Appendix: Graphical analysis of logistical weight and safety response

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1 INTRODUCTION

The appendix presents a graphical and interpretative analysis of the logistic risk assessment mechanism and the associated safety interpretations. The purpose of the document is not to introduce a new model, but to provide a transparent and repeatable presentation of the behavior of the logistic function at different parameter settings, thereby enabling a consistent interpretation of operating modes, transition areas, and limits of applicability of output values.

The first part deals with risk assessment using the logistic function$L$ (R). Graphs are shown that separately analyze the impact of the risk threshold θ at fixed sensitivity values λ and the impact λ at fixed θ. On this basis, the same set also includes a synergistic analysis of the dynamic weight $w(R)$ at fixed input risk values R (t), which shows how the parametric impact changes from the latent regime to saturation and when the model maintains or loses differentiation between states.

The second part mirrors the same mechanism from a security perspective and considers the security factor $V(R)$=1− $w(R)$. The structure of the analysis follows the same logic as in risk assessment: first, curves are shown at fixed λ and θ, then the synergistic effect of parameters at fixed R (t), which allows a direct comparison between risk and safety interpretation of outputs.

Graphical representations are used as the primary analytical tool. Surface (3D) representations provide insight into the entire shape of the parametric space, while heat maps serve as its projection for easier interpretation of value distributions and gradients. In both cases, these are different representations of the same parametric dependence, so the interpretations are designed to be comparative and without duplication of content.

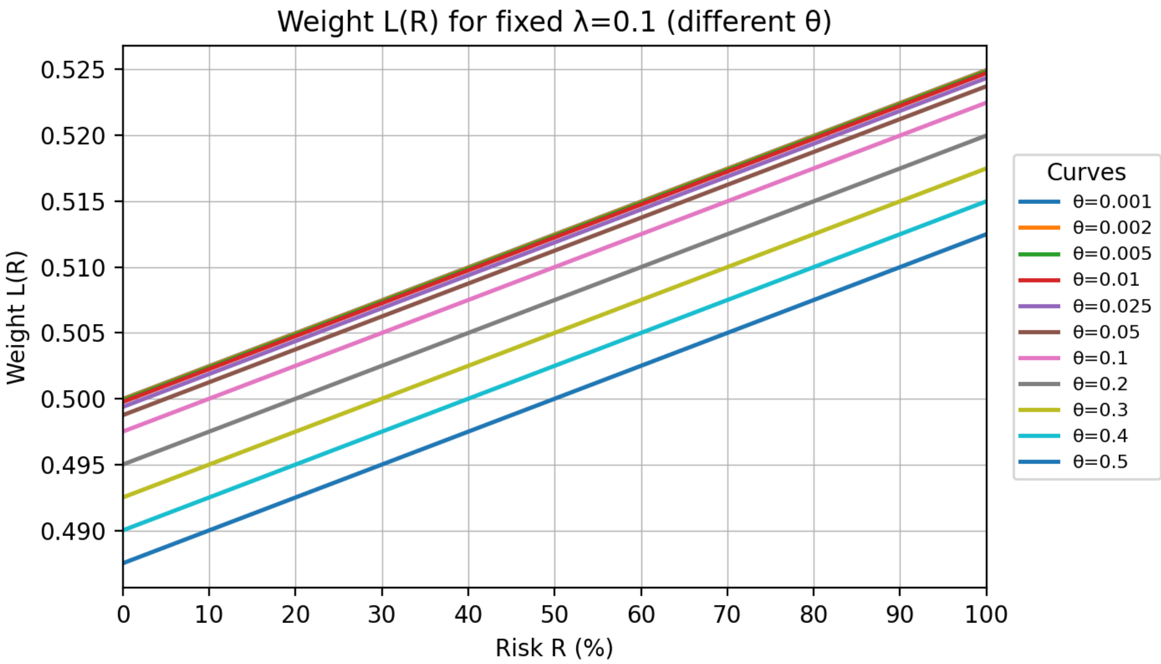
2 RISK ASSESSMENT – LOGISTIC FUNCTION L(R)

2.1 Model analysis at a fixed value of the parameter λ

2.1.1 Low system sensitivity and limited threshold effect (λ = 0.1)

The graph (seeGraph 1) shows the behavior of the logistic function$L$ (R) at a fixed low value of the parameter λ = 0.1, with the risk threshold θ varying. The x-axis shows the risk R in the range from 0% to 100%, and the y-axis shows the logistic risk assessment.

Graph 1 : Effect of threshold θ at low sensitivity (λ = 0.1).



At such a low value of λ, the logistic function is very flat, so the logistic risk assessment changes slowly and continuously as the input risk R increases. The differences between the individual curves representing different threshold values θ are small but systematic.

Lower values of θ cause the logistic risk assessment for the same value of R to be slightly higher. This means that the system detects risk earlier or reacts earlier. Conversely, higher values of θ shift the transition of the function towards higher values of R (to the right), so the assessment is lower for the same R.

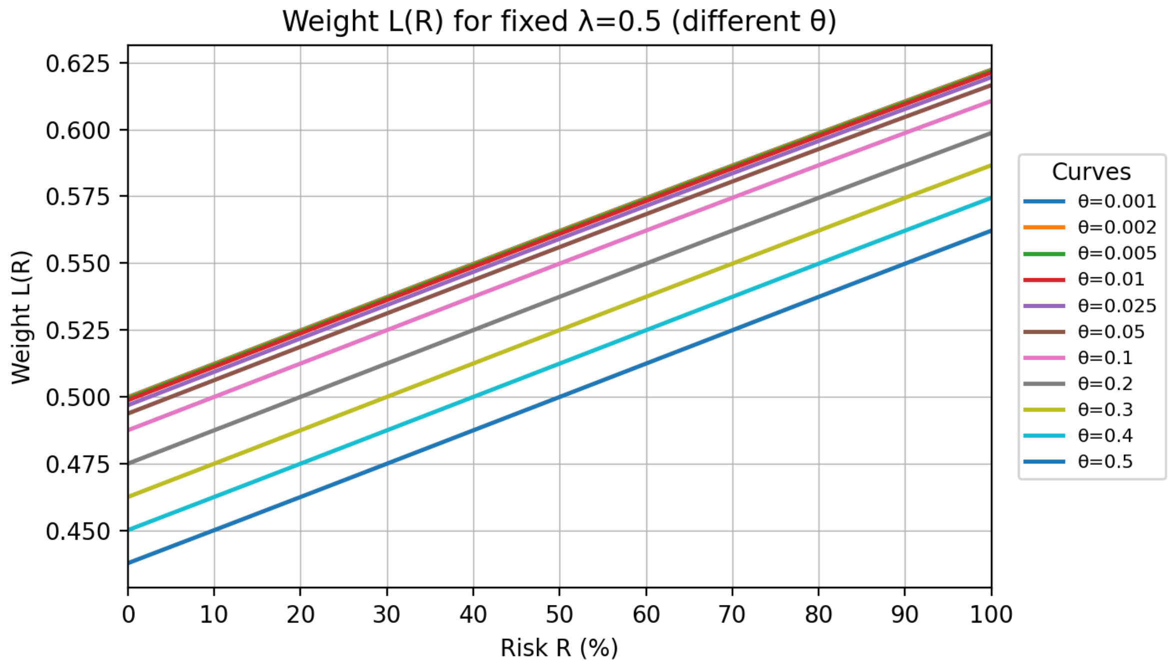
In the set of θ values shown, all curves are within a very narrow range (approximately between 0.49 and 0.525), indicating that at low sensitivity λ, the threshold θ has no significant impact on the dynamics of the model. In this case, the parameter θ acts primarily as a fine-tuning mechanism that allows for minor adjustments to the basic risk estimate, but not structural changes in the response.

Such behavior is characteristic of stable environments where the system deliberately does not react violently to changes in risk, but maintains continuous and predictable dynamics. In the context of the model, this means that a low value of λ reduces the impact of threshold settings and ensures the robustness of the assessment even with different choices of θ.

2.1.2 The beginning of differentiation and the increasing role of the threshold (λ = 0.5)

The graph (seeGraph 2) shows the impact of the risk threshold θ on the logistic risk assessment at a moderate value of the parameter λ = 0.5. Compared to low sensitivity, the curve of the logistic function is more pronounced, which means that the risk assessment responds more quickly to changes in the input risk R.

Graph 2 : Impact of threshold θ at moderate sensitivity (λ = 0.5).



An increase in the value of λ causes the differences between the individual curves for different θ to increase significantly. Lower threshold values θ lead to higher logistic risk estimates across the entire range of R, while higher values θ reduce the risk estimate more significantly under the same input conditions. The threshold thus no longer acts merely as a minor correction parameter, but has a noticeable effect on the distribution of estimates.

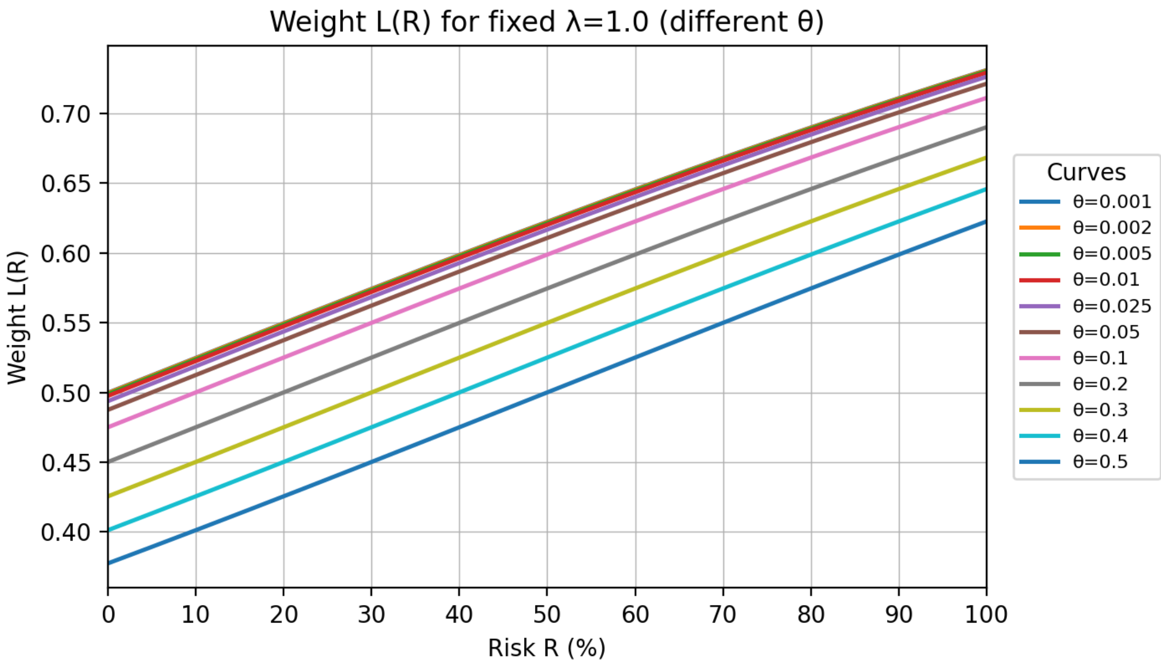
Compared to the case $\lambda = 0.1$, the range of logistic score values increases (from approximately 0.44 to 0.62), indicating greater model discriminative power. With this setting, the model already clearly distinguishes between low, medium, and higher risk levels, with the choice of threshold θ significantly influencing when the system detects a transition to a higher risk level.

This configuration represents a compromise between stability and responsiveness. The model remains continuously behaving and predictable, while allowing sufficient flexibility to respond to changes in risk and different threshold policies. In practice, this means that the parameter θ can effectively reflect different levels of risk tolerance without causing sudden or nonlinear jumps in the assessment.

2.1.3 Balanced response regime and clear regulatory role of the threshold (λ = 1)

The graph (seeGraph 3) shows the behaviour of the logistic function at a parameter value of λ = 1, where the influence of the risk threshold θ is further strengthened. Compared to lower values of λ, the response of the model becomes more pronounced, and the differences between the individual curves are clearly visible across the entire range of input risk R.

Graph 3: Impact of threshold θ at increased sensitivity (λ = 1).



Lower θ values cause the logistic risk assessment to increase more rapidly and reach higher values even at medium risk levels. Higher values of θ systematically lower the risk estimate and shift the perception of increased risk towards higher values of R. The risk threshold thus acts as an actual regulator that determines at what level of risk the system begins to increase the estimate more significantly.

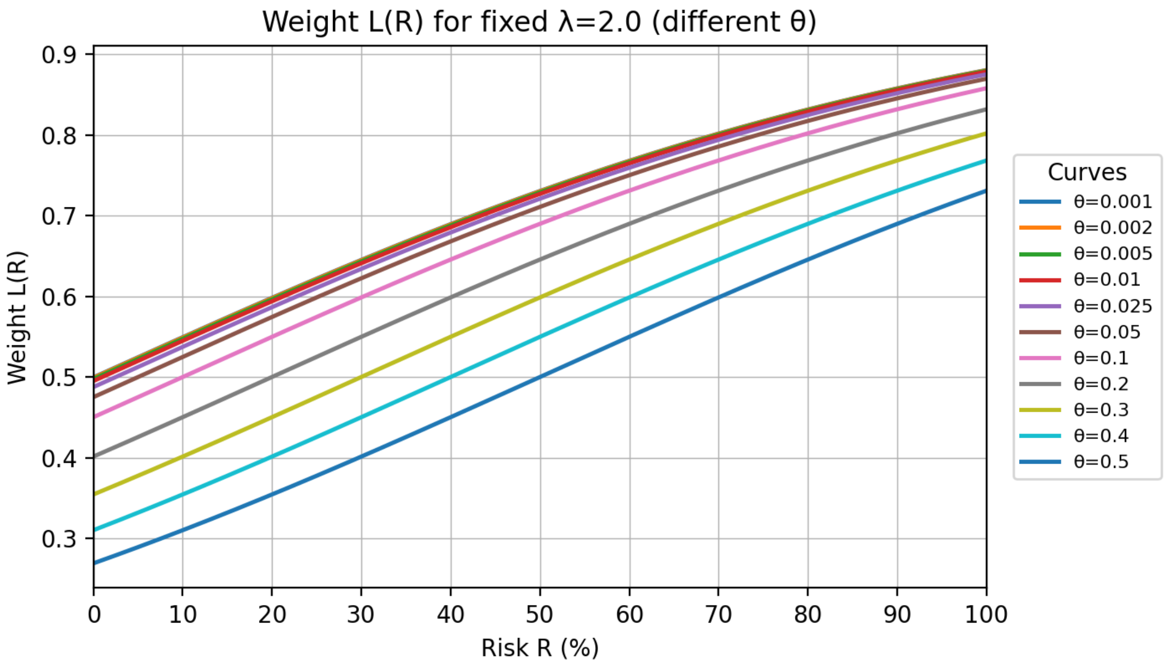
The range of logistic estimates is already much wider with this setting (approximately from 0.38 to 0.73), which indicates increased model discriminativeness. The model is no longer merely mildly adaptive, but allows for a clear distinction between different levels of risk. The influence of θ is no longer marginal, but significantly shapes the dynamics of the assessment.

This configuration represents a transitional area of model operation where the parameters λ and θ are balanced. The system is responsive enough to detect changes in risk, but does not yet operate excessively aggressively. This mode is suitable for environments where active risk monitoring is required, but without sudden and abrupt changes in assessment.

2.1.4 Transition to selective risk perception (λ = 2)

The graph (seeGraph 4) shows the effect of the risk threshold θ on the logistic risk assessment at a high value of the parameter λ = 2. In this mode, the logistic function becomes significantly steeper, which means that the risk assessment increases rapidly even with moderate changes in the input risk R.

Graph 4 : Impact of threshold θ at high sensitivity (λ = 2).



The differences between the curves for different values of θ are very pronounced. Lower threshold values θ cause the system to detect increased risk even at low values of R and quickly reach high logistic estimates. Higher θ values significantly delay this transition, causing the system to maintain a lower risk score for a longer period of time and only respond at higher R levels.

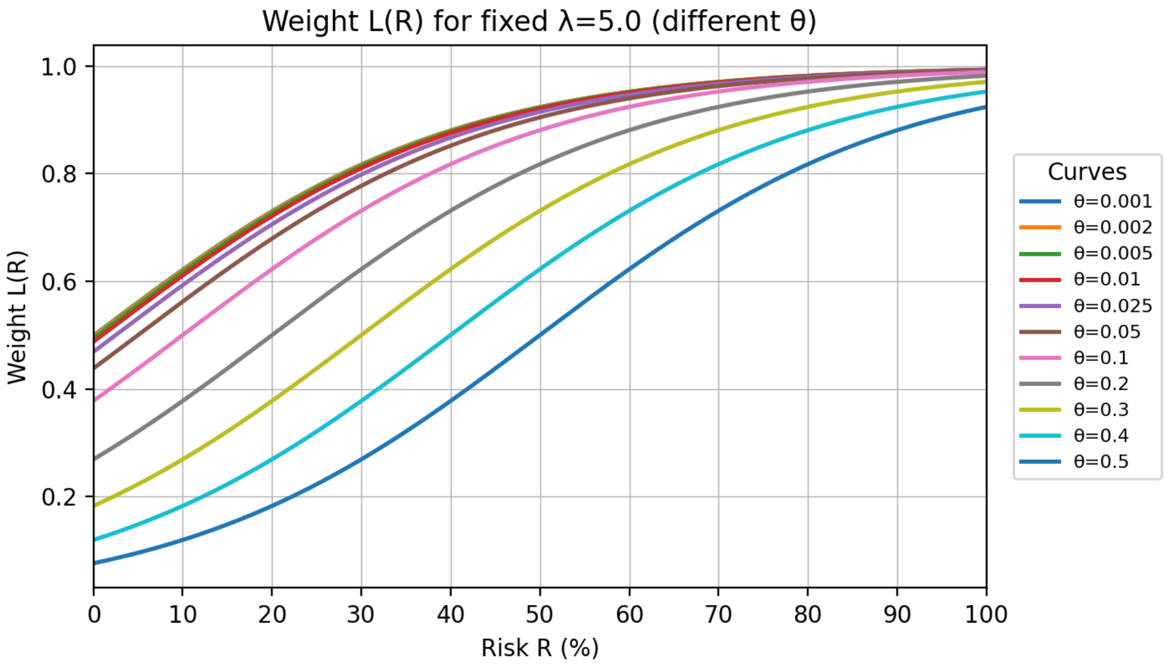
The range of logistic scores is wide in this setting (approximately 0.27 to 0.88), indicating a strong differentiation between different combinations of input risk and threshold settings. In this range, the parameter θ no longer acts merely as a fine-tuning regulator, but becomes one of the central factors determining the dynamics of assessment.

In this mode, the model transitions from a moderately responsive to a highly selective mode of operation. The choice of threshold θ directly influences whether the system will operate in a more preventive or more restrictive manner. Such behavior is appropriate for environments with a higher level of risk, where rapid detection and differentiation of risks is necessary, but it requires careful parameter setting, as the wrong choice of threshold can cause a response that is too early or too late.

2.1.5 Threshold-sensitive behavior and narrowing of the transition range (λ = 5)

The graph (seeGraph 5) shows the operation of the logistic function at a very high parameter value of λ = 5, where the model enters a distinctly nonlinear and threshold-sensitive regime. The logistic curve becomes steep, and the transition from low to high risk assessment values occurs in a relatively narrow range of input risk R.

Graph 5: Effect of threshold θ at very high sensitivity (λ = 5).



In this mode, the threshold θ has a decisive influence on the position and shape of the curve. Lower values of θ cause the logistic risk assessment to increase very rapidly and reach high levels close to the upper limit of the function even at low to medium values of R. Higher values of θ, on the other hand, shift the transition significantly towards higher values of R, which means that the system maintains a low risk assessment for a long time and then quickly transitions to a high state within a short range.

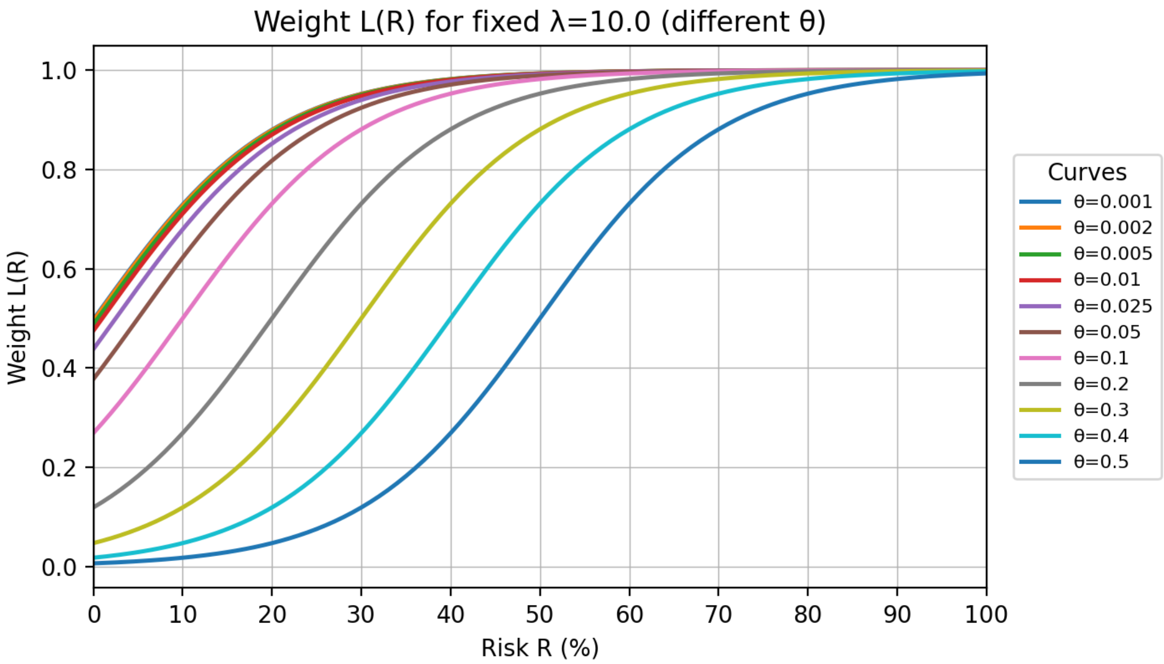
In this case, the range of logistic estimates is almost complete (approximately from 0.08 to 0.99), which indicates a very high resolution of the model. The differences between the individual curves are large, especially in the area around the inflection point, where the growth of the function is fastest. In this mode, the parameter θ directly determines the location of this transition and thus the point in time or the level of risk at which the system changes its assessment.

Such behavior is typical for scenarios where a quick and decisive response to perceived risk is required. In this range, the model acts almost like a threshold mechanism, but retains the continuity of the logistic function. This allows for precise adjustment of the system's response, but requires a very careful choice of the parameter θ, as small changes can cause large differences in the final risk assessment.

2.1.6 Loss of gradualism and approach to threshold decision-making (λ = 10)

The graph (seeGraph 6) shows the behavior of the logistic function at a very high value of the parameter λ = 10, where the model achieves a markedly steep response. The transition of the logistic risk assessment from low to high values occurs in a very narrow range of input risk R, which gives the model the characteristics of an almost discrete threshold mechanism.

Graph 6 : Effect of threshold θ at extremely high sensitivity (λ = 10).



In this mode, the threshold θ becomes the central parameter that determines at which risk level the system changes its assessment. Curves for low values of θ quickly transition to a high risk assessment range even at very low values of R, while higher values of θ shift this transition towards medium or even higher risk levels. The differences between individual curves are very pronounced and concentrated in time around the transition range.

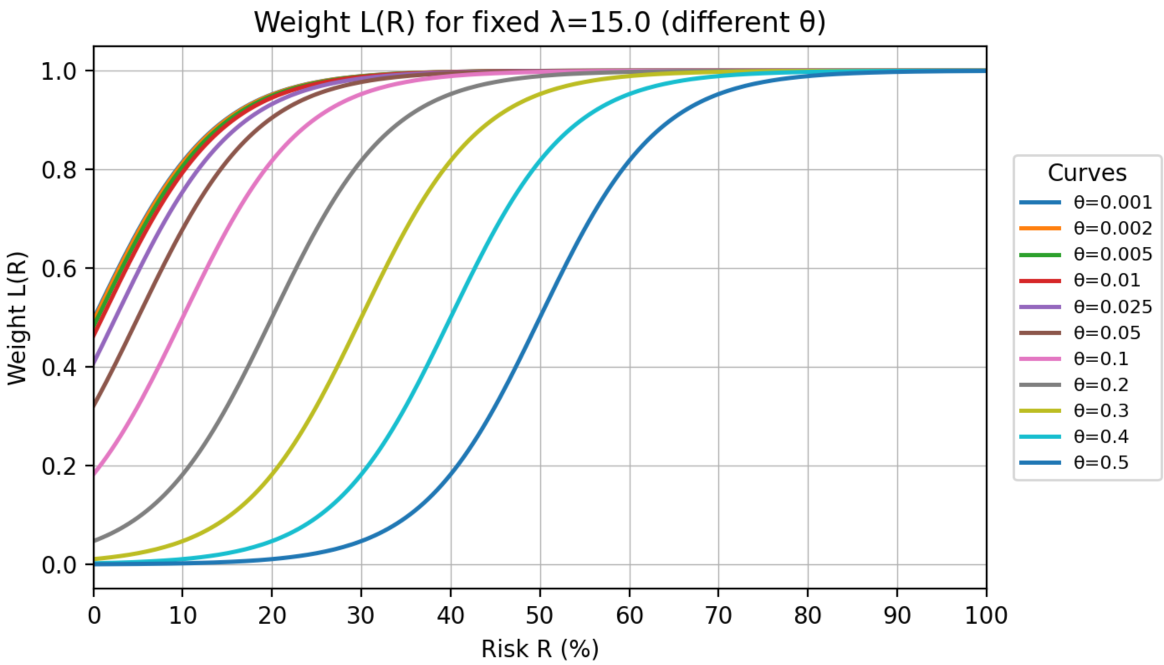
For most curves, the logistic risk assessment quickly approaches the upper limit of the function (L(R) ≈ 1), which means that once the threshold is exceeded, the system almost immediately assesses the risk as very high. In the lower R range, however, the assessment for higher θ values is very low, which further increases the contrast between low and high risk states.

This behavior is appropriate for scenarios where a quick and decisive response is needed, but at the same time requires very precise setting of the threshold θ. Small changes in this parameter can cause large differences in whether the system detects the risk early or late. The gradualness of the response is practically eliminated in this mode, while continuity remains mathematically present, giving the model a clearer and more deterministic switching decision logic.

2.1.7 Almost stepwise response and dominance of threshold over dynamics (λ = 15)

The graph (seeGraph 7) shows the behaviour of the logistic function at an extremely high parameter value of λ = 15, where the transition between low and high risk assessment is particularly steep. In this mode, the logistic function behaves almost like a step function, with most of the change in value occurring in a very narrow risk range R.

Graph 7: Effect of threshold θ at very extreme sensitivity (λ = 15).



In this case, the threshold θ practically determines the position of the transition. Curves with low θ values achieve a high risk rating even at very low R values, while higher θ values shift the transition to the medium or high risk range. The differences between the curves are very pronounced and concentrated around the transition point, while outside this range the rating remains almost unchanged.

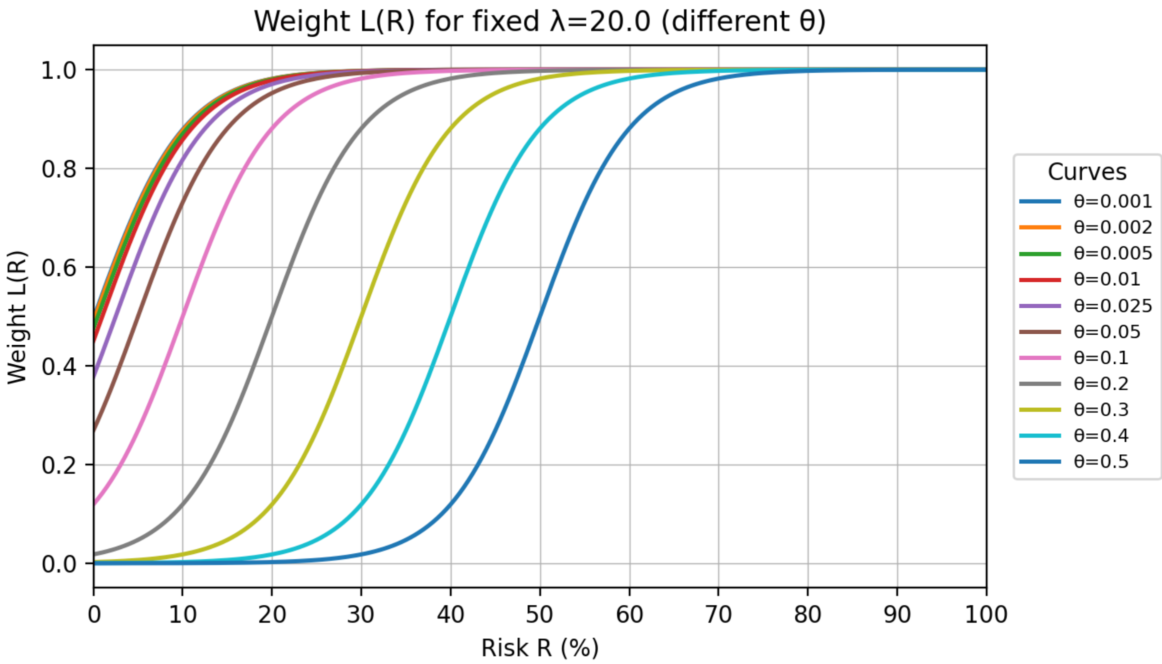
In the lower part of the R range, the logistic assessment for higher θ values is practically zero, while in the upper part it quickly approaches the upper limit of the function for all θ values. The model thus clearly distinguishes between "low" and "high" risk states, with the intermediate classes being very narrow and short-lived.

Such behavior is useful primarily in an analytical sense, as it shows the upper limit of the model's responsiveness. In operational environments, such a setting of the parameter λ would be risky, as small errors in the risk estimate R or in the choice of threshold θ can cause sudden and difficult-to-control jumps in the estimate. Nevertheless, the graph clearly shows how, as λ increases, the role of the threshold θ is transformed from a sensitivity regulator to an almost exclusively decision-making mechanism.

