can be seen when examining the different short-term probabilities of either gaining, losing or (the new option of) remaining at the current reserve level. By including this *play-it-safe* option (i.e., to neither gain nor lose a reserve), individuals may be more inclined to choose this option when they perceive a high probability of environmental infection, even when it comes at a cost of potentially gaining a financial reserve unit, where the immediate probability drastically falls at larger risks of environmental infection. This pattern may be interpreted through Prospect Theory, which posits that people value losses more than gains, thus individuals are likely to avoid having any changes to their reserve level rather than risk losing a financial reserve unit (Bhesania et al., 2024). The findings further evidence the value of modelling sequential decision-making in ESM since prospect theory recognises that future choices depend on past decision outcomes (Bhesania et al., 2024; Lemos, 2020; Raeva et al., 2011).

In contrast, when background mortality acts as a mediator within ESM (i.e., the presence of background mortality activates the relationship between the probability of the environment being infected and the optimal threshold), the results indicate that individuals exhibit more risk-seeking behaviour. A possible explanation from Currie (2020) is that the modern world is filled with considerable pervasive risks from various sources (e.g., infection, environmental catastrophes, violence and war). From an SDDT view, in which decisions are made sequentially, prolonged exposure (over multiple time points) to non-infection threats may lead to *desensitisation*, where individuals become indifferent to these additional threats around them. As well, since the scenario's aim for individuals is to increase their financial reserves for its associated economic and psychological benefits (Cohen et al., 2019; Ryu & Fan, 2023), increasing their probability of death from non-infection sources may foster indifference to additional threats, emboldening the individual to engage in more direct and risk-seeking behaviour, even if it lowers their probability of gaining a financial reserve unit in the long term. The alternative to being bold is the individual choosing to avoid infection, which means that reserves will likely deteriorate, requiring the individual to take on additional risk in the future to recoup their losses (Getty et al., 1987; McNamara & Trimmer, 2019).

Moreover, the findings for the unlucky parameter can be logically reasoned; at an absolute probability of being unlucky, the individual's choice of action becomes inconsequential when the environment is infected, as the optimal threshold remained constant at its maximum value - regardless of the action taken, the individual will likely become infected. Therefore, it may be rational for the individual to take direct action and go to work, as it still presents an (albeit minimal) opportunity to acquire financial reserve units, even if they are ultimately lost due to the inevitable infection. The concept of an individual's action being inconsequential when the environment is infected can be demonstrated in a real-world scenario, such as the COVID-19 pandemic and essential healthcare workers. These workers were constantly in environments where their risk of infection became an unavoidable reality of their job (i.e., the unlucky probability and the probability of the environment being infected was also high) (Lee et al., 2023). Their decision to continue working despite these conditions can be attributed to a commitment to patients (Kruger et al., 2025) as well as financial incentives and compensation (Yarney et al., 2024), highlighting the vital role that financial reserves play in the motivation of risky behaviour. Therefore, even though increasing the unlucky probability generally increases the individual's boldness across all probabilities of the environment being infected, the subsequent drawback is that the individual is risking their ability to maximise their long-term probability of gaining a financial reserve unit.

Limitations and Future Directions

While a pioneering model to explore human risk-taking responses to new diseases, the ESM's applicability is limited by its ecological validity. For instance, the ESM unrealistically assumes that the infection probability changes daily. In reality, if an event is expected to occur with probability p, it is likely to persist over multiple time steps rather than occurring only once; if the probability of rain today is $p = 0.6$, it is unlikely that the probability of rain tomorrow will be 0.1, because it is generally understood that underlying conditions (e.g., weather patterns) persist over time (e.g., Goodwell & Kumar, 2019). Therefore, a promising future direction for this model involves incorporating *autocorrelation* - the correlation of a variable (e.g., x_T) with itself across different time points (Kamalov et al., 2021), or, in this case, the persistence of environmental conditions (i.e., infection) over time. Modelling autocorrelation is vital because it directly influences current decision-making behaviour for the future (e.g., knowing it is rainy today increases my likelihood of bringing an umbrella). For instance, prior research by (Trimmer, Ehlman & Sih, 2017) examined autocorrelation within SDT and found that under high autocorrelation ($p \approx 1$), optimal thresholds increased alongside the probability of danger, mirroring SDDT predictions. Hence, extending the present model to incorporate autocorrelation would provide deeper insights into how individuals adapt their strategies in autocorrelated environments and how risk-taking unfolds in such contexts.

Moreover, this model is an extreme oversimplification of real-life behaviour. Several assumptions were necessary to allow the simulations to be carried out. An important yet undiscussed simplifying assumption is that the individual acts alone, and the consequences of their choices remain isolated, whose outcomes affect only the individual and not others. This assumption overlooks the role of social context and *game theory*, where outcomes depend not only on an individual's own choices but also on the decisions of others, which can in turn shape their current and future behaviour (Colantonio et al., 2021; Wu, 2023). Game theory, in particular, becomes especially relevant in this scenario, since the modelled danger arises from infection, like the COVID-19 global pandemic. Several research papers explored COVID-19 quarantine using game theory and examined its impact on disease transmission and hospitalisation rates. For example, Alam and Tanimoto (2022) highlighted that timely and coordinated measures are crucial for effective disease containment using game-theoretic models of human behaviour. Therefore, more advanced modelling should consider incorporating elements of game theory. One possible approach could be a *strategy-based risk assessment* where an individual compares their own payoff with the average payoff of others (Alam & Tanimoto, 2022). This approach allows payoffs to be compared between individuals and groups, providing insight into how individual decisions align with or diverge from collective outcomes.