2.1.8 Almost discrete behavior and deterministic transition location (λ = 20)

The graph (seeGraph 8) shows the behavior of the logistic function at a very high value of the parameter λ = 20, where the transition between low and high risk ratings is practically instantaneous. In this mode, the logistic curve behaves almost like a discrete step, with most of the change in value occurring in an extremely narrow risk interval R.

Graph 8: Effect of threshold θ at almost discrete sensitivity (λ = 20).



The threshold θ in this range completely determines the location of the transition. For low values of θ, the system transitions to a high risk state even at very small values of R, while higher values of θ shift the transition towards medium or higher risk levels. The differences between the curves are pronounced but very concentrated in time, as the value of the logistic estimate remains virtually unchanged outside the transition range.

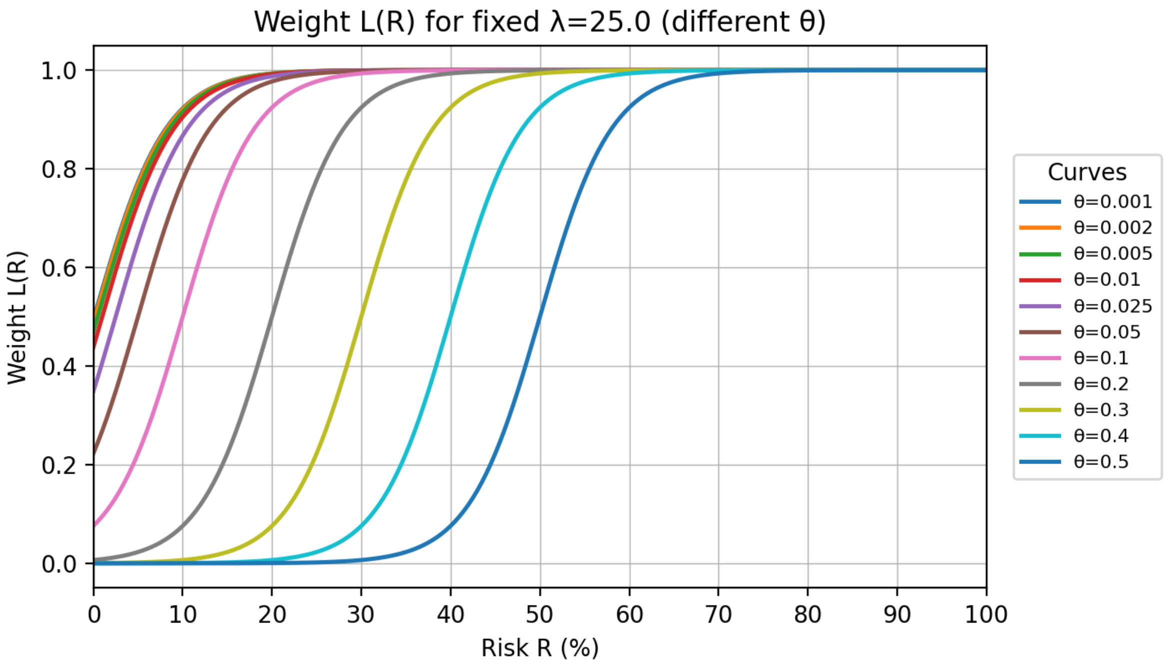
In the lower risk range R, the estimate for higher θ values is almost zero, while in the upper range it very quickly approaches the upper limit of the function for all curves. Compared to lower values of λ, the gradualness is practically lost, but the continuity remains; the model therefore takes on the characteristics of an almost deterministic decision rule.

This regime clearly illustrates the upper limit of the model's responsiveness. In practical applications, setting λ = 20 would only make sense in exceptional cases where a binary decision is required and where the input data is very reliable. In most real-world environments, however, such a setting would increase the risk of incorrect or premature decisions, as even a minimal change in the risk R or threshold θ causes a complete shift in the estimate.

2.1.9 Idealized threshold behavior without intermediate stages (λ = 25)

The graph (seeGraph 9) shows the behaviour of the logistic function at a very high parameter value λ = 25, where the transition from low to high risk assessment is extremely steep. In this mode, the logistic function behaves practically as an idealised threshold function, where the change in value occurs almost at a single point.

Graph 9 : Effect of threshold θ at nearly ideal threshold behavior (λ = 25).



In this range, the threshold θ plays an exclusive role in determining the location of the transition. Curves with low θ values very quickly reach a high risk assessment even at very low R levels, while higher θ values shift the transition to the medium or high risk range. The differences between individual curves are very sharp and concentrated around the transition point, while outside this range the values are almost unchanged.

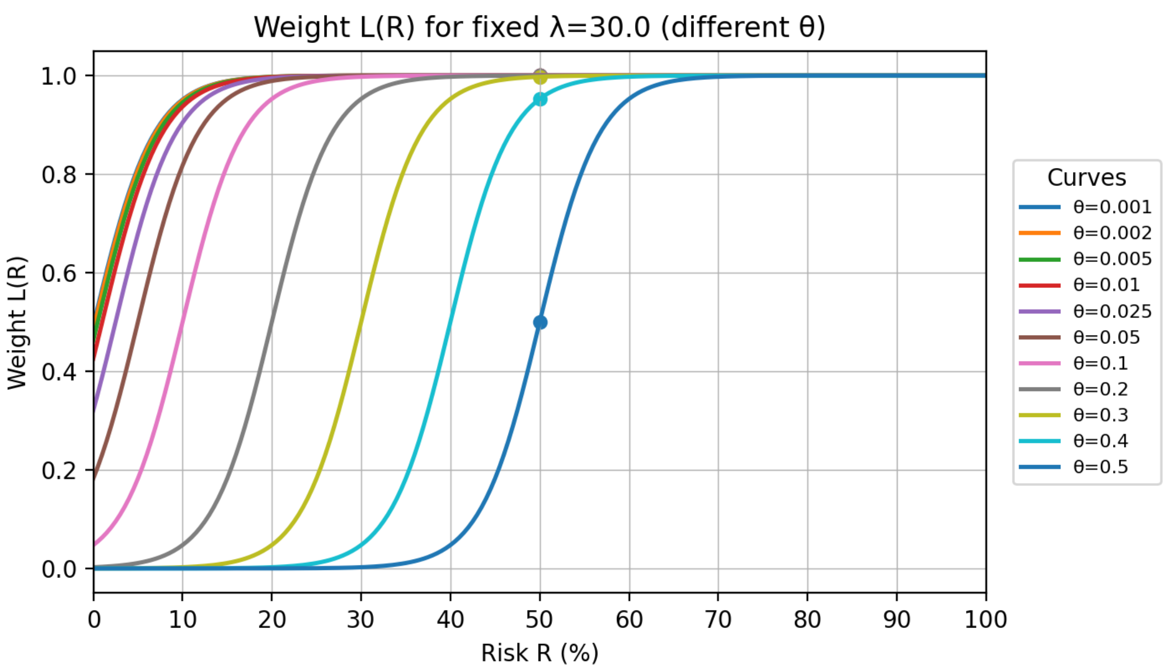
The logistic risk assessment is practically zero at low R values for larger θ, while at high R values it quickly approaches the upper limit of the function for all curves. The model thus loses almost all of the response continuity that was present at lower λ values and behaves almost binarily.

This behavior clearly illustrates the upper limit of the usefulness of the logistic function as a smooth assessment mechanism. Although such settings allow for a very clear distinction between risk states, they are problematic in real systems, as small changes in input risk or threshold cause complete jumps in the assessment. The graph therefore serves primarily as a reference example illustrating what happens when the parameter λ exceeds the range of meaningful operational use.

2.1.10 Theoretical upper limit of the responsiveness of the logistic model (λ = 30)

The graph (seeGraph 10) shows the behaviour of the logistic function at a very high value of the parameter λ = 30, where the model practically reaches its theoretical limit. The transition of the logistic risk assessment from low to high values occurs almost instantaneously, in an extremely narrow range of input risk R, causing the function to behave almost identically to a discrete threshold function.

Graph 10: Effect of threshold θ at extreme sensitivity (λ = 30).



In this mode, the threshold θ completely determines the location of the transition. Curves with low θ values transition to a high risk state even at very low R values, while higher θ values shift the transition towards medium or higher risk levels. The differences between individual curves are very pronounced, but limited almost exclusively to the area around the threshold.

Outside the transition area, the logistic risk assessment practically does not take intermediate values. At low R, the assessment is almost zero, while at higher R it almost immediately approaches the upper limit of the function. The model maintains continuity, but the transition is concentrated in an extremely narrow area around the threshold, so in practice it behaves as an almost binary decision mechanism, where the decision is highly sensitive to the accuracy of the input data.

Such a setting of the parameter λ represents the upper limit of responsiveness and serves primarily for analytical purposes. In real applications, its usefulness is limited, as even small changes in risk R or threshold θ cause a complete jump in the estimate. The graph clearly shows why extreme values of λ are not suitable for stable operational use, but are important for understanding the limits of the model and the role of threshold θ as a decisive parameter.

2.1.11 The impact of the threshold θ at a fixed value of the parameter λ

An analysis of the impact of the risk threshold θ at fixed values of the parameter λ reveals a gradual but very clear transformation of the role of the threshold in the logistic risk model. At low values of λ, the logistic function retains its pronounced flatness, so that changes in the threshold θ cause only small and almost linear shifts in the logistic risk estimate. In this range, the threshold acts primarily as a fine-tuning parameter that allows minor adjustments to the basic estimate without significantly changing the dynamics of the model's response. This mode is typical of stable environments where the emphasis is on robustness and predictability rather than rapid detection of changes.

As the value of λ increases, the influence of the threshold θ gradually becomes more pronounced. The logistic function steepens, the range of logistic estimates increases, and the differences between individual threshold values become clearly distinguishable. In this range, the threshold θ takes on the role of an actual risk perception regulator, as it determines at which level of input risk R the model begins to increase the estimate more significantly. In this mode, the model achieves high discriminative power and allows for meaningful differentiation between low, medium, and high risk levels, with the choice of threshold directly reflecting the system's risk tolerance level.

At very high values of λ, the logistic model gradually approaches almost discrete threshold behaviour. The transition between low and high risk scores is concentrated in a very narrow range around the threshold θ, outside of which the function takes on almost constant values. In this mode, the threshold θ practically determines the decision point, while the gradual response is practically eliminated and continuity remains mathematically present. This gives the model clarity and determinism in decision-making, but at the same time makes it extremely sensitive to small changes in input risk or inaccuracies in threshold selection.

The overall analysis shows that as the parameter λ increases, the role of the threshold θ changes systematically: from a correction parameter at low sensitivity, through a central regulator of risk perception at moderate values of λ, to an almost exclusively decision-making mechanism at extremely high values of λ. This transition clearly defines the limits of the model's meaningful operational use. While very low λ values ensure stability but limit differentiation, and very high λ values enable sharp differentiation but increase the risk of sudden and unpredictable jumps, the optimal applicability of the logistic model lies in the intermediate range where responsiveness and stability are balanced.

This set of graphs confirms that the threshold θ does not have absolute significance in itself, but its role is inextricably linked to the selected value of the parameter λ. Understanding their interdependence is therefore a prerequisite for the correct setting of the model and its use as a reliable tool for quantitative risk assessment.

2.1.12 Practical implications of choosing the parameter λ in risk assessment

In practice, the parameter λ determines whether the logistic part of the model behaves as a soft, gradual weighting or as a sharp threshold trigger. This directly affects how useful the assessment is for decision-making, how sensitive the system is to errors in the input risk R, and how "aggressively" the system triggers actions. The selected value of λ is therefore not just a mathematical setting, but an operational policy: it determines whether the system prioritizes stability or rapid responsiveness.

At very low sensitivity ($\lambda = 0.1$), the influence of the threshold θ on the output is minimal and the risk assessment remains within a narrow range. In practice, this means that in such a setting, the model cannot serve as a decision-making mechanism, but primarily as a stable trend indicator, as the differences between low and high risk in the output are not pronounced. The advantage of this mode is its robustness: minor fluctuations in the input data or errors in the R estimate will not cause sudden changes in the output. The disadvantage, however, is low resolution: the system has difficulty distinguishing between risk levels and, as a result, finds it more difficult to support the prioritization of measures.

At moderately low sensitivity ($\lambda = 0.5$), useful differentiation begins. The threshold θ becomes operationally relevant as the output range increases and the system already detects differences between risk levels. In practice, this is suitable for environments where you want moderate responsiveness, but still without abrupt decisions. The setting allows θ to represent the organization's risk tolerance (policy), while λ determines how strictly this policy is reflected in the output.

In a balanced regime ($\lambda \approx 1$), the logistic estimate becomes informative enough to support decision-making without the model behaving like an almost binary rule. In practice, this range is useful when the system supports processes where it is important to distinguish between several levels of risk (e.g., prioritizing suppliers or transit routes), while the input estimates R are still subject to uncertainty. This regime enables stable decision-making, where changes in R cause understandable and gradual changes in the output.

At higher sensitivities ($\lambda = 2$), the model becomes highly selective: the threshold θ begins to determine whether the system reacts early or late. In practice, this means that the settings of θ directly influence the scope of the measures taken, as transitions occur more quickly and more clearly. This mode is suitable when faster responses are required, but it requires more consistent threshold management and better quality input data, as there is an increased risk that small changes in input R will cause a larger change in the output estimate.

At very high sensitivity (λ = 5), the model begins to operate in an almost threshold-like manner: small differences in R near θ cause large changes in the output. In practice, this is only useful if the purpose of the system is to switch quickly to alarm mode, where you want a clear distinction between "acceptable" and "unacceptable" levels of risk. Such a setting only makes sense with relatively reliable input estimates, as uncertain data increases the number of false alarms or sudden status changes.

At extreme values (λ ≥ 10), the logistic part of the model behaves in practice as an almost binary trigger. This means that in an environment with natural variability or measurement errors, the system becomes difficult to control, as small shifts in R around θ lead to a complete jump in the assessment. Operationally, such a regime only makes sense in special cases where the input data is highly reliable and the threshold θ is normatively defined (e.g., strictly defined compliance limits). In most real-world scenarios, however, such sensitivity reduces the usefulness of the model as a risk classification tool, as the output loses intermediate levels and thus informational value.

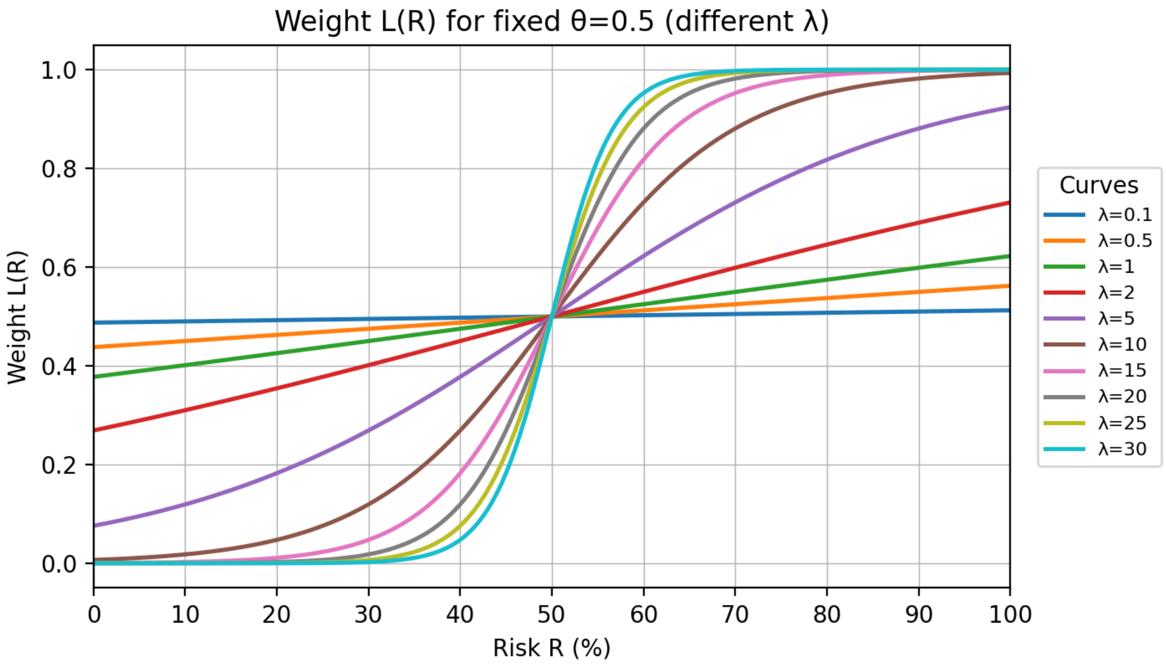
The overall practical conclusion is that λ determines the trade-off between stability and responsiveness. Low values of λ provide robustness but weak resolution; high values of λ provide sharp resolution but low tolerance to uncertainty and a greater risk of sudden jumps. Therefore, in operational use, it makes sense to choose λ in a range where the model still maintains continuous and informative dynamics, while the threshold θ remains an instrument of risk tolerance policy rather than the sole trigger for a decision.

2.2 Model analysis at a fixed threshold value θ

2.2.1 Reference threshold and balanced relationship between responsiveness and stability (θ = 0.5)

The graph (seeGraph 11) shows the performance of the logistic risk model at a fixed threshold value θ = 0.5, with the sensitivity parameter λ varying. The x-axis shows the input risk R (0–100%), while the y-axis shows the logistic risk assessment L(R).

Graph 11 : Effect of sensitivity λ at a fixed risk threshold (θ = 0.5).



Since the threshold θ is equal to 0.5, all curves intersect the value L(R) = 0.5 at R = 50%. The inflection point is the same for all curves, which clearly shows that θ determines the location of the transition, while the parameter λ determines the slope and speed of the transition.

At very low values of λ (e.g., λ = 0.1 and λ = 0.5), the logistic function is very flat. The risk assessment increases slowly and continuously, which means that the system reacts cautiously and gradually. In this mode, the model operates stably, but poorly distinguishes between low, medium, and higher risk levels.

As the value of λ increases (λ = 1, 2, 5), the transition becomes more pronounced. The logistic estimate moves away from the mean value more quickly and begins to clearly distinguish between the low and high risk areas. In this range, the model achieves a balanced relationship between responsiveness and stability, as it allows changes in risk to be detected without sudden jumps.

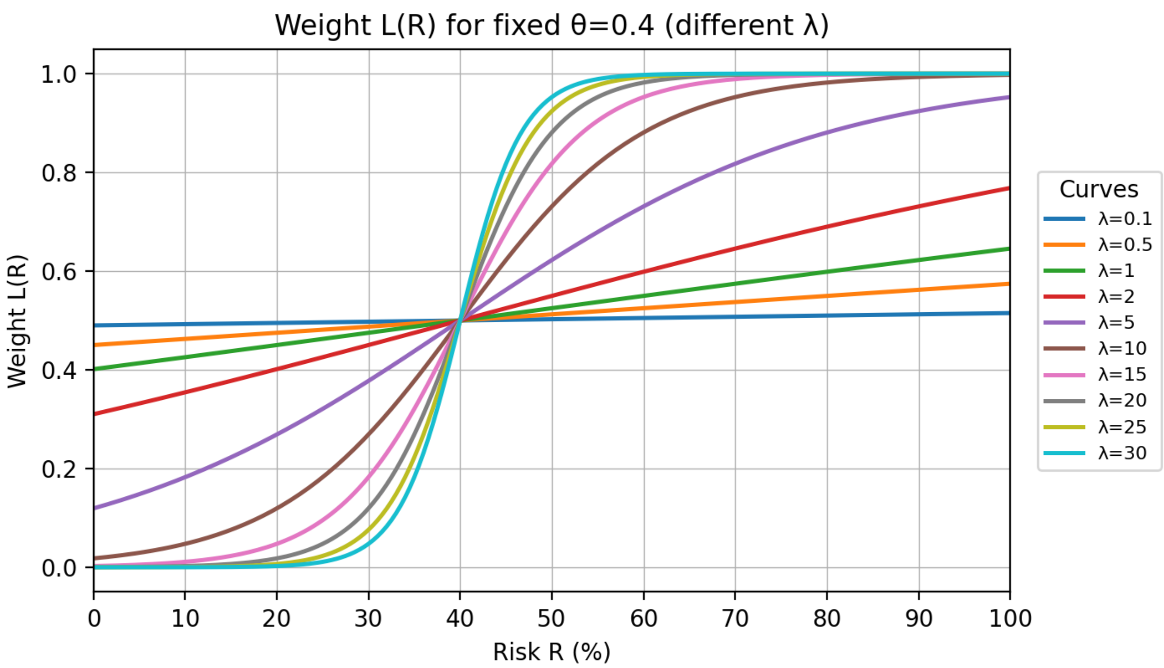
At very high values of λ (λ ≥ 10), the logistic function becomes very sharp. The transition from low to high risk assessment occurs in a very narrow range around R = 50%, outside of which the assessment quickly approaches values close to 0 or 1. In this mode, the model acts almost like a threshold decision mechanism, where the result is very sensitive to small changes in the input risk.

The graph clearly shows that the parameter λ does not affect the position of the threshold, but only the dynamics of the system's response. Low values of λ ensure continuity and robustness, while high values of λ increase resolution but at the same time reduce tolerance to uncertainty in the input data.

2.2.2 Earlier model activation and increased response preventiveness (θ = 0.4)

The graph (Graph 12) shows the performance of the logistic risk model at a fixed threshold value of θ = 0.4, with the sensitivity parameter λ varying. Compared to the case θ = 0.5, the entire transition of the logistic function is shifted towards lower risk values R, as the inflection point is now located at R = 40%.

Graph 12 : Effect of sensitivity λ at a fixed risk threshold (θ = 0.4).



All curves intersect the value of the logistic estimate L(R) = 0.5 at R = 40%, confirming that the parameter θ determines the location of the transition regardless of the value of λ. The parameter λ, as in the previous graph, regulates the slope of the curve and thus the rate of change of the risk estimate around the threshold.

At low values of λ ($\lambda = 0.1$ and $\lambda = 0.5$), the logistic function remains flat and the risk assessment increases slowly. In this mode, the system operates tolerantly and continuously, but due to the lower threshold θ, the transition zone shifts towards lower R values, so the model reaches higher L(R) values earlier than at $\theta = 0.5$.

With moderate values of λ ($\lambda = 1, 2, 5$), the transition is strengthened and becomes clearly visible. The logistic risk assessment begins to increase more rapidly even at risks below 50%, which means that the model detects the transition to the high-risk zone earlier. This represents a more preventive mode of operation.

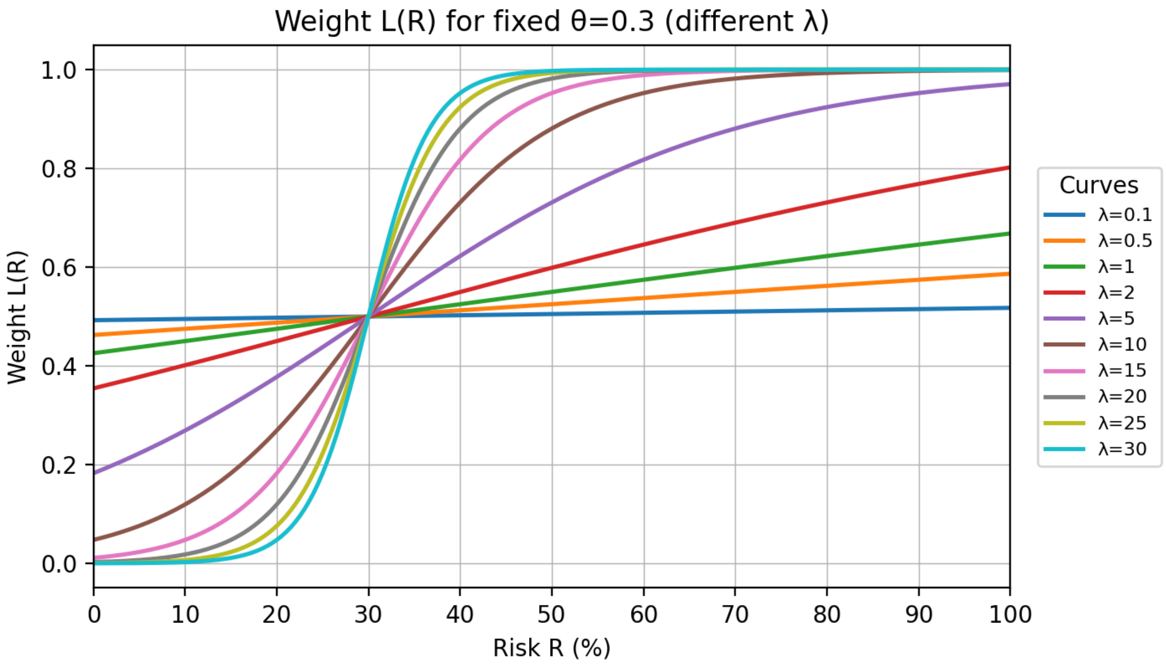
At very high λ values ($\lambda \geq 10$), the transition is concentrated in a very narrow range around R = 40%. Outside this range, the risk assessment quickly saturates towards 0 or 1. In this mode, the model operates in an almost binary manner, with even small changes in risk causing a complete shift in the assessment.

Compared to the case of $\theta = 0.5$, this graph clearly shows that lowering the threshold θ causes earlier activation of the model, while the parameter λ continues to determine whether this activation will be gradual or abrupt. The combination of a lower θ and a high λ represents a very aggressive response regime that requires highly reliable input data.

2.2.3 Shifting risk perception to an early stage while maintaining continuity ($\theta = 0.3$)

The graph (seeGraph 13) shows the operation of the logistic risk model at a fixed threshold value of $\theta = 0.3$, which means that the inflection point of the logistic function is set at R = 30%. Compared to the previous examples ($\theta = 0.5$ and $\theta = 0.4$), the transition to the increased risk area is further shifted towards lower input risk values.

Graph 13: Effect of sensitivity λ at a fixed risk threshold ($\theta = 0.3$).



Regardless of the value of the λ parameter, all curves intersect at the point L(R) = 0.5 at R = 30%, which again confirms that the θ parameter determines the location of the threshold, while the λ parameter determines the dynamics of the transition around this point.

At low values of λ (λ = 0.1 and λ = 0.5), the logistic function is still relatively flat. The risk assessment increases gradually and continuously, but due to the lower threshold θ, the system has a higher logistic assessment at with the same low values of R than in the cases θ = 0.4 and θ = 0.5. This means early but restrained risk perception.

At moderate values of λ (λ = 1, 2, 5), the transition becomes more pronounced. The logistic risk assessment begins to rise rapidly at risks of around 30%, allowing the model to clearly distinguish between low and medium risk at an early stage. This setting represents a preventive mode, where risks are detected in a timely manner, but without a completely binary response.

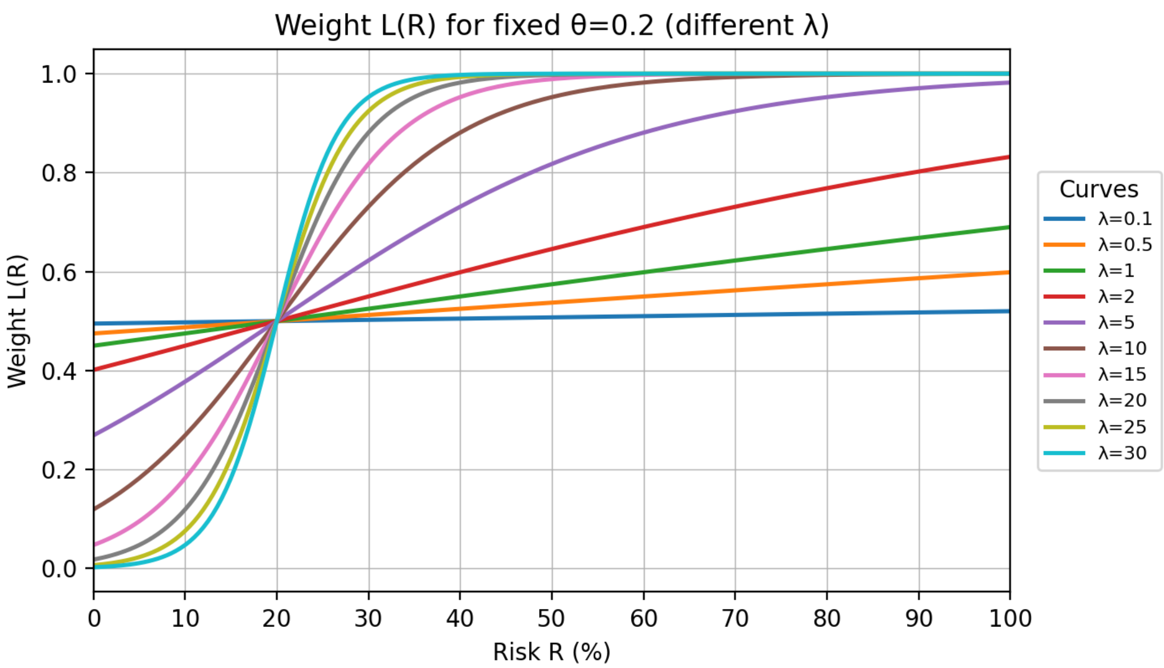
At high λ values (λ ≥ 10), the transition is concentrated in a very narrow range around R = 30%. Outside this range, the logistic risk assessment quickly saturates towards 0 or 1, meaning that the model acts almost as a threshold mechanism. The combination of low θ and high λ causes a very aggressive response, where even small changes in input risk lead to a complete change in assessment.

Compared to the cases θ = 0.4 and θ = 0.5, this graph clearly shows that lowering the threshold θ systematically shifts risk perception to an earlier stage, while the parameter λ determines whether this perception will be gradual or abrupt. Such a setting is suitable for environments with low risk tolerance, but requires high quality and reliability of input data, as the sensitivity of the system increases significantly.

2.2.4 Highly preventive mode and reduced tolerance to uncertainty (θ = 0.2)

The graph (seeGraph 14) shows the operation of the logistic risk model at a fixed threshold value of θ = 0.2, which means that the inflection point of the logistic function is located at R = 20%. Compared to the cases θ = 0.5, 0.4, and 0.3, the perception of increased risk is significantly shifted towards very low input risk values.