Conclusion

In conclusion, the presented Extended Severity Model (ESM) is built upon established decision-making frameworks like Signal Detection Theory (SDT) and State-Dependent Detection Theory (SDDT) by incorporating a non-foraging context with financial reserves and new severity parameters (e.g., z, u, λ). This adaptation provides a more realistic framework for analysing human behaviour in response to infection within a financial context. The results yielded several noteworthy insights, including the finding that individuals may be more risk-seeking in specific scenarios that is neither entirely similar nor entirely variable to the results of established classical models and that facing unavoidable, pervasive risks from background mortality and the unlucky parameters can lead to a form of desensitisation, encouraging further risk-taking. Ultimately, this research provides a theoretical foundation for understanding how individuals make risky financial decisions within a scenario of infection and highlights future directions to expand this model further to incorporate autocorrelation and game theory.

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I hope I have done you all proud with this Master's Thesis (an achievement 10-year-old me would not have thought was possible)!

References

Alam, M., & Tanimoto, J. (2022). A Game-Theoretic Modeling Approach to Comprehend the Advantage of Dynamic Health Interventions in Limiting the Transmission of Multi-Strain Epidemics. *Journal of Applied Mathematics and Physics*, *10*(12), 3700–3748. https://doi.org/10.4236/jamp.2022.1012248

Aufenanger, T., & Wrede, M. (2017). Schützt finanzielle Bildung vor der Unsicherheitsfalle? *Vierteljahrshefte zur Wirtschaftsforschung*, *86*(4), 51–66. https://doi.org/10.3790/vjh.86.4.51

Aven, T. (2015, September). *Risk Analysis* (1st ed.). Wiley. https://doi.org/10.1002/9781119057819

Bhesania, T., Kumar, S., Sharanya, Javar, D., Rampurawala, T., & Harshita. (2024). Behavioural Economics and Decision Making. *International Journal For Multidisciplinary Research*, *6*(2), 16317. https://doi.org/10.36948/ijfmr.2024.v06i02.16317

Chowdhury, M. (2024). What Is Money? In *Money and Inflation* (pp. 19–33). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-52356-4_3

Cohen, D., Shin, F., & Liu, X. (2019). Meanings and Functions of Money in Different Cultural Milieus. *Annual Review of Psychology*, *70*(1), 475–497. https://doi.org/10.1146/annurev-psych-010418-103221

Colantonio, J., Durkin, K., Caglar, L. R., Shafto, P., & Bonawitz, E. (2021). The Intentional Selection Assumption. *Frontiers in Psychology*, *12*, 569275. https://doi.org/10.3389/fpsyg.2021.569275

Currie, E. (2020). Thinking About Risk: Responding to Threat and Disintegration in a Fraught World. In J. Pratt & J. Anderson (Eds.), *Criminal Justice, Risk and the Revolt against Uncertainty* (pp. 301–318). Springer International Publishing. https://doi.org/10.1007/978-3-030-37948-3_13

Gasiorowska, A., & Zaleskiewicz, T. (2023, March). The psychology of money. In M. Altman (Ed.), *Handbook of Research Methods in Behavioural Economics* (pp. 209–225). Edward Elgar Publishing. https://doi.org/10.4337/9781839107948.00021

Getty, T., Kamil, A. C., & Real, P. G. (1987). Signal Detection Theory and Foraging for Cryptic or Mimetic Prey. In A. C. Kamil, J. R. Krebs & H. R. Pulliam (Eds.), *Foraging Behavior* (pp. 525–548). Springer US. https://doi.org/10.1007/978-1-4613-1839-2_18

Goodwell, A. E., & Kumar, P. (2019). A Changing Climatology of Precipitation Persistence across the United States Using Information-Based Measures. *Journal of Hydrometeorology*, *20*(8), 1649–1666. https://doi.org/10.1175/JHM-D-19-0013.1

Green, D., & Swets, J. (1966). *Signal detection theory and psychophysics* (Vol. 1). New York: Wiley.