Graph 14: Effect of sensitivity λ at a fixed risk threshold (θ = 0.2).



All curves, regardless of the value of the parameter λ, intersect the value L(R) = 0.5 at R = 20%, which again confirms the role of the threshold θ as the determinant of the transition location.

The parameter λ, on the other hand, regulates the slope and thus the rate of change of the risk assessment around this point.

At low values of λ (λ = 0.1 and λ = 0.5), the logistic function remains flat and the risk assessment increases gradually. Nevertheless, the basic level of risk assessment in the entire R range is higher than at higher θ values, which means that the system signals potential risk very early on, but without sudden changes.

At moderate values of λ (λ = 1, 2, 5), the transition becomes more pronounced. The logistic risk assessment begins to increase rapidly even at very low values of R, which means a distinctly preventive response. In this mode, the model clearly distinguishes between low and elevated risk at an early stage.

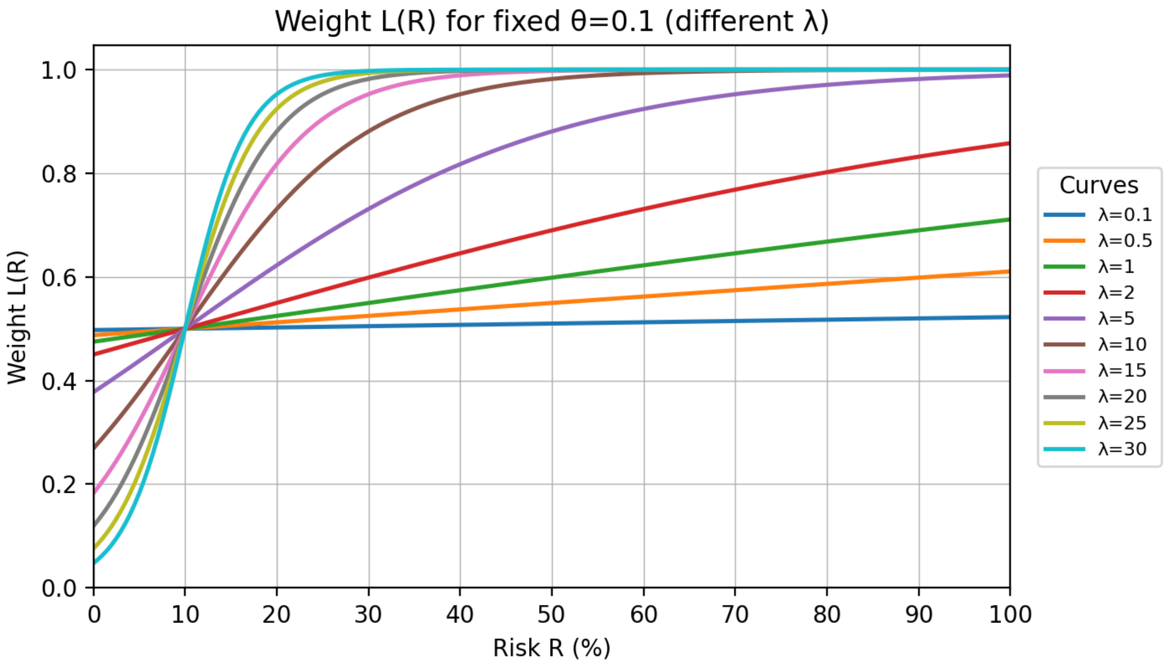
At high λ values (λ ≥ 10), the transition is concentrated in an extremely narrow range around R = 20%. Outside this range, the logistic estimate quickly saturates towards 0 or 1, which means that the model behaves almost binarily. The combination of a low threshold θ and a high λ causes a very aggressive response, where even minimal changes in the input risk cause a complete jump in the estimate.

Compared to the cases of θ = 0.3 and higher, this graph clearly shows that further lowering the threshold θ significantly increases the sensitivity of the system, while reducing the tolerance to uncertainty in the input data. Such a regime is only suitable in environments with very low risk tolerance and highly reliable input estimates.

2.2.5 Very early risk detection and increasing response aggressiveness (θ = 0.1)

The graph (seeGraph 15) shows the operation of the logistic risk model at a very low threshold value of θ = 0.1, which means that the inflection point of the logistic function is already at R = 10%. In this case, the model detects a transition to the high-risk zone even at very low input risk values.

Graph 15 : Effect of sensitivity λ at a fixed risk threshold (θ = 0.1).



All curves intersect at the point L(R) = 0.5 at R = 10%, which confirms that the parameter θ determines the location of the transition regardless of the value of the parameter λ. As in all previous cases, the parameter λ determines the slope and dynamics of the transition around this point.

At low values of λ (λ = 0.1 and λ = 0.5), the logistic function is very flat. The risk assessment increases slowly and remains relatively high even at very low values of R, but without sudden changes. In this mode, the model activates detection very early, but the response remains extended and without sudden jumps due to the low λ.

At moderate values of λ (λ = 1, 2, 5), the transition begins to take shape more clearly. The logistic risk assessment quickly moves away from the mean value even at risks of around 10–20%, which means a very early distinction between low and elevated risk. This regime is distinctly preventive, but still maintains a certain continuity of response.

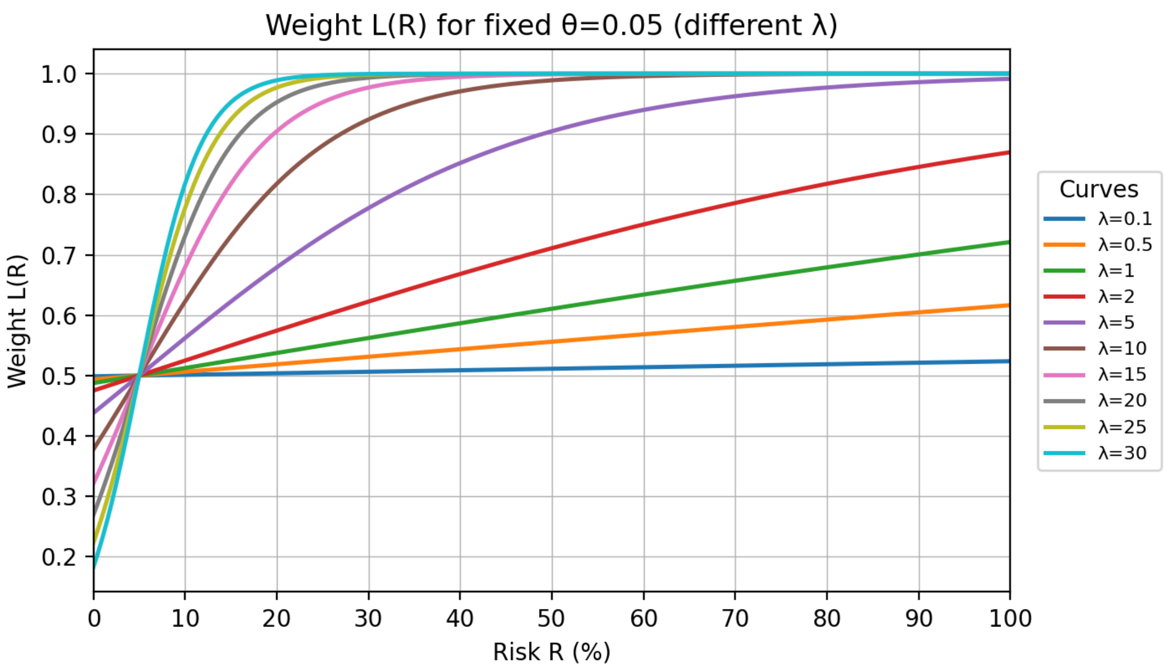
At high λ values (λ ≥ 10), the transition condenses into an extremely narrow range around R = 10%. Outside this range, the logistic risk assessment almost immediately approaches values of 0 or 1. In this mode, the model operates in an almost binary manner, with even minimal changes in input risk causing a complete shift in the assessment.

The combination of a very low threshold θ and a high parameter λ represents the most aggressive response mode of the logistic model. Such a setting is only appropriate in environments with extremely low risk tolerance and very high reliability of input data. Otherwise, it enables early detection, but significantly increases the risk of false alarms and unstable decisions.

2.2.6 Almost immediate activation and limited differentiation of risk levels (θ = 0.05)

The graph (seeGraph 16) shows the operation of the logistic risk model at an extremely low threshold value of θ = 0.05, which means that the inflection point of the logistic function is already at R = 5%. In this case, the model detects the transition to the area of increased risk almost immediately upon the occurrence of risk, regardless of its further growth.

Graph 16: Effect of sensitivity λ at a very low risk threshold (θ = 0.05).



All curves intersect at L(R) = 0.5 at the point R = 5%, which again confirms that the parameter θ determines the location of the threshold. The parameter λ only regulates the steepness of the transition and thus the speed at which the risk assessment changes around this extremely low threshold.

At low values of λ (λ = 0.1 and λ = 0.5), the logistic function remains very flat, so the risk assessment changes slowly and continuously. The risk assessment is already relatively high at zero or very low risk and increases only gradually as R increases. In this mode, the model acts as a constant indicator of heightened attention, but without a clear distinction between risk levels.

At moderate values of λ (λ = 1, 2, 5), a more pronounced transition begins to form, but still relatively early. The logistic risk assessment quickly exceeds the mean value even at very low risk levels, which means that the model acts in a distinctly preventive manner, while still maintaining a certain continuity of response.

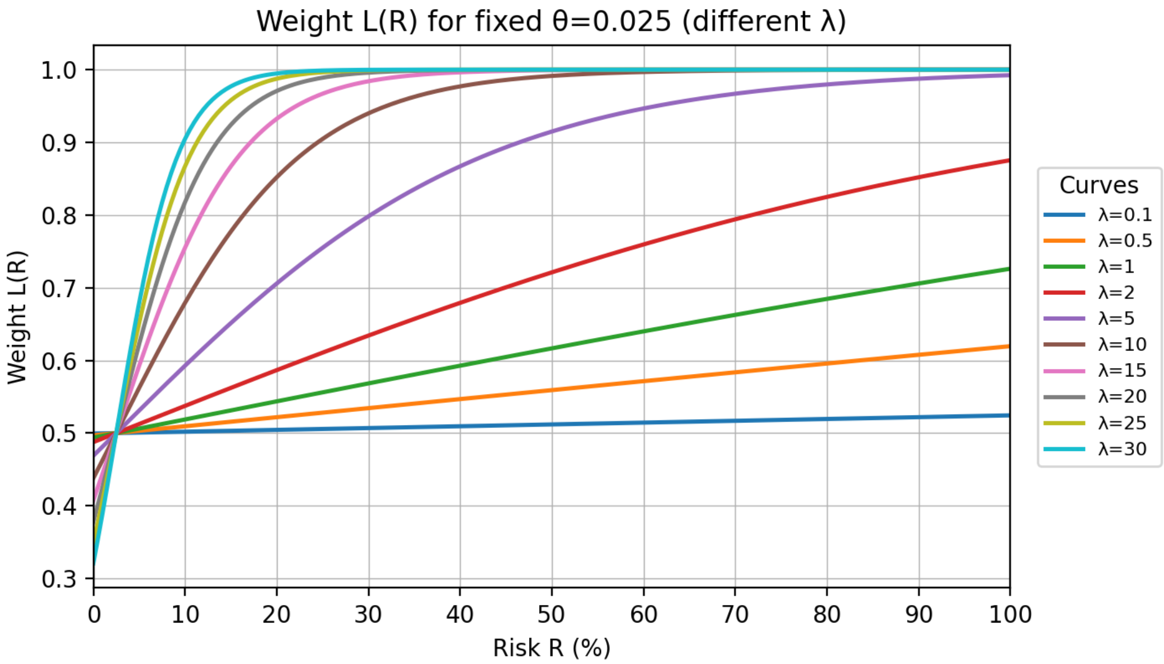
At high λ values (λ ≥ 10), the transition becomes concentrated in an extremely narrow range around R = 5%. Outside this range, the logistic risk assessment almost immediately approaches a value of 1, which means that the model practically immediately assesses the risk as very high. This behavior is almost binary and very sensitive to minimal changes in the input risk.

The combination of a very low threshold θ and a high parameter λ represents the most aggressive possible regime of the logistic model. In this case, the system acts almost like a constant alarm, where most of the input risk range is assessed as high risk. Such a setting is useful primarily as a theoretical or analytical example, as in real environments it significantly increases the risk of false alarms and loss of model discriminativeness.

2.2.7 Loss of discriminative ability and predominance of a constant state of alertness (θ = 0.025)

The graph (seeGraph 17) shows the performance of the logistic risk model at a very low threshold value of θ = 0.025, which means that the inflection point of the logistic function is already at R = 2.5%. In this case, the model treats almost every detected risk as potentially critical at a very early stage.

Graph 17 : Effect of sensitivity λ at an extremely low risk threshold (θ = 0.025).



All curves intersect at the point L(R) = 0.5 at R = 2.5%, which again confirms that the parameter θ determines the location of the transition. The parameter λ only affects the slope of the function and thus the speed at which the risk assessment moves away from this point.

At low values of λ (λ = 0.1 and λ = 0.5), the logistic function remains almost completely flat. The risk assessment is relatively high across the entire range of R and increases only slowly. In this mode, the model loses its ability to distinguish between risk levels, as it maintains an elevated assessment even at negligible values of R.

At moderate values of λ (λ = 1, 2, 5), a slightly more pronounced transition begins to form, but it still occurs very early. The logistic risk assessment quickly exceeds the mean value even at very low R values, which means that the model treats almost the entire range of input risk as elevated or high risk.

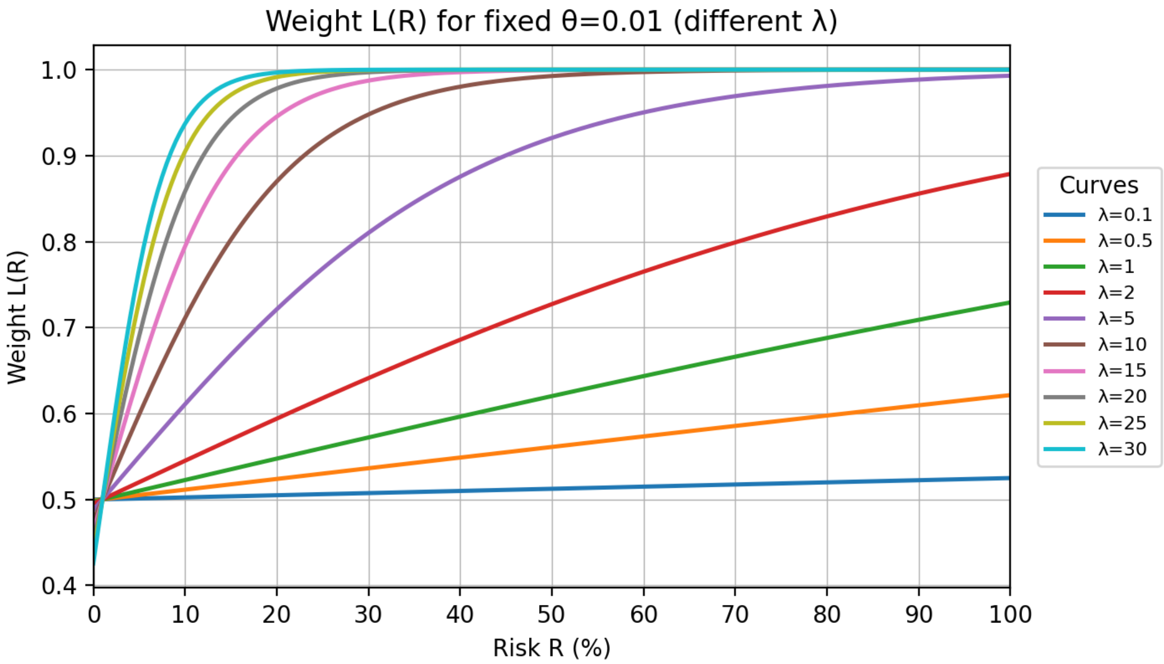
At high λ values (λ ≥ 10), the transition narrows to an extremely narrow range around R = 2.5%. Outside this range, the logistic risk assessment almost immediately approaches a value of 1. In this mode, the model essentially functions as a constant alarm mechanism, where most input states are classified as high risk.

The combination of an extremely low threshold θ and medium to high values of λ results in a loss of model discriminativeness. Although the system detects risk very early, this detection no longer has any practical value, as it does not allow for differentiation between low, medium, and high levels of risk. Such a setting therefore makes sense primarily as a theoretical illustration of the lower limit of the model, but not as an operationally useful configuration.

2.2.8 Lower limit of a meaningful threshold and the beginning of model degeneration (θ = 0.01)

At θ = 0.01, the inflection point of the logistic function (seeGraph 18) is at R = 1%, which means that the model treats even the minimum perceived risk as a turning point. The graph clearly shows that all curves intersect at the point L(R) = 0.5 at R = 1%, regardless of the value of the parameter λ, which confirms the theoretical property of the logistic function.

Graph 18: The effect of sensitivity λ at an extremely low risk threshold (θ = 0.01).



At very low values of λ (λ = 0.1 and λ = 0.5), the transition is greatly extended, so the curve remains close to the mean value for a long time, but gradually shifts towards higher values as R increases. In this range, the model practically loses its responsiveness to changes in input risk, as the differences between low and high values of R do not cause significant changes in the logistic estimate.

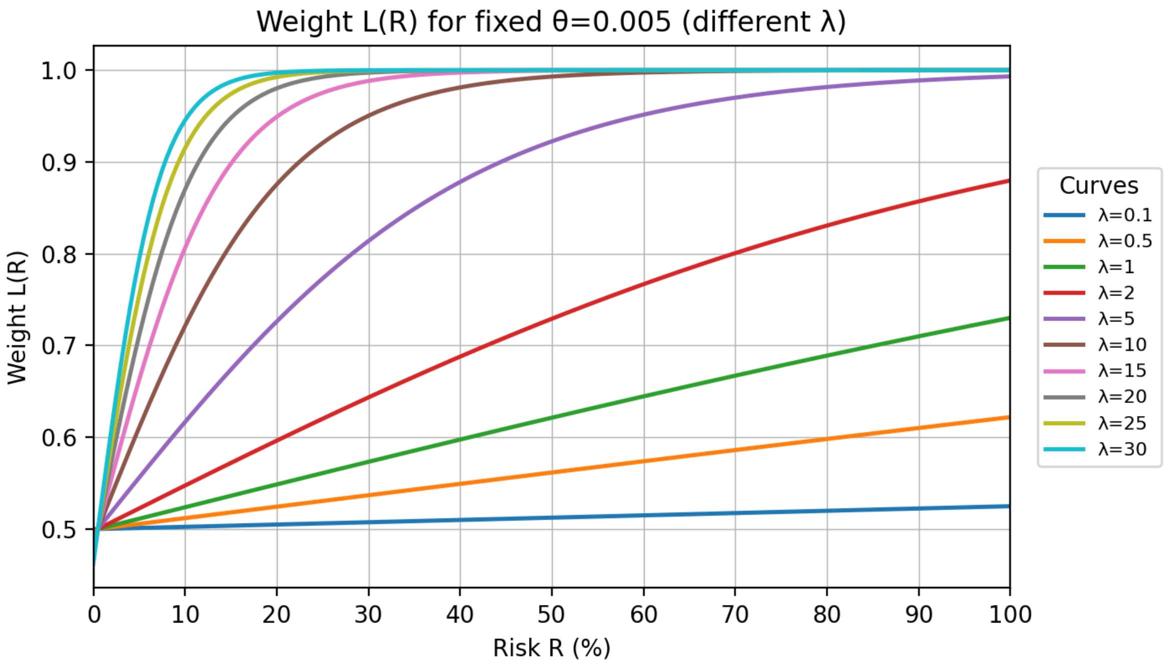
At medium values of λ (λ = 1, 2, 5), the risk estimate does begin to increase, but very slowly. Despite the fact that the input risk increases to 100%, the logistic estimate in these cases does not reach complete saturation, which means that the model does not provide a clear differentiation between moderate and very high levels of risk.

At high λ values (λ ≥ 10), the transition becomes concentrated in an extremely narrow range around R = 1%. In this case, the logistic risk assessment approaches the value of 1 almost immediately, even at very low R values. As a result, most of the input risk range does not contribute additional information value, as the model classifies most states as high risk.

2.2.9 Transition to an almost binary trigger mechanism (θ = 0.005)

At θ = 0.005, the inflection point of the logistic function (seeGraph 19) is already at R = 0.5%. This means that the model treats virtually every detected risk as a turning point even at a negligible input signal. All curves intersect at the point L(R) = 0.5 at R = 0.5%, which confirms the mathematical correctness of the model and at the same time reveals its practical limitation.

Graph 19: Effect of sensitivity λ at an extremely low risk threshold (θ = 0.005).



At very low values of λ (λ = 0.1 and λ = 0.5), the function is almost completely linear and remains close to the mean value for a long time, then slowly moves towards the upper limit at higher values of R. In this range, the model does not respond to changes in input risk in a meaningful way, as the logistic estimate changes minimally even with large changes in R.

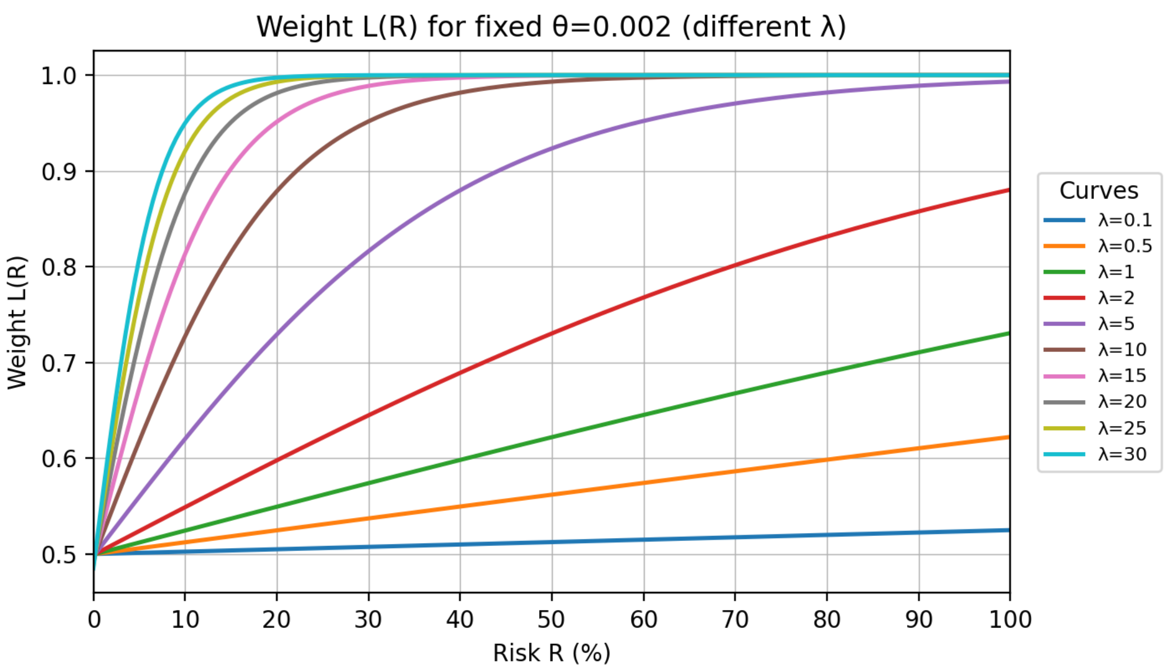
At medium values of λ (λ = 1, 2, 5), the function does begin to rise, but very gradually. Even at high risk values, the logistic estimate does not reach rapid saturation, which means that the model does not allow for a clear distinction between moderate and very high levels of risk.

At high values of λ (λ ≥ 10), the transition is concentrated in an extremely narrow range around R = 0.5%. Even a minimal increase in input risk causes the logistic estimate to jump to almost 1. As a result, the model classifies most of the input space as high risk, without the possibility of further differentiation.

2.2.10 Theoretical lower limit of the threshold and collapse of the evaluation function (θ = 0.002)

At θ = 0.002, the inflection point of the logistic function (seeGraph 20) is set at R = 0.2%. The model therefore detects a break even at a practically negligible input risk, which significantly affects its interpretability and usability.

Graph 20 : Impact of sensitivity λ at an extremely low risk threshold (θ = 0.002).



All curves intersect at point L(R) = 0.5 at R = 0.2%, which confirms the correctness of the mathematical design. However, even a minimal deviation from this point causes very different responses depending on the value of the parameter λ.

At low values of λ (λ = 0.1 and λ = 0.5), the function is almost linear and remains close to the mean value for a long time, then gradually shifts towards higher values as R increases. In this range, the model makes virtually no distinction between low and high risk, as changes in R have no significant impact on the logistic estimate.

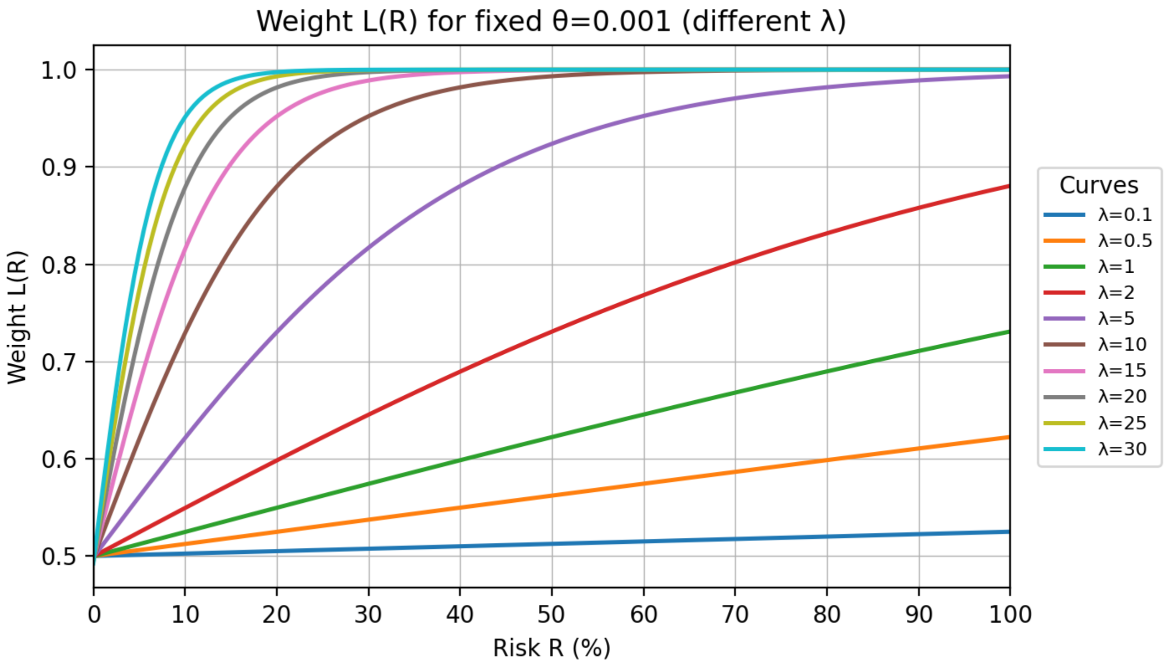
At medium values of λ (λ = 1, 2, 5), the logistic function rises gradually, but still very slowly. Even at high values of R, the risk estimate does not reach clear saturation, which means that the model does not allow for decision clarity.

At high λ values (λ ≥ 10), the transition becomes concentrated in an extremely narrow range around R = 0.2%. Even a very small change in the input risk causes an almost complete jump in the logistic estimate towards the value 1. Thus, the model treats almost the entire input space as high risk, without further differentiation.

2.2.11 Extreme case: destruction of continuity and loss of informational value of the model (θ = 0.001)

At the threshold θ = 0.001, the inflection point of the logistic function (seeGraph 21) is already set at R = 0.1%. The model therefore treats virtually every perceived risk as potentially critical. All curves intersect at the point L(R) = 0.5 at R = 0.1%, which again confirms the mathematical consistency of the model.

Graph 21 : Effect of sensitivity λ at an extremely low risk threshold (θ = 0.001).



At very low values of λ (λ = 0.1 and λ = 0.5), the logistic function remains almost unchanged and rises very slowly above 0.5 even at high risk levels. Such a response means that the model does not express either risk escalation or differentiation.

At medium λ values (λ = 1, 2, 5), the function rises moderately but is still spread across the entire input risk interval. Risk estimates remain continuous, but the transition is spread across a wide part of the interval, which reduces its usefulness for operational decision-making.

At high values of λ (λ ≥ 10), the transition of the logistic function is concentrated in an extremely narrow range around R = 0.1%. Even a minimal increase in input risk causes almost immediate saturation of the logistic estimate towards the value 1. In this case, the model acts almost exclusively as a binary trigger mechanism, without the possibility of further risk classification.

2.2.12 The effect of sensitivity λ at a fixed threshold value θ

An analysis of the impact of the sensitivity parameter λ at a fixed risk threshold θ shows that the threshold θ determines the location of the transition of the logistic function, while the parameter λ determines the mode of transition or the dynamics of the model's response.

Regardless of the selected value of λ, all curves in a given graph intersect at the point$L$ (R)=0.5 at $R=$ θ, which confirms that the inflection point is always linked to the threshold. The differences between the curves therefore do not result from a shift in the threshold, but from a change in the slope around this point: as λ increases, the transition becomes faster and more concentrated, while as λ decreases, it becomes more extended and gradual.

At low values of λ (e.g., 0.1 and 0.5), the logistic function behaves very flatly, so the risk assessment increases slowly and continuously. In this mode, the model is stable and robust, but it does not distinguish well between different levels of risk, as the logistic estimate changes only minimally over a wide range of input values. This mode is useful when we want a continuous, restrained response and high tolerance to uncertainty or noise in the input risk R, but its resolution is limited.

With moderate values of λ (approximately 1 to 5), the model transitions to a balanced mode of operation. The transition around the threshold becomes more pronounced, the logistic estimate moves away from the mean value more quickly and begins to clearly distinguish between areas of lower and higher risk, while maintaining the continuity and gradualness of the response. In this range, λ acts as an effective regulator of discriminative power, as it allows for sufficiently rapid detection of changes in risk without transforming the model into an almost binary mechanism.

At high λ values (≥ 10), the logistic function becomes very sharp. The transition from low to high risk assessment occurs in a very narrow range around $R=$ θ, outside of which the assessment quickly saturates towards 0 or 1. This gives the model a distinctly decisive nature: small changes in the input risk near the threshold cause large changes in the logistic assessment, which increases the sensitivity of the system while reducing the tolerance to inaccuracies in the input data. In this mode, the model becomes particularly useful where the input estimates are very reliable and where a sharp break between risk states is desirable, but in general it is more prone to false alarms or sudden jumps.

A comparison of graphs with different fixed values of θ further shows that lowering the threshold shifts the transition range towards lower risk values, making the model more preventive, but at the same time increasing the probability of early saturation (i.e., that the system assesses most of the range R as high risk). At very low θ values (e.g., 0.01, 0.005, 0.002, 0.001), the operational usefulness of the model begins to decline because the break occurs at negligible risk values. In combination with higher λ, this leads to a regime where the logistic estimate almost immediately reaches its upper limit and thus loses its ability to further differentiate between medium and high risk. In combination with very low λ, however, the function remains close to the mean value and likewise loses its informational value because changes in R do not cause sufficient differences in the estimate.

The overall analysis confirms that, for a fixed θ, the parameter λ is the primary regulator of responsiveness: it determines whether the model will act as a smooth evaluation mechanism, a balanced discriminator, or an almost binary trigger. At the same time, cases with very low θ reveal a practical limitation: if the threshold is set too low, the model either saturates too quickly (for large λ) or becomes insufficiently informative (for small λ). Therefore, the choice of θ only makes sense in the range where the threshold represents a real relevant risk boundary, and λ is then used to set the desired response steepness depending on the stability of the environment and the reliability of the input data.

2.2.13 Practical implications of choosing the threshold θ

With a fixed threshold θ, the model first answers the question: when (at what risk level R) should the system start to seriously raise the rating? This is the content of the threshold. The parameter λ then determines how this happens: gradually (tolerantly) or almost binary (strictly). Therefore, in operational terms, θ is primarily a setting of the activation policy (where the "limit" is), while λ is a setting of the decisive temperament (soft vs. sharp).

When θ = 0.5, the system only enters the elevated risk zone at approximately 50% of the input risk. In practice, this is an appropriate threshold when an organization assesses that greater tolerance is permissible for medium levels of risk, and measures are only escalated when the risk is already clearly expressed. At low λ, this regime will function as stable monitoring without sharp decisions; at moderate λ, it becomes useful for classifying the level of risk; and at high λ, it changes to the rule "over 50% → alarm," where the result is very sensitive to estimates close to this limit. Operationally, this means: $\theta = 0.5$ is the threshold where the system does not normally give "excessive" alarms, but at high λ it can cause sharp jumps precisely in the area where there is the most uncertainty in the assessment.

At $\theta = 0.4$, activation shifts to 40% risk, which in practice means that you want to act sooner rather than wait for the risk to approach half the range. Such a threshold is useful where the consequences of delay are greater (e.g., critical suppliers, sensitive transit channels, high dependence on availability). In combination with a low λ, the system remains tolerant, but "skews" the assessment upward earlier; at moderate λ, it begins to distinguish between low and elevated risk earlier; at high λ, it quickly approaches the binary trigger at 40%, which means more alarms and a greater need for accurate input estimates of R.

At $\theta = 0.3$, the system begins to react "seriously" at around 30% risk. In practice, this corresponds to organizations with lower risk tolerance and a greater emphasis on early detection. Such a threshold has practical value if the model still retains some continuity (typically at moderate λ values), as it allows risks to be classified and addressed early on, but does not necessarily lead to constant alarms. However, if λ is high, the threshold transition becomes denser and the model quickly starts to behave like a , with "around 30% causing a jump", which can cause unstable state switching in environments with uncertain data.

At $\theta = 0.2$, activation occurs at a 20% risk, which is very early. In practice, this means that the system treats even relatively small signs of risk as significant and wants to trigger measures at an early stage. This is only useful if there is a clear reason for such a low tolerance (e.g., highly sensitive functions, low risk tolerance, high value of protected resources). The disadvantage is that such a threshold quickly increases the number of situations where the system is "on the edge" and therefore sensitive to errors in R; at higher λ values, this turns into almost binary operation at 20%, which in practice can mean more frequent alarms and more unnecessary escalations.

At $\theta = 0.1$ (10%), the model activates the transition very early. In practice, this means that the system is designed as a distinctly "nervous" protection: even a small detected risk signal can trigger an elevated assessment, and at high λ, an almost immediate switch to a high state.

This may work in environments where the goal is immediate prevention and the inputs are very reliable, but in most real-world cases it increases the likelihood of false alarms and constant escalation.

At θ = 0.05, 0.025, 0.01, 0.005, 0.002, 0.001, the threshold becomes so low that the model often loses its operational value. At high λ, most of the R range is quickly assessed as "high risk" (early saturation), so the output no longer distinguishes meaningfully between risk levels. At low λ, the output remains close to the mean and also does not carry enough information. In practice, this means that such θ is suitable primarily as an analytical illustration of the model's limits, rather than as a setting that would help prioritize actions.

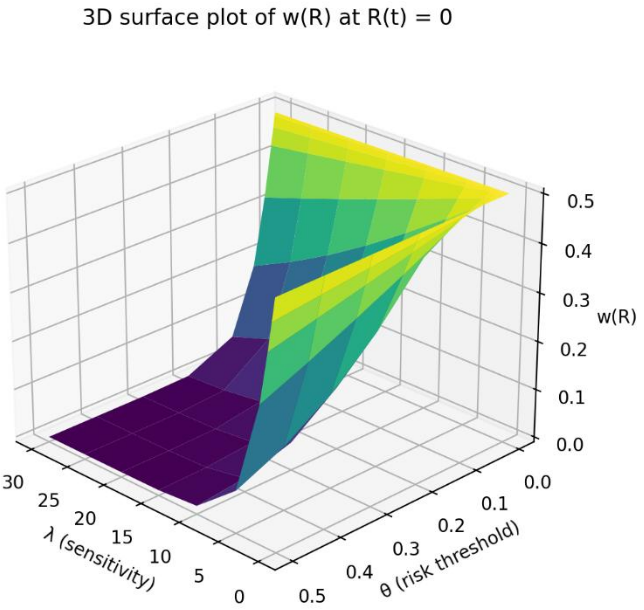
With a fixed θ, the most important consequence is that θ defines how "early" the system starts to transition to an elevated assessment, thereby directly determining the preventiveness of the policy. A lower θ means earlier activation, but also a greater likelihood that the model will either saturate quickly or become too sensitive to input data uncertainty. The parameter λ then determines whether this policy will be implemented gradually (moderate λ) or as an almost binary decision (high λ). Operationally, it therefore makes sense to choose θ in a range where the threshold still represents a real relevant risk limit, and only then use λ to set the desired sharpness of the response based on the quality of the input estimates R and the need for stable decision-making.

2.3 Synergistic effect of parameters λ and θ at fixed risk R

2.3.1 Latent weighting regime in the absence of risk (R(t)=0)

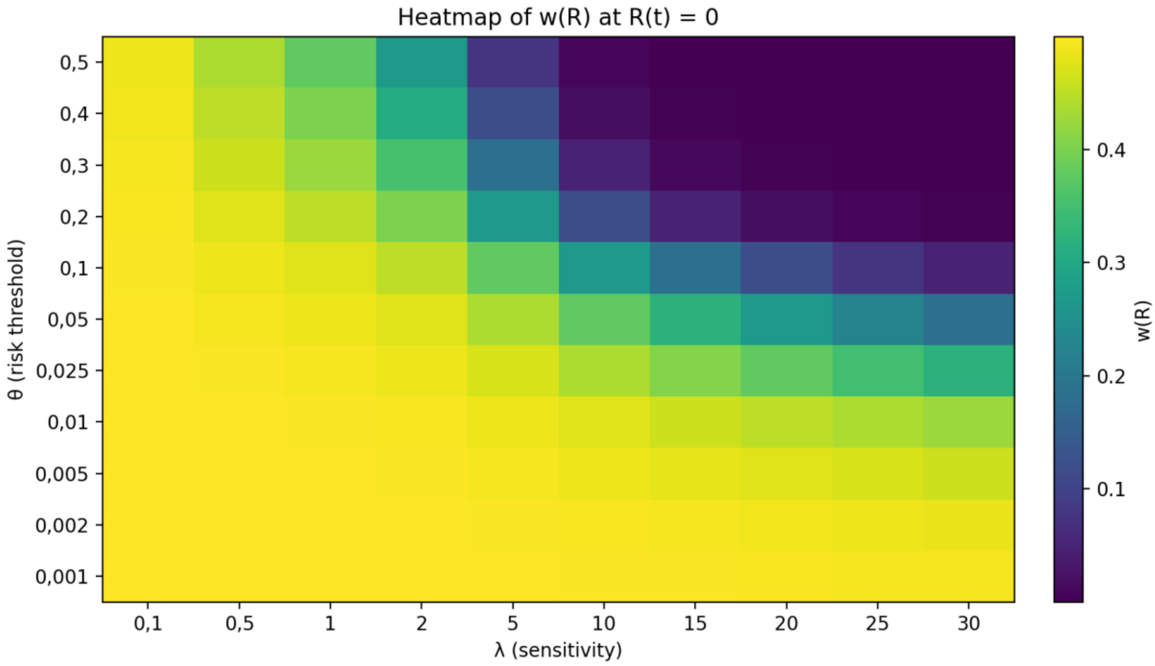
The graph (seeGraph 22) shows the three-dimensional distribution of the dynamic weight $w(R)$ at input risk $R\ (t)$=0 depending on the sensitivity parameter λ and the risk threshold θ. The area shown provides a comprehensive insight into the operation of the logistic function in the area where there is no risk, but the system nevertheless performs evaluation based on the set parameters.

Graph 22 : Influence of parameters λ and θ on the dynamic weight at zero risk (R(t) = 0).



At zero input risk, the logistic function is located significantly to the left of the inflection point $R= \theta$, so the weight values are generally low. Nevertheless, the graph clearly shows that the weight is not constant, but varies significantly depending on the combination of parameters. The highest (least low) weight values occur at very low thresholds θ and simultaneously low values λ, where the product$\lambda\ \theta$ is small, so the value$w$ (0) approaches 0.5, but remains less than 0.5 for all configurations considered. This behavior indicates a distinctly conservative operating mode, in which the system assumes the possibility of latent or unexpressed risks.

Graph23 : Heat map of dynamic weights w(R) at zero input risk (R(t)=0).



The heat map (seeGraph23) represents a discrete projection of the same parametric dependence shown by the surface graph and allows direct comparison of individual parameter combinations.

As the threshold θ increases, the weight value decreases rapidly, which means that the system effectively filters out zero or negligible risk at stricter threshold settings. This effect is particularly pronounced at higher values of the parameter λ, where the increased steepness of the logistic function causes the weight in the range $R < \theta$ to collapse almost entirely towards zero. In this mode, the system practically does not react to absent risk and maintains a passive stance until the input signal approaches the transition threshold.

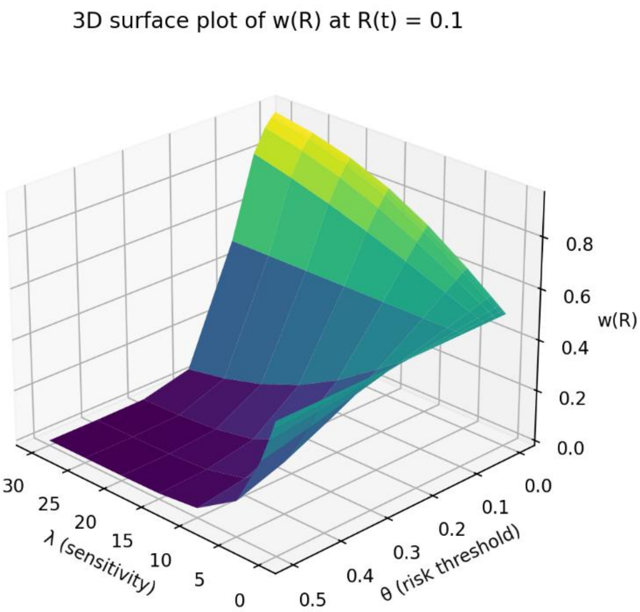
The graph also reveals that the parameter λ plays the role of a threshold effect amplifier at zero risk. At low values of λ, the transitions are smoother and the weight remains moderate even at higher thresholds, while high values of λ cause a pronounced polarization between the negligible weight range and the rapid increase range. Consequently, at $R\ (t)$=0, a high λ generally further reduces the weight (pushing it faster towards 0), especially when θ is greater than 0. The lowest weights occur in combinations where$\lambda\,\theta$ is small (typically low λ and lowθ).

This behavior confirms that the model does not function merely as a passive map of the input risk, but also incorporates an implicit safety attitude that is entirely determined by the choice of parameters. The mode $R\ (t)$=0 is therefore not a trivial case, but reveals the basic philosophy of the system's operation – whether it trusts the environment by default or operates cautiously and restrictively from the outset.

2.3.2 Transition to active perception at low risk (R(t)=0.1)

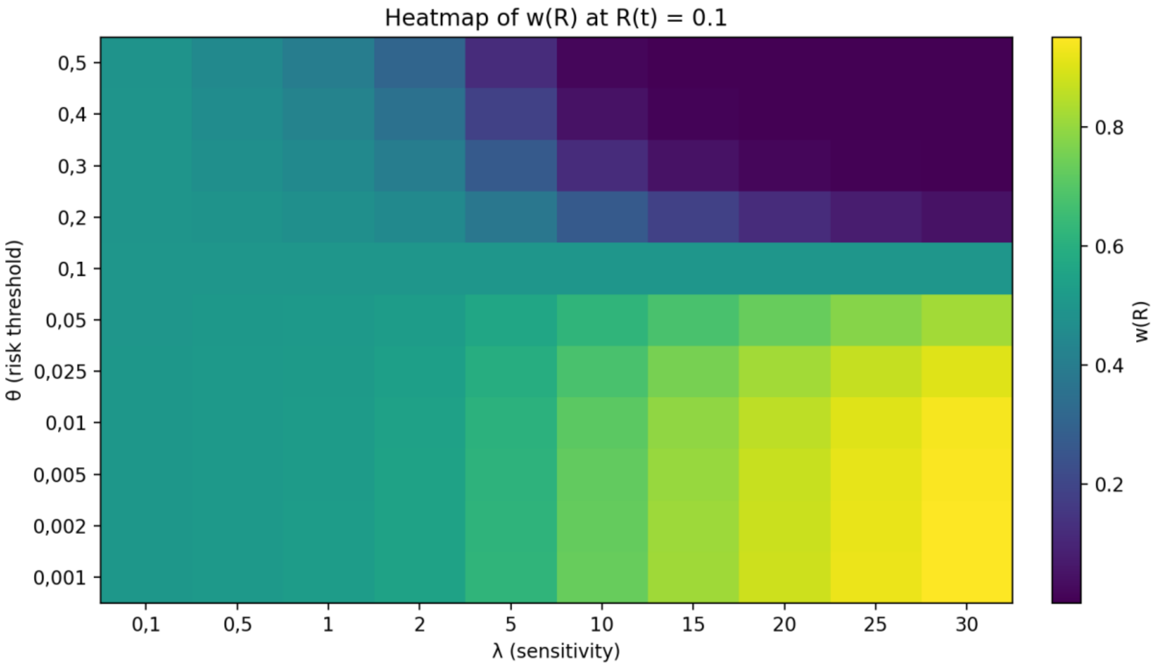
The graph (seeGraph 24) shows the three-dimensional distribution of the dynamic weight $w(R)$ at a low but non-zero input risk value $R\ (t)$=0.1 depending on the sensitivity parameter λ and the risk threshold θ. Compared to the zero-risk regime, the logistic function in this case shifts closer to the threshold value, which is clearly reflected in the increased amplitude of the weight and the more pronounced differentiation between individual parameter configurations.

Graph 24 : Influence of parameters λ and θ on the dynamic weight at low input risk (R(t) = 0.1).



At low threshold values θ, the weight $w(R)$ reaches very high values, especially at higher values of the parameter λ. This means that even at a relatively low perceived risk, the system assigns a very high weight to the evaluation mechanism, which indicates a distinctly preventive and sensitive mode of operation. In this range, the input risk $R\ (t)$=0.1 is already to the right of or very close to the inflection point, so the logistic function transitions to a steeper part of the increase.

Graph 25 : Heat map of dynamic weights w(R) at low input risk (R(t) = 0.1).



The heat map (seeGraph 25) represents a discrete projection of the same parametric dependence shown by the surface graph and allows a direct comparison of individual parameter combinations at low but non-zero input risk.

As the threshold θ increases, the weight values gradually decrease as the input risk moves back into the range below the transition threshold. This effect is more pronounced at higher values of λ, where the increased steepness of the logistic function causes a sharper transition between the low and high weight ranges. At lower values of λ, the transitions are smoother and the weight remains moderate over a wider range of threshold settings, reflecting a more tolerant and stable system response.

The range of weight values is significantly wider for this setting than for $R\ (t)$=0, indicating that even a small increase in input risk triggers a significant differentiation between configurations. In this mode, the parameter

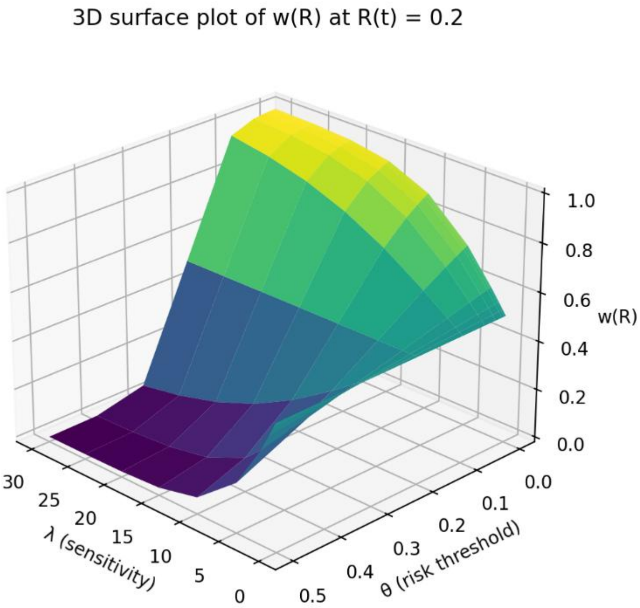
θ in this mode no longer acts merely as a filtering mechanism for negligible risk, but directly determines whether the system will detect the risk as relevant or still consider it acceptable.

At $R\ (t)$=0.1, the model thus transitions from exclusively latent assessment to the active detection phase. The combination of a low threshold θ and a high parameter λ causes a very rapid increase in weight, while higher thresholds and lower values of λallow for a more restrained response. This mode clearly illustrates the transitional range of the model's operation, in which the system is not yet in a full alarm state, but is already actively distinguishing between levels of risk and preparing for a possible further escalation of the situation.

2.3.3 Consistent detection and high sensitivity to parameters (R(t)=0.2)

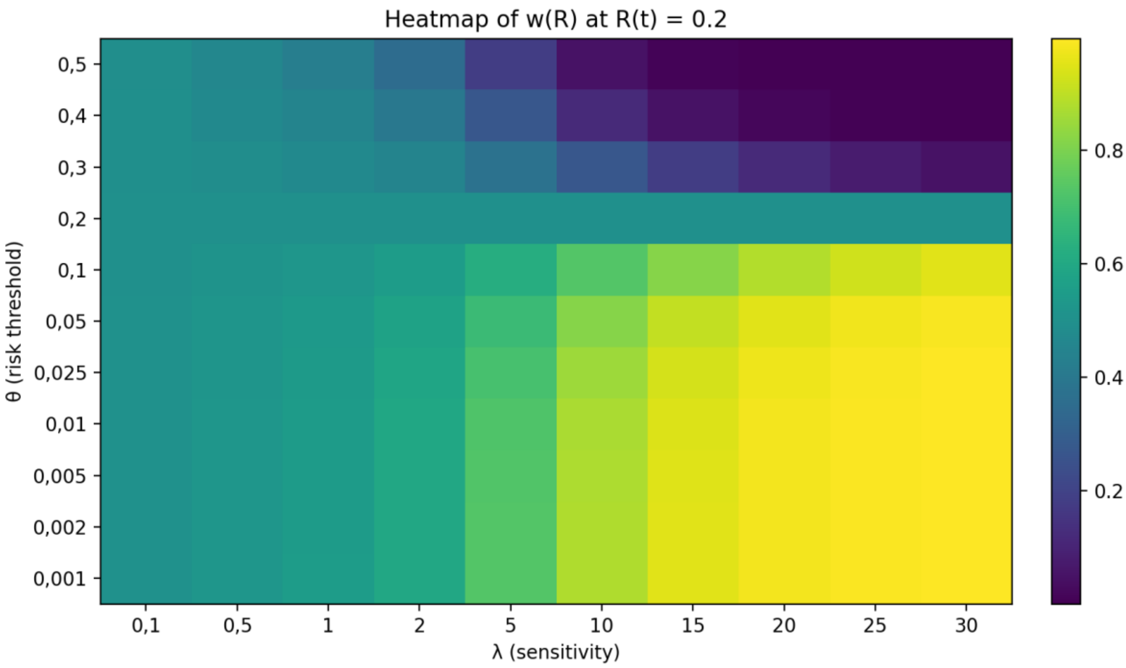
The graph (seeGraph 26) shows the three-dimensional distribution of the dynamic weight $w(R)$ at a moderately low input risk value $R\ (t)$=0.2 depending on the sensitivity parameter λ and the risk threshold θ. Compared to the low-risk regime, the logistic function in this case further approaches the threshold value or even exceeds it for certain combinations of parameters, which is reflected in a further increase in weight and an even more pronounced differentiation between system configurations.

Graph 26 : Influence of parameters λ and θ on the dynamic weight at moderately low input risk (R(t) = 0.2).



At low threshold values θ, the weight $w(R)$ reaches very high values across almost the entire range of the parameter λ, which means that the system detects the risk as highly relevant even at this level of input signal. In this range, the input risk $R\ (t)$=0.2 is clearly to the right of the inflection point, so the logistic function is often above the inflection point in this range and the weight increases towards high values in many configurations, with the rate of convergence depending on λ.

Graph 27 : Heat map of dynamic weights w(R) at moderately low input risk (R(t) = 0.2).



The heat map (seeGraph 27) represents a discrete projection of the same parametric dependence shown by the three-dimensional surface graph and allows a direct comparison of the influence of the parameters λ and θ at moderately low input risk.

As the threshold θ increases, the high weight range gradually recedes as the input risk moves back toward or below the transition threshold. This shift is particularly pronounced at higher values of the parameter λ, where the increased steepness of the logistic function causes a sharper distinction between the low and high weight ranges. At lower values of λ, the transitions are more gradual, and the weight remains moderate over a wider range of threshold settings, indicating a more balanced and less impulsive response of the system.

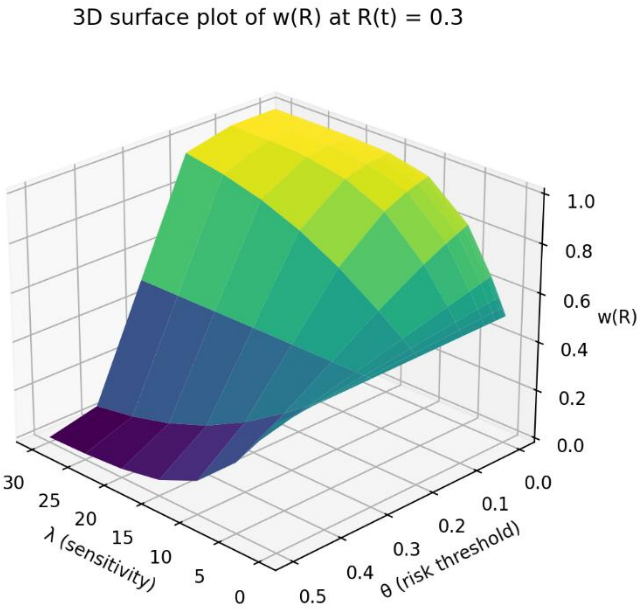
The range of weight values is even wider with this setting than with $R\ (t)$=0.1, confirming that as the input risk increases, so does the sensitivity of the model to the parameter configuration. The parameter θ takes on a distinctly decisive role in this mode, as it clearly determines whether the risk will be treated as already exceeded or whether the system will continue to operate in a restrained mode.

At $R\ (t)$=0.2, the model enters a phase of consistent risk detection, where the weight is no longer limited to the transition range but reaches high values in many configurations. The combination of a low threshold for θ and medium to high values for λ leads to stable and decisive responsiveness, while higher thresholds and lower values for λ allow for a more gradual and tolerant response. This mode represents a transition from initial activation to a more consolidated assessment phase, in which the system already clearly distinguishes between acceptable and unacceptable levels of risk.

2.3.4 Stabilization of high weights in the moderate risk range (R(t)=0.3)

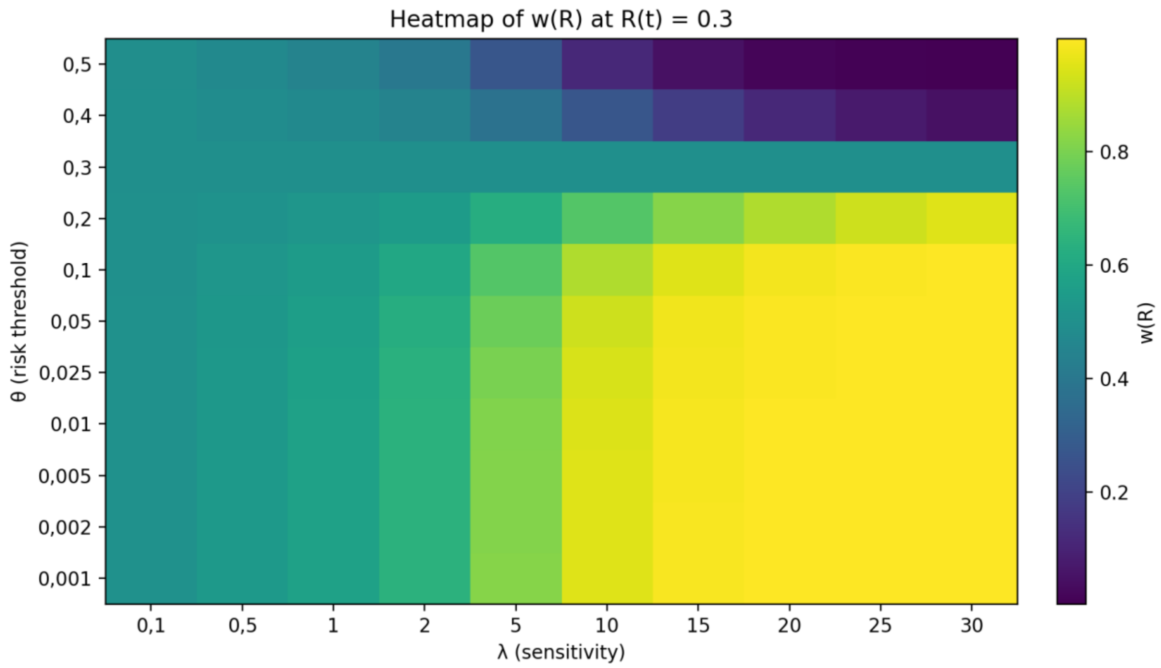
The graph (seeGraph 28) shows the three-dimensional distribution of the dynamic weight $w(R)$ at a moderate input risk value $R\ (t)$=0.3 depending on the sensitivity parameter λ and the risk threshold θ. Compared to previous regimes, in this case the logistic function is already close to or above the inflection point in most configurations, which is reflected in high weight values and further stabilization of the system response.

Graph 28 : Influence of parameters λ and θ on the dynamic weight at moderate input risk (R(t) = 0.3).



At low and medium threshold values θ, the weight $w(R)$ reaches very high values across almost the entire range of the parameter λ. This means that at this level of input risk, the system perceives the risk as extremely significant, regardless of the degree of sensitivity. In this range, the input risk $R\ (t)$=0.3 is clearly to the right of the inflection point, so the logistic function operates in the upper, saturated part, where the weight approaches maximum values.

Graph29 : Heat map of dynamic weights w(R) at moderate input risk (R(t) = 0.3).



The heat map (seeGraph29) represents a discrete projection of the same parametric dependence shown by the surface graph and allows a direct comparison of parameter combinations in the moderate input risk mode.

As the threshold θ increases, the high weight range gradually narrows, especially at lower values of the parameter λ. At higher values of λ, the transition is much sharper, causing the weight at higher thresholds to quickly transition from near-maximum to moderate values. At lower values of λ, the transition is more gradual, allowing for a softer and more moderate response of the system even at stricter threshold settings.

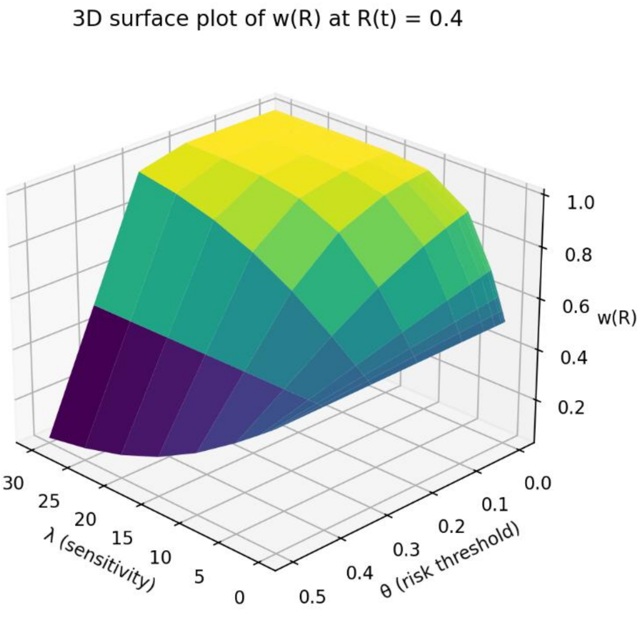
The range of weight values in this mode is still wide, but it gradually decreases compared to lower risk levels, as most of the area approaches the upper weight limit. The parameter θ in this range acts primarily as a saturation limit regulator, as it determines at which configurations the system maintains the maximum weight and when it begins to gradually reduce the weight.