Hills, S., & Eraso, Y. (2021). Factors associated with non-adherence to social distancing rules during the COVID-19 pandemic: A logistic regression analysis. *BMC Public Health*, *21*(1), 352. https://doi.org/10.1186/s12889-021-10379-7

Kamalov, F., Thabtah, F., & Gurrib, I. (2021). Autocorrelation for time series with linear trend. *2021 International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies (3ICT)*, 181–185. https://doi.org/10.1109/3ICT53449.2021.9581809

Kruger, K., Kuhnmuench, C., Ikari, R., Gates, K., & Bell, S. A. (2025). “I Don’t Know What I’m Going to Meet Today”: Home Care Workers’ Decision-Making About Safety During the COVID-19 Pandemic. *Journal of Applied Gerontology*, *44*(5), 838–845. https://doi.org/10.1177/07334648241288659

Lee, B., Sheen, J., Clancy, E. M., Dwyer, A., Aridas, A., Considine, J., Tchernegovski, P., Reupert, A., Bufton, K., & Boyd, L. (2023). Frontline healthcare workers’ lived experiences of healthcare work during the COVID-19 pandemic. *European Journal of*

Public Health, *33*(Supplement_2), ckad160.707. https://doi.org/10.1093/eurpub/ckad160.707

Lemos, F. (2020). On the definition of risk. *Journal of Risk Management in Financial Institutions*, *13*(3), 266. https://doi.org/10.69554/CNYT2714

Mattos, F. (2022). Measuring the degree to which probability weighting affects risk-taking Behavior in financial decisions. *Journal of Finance and Investment Analysis*.

McNamara, J. M., & Trimmer, P. C. (2019). Sequential choices using signal detection theory can reverse classical predictions. *Behavioral Ecology*, *30*(1), 16–19. https://doi.org/10.1093/beheco/ary132

Nesse, R. M. (2005). Natural selection and the regulation of defenses. *Evolution and Human Behavior*, *26*(1), 88–105. https://doi.org/10.1016/j.evolhumbehav.2004.08.002

Nettle, D., & Bateson, M. (2012). The Evolutionary Origins of Mood and Its Disorders. *Current Biology*, *22*(17), R712–R721. https://doi.org/10.1016/j.cub.2012.06.020

Oliver, B. R. (2013). Decision Making Under Risk in the 21st Century. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2286976

Onyeaka, H., Anumudu, C. K., Al-Sharify, Z. T., Egele-Godswill, E., & Mbaegbu, P. (2021). COVID-19 pandemic: A review of the global lockdown and its far-reaching effects. *Science Progress*, *104*(2), 00368504211019854. https://doi.org/10.1177/00368504211019854

Pastore, R. E., & Scheirer, C. J. (1974). Signal detection theory: Considerations for general application. *Psychological Bulletin*, *81*(12), 945–958. https://doi.org/10.1037/h0037357

Raeva, D., Van Dijk, E., & Zeelenberg, M. (2011). How comparing decision outcomes affects subsequent decisions: The carry-over of a comparative mind-set. *Judgment and Decision Making*, *6*(4), 343–350. https://doi.org/10.1017/S1930297500001959

Ryu, S., & Fan, L. (2023). The Relationship Between Financial Worries and Psychological Distress Among U.S. Adults. *Journal of Family and Economic Issues*, *44*(1), 16–33. https://doi.org/10.1007/s10834-022-09820-9

Shirai, S. (2019). Money and Central Bank Digital Currency. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3362952

Singh, S. N., & Churchill, G. A. (1986). Using the Theory of Signal Detection to Improve Ad Recognition Testing. *Journal of Marketing Research*, *23*(4), 327–336. https://doi.org/10.1177/002224378602300402

Sumner, C. J., & Sumner, S. (2020). Signal detection: Applying analysis methods from psychology to animal behaviour. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *375*(1802), 20190480. https://doi.org/10.1098/rstb.2019.0480

Trimmer, P. C., Ehlman, S. M., McNamara, J. M., & Sih, A. (2017). The erroneous signals of detection theory. *Proceedings of the Royal Society B: Biological Sciences*, *284*(1865), 20171852. https://doi.org/10.1098/rspb.2017.1852

Trimmer, P. C., Ehlman, S. M., & Sih, A. (2017). Predicting behavioural responses to novel organisms: State-dependent detection theory. *Proceedings of the Royal Society B: Biological Sciences*, *284*(1847), 20162108. https://doi.org/10.1098/rspb.2016.2108

Wang, X., Chen, Z., & Krumhuber, E. G. (2020). Money: An Integrated Review and Synthesis From a Psychological Perspective. *Review of General Psychology*, *24*(2), 172–190. https://doi.org/10.1177/1089268020905316

Wixted, J. T. (2020). The forgotten history of signal detection theory. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *46*(2), 201–233. https://doi.org/10.1037/xlm0000732

Wu, W. (2023). Theory and Practical Application Based on Game Theory. *BCP Business & Management*, *44*, 919–925. https://doi.org/10.54691/bcpbm.v44i.4978

Yarney, L., Konadu, E., & Ayisi, E. (2024). Financial incentives and work commitment among Ghanaian COVID-19 frontline healthcare workers: The mediating role of job satisfaction. *International journal of health sciences*, *8*(S1), 1093–1113. https://doi.org/10.53730/ijhs.v8nS1.14965

Appendix

GitHub Link for Code

- GitHub Folder: ps939-rp

- Raw URL: https://github.com/joanne-ev/warwick-bds/tree/main/ps939-rp