At $R\ (t)$=0.3, the model enters a phase of stable risk detection, in which the weight is high in most cases and relatively independent of minor changes in input parameters. The combination of a low threshold θ and medium to high values of the parameter λ leads to almost immediate saturation of the weight, while higher thresholds and lower values of λ still allow for a certain degree of restraint. This regime represents a transition from selective perception to a state where the system treats risk as permanently present and requires consistent treatment in subsequent phases of the model.

2.3.5 Almost complete activation and reduction of variability (R(t)=0.4)

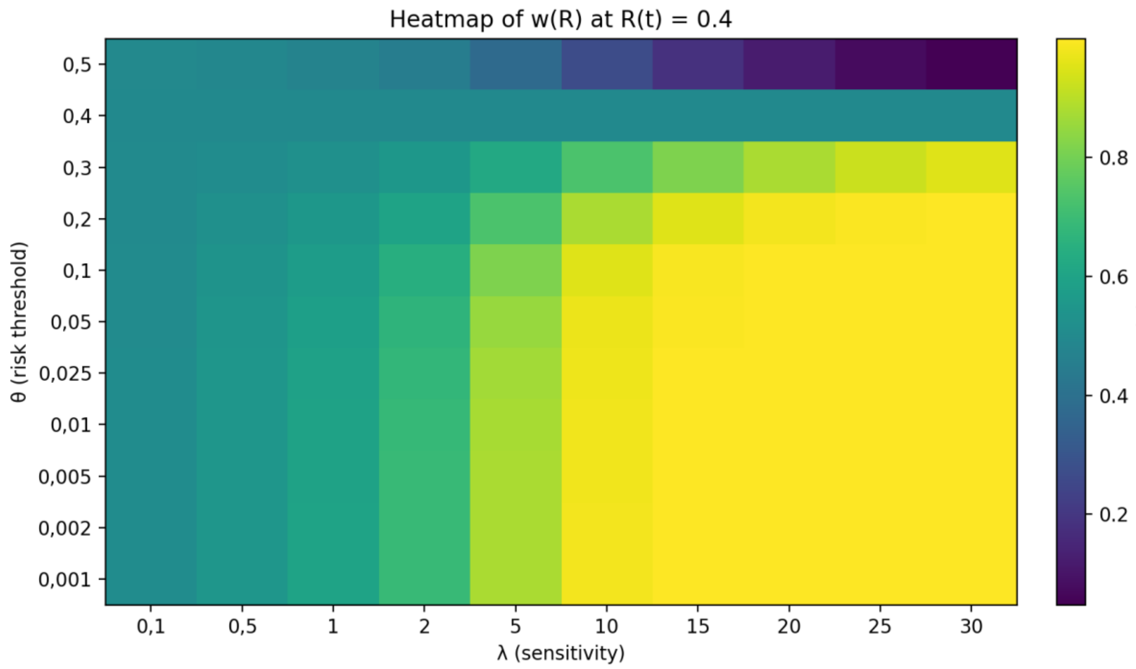
The graph (seeGraph 30) shows the three-dimensional distribution of the dynamic weight $w(R)$ at an increased input risk value $R\ (t)$=0.4 depending on the sensitivity parameter λ and the risk threshold θ. In this mode, the logistic function is already significantly above the inflection point in the vast majority of configurations, which is reflected in the predominantly high weight values and reduced response variability.

Graph 30 : Influence of parameters λ and θ on the dynamic weight at increased input risk (R(t) = 0.4).



At low and medium threshold values θ, the weight $w(R)$ reaches very high, often almost saturated values across almost the entire range of the parameter λ. This means that the system perceives the risk as highly relevant and requires consistent treatment regardless of the degree of sensitivity. In this range, the input risk $R\ (t)$=0.4 is clearly to the right of the inflection point, so the logistic function operates in the upper part of its domain, where the additional effects of the parameters are limited.

Graph 31 : Heat map of the dynamic weight w(R) at increased input risk (R(t) = 0.4).



The heat map (seeGraph 31) represents a discrete projection of the same parametric dependence shown by the three-dimensional surface graph and allows direct comparison of parameter combinations in the mode of increased input risk.

As the threshold θ increases, there is a gradual decrease in weight, which is most pronounced at lower values of the parameter λ. At higher values of λ, the transition is much sharper, causing the weight to remain high even at relatively high thresholds until the threshold exceeds the input risk value. This dynamic shows that in this mode, the parameter λ primarily determines the speed and sharpness of the transition, while the parameter θ determines the limit at which the weight begins to decrease.

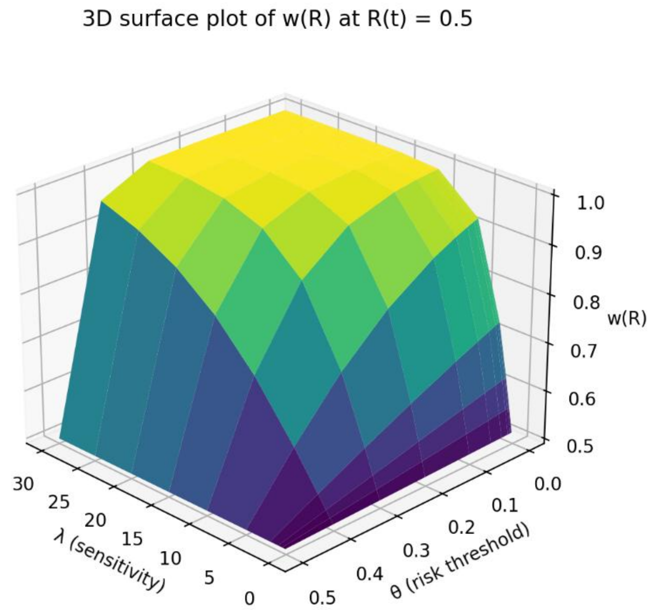
The range of weight values in this mode is noticeably narrower than at lower risk levels, as most of the area is in the high value range. The parameter θ acts primarily as a regulator of the system's edge behavior, as it influences the configurations at which the weight is still maintained at the maximum level and when it begins to gradually decrease.

At R (t)=0.4, the model enters a phase of almost complete activation, in which the weight is high and relatively stable in most configurations. The combination of a low threshold θ and medium to high values of the parameter λ leads to almost immediate saturation of the weight, while higher thresholds and lower values λ still allow for a limited degree of differentiation. This mode represents a transition to a state of permanently elevated risk, where the system operates in a state of constant readiness and requires further action in the subsequent phases of the model.

2.3.6 Full alarm mode and narrowing of differentiation (R(t)=0.5)

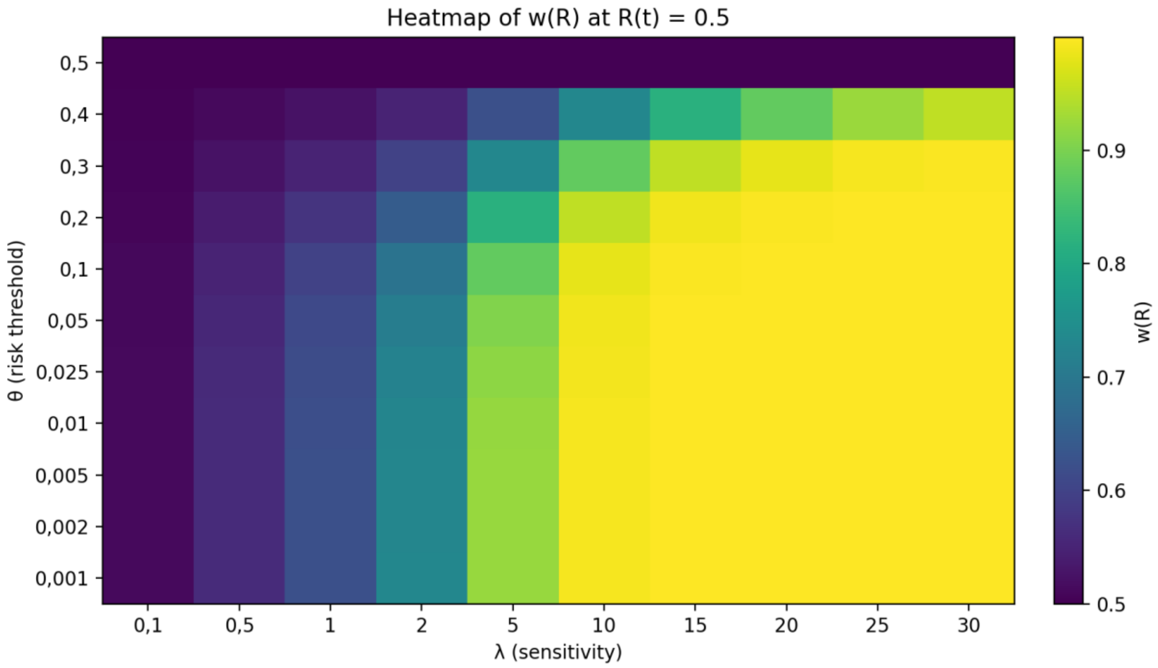
The graph (seeGraph 32) shows the three-dimensional distribution of the dynamic weight $w(R)$ at a high input risk value R (t)=0.5 depending on the sensitivity parameter λ and the risk threshold θ. In this mode, the logistic function is located in the upper part of its domain in most configurations, especially when $\theta \leq 0.5$.

Graph 32 : Influence of parameters λ and θ on the dynamic weight at high input risk (R(t) = 0.5).



At low and medium threshold values θ, the weight $w(R)$ reaches very high, almost maximum values across the entire range of the parameter λ. This means that the system treats the risk as clearly exceeded and requires immediate and consistent action, regardless of the sensitivity level. In this range, the input risk R (t)=0.5 is significantly to the right of the inflection point, so the logistic function operates in the saturation range, where additional parameter changes are only of limited effectiveness.

Graph33 : Heat map of dynamic weights w(R) at high input risk (R(t) = 0.5).



The heat map (seeGraph33) represents a discrete projection of the same parametric dependence shown by a three-dimensional surface graph and allows direct comparison of parameter combinations in full alarm mode.

As the threshold θ increases, there is a moderate decrease in weight, which is most noticeable at lower values of the parameter λ. At higher values of λ, the transition from high to moderate values is particularly steep, which means that the weight remains almost at its maximum until the threshold exceeds the input risk value. This dynamic confirms that in this mode, the parameter λ acts primarily as a regulator of the sharpness of the transition, while the parameter θ determines the limit at which the system can still differentiate the response.

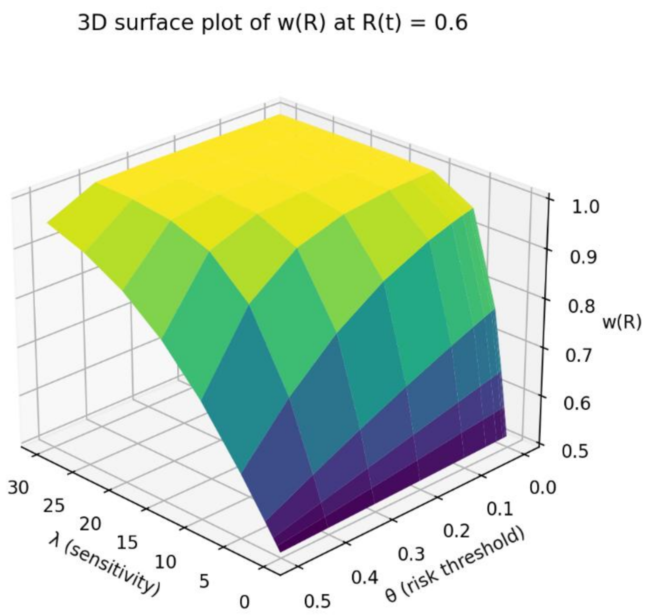
The range of weight values is significantly narrowed in this mode, as the vast majority of the area is in the high value range. The parameter θ therefore has a limited role and acts primarily as an edge corrector, allowing only minor adjustments in specific configurations. The model operates in a distinctly binary manner in this range, as the weight remains close to the maximum value in most cases.

At R (t)=0.5, the model enters full alarm mode, in which the risk is considered to be unquestionably present and high. A combination of a low or medium threshold for θ and practically any value for the parameter λ leads to immediate saturation of the weight, while only very high thresholds and low values for λ allow for a minimum level of restraint. This mode represents the extreme phase of the model's operation, where the main purpose is no longer to detect or differentiate risk, but to support decision-making in conditions of permanently elevated risk.

2.3.7 The onset of saturation and the elimination of the influence of parameters (R(t)=0.6)

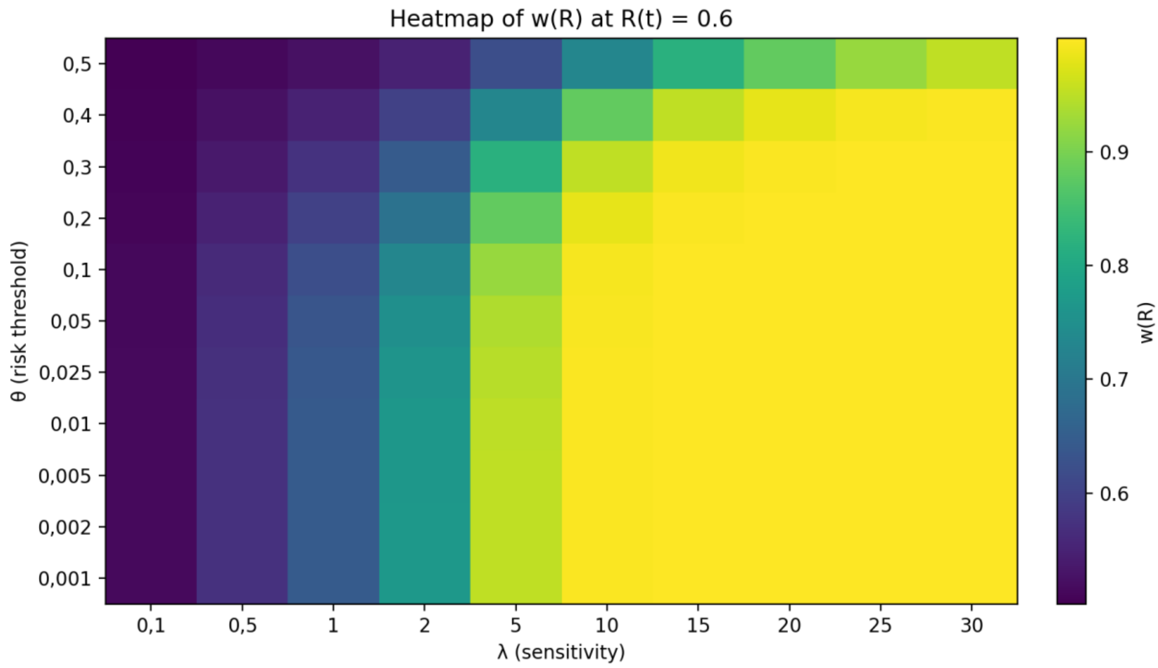
The graph (seeGraph 34) shows the three-dimensional distribution of the dynamic weight $w(R)$ at a very high input risk value R (t)=0.6 depending on the sensitivity parameter λ and the risk threshold θ. In this mode, the logistic function is located deep in the saturation range in practically all configurations, which is reflected in the almost complete stabilization of the weight and minimal sensitivity to changes in input parameters.

Graph 34 : Influence of parameters λ and θ on the dynamic weight at very high input risk (R(t) = 0.6).



At low and medium threshold values θ weight $w(R)$ remains very high and close to maximum values across the entire range of the parameter λ. This means that the system perceives the risk as permanently exceeded and no longer allows for a phased or selective response. In this range, the input risk $R\ (t)$=0.6 is located significantly to the right of the inflection point, so the logistic function operates almost exclusively in the upper, saturated part.

Graph 35 : Heat map of the dynamic weight w(R) at a very high input risk (R(t) = 0.6).



The heat map (see Graph 35) represents a discrete projection of the same parametric dependence shown by the three-dimensional surface graph and allows direct comparison of parameter combinations at very high input risk.

As the threshold θ increases, the weight decreases, but compared to lower modes, this is only more pronounced at low values of the parameter λ. At higher values of λ, the weight remains high even with relatively strict threshold settings, indicating a very decisive and uncompromising response of the system. In this mode, the parameter λ acts primarily as a saturation amplifier, while the parameter θ determines the extreme limit at which differentiation is still possible.

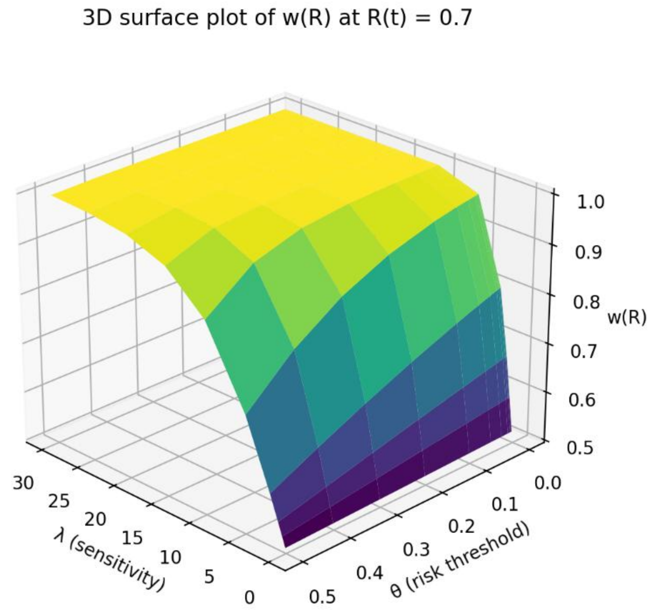
The range of weight values in this mode is very narrow, as most of the surface area is in the high value range. The parameter θ therefore has a very limited role and acts only as a marginal corrective in specific configurations where the threshold exceeds even a very high input risk. The model operates almost deterministically in this range, as the weight remains close to the maximum value in most cases.

At R (t)=0.6, the model operates in a state of constant alert, where risk detection is no longer gradual or selective, but continuous and unambiguous. The combination of any medium or high value of the parameter λ with a low or medium threshold θ leads to immediate and stable saturation of the weight. This mode represents the extreme phase of the model's operation, in which the basic task of the system is to support decision-making in situations of permanently high threat, rather than to distinguish between degrees of risk.

2.3.8 Persistent critical threat and almost binary operation (R(t)=0.7)

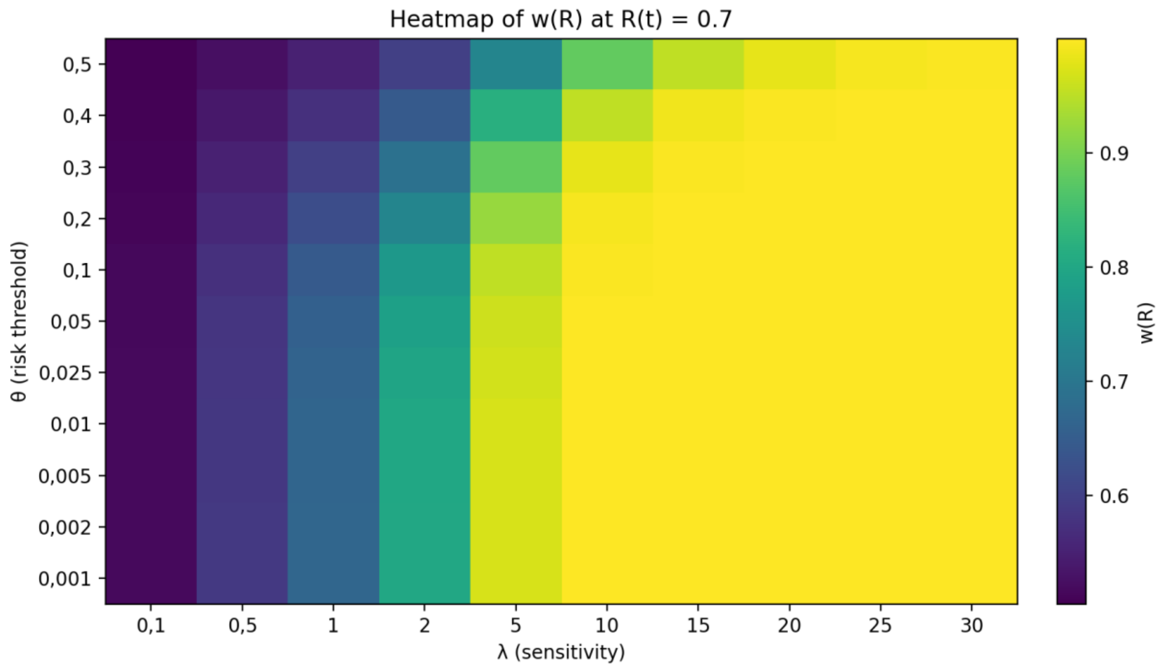
The graph (seeGraph 36) shows the three-dimensional distribution of the dynamic weight $w(R)$ at an extremely high input risk value R (t)=0.7 depending on the sensitivity parameter λ and the risk threshold θ. In this mode, the logistic function is located in the extreme upper part of its domain in practically all configurations, which is reflected in the almost complete saturation of the weights and a further reduction in the importance of parametric adjustment.

Graph 36 : The influence of parameters λ and θ on the dynamic weight at extremely high input risk (R(t) = 0.7).



At low and medium threshold values θ, the weight $w(R)$ remains practically maximum across the entire range of the parameter λ. This means that the system treats the risk as permanent and critical, no longer allowing for a phased or selective response. In this range, the input risk $R\ (t)$=0.7 is significantly to the right of the inflection point, so the logistic function operates almost exclusively in the range of complete saturation.

Graph 37 : Heat map of the dynamic weight w(R) at extremely high input risk (R(t) = 0.7).



The heat map (seeGraph 37) represents a discrete projection of the same parametric dependence shown by the three-dimensional surface graph and allows direct comparison of parameter combinations in the saturation regime.

As the threshold θ increases, the weight decreases, but this is only noticeable at very low values of the parameter λ. At medium and high values of λ, the weight remains very high even with strict threshold settings, confirming that the influence of the threshold in this mode is very limited. The parameter λ acts primarily as a saturation amplifier, while the parameter θ only determines the extreme limit at which differentiation is still possible.

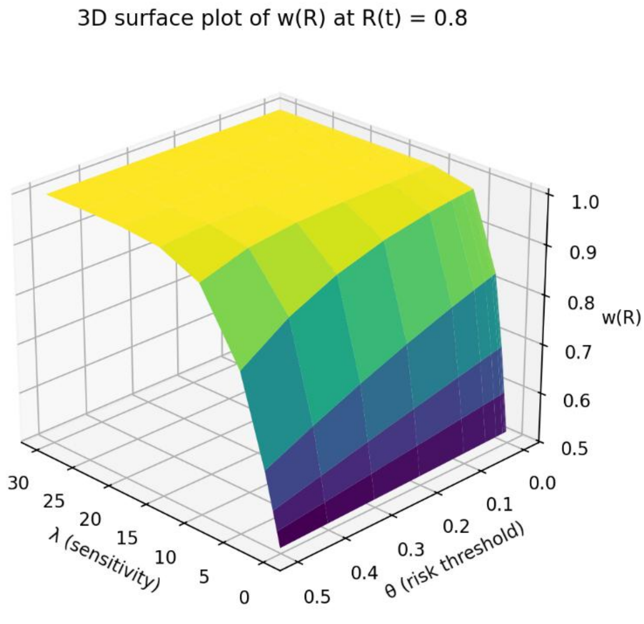
The range of weight values in this mode is extremely narrow, as almost the entire surface of the graph is in the range of very high values. The model operates almost binarily in this range, as the weight only deviates from the maximum value in extreme configurations. This indicates that the system has completely transitioned from the detection phase to the constant responsiveness phase.

At $R\ (t)$=0.7, the model operates in a state of constant critical threat, where risk perception is no longer a matter of degree or threshold, but a constantly present state. The combination of almost any value of the parameter λ with a low or medium threshold θ leads to immediate and permanent saturation of the weight. This mode represents the practical upper limit of the usefulness of logistic differentiation and clearly marks the transition to a state where the model primarily supports decision-making in conditions of continuous crisis.

2.3.9 Upper limit of differentiation and weight saturation (R(t)=0.8)

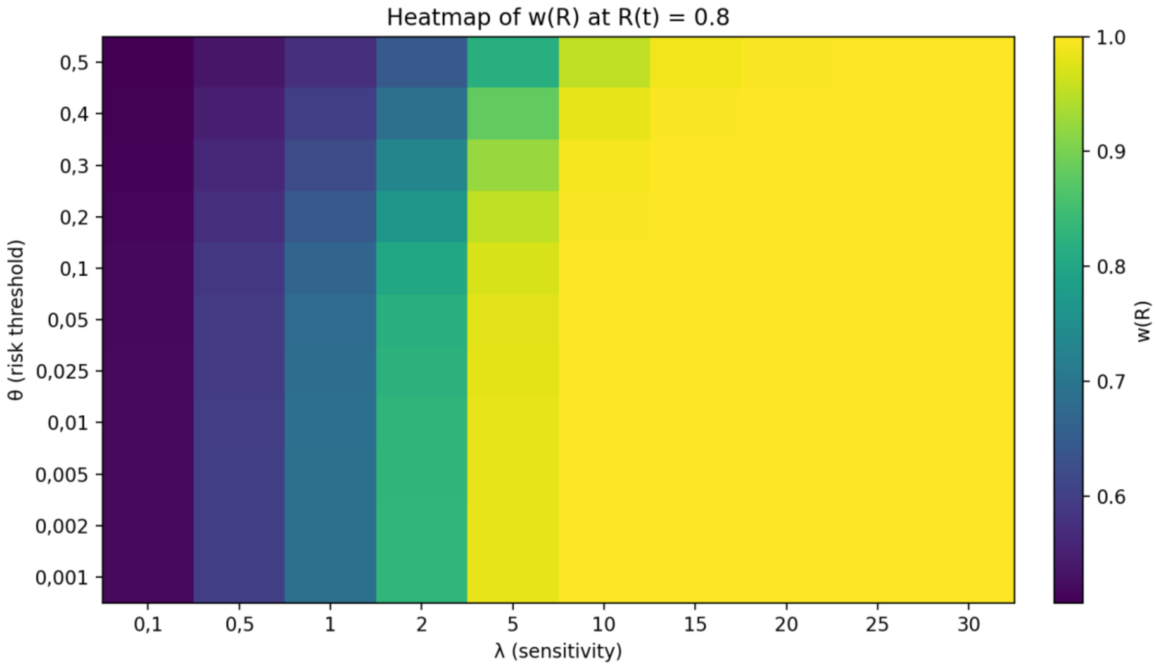
The graph (seeGraph 38) shows the three-dimensional distribution of the dynamic weight $w(R)$ at an extremely high input risk value $R\ (t)$=0.8 depending on the sensitivity parameter λ and the risk threshold θ**.** In this mode, the logistic function is practically at the upper asymptote in all configurations considered, which is reflected in almost complete saturation of the weight and a minimal role of parametric adjustment.

Graph 38 : The influence of parameters λ and θ on the dynamic weight at extremely high input risk (R(t) = 0.8).



At low and medium threshold values θ, the weight $w(R)$ remains very close to the maximum value across the entire range of the parameter λ. This means that the system treats the risk as absolutely exceeded and no longer allows for any degree of gradual response. In this range, the input risk $R\ (t)$=0.8 is located deep to the right of the inflection point, so the logistic function operates almost exclusively in the range of complete saturation.

Graph 39 : Heat map of the dynamic weight w(R) at extremely high input risk (R(t) = 0.8).



The heat map (seeGraph 39) represents a discrete projection of the same parametric dependence shown by the three-dimensional surface graph and allows direct comparison of parameter combinations in the saturation regime.

As the threshold θ increases, the weight decreases only in a very limited part of the configuration space, mainly at the lowest values of the parameter λ. At medium and high values of λ, the weight remains practically unchanged even with strict threshold settings, confirming that the influence of the threshold in this mode is almost completely eliminated. The parameter λ only acts as a regulator of edge transition sharpness, while the parameter θ only determines the extreme limit at which the weight can still decrease slightly.

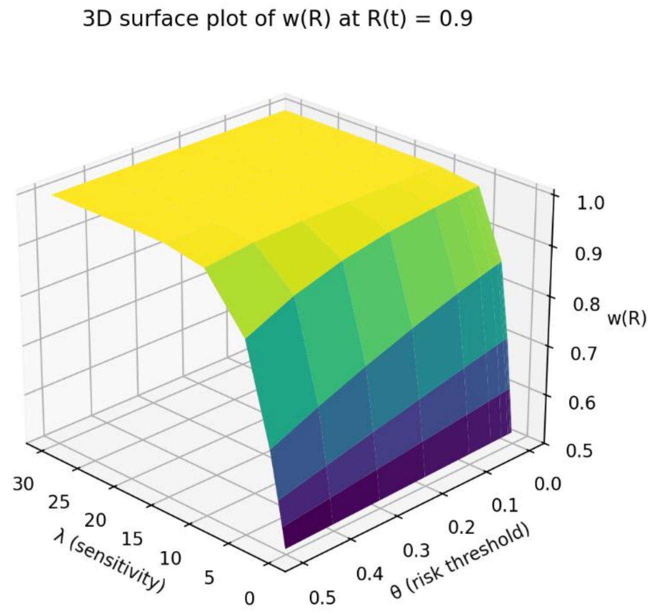
The range of weight values in this mode is extremely narrow, as almost the entire surface is in the range of very high values. The model operates almost deterministically in this range, as the weight deviates from the maximum value only in extreme and methodologically less relevant configurations. The differentiation between configurations is therefore largely exhausted.

At $R\ (t)$=0.8, the model operates in a state of permanent and unambiguous critical threat. Risk perception is no longer gradual or conditioned by settings, but represents a permanent state that requires continuous system responsiveness. This mode represents the practical upper limit of the functional use of the logistic weight and clearly shows that, in conditions of extremely high risk, the primary role of the model is to support decision-making and consequence management, rather than differentiation or early detection.

2.3.10 Limit maximum state and deterministic weight (R(t)=0.9)

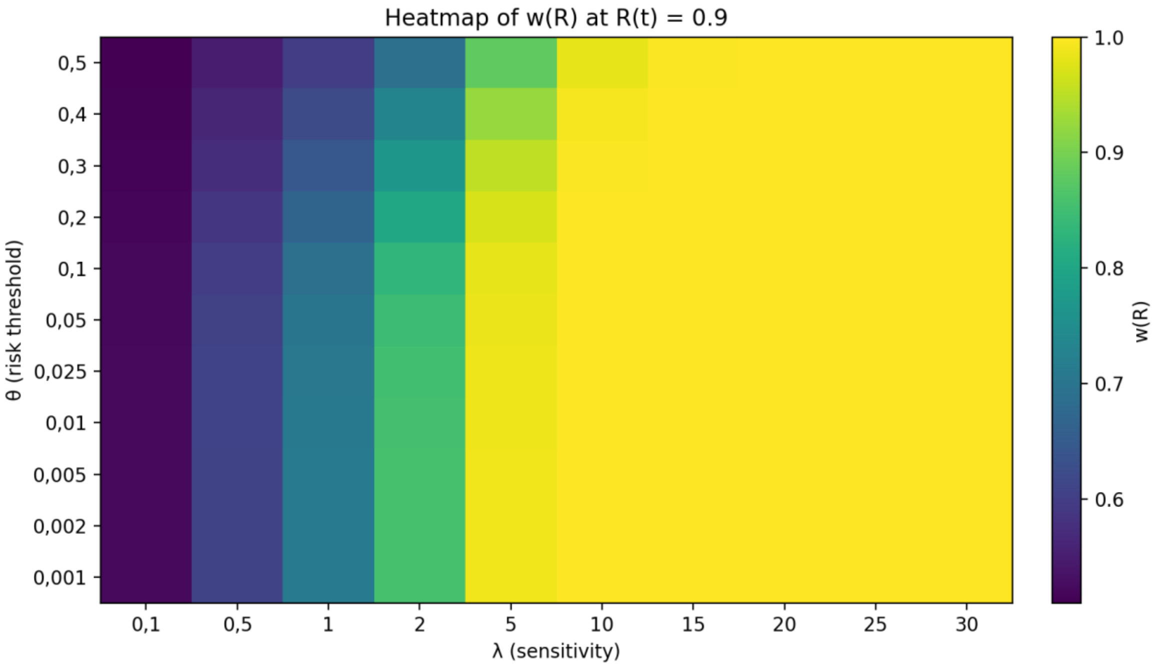
The graph (seeGraph 40) shows the three-dimensional distribution of the dynamic weight $w(R)$ at the marginal maximum value of the input risk $R\ (t)$=0.9 depending on the sensitivity parameter λ and the risk threshold θ. In this mode, the logistic function is located directly on the upper asymptote in all configurations considered, which is reflected in almost complete and stable weight saturation.

Graph 40 : Influence of parameters λ and θ on the dynamic weight at the maximum input risk (R(t) = 0.9).



At low and medium threshold values θ, the weight $w(R)$ reaches its practical maximum value across the entire range of the parameter λ. This means that the system treats the risk as absolutely and permanently exceeded, with the parameters no longer affecting the detection level, but only the edge transitions in extremely limited configurations. In this range, the input risk $R\ (t)$=0.9 is located to the extreme right of the inflection point, so the logistic function operates exclusively in the range of complete saturation.

Graph 41 : Heat map of dynamic weights w(R) at the marginal maximum input risk (R(t) = 0.9).



The heat map (see Graph 41) represents a discrete projection of the same parametric dependence shown by the three-dimensional surface graph and allows direct comparison of parameter combinations at the marginal maximum input risk.

As the threshold θ increases, the weight is reduced only in a very narrow part of the configuration space, mainly at the lowest values of the parameter λ. At medium and high values of λ, the weight remains practically unchanged even with very strict threshold settings, which confirms that the influence of the parameter θ is almost completely eliminated in this mode. The parameter λ now functions solely as a mathematical regulator of the edge transition slope, without any significant influence on the actual weight value.

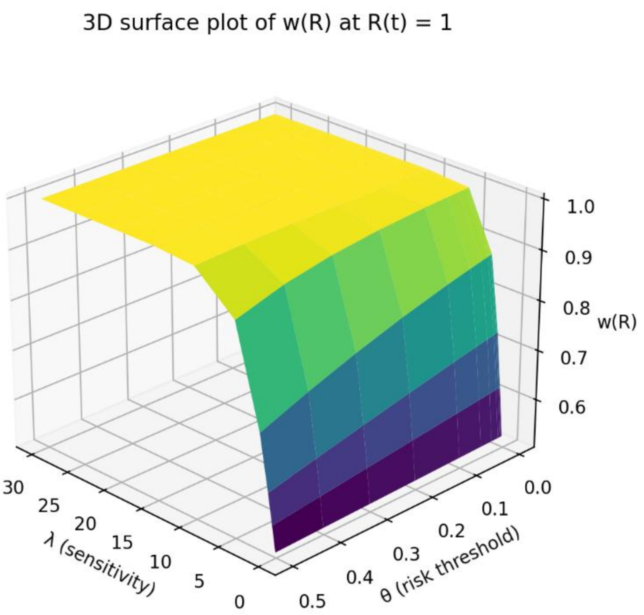
The range of weight values is extremely narrow in this mode, as almost the entire surface of the graph is in the maximum value range. The differentiation between configurations is practically eliminated, and the model operates almost deterministically. This clearly shows that the functional role of the logistic weight in this range is limited to confirming a permanently exceeded risk status.

At $R\ (t)$=0.9, the model operates in a state of absolute risk, where risk perception is no longer subject to assessment but represents a permanent and unchanging state. In this mode, the logistic weight no longer serves to differentiate or provide early warning, but exclusively supports decision-making and consequence management in conditions of a permanently critical situation. This example represents the upper limit of the model's operation and at the same time clearly concludes the sequence of modes from latent to fully saturated response.

2.3.11 Absolute saturation and complete loss of parametric influence (R(t)=1.0)

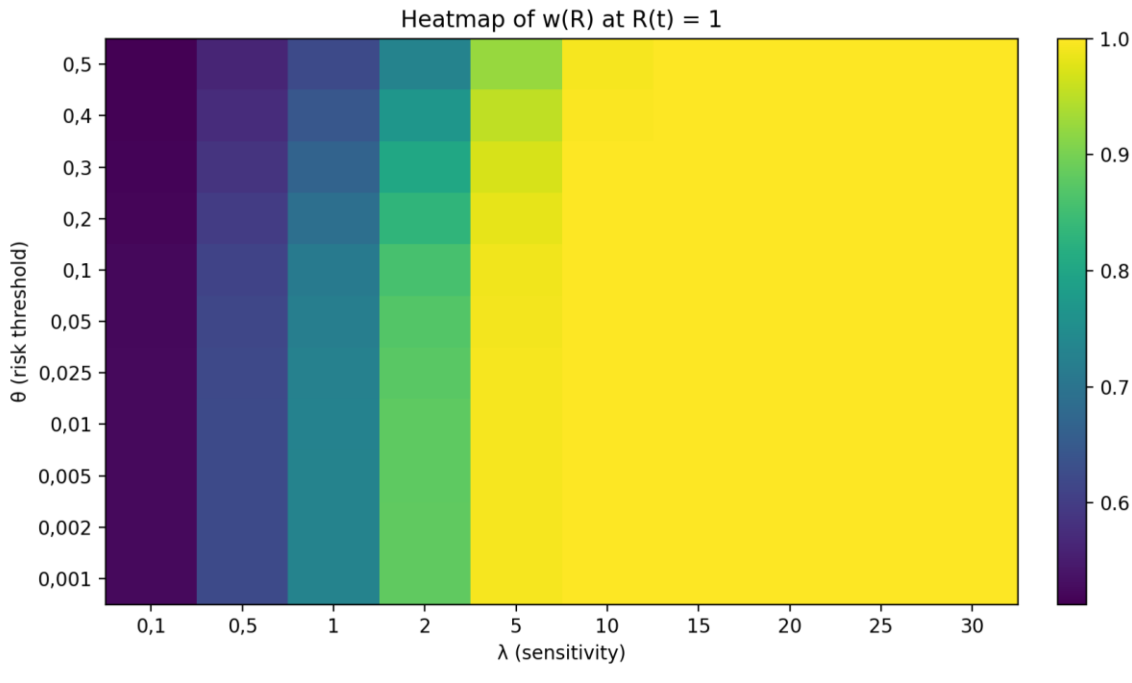
The graph (seeGraph 42) shows the three-dimensional distribution of the dynamic weight $w(R)$ at the maximum value of the input risk $R\ (t)$=1.0 depending on the sensitivity parameter λ and the risk threshold θ. In this mode, the logistic function is located on the upper asymptote throughout the entire parameter space under consideration, which is reflected in the complete saturation of the weight and the complete loss of the differentiation effect of the parameters.

Graph 42 : Influence of parameters λ and θ on the dynamic weight at maximum input risk (R(t) = 1.0).



Regardless of the value of the threshold θ or the sensitivity parameter λ, the weight $w(R)$ reaches its maximum value or remains very close to it in practically all configurations. This means that the system treats the risk as absolutely, definitively, and irreversibly exceeded. The input risk $R\ (t)$=1.0 is located to the far right of the inflection point, so the logistic function operates exclusively in the area of complete saturation, where parameter changes no longer have a functional impact.

Graph 43 : Heat map of dynamic weights w(R) at maximum input risk (R(t) = 1.0).



The heat map (see Graph 43) represents a discrete projection of the same parametric dependence shown by the three-dimensional surface graph and allows direct comparison of parameter combinations at the maximum input risk.

Even at high threshold values θ, the weight remains very high; any deviations from saturation are limited to marginal combinations (very low λ and θ close to$R$). At medium and high values λ, the weight is completely stable and independent of the threshold settings, confirming that both parameters are practically eliminated from the decision-making process in this mode. The parameter λ no longer acts as a sensitivity regulator in this range, and the parameter θ no longer acts as a transition threshold; instead, both lose their operational role.

The range of weight values in this mode is practically zero, as the entire area of the graph is in the maximum value range. In this state, the model operates deterministically, without any possibility of a phased, selective, or gradual response. Risk differentiation is completely exhausted.

The model at $R\ (t)$=1.0 represents the absolute final state of the logistic weight. In this mode, the weight no longer serves to detect, warn, or differentiate, but merely confirms the permanent and complete vulnerability of the system. This example clearly marks the upper limit of the model and logically concludes the sequence of modes from latent risk to complete saturation, while confirming the mathematical and conceptual correctness of the logistic formulation of the dynamic weight.

2.3.12 The combined effect of the parameters λ, θ, and input risk R on the dynamic weight w(R)

A comprehensive analysis of three-dimensional graphs of the dynamic weight $w(R)$ for sequential values of the input risk $R\ (t)$ from 0 to 1 shows that the model's operation is based on the clearly defined and interdependent roles of three elements: the input risk R, the risk threshold θ, and the sensitivity parameter λ. The input risk determines the current position of the system on the logistic curve, the threshold θ determines the reference transition limit, and the parameter λ determines the dynamics or sharpness of the response around this limit.

At low input risk values R (R ≈0–0.2), the model operates in a latent or transitional mode, where the weight is not yet saturated and is highly dependent on the parameter configuration. In this range, the threshold θ has a pronounced filtering role, as it determines whether the system will even detect the risk as relevant, while the parameter λ determines whether the response will be moderate or strongly preventive. The differences between configurations are greatest in this mode, confirming that this part of the domain is the most important for early risk detection and differentiation.

At moderate values of the input risk R (approximately 0.3–0.5), the model enters the stable detection range. For most parameter combinations, the logistic function is close to or above the inflection point, so the weight reaches high values, but not yet completely saturated. In this range, the influence of the parameter θ gradually decreases, while the parameter λ takes on the role of regulating the sharpness of the transition between moderate and high response. In this mode, the model still allows differentiation between configurations, but this is already significantly smaller than at low risk values.

At high and very high input risk values (R, R ≥0.6), the model gradually moves into the saturation range. The weight $w(R)$ reaches or comes very close to the maximum value in most configurations, regardless of the choice of parameters. In this mode, the threshold θ loses its operational role, as the input risk is located far to the right of the inflection point, and the parameter λ acts only as a regulator of the edge transition in extreme cases. The differentiation between risk levels is practically exhausted in this range, and the model behaves almost deterministically.

An analysis of the entire range R clearly shows that the information value of the dynamic weight is highest in the area around the risk threshold. It is precisely in this range that the intersection of the influences R, θ, and λ is most clearly reflected in the changes in weight. At very low or very high values of R, the model approaches edge conditions where the weight either remains low or becomes completely saturated, thereby reducing the usefulness of parametric adjustment.

Viewed holistically, the model does not function as a single response mechanism, but rather as a sequence of functional modes: from latent assessment, through transitional and selective perception, to alarm and saturation states. The threshold θ determines where these transitions occur, while the parameter λ determines how sharply these transitions occur. The input risk R acts as a trigger that gradually moves the system through these modes.

A joint analysis confirms that the meaningful use of the model is primarily linked to the correct selection of the threshold θ, which must represent a realistic and relevant risk limit, and to the adjustment of the parameter λ according to the stability of the environment and the reliability of the input data. Only in this case does the dynamic weight retain its discriminatory and interpretative value and effectively support further stages of assessment and decision-making.

2.3.13 Practical implications of using the dynamic weight w(R)

The results of the analysis of the dynamic weight $w(R)$ have direct practical implications for the use of the model in real environments where risk assessment is associated with uncertainty, incomplete data, and dynamically changing conditions. The model does not behave uniformly across the entire range of input risks, but rather transitions through different functional modes, which means that its application must be adapted to the context and purpose of the decision-making process.

In phases of low perceived risk, dynamic weighting proves to be an effective mechanism for filtering noise and negligible deviations. In this mode, the choice of threshold θ is crucial, as it determines whether the system will detect changes in the input signals at all. A threshold that is too low leads to premature activation and reduced discrimination, while a threshold that is too high can cause early risk indicators to be overlooked. In practical terms, this means that the threshold must be set based on real operational experience and not merely theoretical estimates, as it directly affects the detection of initial anomalies.

In transitional and moderate risk regimes, where the weight is close to the inflection point, the model achieves maximum informational value. In this range, the parameter λ allows the responsiveness to be adjusted according to the stability of the environment and the reliability of the input data. In environments with a high degree of uncertainty or frequent fluctuations, a lower value of λ is appropriate, ensuring a more continuous and tolerant response. Conversely, in environments with well-calibrated and reliable input estimates, higher values of λ allow for faster and clearer differentiation between acceptable and unacceptable states.

At elevated and high risk levels, the model enters a saturation zone where the dynamic weight loses its differentiating role. In this mode, further parameter adjustment no longer has a significant impact on the output, which means that further weight optimization is not meaningful. In practical terms, this indicates that in these phases, the focus of risk management should shift from detection to response and mitigation, as the model clearly signals a state of permanent threat.

An important implication is also that the model is not intended for universal use with a single parameter setting. Instead, it requires conscious configuration according to the operational context. In more stable environments, where the goal is to gradually monitor trends, moderate or lower sensitivity is more appropriate. In environments with high security requirements, however, the use of higher values is justified λ, but only with an appropriately selected threshold that prevents premature saturation.

The analysis further shows that dynamic weighting is most appropriate as part of a multi-stage decision-making process. Its role is not to replace substantive judgment or additional indicators, but to act as a flexible regulator that amplifies or attenuates the impact of input risk depending on the current operating regime. Such use allows for greater model robustness and reduces the likelihood of extreme responses due to one-off or short-term deviations.

Overall, the dynamic weighting of $w(R)$ enables a transition from static assessment to flexible and context-sensitive risk management. Its practical value is particularly evident in areas where the risk is developing and has not yet been unequivocally exceeded. The correct setting of parameters is therefore not merely a technical optimization, but a strategic decision that affects the timeliness of detection, the quality of decision-making, and the effectiveness of further measures.

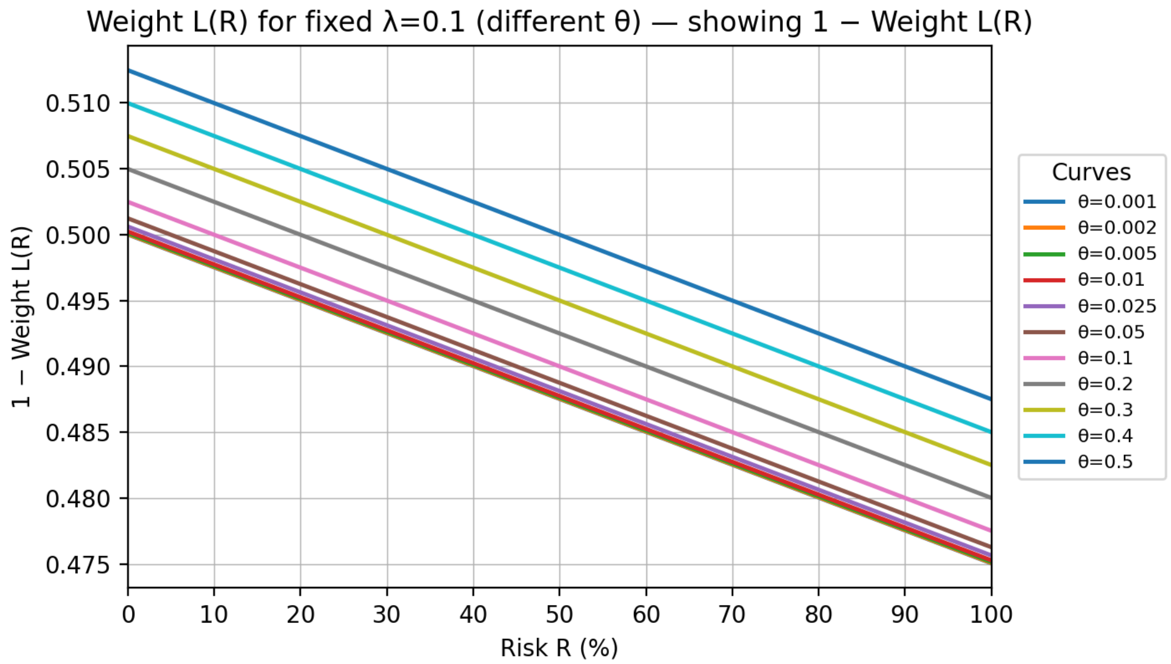
3 ANALYSIS OF THE SAFETY FACTOR V(R)

3.1 Model analysis at a fixed parameter value λ

3.1.1 Low sensitivity of the safety factor and limited influence of the threshold (λ = 0.1)

The graph (seeGraph 44) shows the behavior of the safety factor $V(R)$=1−L (R) at a fixed low value of the sensitivity parameter λ = 0.1, with the risk threshold θ varying. The x-axis shows the input risk R in the range from 0% to 100%, while the y-axis shows the value of the safety factor $V(R)$.

Graph 44: Effect of threshold θ on the safety factor at low sensitivity (λ = 0.1).



At such a low value of the parameter λ, the response of the safety factor is very flat, which means that the value of $V(R)$ decreases slowly and continuously, with the curve being very flat due to the low value of λ (the S-shape is present but not very pronounced). The differences between the individual curves representing different threshold values θ are small but consistent and systematic.

Lower threshold values θ result in slightly lower safety factor values for the same risk level R, which means that the system detects a decrease in safety more quickly or switches to a more cautious operating mode sooner. Conversely, higher θ values cause the safety factor to remain slightly higher across the entire R range, reflecting the system's greater tolerance to increasing risk and slower response.

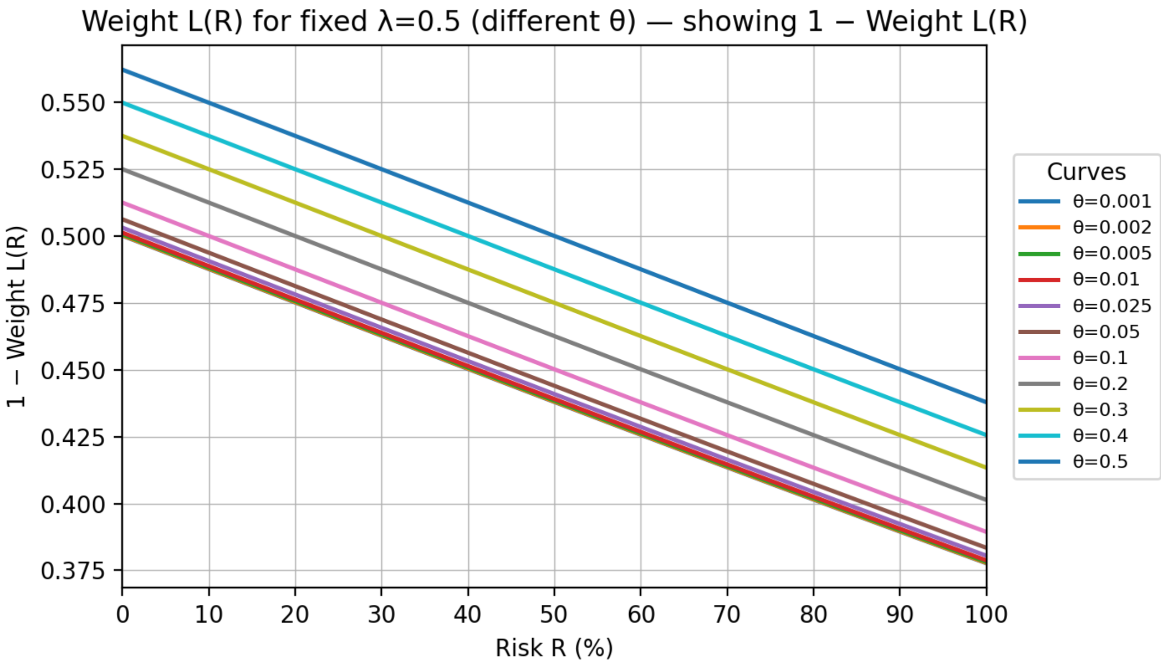
It can be seen that all curves lie within a very narrow range of values (approximately between 0.475 and 0.515), which clearly shows that at low sensitivity λ, the threshold θ has a limited effect on the dynamics of the safety factor. The parameter θ in this range does not cause structural changes in the response, but acts primarily as a mechanism for fine-tuning the basic level of safety.

Such behavior is characteristic of stable operating environments, where the system deliberately does not react abruptly to changes in risk, but maintains continuous, predictable, and robust dynamics. In the context of the model, this means that a low value of λ reduces the sensitivity of the safety factor to threshold settings and ensures stable safety assessment even with different choices of threshold θ.

3.1.2 The beginning of safety factor differentiation and the increasing role of the threshold (λ = 0.5)

The graph (seeGraph 45) shows the behavior of the safety factor $V(R)$=1−L (R) at a fixed moderate value of the sensitivity parameter λ = 0.5, with the risk threshold θ varying. The x-axis shows the input risk R in the range from 0% to 100%, while the y-axis shows the value of the safety factor $V(R)$.

Graph 45: Effect of threshold θ on the safety factor at moderate sensitivity (λ = 0.5).



Compared to low sensitivity (λ = 0.1), the response of the safety factor at λ = 0.5 is already more pronounced. The value of $V(R)$ decreases more rapidly as the risk R increases, and the differences between the individual curves for different threshold values θ are clearly visible, most pronounced in the transition region ($R \approx \theta$), while at very low and very high values of R, the curves approach their asymptotes. This means that at this setting, the model begins to differentiate between different threshold policies.

Lower threshold values θ cause a faster decrease in the safety factor, which means that the system perceives safety as reduced even at lower risk levels. Higher θ values, on the other hand, maintain higher values of $V(R)$ over a larger part of the R range, reflecting greater risk tolerance and a slower transition to a more restrictive security regime.

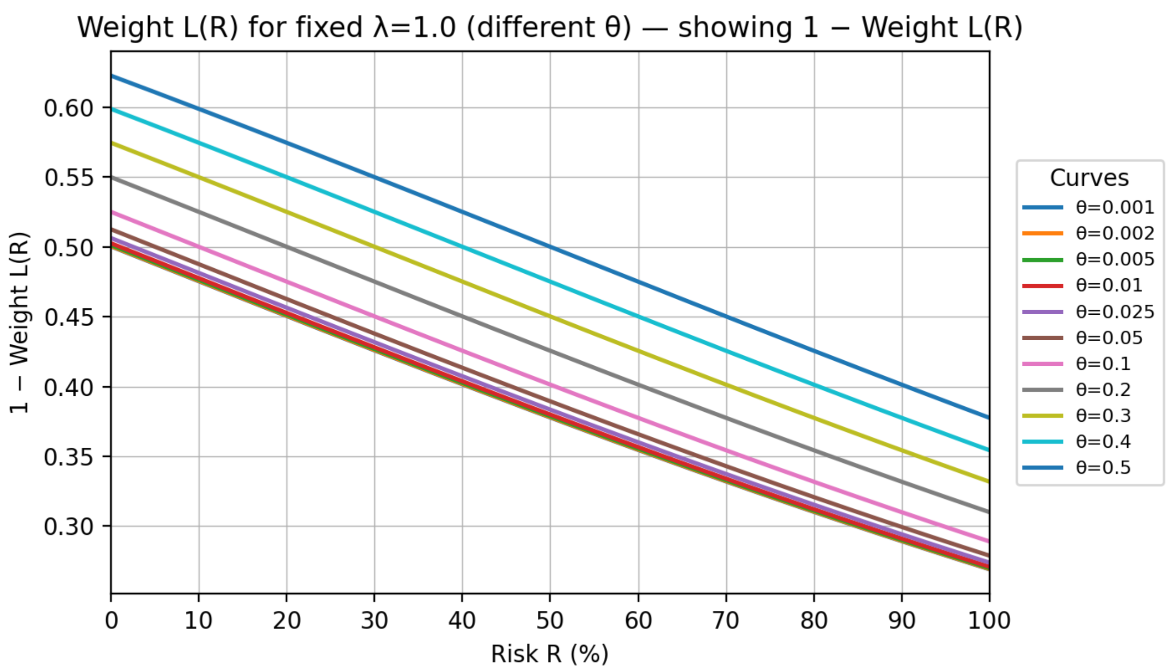
The range of safety factor values is significantly wider for this setting than for λ = 0.1 (approximately from 0.38 to 0.56), which indicates increased model discriminativeness. In this range, the parameter θ no longer acts solely as a fine-tuning mechanism, but shifts the position of the safety factor transition along the axis R, making the threshold policy operationally noticeable.

This behavior represents a transition from a very stable to a more responsive operating mode. The model still maintains continuous and predictable dynamics, but it is sensitive enough that differences in threshold settings become operationally relevant. In the context of application, this means that the combination of λ = 0.5 and an appropriately selected threshold θ is suitable for environments where a balanced relationship between robustness of assessment and the ability to distinguish between levels of security risk is desirable.

3.1.3 Balanced response mode and clear regulatory role of the threshold (λ = 1)

The graph (seeGraph 46) shows the behavior of the safety factor $V(R)$=1−L (R) at a fixed sensitivity parameter value λ = 1, with the risk threshold θ varying. The x-axis shows the input risk R in the range from 0% to 100%, and the y-axis shows the value of the safety factor $V(R)$.

Graph 46: Effect of threshold θ on the safety factor at increased sensitivity (λ = 1).



Compared to the cases λ = 0.1 and λ = 0.5, at λ = 1 the influence of the threshold θ is already pronounced and systematic. V 's safety factor (R) decreases more rapidly as the risk R increases, and the differences between the individual curves are clearly distinguishable throughout the entire risk interval. This means that in this mode, the threshold θ no longer acts merely as a correction parameter, but takes on a clear regulatory role.

Lower threshold values θ cause a faster decrease in the safety factor, which means that the system perceives safety as reduced even at medium risk levels. Higher θ values maintain higher values of the safety factor ($V\ R$) even at higher R levels, reflecting greater risk tolerance and a slower transition to a more safety-restrictive state.

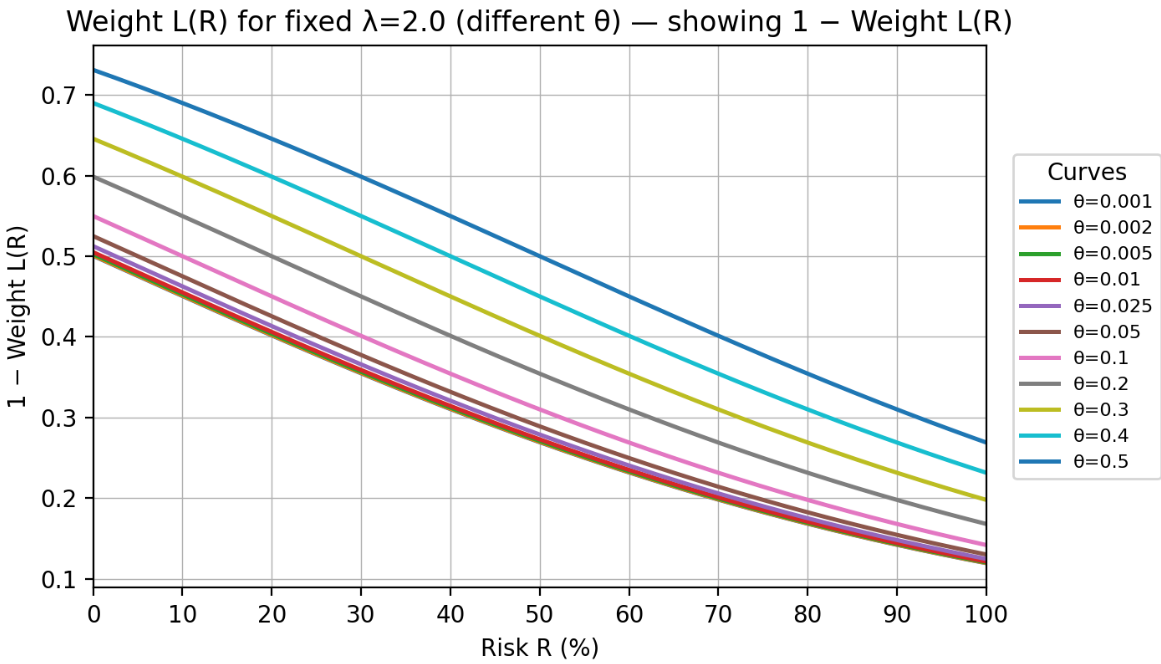
The range of safety factor values is wide for this setting (approximately 0.27 to 0.62), indicating high model discriminative power. The differences between the curves are most pronounced in the transition range ($R \approx \theta$), while they decrease towards the edges of the interval (very low or very high$R$) due to saturation.

This behavior represents a balanced mode of operation of the logistic model. The system is responsive enough to detect changes in risk and clearly distinguish between different security states, while not yet operating in a jerky or threshold manner. In the context of application, this means that a combination of λ = 1 and an appropriately selected threshold θ is suitable for environments where active risk monitoring is required, while maintaining the stability and interpretability of the safety assessment.

3.1.4 Transition to selective security detection and the increasing role of the threshold (λ = 2)

The graph (seeGraph 47) shows the behavior of the safety factor $V(R)$=1−L (R) at a fixed sensitivity parameter value λ = 2, with the risk threshold θ varying. The x-axis shows the input risk R in the range from 0% to 100%, and the y-axis shows the value of the safety factor $V(R)$.

Graph 47: Effect of threshold θ on the safety factor at high sensitivity (λ = 2).



Compared to the case λ = 1, at λ = 2 the decline in the safety factor becomes more pronounced and faster as the risk R increases. The curves for individual threshold values θ are clearly separated from each other, with the differences being most pronounced in the transition range, where the safety factor decreases most rapidly; outside this transition zone, the curves gradually approach their asymptotes. This shows that in this mode, the threshold θ plays a central role in determining the rate of loss of the safety reserve.

Lower θ threshold values cause a steeper decline in the safety factor, which means that the system detects a reduction in safety even at relatively low to medium risk levels. Higher θ threshold values, on the other hand, maintain higher$V$ values (R) even at higher R values, reflecting a more cautious and tolerant response by the system.

The range of safety factor values is very wide for this setting (approximately 0.12 to 0.73), indicating a significantly increased discriminative power of the model. The differences between the individual curves are no longer limited to the initial part of the graph, but are maintained and deepened towards higher risk levels, allowing for a clear distinction between different safety states.

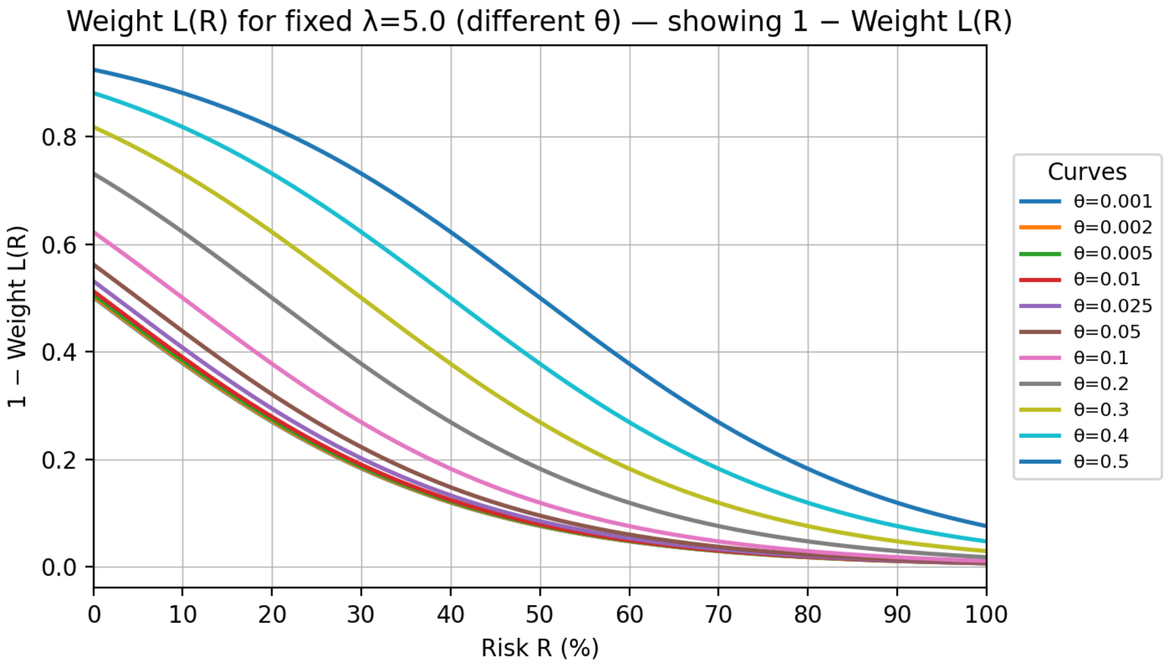
This behavior represents the model's transition to a selective mode of operation. The system is no longer merely continuously adaptable, but begins to distinguish more clearly between acceptable and unacceptable levels of risk. In practice, this means that the combination of λ = 2 and an appropriately selected threshold θ enables target-oriented security management, where it is possible to consciously choose a more preventive or more restrictive response policy.

At the same time, the increased steepness of the response also means reduced tolerance to input data uncertainty. In this mode, an incorrect risk assessment or an inappropriately selected threshold θ can lead to a more rapid and significant reduction in the security rating. Therefore, this configuration is particularly suitable for environments where the input data is relatively reliable and where a clear differentiation between security levels is required.

3.1.5 Threshold-sensitive behavior and rapid decline in the safety factor (λ = 5)

The graph (seeGraph 48) shows the behavior of the safety factor $V(R)$=1−L (R) at a fixed sensitivity parameter value λ = 5, with the risk threshold θ varying. The x-axis shows the input risk R in the range from 0% to 100%, and the y-axis shows the value of the safety factor $V(R)$.

Graph 48: Effect of threshold θ on the safety factor at very high sensitivity (λ = 5).



Compared to the cases λ = 1 and λ = 2, the behavior of the model changes significantly at λ = 5. The decline in the safety factor with increasing risk R becomes highly non-linear, with the largest changes concentrated in the area around the threshold θ. The curves are very clearly separated from each other, indicating a greatly increased sensitivity of the model to the choice of threshold.

Lower threshold values θ cause a very rapid decline in the safety factor even at low to medium risk levels. In these cases, the safety reserve is depleted early, resulting in a markedly preventive and aggressive response by the system. Higher θ values shift this transition towards higher R values, but even in these cases the transition is steep and concentrated in a relatively narrow range.

The range of safety factor values is very wide in this setting, with most of the change concentrated in a narrow range around the threshold θ. The differences between the individual curves are no longer gradual, but threshold-emphasized, which means that in this mode, the parameter θ directly determines when the system transitions from a high-safety state to a low-safety state.

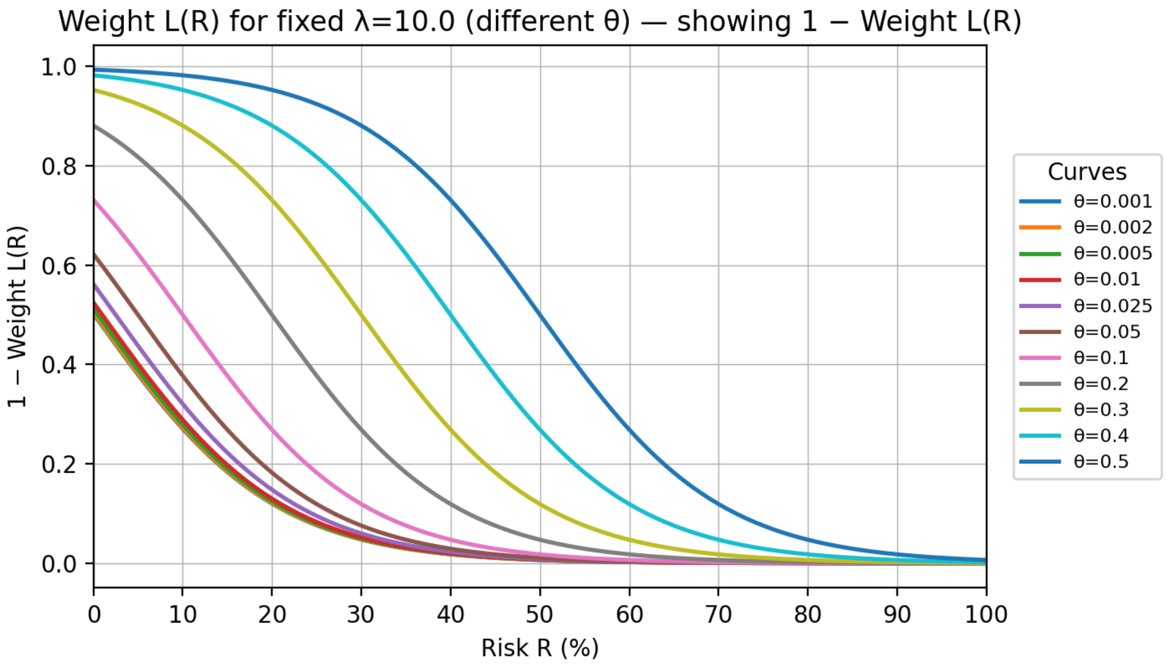
Such behavior is typical for environments where a quick and decisive response to perceived risk is required. At λ = 5, the model still maintains the continuity of the logistic function, but in practice it already approaches threshold decision-making. This allows for precise adjustment of the moment of loss of the safety reserve, while significantly reducing the tolerance to inaccuracies in the input data.

In operational terms, this configuration requires a very careful choice of the threshold θ. Small changes in the threshold or minor errors in the risk assessment R can cause large differences in the final safety assessment. Therefore, λ = 5 is particularly suitable for environments with relatively reliable input estimates and clearly defined acceptable risk limits, where detection speed is more important than response gradualism.

3.1.6 Near-threshold response and deterministic safety factor decay (λ = 10)

The graph (seeGraph 49) shows the behavior of the safety factor $V(R)$=1−L (R) at a fixed, very high sensitivity parameter value λ = 10, with the risk threshold θ varying. The x-axis shows the input risk R in the range from 0% to 100%, while the y-axis shows the value of the safety factor $V(R)$.

Graph 49: Effect of threshold θ on the safety factor at extremely high sensitivity (λ = 10).



At this value of the parameter λ, the logistic function transitions to a mode of nearly threshold behavior. The drop in the safety factor is no longer spread across a wide range of risks, but is concentrated in a very narrow range around the threshold θ. Outside this range, $V(R)$ quickly saturates: at $R \ll \theta$, it remains high, and at $R \gg \theta$, it remains low, while almost the entire transition occurs in a narrow band around $R \approx \theta$.

The differences between the individual curves are pronounced and clearly delineated. In this mode, the parameter θ directly determines the point at which the system loses most of its safety reserve. Lower values of θ cause a very early and almost immediate loss of the safety factor, which means an extremely preventive and aggressive response of the system. Higher θ values shift this transition towards higher risk values, but even in these cases the drop is very steep and practically discrete.

The range of safety factor values covers almost the entire interval from 0 to 1, but most of the change takes place in a very short section of the risk axis. This means that at λ = 10, the model loses most of the gradualness characteristic of lower λ values and, in terms of behavior, comes very close to a binary decision mechanism.

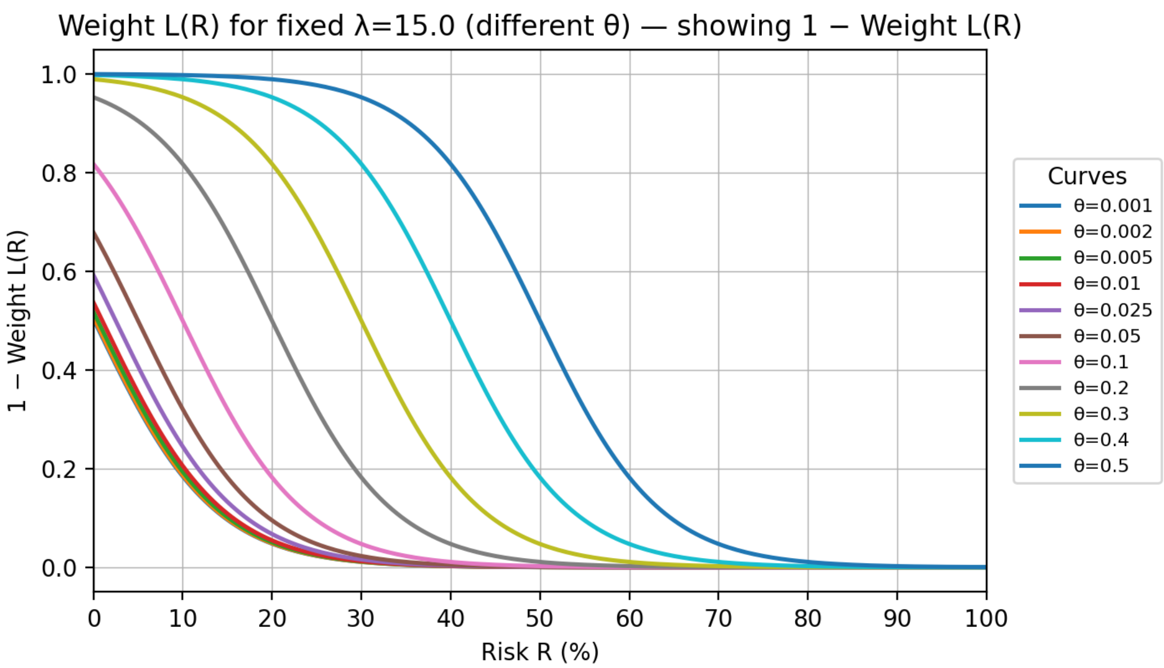
Such a mode of operation is only appropriate in environments where risk thresholds are clearly defined and where input estimates are extremely reliable. Small errors in risk assessment or minimal deviations around the threshold θ can cause completely different safety factor outputs. In practice, this means high resolution but very low tolerance to uncertainty.

In the context of the λ = 10 model, it represents a transition point between continuous logistic assessment and an almost discrete trigger system. In this mode, the parameter θ is no longer just a setting element, but becomes the central decision criterion that directly determines the moment of collapse of the safety reserve.

3.1.7 Almost discrete threshold behavior and loss of continuity (λ = 15)

The graph (seeGraph 50) shows the behavior of the safety factor $V(R)$=1−L (R) at a fixed, very high sensitivity parameter value λ = 15, with the risk threshold θ varying. The x-axis shows the input risk R in the range from 0% to 100%, while the y-axis shows the value of the safety factor.

Graph 50: Effect of threshold θ on the safety factor at nearly discrete sensitivity (λ = 15).



At this value of the parameter λ, the logistic model definitively transitions from a continuous evaluation regime to nearly discrete threshold behavior. The drop in the safety factor is extremely steep and limited to a very narrow range around the threshold θ, while outside this interval the value of $V(R)$ remains either close to 1 (at low risk) or almost equal to 0 (at higher risk).

The influence of the threshold θ is particularly dominant in this mode. The individual curves are clearly separated from each other, mainly by the position of the almost vertical transition. Lower values of θ cause an almost immediate loss of the safety factor even at very low risk levels, which means an extremely aggressive and distinctly preventive response of the system. Higher values of θ shift this breakpoint towards higher risk values, but the shape of the transition remains equally steep.

The safety factor range covers almost the entire interval from 0 to 1, but most of the information content of the model is no longer distributed continuously. Intermediate values ($V\ R$) exist only in a very narrow range around the threshold, which means that the model practically no longer allows for a gradual differentiation between risk levels.

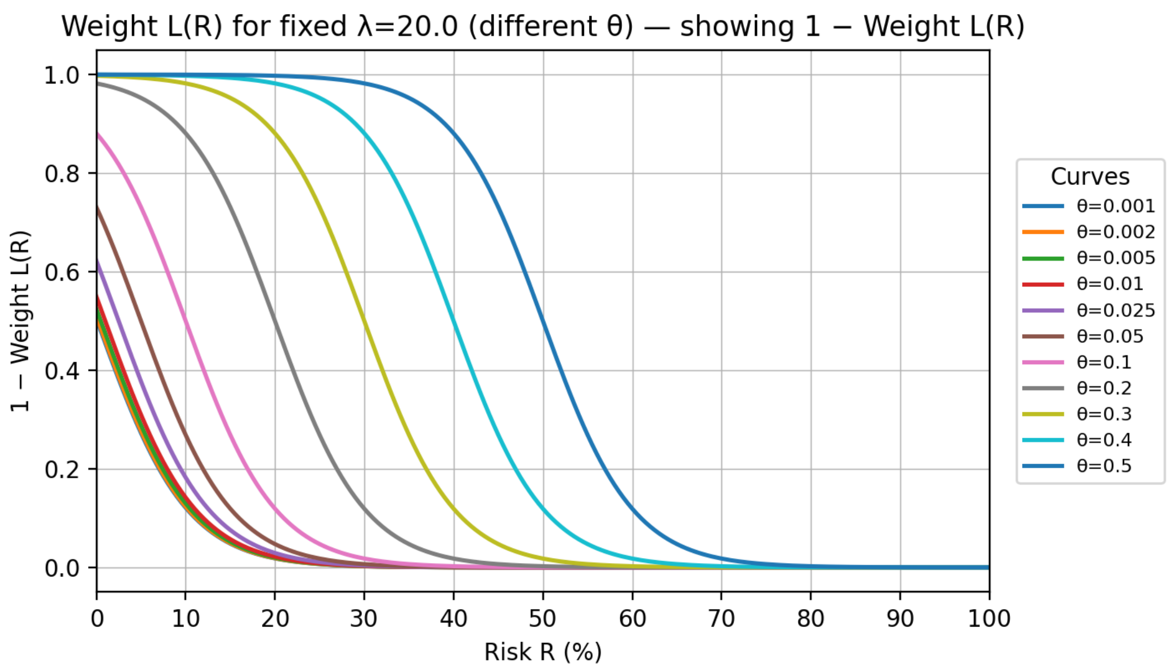
This behavior means a significantly reduced tolerance to uncertainty in the input data. Even a minimal change in risk near the threshold θ can cause a complete jump in the safety factor from almost maximum to almost zero. In this mode, the model acts as a deterministic trigger mechanism, with the parameter θ taking on the role of an almost exclusive decision criterion.

In the context of the λ = 15 model, this represents the upper practical range of application of the logistic function as a smooth safety factor. Although this setting allows for a very clear distinction between safe and unsafe states, its operational applicability is limited to environments with extremely well-defined thresholds and highly reliable input risk assessments. In most real-world systems, such a configuration increases the risk of sudden, abrupt, and difficult-to-control decisions.

3.1.8 Almost discrete decision-making and complete threshold dominance (λ = 20)

The graph (seeGraph 51) shows the behavior of the safety factor $V(R)$=1−L (R) at a fixed, very high sensitivity parameter value λ = 20, with the risk threshold θ varying. The x-axis shows the input risk R in the range from 0% to 100%, while the y-axis shows the value of the safety factor.

Graph 51: Effect of threshold θ on the safety factor at extreme sensitivity (λ = 20).



With this setting of the parameter λ, the logistic model practically loses the continuous nature of the response and behaves almost identically to a discrete threshold mechanism. The transition of the safety factor from a value close to 1 to a value close to 0 occurs in an extremely narrow range of input risk, which is directly related to the selected threshold θ. Outside this range, the function is almost constant.

The role of the threshold θ is absolutely dominant in this mode. The individual curves differ almost exclusively in the horizontal position of the transition, while the shape of the transition is practically the same for all values of θ. Lower values of θ cause the safety factor to drop very quickly even at minimal risk levels, resulting in an extremely early and very strict assessment of danger. Higher values of θ shift this transition towards medium or higher risk levels, but without affecting the steepness of the drop itself.

The range of the safety factor is fully exploited, but the informational value of the model exists only in a very narrow transition band. The intermediate values of $V(R)$ are negligible in terms of time and value, which means that the model no longer allows for a gradual differentiation between risk levels, but operates on a "safe – unsafe" logic.

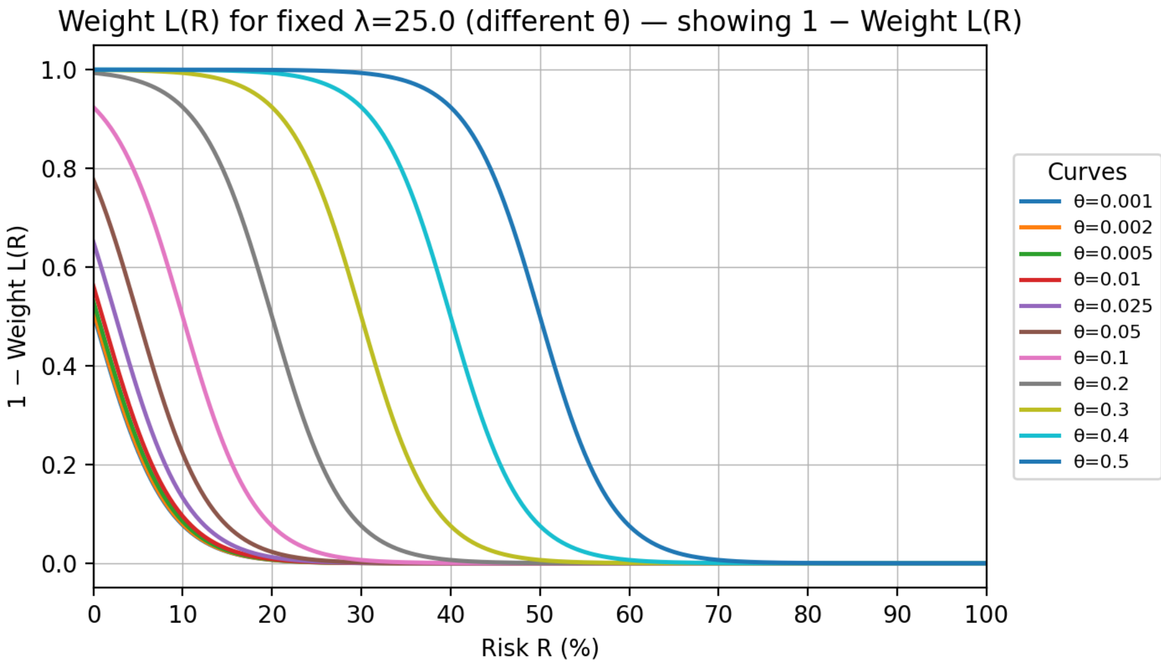
Such behavior means an almost complete loss of tolerance for uncertainty in the input data. Even a minimal error in risk assessment or a slight change in the threshold θ can cause a completely different decision by the system. In this mode, the model becomes highly deterministic and sensitive, which increases the risk of sudden and difficult-to-explain jumps in the safety assessment.

In the context of the λ = 20 model, it represents the practical upper limit of the applicability of the logistic function as a safety factor. Although this setting allows for a very clear and sharp distinction between risk states, its use only makes sense in environments with extremely precisely defined thresholds and highly reliable input data. In most real-world systems, such a regime would lead to overly rigid decision-making and increased sensitivity to false triggers.

3.1.9 Idealized threshold behavior and disappearance of gradualism (λ = 25)

The graph (seeGraph 52) shows the behavior of the safety factor $V(R)$=1−L (R) at a fixed, very high sensitivity parameter value λ = 25, with the risk threshold θ varying. The x-axis shows the input risk R in the range from 0% to 100%, while the y-axis shows the value of the safety factor.

Graph 52: Effect of threshold θ on the safety factor in an almost ideal threshold regime (λ = 25).



At this value of the parameter λ, the logistic model practically loses all the properties of a continuous evaluation mechanism. The transition of the safety factor from a value close to 1 to a value close to 0 occurs almost instantaneously and is concentrated in an extremely narrow range of input risk around the threshold θ. Outside this range, the function takes on almost constant values, which means that changes in risk no longer have a gradual effect on the model output.

The threshold θ in this mode completely determines the location of the transition. Individual curves differ almost exclusively in their horizontal offset, while the steepness of the transition is practically the same for all values of θ. Lower values of θ cause an immediate drop in the safety factor even at very low risk levels, which means extremely strict and early detection of danger. Higher values of θ shift this transition towards medium or higher risk values, but without mitigating the intensity of the response.

Intermediate values of the safety factor have negligible informational value in this mode. The model no longer allows for differentiation between gradual levels of risk, but operates almost exclusively in binary logic, where the system very quickly transitions from a state of "high security" to a state of "low security." This negates the basic advantage of the logistic function, which is the continuous and interpretable dynamics of assessment.

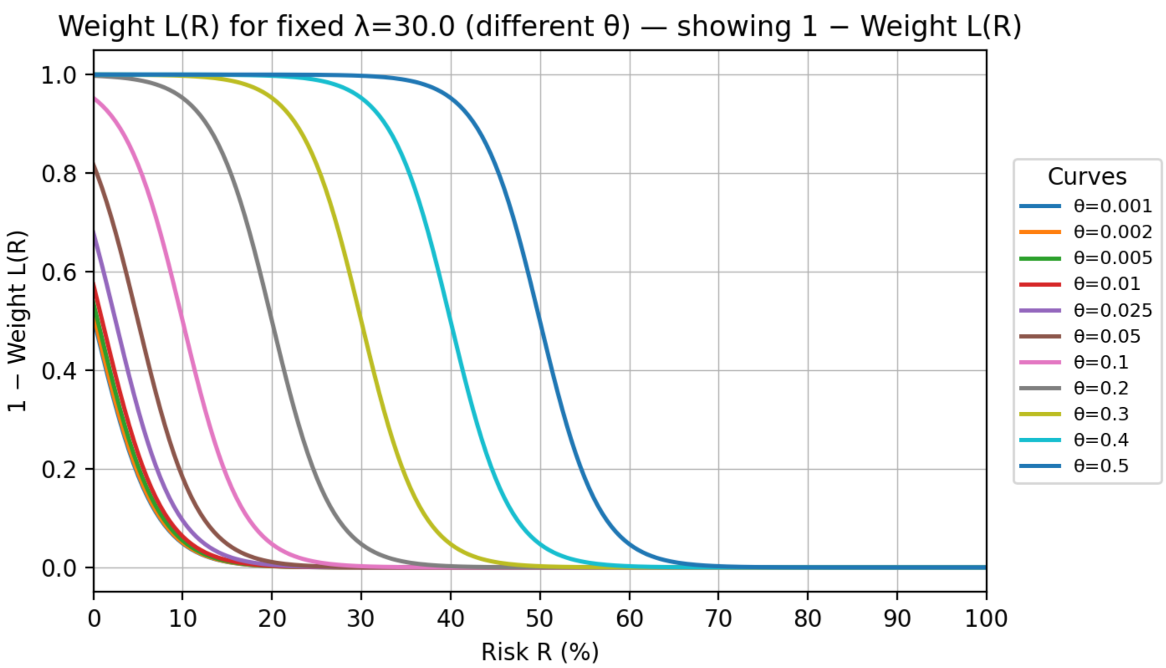
Such behavior also means extremely low tolerance for uncertainty in input data. Even minimal changes in input risk or small deviations in the choice of threshold θ cause a complete jump in the safety factor. In this mode, the model becomes extremely sensitive and difficult to control in operational terms, as it does not allow for mitigating effects or gradual responses.

In the context of the entire model, λ = 25 represents an almost idealized threshold behavior, which is useful primarily for analytical and illustrative purposes. In real environments, such a parameter setting would lead to overly rigid and potentially unstable decision-making, so its practical application only makes sense in highly controlled systems with very precisely defined thresholds and highly reliable input data.

3.1.10 Theoretical upper limit of responsiveness and complete threshold dominance (λ = 30)

The graph (seeGraph 53) shows the behavior of the safety factor $V(R)$=1−L (R) at a fixed, extremely high sensitivity parameter value λ = 30, with the risk threshold θ varying. The x-axis shows the input risk R in the range from 0% to 100%, while the y-axis shows the value of the safety factor.

Graph 53: Effect of threshold θ on the safety factor at extreme sensitivity (λ = 30).



With this setting, the parameter λ reaches the practical theoretical upper limit of the responsiveness of the logistic model. The transition of the safety factor from a value close to 1 to a value close to 0 occurs almost instantaneously and is concentrated in an extremely narrow range of input risk around the threshold θ. Outside this range, the function practically does not take intermediate values, but remains either in a state of high or low safety.

The role of the threshold θ is absolute in this mode. The individual curves differ only in the horizontal position of the transition, while the shape of the transition is almost identical for all values of θ. Lower values of θ cause an immediate loss of the safety factor even at negligible levels of risk, while higher values of θ shift the transition towards medium or higher values of R, but without any mitigation of the intensity of the response.

In this mode, the model completely loses the gradualness and continuity that are characteristic of the logistic function at lower λ values. Intermediate values of the safety factor have practically no interpretative value, as the range in which they occur is negligibly narrow. As a result, the model no longer allows for the assessment of risk levels, but acts almost exclusively as a deterministic threshold trigger.

Such behavior also means extreme sensitivity to inaccuracies in the input data. Even a minimal change in the input risk or a very small change in the threshold θ can cause a complete jump from a high to a low security state. This significantly increases the risk of unstable or unpredictable decision-making in real systems, especially in environments with incomplete or noisy data.

In the context of the entire model, λ = 30 represents the analytical upper limit of the applicability of the logistic function as a smooth evaluation mechanism. This example clearly illustrates how, as λ increases, the role of the threshold θ transforms from a regulatory parameter to an almost exclusively decisive criterion. Although such a regime is useful for understanding the limiting behavior of the model, it is generally not suitable for operational use, as it sacrifices stability, interpretability, and tolerance to uncertainty in exchange for maximum response sharpness.

3.1.11 The influence of the threshold θ at a fixed value of the parameter λ

An analysis of the influence of the risk threshold θ at fixed values of the sensitivity parameter λ reveals a gradual but very clear transformation of the role of the threshold in the logistic safety model, expressed by the safety factor $V(R)$=1−L (R). At low values of λ, the logistic function retains a distinctly continuous and flat shape, which means that changes in the threshold θ mainly cause a shift in the position of the transition along the axis R. However, at low λ, this shift in the output $V(R)$ is less pronounced because the curve is very flat. In this mode, the threshold does not define a sharp boundary between safety states, but acts as a correction parameter that slightly increases or decreases the base level of the safety factor across the entire range of input risk.

As the value of λ increases, the influence of the threshold θ gradually strengthens. The safety factor curves begin to differ not only in absolute value, but also in the position of the area where the safety factor decreases most rapidly. The threshold in this area acts as a transition regulator: it determines at which level of input risk R the system begins to lose its safety factor more rapidly. In this mode, the model allows for a meaningful distinction between areas of high, moderate, and low safety, with the choice of threshold directly reflecting the level of acceptable risk and the preventive orientation of the system.

At high values of λ, the role of the threshold θ becomes even more pronounced. The transition of the safety factor from a value close to 1 to a value close to 0 is concentrated in a very narrow range around the threshold, outside of which the function quickly saturates. In this mode, the threshold almost completely determines the decision point, while the gradualness and continuity of the response are almost completely lost. The differences between individual θ values are no longer reflected in the shape or intensity of the response, but almost exclusively in the horizontal shift of the transition location.

An analysis of extreme cases further shows that at very low θ values, the model loses its discriminative power, as the safety factor drops very quickly to low values even at negligible input risk. In combination with high values of λ, this leads to a regime of constant safety loss, where most of the range of R no longer contributes additional information value. Conversely, at higher values of θ and moderate values of λ, the model maintains a balance between early detection and stability, enabling useful and interpretable safety assessment.

The overall analysis confirms that the threshold θ does not have absolute significance in itself, but its function is inextricably linked to the selected value of the parameter λ. At low λ, the threshold acts as a fine-tuning mechanism, at moderate λ as a transition regulator, and at very high λ as an almost exclusive decision criterion. Understanding this interdependence is essential for the meaningful application of the logistic safety model, as it allows for a conscious choice of compromise between stability, responsiveness, and tolerance to input data uncertainty.

3.1.12 Practical implications of a fixed value of the parameter λ

Fixing the sensitivity parameter λ in the logistic safety model means that the overall dynamics of the system's response are predetermined, while the flexibility of the model is transferred primarily to the risk threshold θ. In practice, this means that the organization or decision-maker first selects the desired level of system responsiveness—i.e., whether the response should be restrained, balanced, or highly selective—and then uses the threshold θ to adjust the level of input risk at which this response will be activated.

At low values of λ, the model behaves in a distinctly stable and continuous manner. Changes in the threshold θ in this case do not cause sudden breaks in the safety factor, but rather a uniform shift in the overall assessment. In practice, this setting is suitable for environments with a high degree of uncertainty in the input data, where the risk is difficult to quantify accurately or where there is noise in the detection of threats. The threshold θ in this mode allows the overall level of caution to be adjusted without making the system unstable or overly sensitive to minor changes in input risk.

At moderate values of λ, the threshold θ acts as the central regulatory element. Changing the threshold directly affects when the safety factor begins to decline more rapidly, while the model still retains its continuity and interpretability. In practice, this allows for a clear link between organizational risk policy and quantitative safety assessment. Lowering the threshold means a more preventive stance and earlier detection of deterioration in safety, while raising the threshold means greater risk tolerance and greater resistance to short-term fluctuations in input assessments.

At high λ values, the fixed sensitivity of the system is reflected in a very steep response, which means that the threshold θ takes on an almost exclusively decisive role. In this mode, even small changes in the threshold or input risk cause large changes in the security factor. The practical consequence is that the threshold must be chosen very carefully and judiciously, as incorrect settings can lead either to a premature drop in security and frequent alarms or to a delayed system response. This configuration is particularly suitable for environments where the input data is very reliable and where a sharp distinction between safe and unsafe conditions is desirable.

An especially important implication of the fixed value of λ is organizational and operational consistency. Since the sensitivity of the model remains unchanged, the threshold θ can serve as a transparent and communicatively understandable risk management instrument. Changes in the threshold can be directly linked to changes in threats, the regulatory environment, or strategic priorities without having to interfere with the mathematical structure of the model itself.

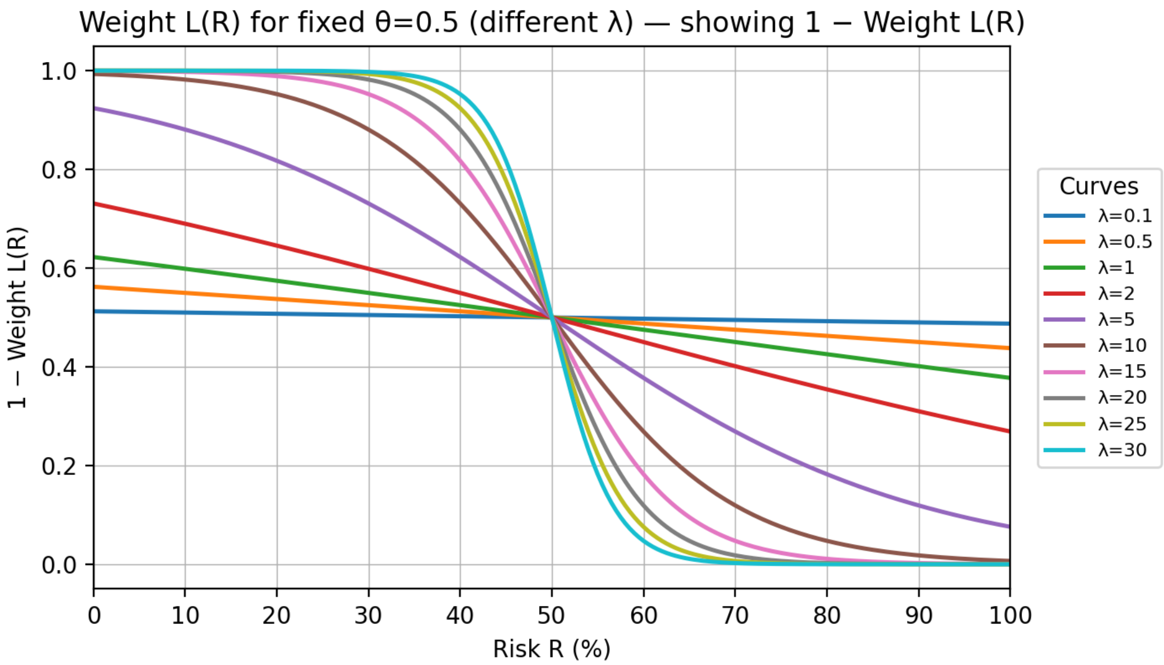
Overall, the fixed value of λ provides a stable framework for the model's operation, within which the threshold θ acts as an adjustment lever. Such a design makes sense in practice when we want a long-term consistent response from the system and, at the same time, sufficient flexibility to allow the model to adapt to different levels of risk and organizational tolerances without recalibrating the underlying dynamics.

3.2 Model analysis at a fixed threshold value θ

3.2.1 Moderate risk tolerance and transition at the midpoint of the interval (θ = 0.5)

The graph (seeGraph 54) shows the behavior of the safety factor $V(R)$=1−L (R) at a fixed risk threshold value θ = 0.5, with the sensitivity parameter λ varying. The x-axis shows the input risk R in the range from 0% to 100%, while the y-axis shows the value of the safety factor.

Graph 54: Effect of parameter λ on the safety factor at a fixed threshold θ = 0.5.



Since the threshold θ is equal to 0.5, all curves intersect at the point R= 50%, where the safety factor takes the value $V(R)$=0.5. This common point clearly confirms that the threshold θ determines the location of the transition, while the parameter λ does not affect the position of the threshold, but only the dynamics of the transition around it.

At low λ values (e.g., λ = 0.1 and λ = 0.5), the transition of the safety factor is very gradual. Safety decreases gradually and continuously as risk increases; due to the low λ value, the transition is very gradual, so the non-linearity is less pronounced. In this mode, the system maintains high stability and continuity, with the distinction between risk values being most pronounced in the wider range around R ≈0.5, but due to the low slope, the response remains extended and less selective. This setting is suitable for environments where robustness is important and where sudden changes in the output estimate are undesirable.

At moderate values of λ (λ = 1, 2, 5), the transition around the threshold begins to take shape clearly. The safety factor decreases more rapidly near R= 50%, and the differences between lower and higher risk become more pronounced. The model achieves a balanced mode of operation in this range, as it allows for meaningful risk differentiation while maintaining a continuous and interpretable response. This configuration represents a compromise between stability and responsiveness.

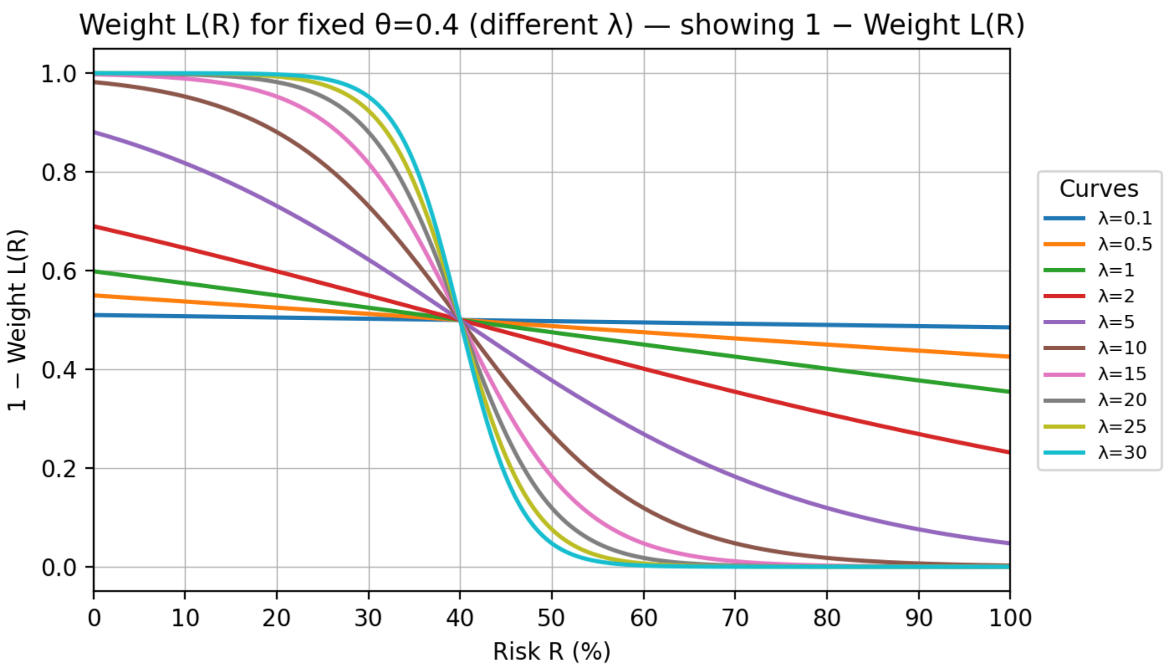
At high λ values (λ ≥ 10), the transition of the safety factor becomes very steep and concentrated in a narrow range around the threshold. Outside the transition band around $R \approx \theta$, the safety factor rapidly approaches the asymptote: it remains high at $R \ll \theta$ and low at $R \gg \theta$. In this mode, the model behaves almost like a threshold, as even small changes in the input risk near R= 50% cause large changes in the output estimate. This increases the resolution of the model, but at the same time significantly reduces the tolerance to uncertainty in the input data.

The overall analysis shows that, at a fixed threshold θ, the parameter λ takes on the role of the main regulator of the system's responsiveness. Low values of λ ensure continuity and robustness, moderate values enable balanced risk differentiation, and high values transform the model into an almost binary decision-making mechanism. The choice of λ must therefore be closely linked in practice to the reliability of the input risk assessments and whether a gradual or highly selective response of the security model is desirable in a specific environment.

3.2.2 Transition to a more cautious mode at lower risk and reduced tolerance (θ = 0.4)

The graph (seeGraph 55) shows the behavior of the safety factor $V(R)$=1−L (R) at a fixed risk threshold value θ = 0.4 and a changing sensitivity parameter λ. The x-axis shows the input risk R in the range from 0% to 100%, and the y-axis shows the value of the safety factor.

Graph 55: Effect of the λ parameter on the safety factor at a fixed threshold θ = 0.4.



Since the threshold θ is set at 0.4, all curves intersect at the point R= 40%, where the safety factor reaches the value $V(R)$=0.5. This clearly confirms that the parameter θ determines the position of the breakpoint on the risk axis, regardless of the selected value of λ. In this context, the parameter λ exclusively regulates the steepness of the transition through the threshold.

At low values of λ, the transition of the safety factor is very gradual. Safety decreases gradually with increasing risk, without a distinct breakpoint, which means high tolerance to changes in input risk near the threshold. This response is typical for systems where continuity and stability of assessment are desirable and sensitivity to short-term risk fluctuations is reduced.

At moderate values of λ, the transition around the threshold becomes more pronounced. The safety factor near R= 40% begins to decline more rapidly, allowing for a clearer distinction between acceptable and less acceptable levels of risk. In this mode, the model achieves a balance between responsiveness and robustness and enables interpretable decision-making without sudden jumps in the output assessment.

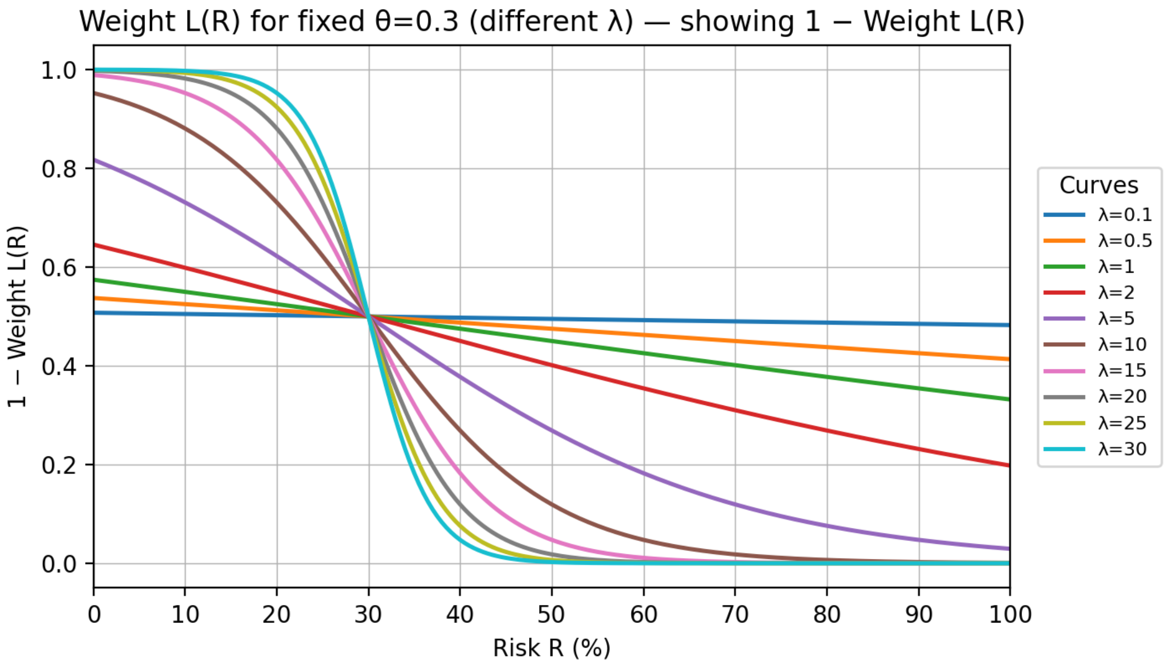
At high values of λ, the transition of the safety factor becomes much sharper and concentrated in a narrow range around the threshold. Outside this range, the safety factor quickly converges towards values close to 1 for low risk and 0 for high risk. In this mode, the model behaves almost discretely, as even small changes in input risk around R= 40% cause significant changes in the output estimate. This increases the resolution of the assessment, but at the same time requires high reliability of the input data.

The analysis shows that at a lower threshold θ, the system enters the area of increased response even at lower risk values, which makes sense in environments with low risk tolerance. In such a setting, the parameter λ determines whether this transition will be gradual or sharply defined, which directly shapes the operational character of the security model.

3.2.3 Earlier detection of security degradation and a more restrictive threshold (θ = 0.3)

The graph (seeGraph 56) shows the behavior of the safety factor $V(R)$=1−L (R) at a fixed risk threshold value θ = 0.3 and a changing sensitivity parameter λ. The x-axis shows the input risk R in the range from 0% to 100%, and the y-axis shows the value of the safety factor.

Graph 56 : Effect of the λ parameter on the safety factor at a fixed threshold θ = 0.3.



Since the threshold θ is set at 0.3, all curves intersect at the point R= 30%, where the safety factor reaches the value $V(R)$=0.5. This property confirms that the threshold θ determines the location of the breakpoint on the risk axis, regardless of the selected value of λ, while the parameter λ affects the shape and steepness of the transition.

At low λ values, the transition of the safety factor from the upper to the lower range is very gradual. Safety decreases slowly as risk increases, which means that the model allows for greater risk tolerance even in the range around the threshold. This behavior is typical of systems where the emphasis is on stability and continuity of assessment and on reducing the risk of oversensitive responses.

At medium values of λ, the decline in the safety factor near the threshold becomes more pronounced. The model begins to distinguish more clearly between risk levels below and above the threshold, with the transition still sufficiently extended to allow for interpretability and gradual adjustment of responses.

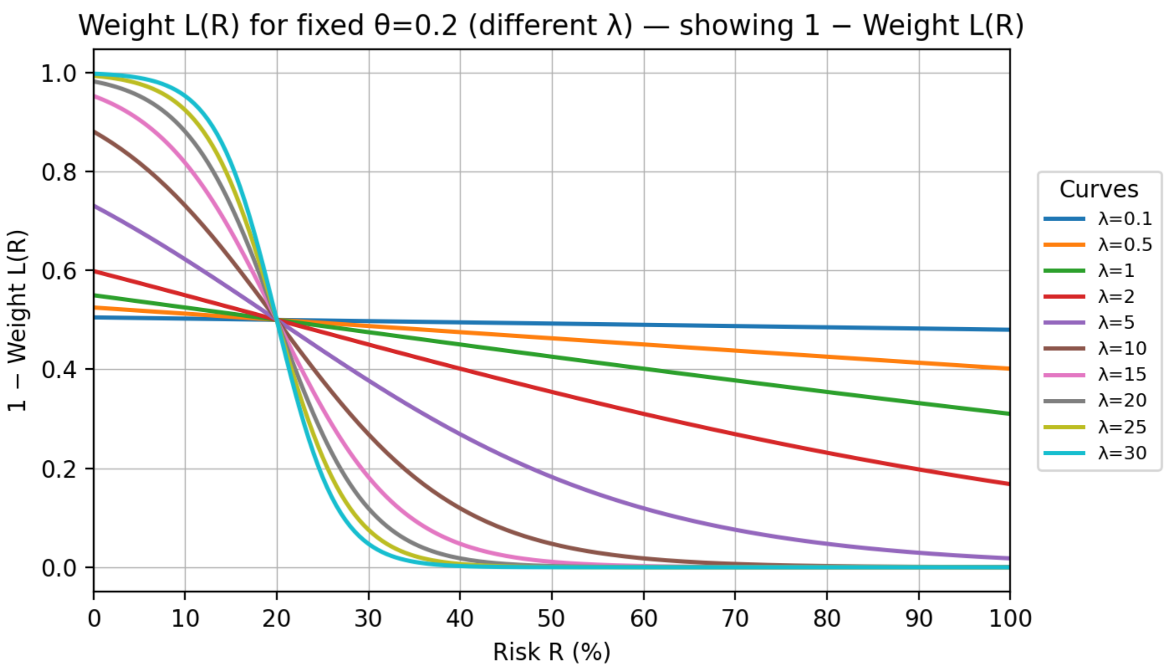
At high λ values, the transition narrows significantly and concentrates in a narrow range around R= 30%. In this case, the safety factor for risks below the threshold quickly remains close to 1, while for risks above the threshold it quickly converges towards 0. The model thus approaches discrete- e decision-making, where even small changes in the input risk near the threshold cause significant changes in the output estimate.

Lowering the threshold θ to 0.3 means that the system enters the area of increased response even at relatively low risk values. In combination with higher λ values, this leads to a markedly restrictive safety regime, where risk tolerance is rapidly reduced. Conversely, low λ values maintain continuity and gradualness of assessment even at lower thresholds, which is appropriate for environments with greater uncertainty and a need for stable response.

3.2.4 Restrictive threshold and early loss of safety margin (θ = 0.2)

The graph (seeGraph 57) shows the behavior of the safety factor $V(R)$=1−L (R) at a fixed risk threshold value θ = 0.2 and a changing sensitivity parameter λ. The x-axis shows the input risk R in the range from 0% to 100%, and the y-axis shows the value of the safety factor.

Graph 57: Effect of the λ parameter on the safety factor at a fixed threshold θ = 0.2.



All curves intersect at the point R= 20%, where the safety factor reaches the value $V(R)$=0.5. This property confirms the role of the threshold θ as a reference point for the transition between higher and lower levels of safety, while the parameter λ determines the speed and steepness of this transition.

At low values of λ, the transition of the safety factor is very gradual. Safety decreases gradually as risk increases, which means that even for risks above the threshold, the model still maintains relatively high values of the safety factor. This behavior reflects a more restrictive threshold policy (lower θ), while the stability and gradualness of the response are still primarily determined by the low value of λ.

At medium values of λ, the decline in the safety factor near the threshold accelerates more markedly. The model begins to distinguish more clearly between the acceptable risk range below the threshold and the elevated risk range above the threshold, with the transition still sufficiently extended to allow for a continuous interpretation and gradual adjustment of responses.

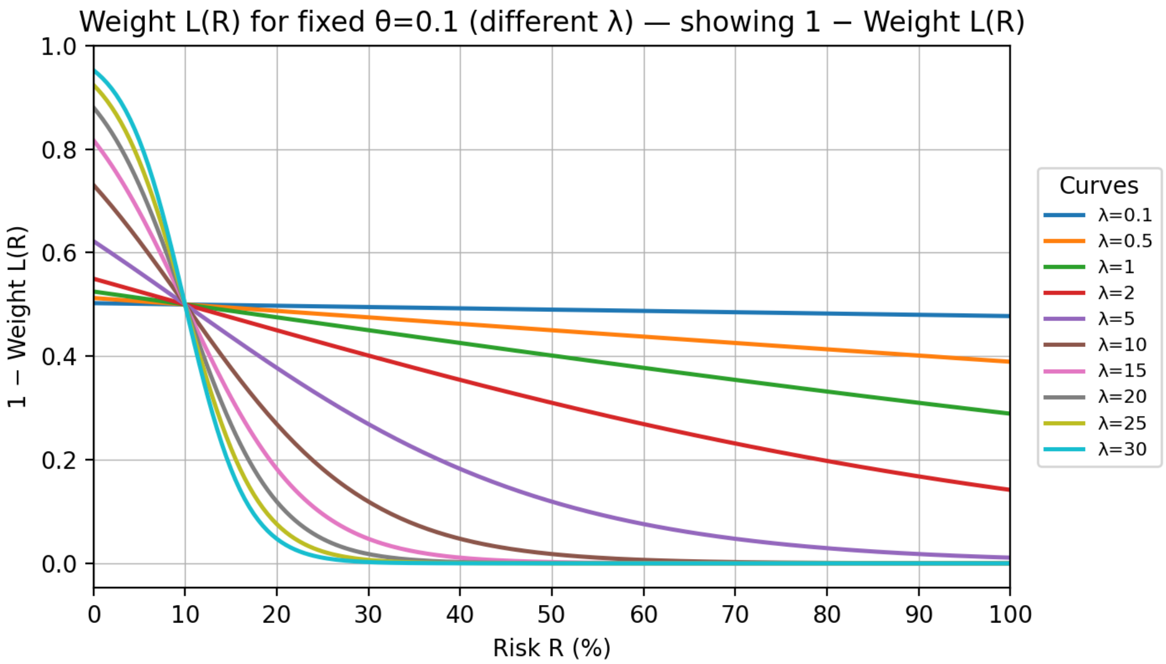
At high values of λ, the transition of the safety factor narrows significantly to a narrow range around $R=$ 20%. In this case, the safety factor for risks below the threshold quickly remains close to 1, while for risks above the threshold it converges very quickly towards 0. The model thus approaches discrete decision-making, where even small deviations of the input risk around the threshold cause significant changes in the output estimate.

A low threshold θ = 0.2 means that the system enters the reduced safety zone even at relatively low risk values. In combination with higher λ values, this leads to a very restrictive response regime, where risk tolerance is limited to a narrow interval below the threshold. Conversely, low λ values maintain the continuity and stability of the assessment even at such a low threshold, which is appropriate for environments with high uncertainty or for the purpose of preventing excessive responses to minor risk fluctuations.

3.2.5 Very low risk tolerance and very early transition (θ = 0.1)

The graph (seeGraph 58) shows the behavior of the safety factor $V(R)$=1−L (R) at a fixed risk threshold value θ = 0.1 and a changing sensitivity parameter λ. The x-axis shows the input risk R in the range from 0% to 100%, and the y-axis shows the value of the safety factor.

Graph 58 : Effect of the λ parameter on the safety factor at a fixed threshold θ = 0.1.



All curves intersect at the point R= 10%, where the safety factor reaches the value $V(R)$=0.5. This property directly reflects the mathematical role of the threshold θ, which determines the reference point of transition between the higher and lower perceived safety ranges, while the parameter λ affects only the slope and dynamics of the transition.

At low values of λ, the change in the safety factor is very gradual. Safety decreases slowly and almost linearly as risk increases, which means that even at risks above the threshold, the system still maintains moderate safety factor values. Such a response is typical for environments where continuous and stable assessment without pronounced jumps in response is desirable.

At medium values of λ, the drop in the safety factor around the threshold becomes more pronounced. The model begins to clearly distinguish between risks below and above the threshold θ, with the transition still sufficiently extended to allow for gradual adjustment of decisions and interpretations.

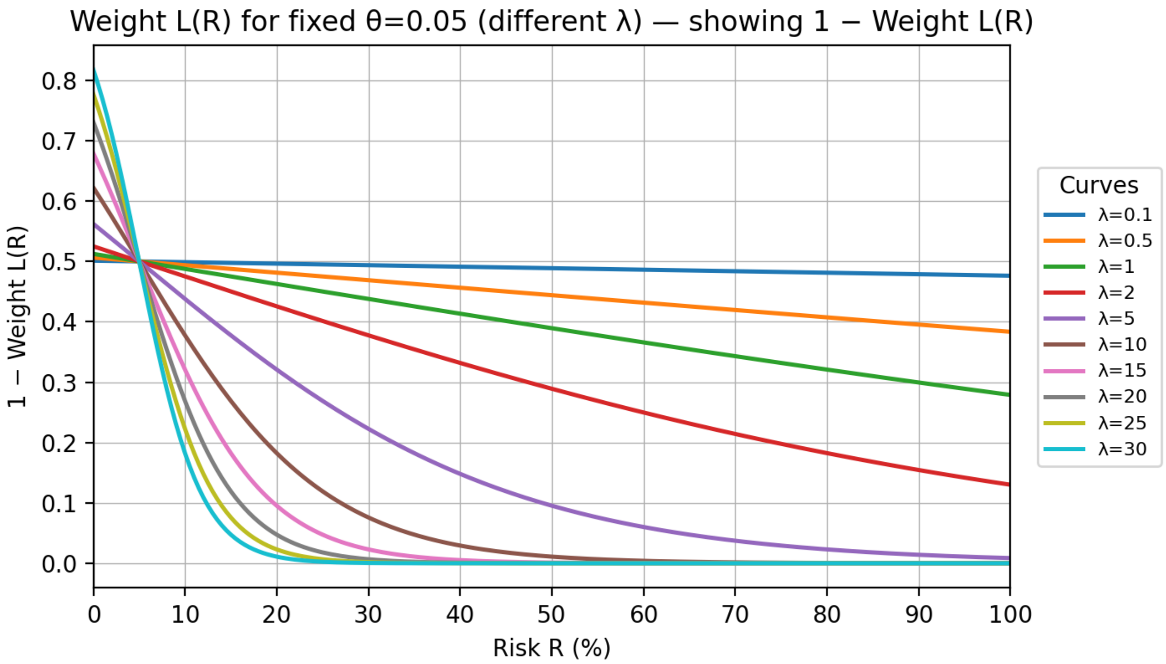
At high λ values, the transition of the safety factor narrows significantly and concentrates in a narrow range around R= 10%. In this case, the model behaves almost discretely: even small increases in risk above the threshold cause a rapid drop in the safety factor towards zero, while risks below the threshold maintain a very high level of perceived safety.

A low threshold θ = 0.1 means that the system moves very early from the high safety range to the reduced safety range. In combination with high λ values, this leads to a highly restrictive response mode, where risk tolerance is limited to a very narrow interval. Conversely, low λ values, even at such a low threshold, allow for a softer and more tolerant response, which increases the robustness of the model in environments with high uncertainty or noise in the input data.

3.2.6 Extremely conservative threshold and transition even at minimal risk (θ = 0.05)

The graph (seeGraph 59) shows the behavior of the safety factor $V(R)$=1−L (R) at a fixed risk threshold value θ = 0.05 and a changing sensitivity parameter λ. The x-axis shows the input risk R in the range from 0% to 100%, while the y-axis shows the value of the safety factor.

Graph 59 : Effect of the λ parameter on the safety factor at a fixed threshold θ = 0.05.



All curves intersect at the point R= 5%, where the safety factor reaches the value $V(R)$=0.5. This intersection point represents the threshold at which the system transitions from the area of predominantly perceived safety to the area of reduced safety, regardless of the selected value of the parameter λ. The parameter λ exclusively affects the speed and steepness of this transition.

At low values of λ, the drop in the safety factor is very slight. Even for risks that significantly exceed the threshold θ, safety decreases gradually, which means that the system has a high tolerance for increasing risk. This type of response is typical for stable or poorly measurable environments where the aim is to prevent an overly rapid response to short-term or noisy fluctuations in input data.

At medium values of λ, the transition around the threshold becomes much more pronounced. The safety factor begins to decrease more rapidly in the narrower risk range, and the model already clearly distinguishes between values below and above the threshold θ without losing the continuity of the response. This allows for a balanced compromise between responsiveness and stability of the assessment.

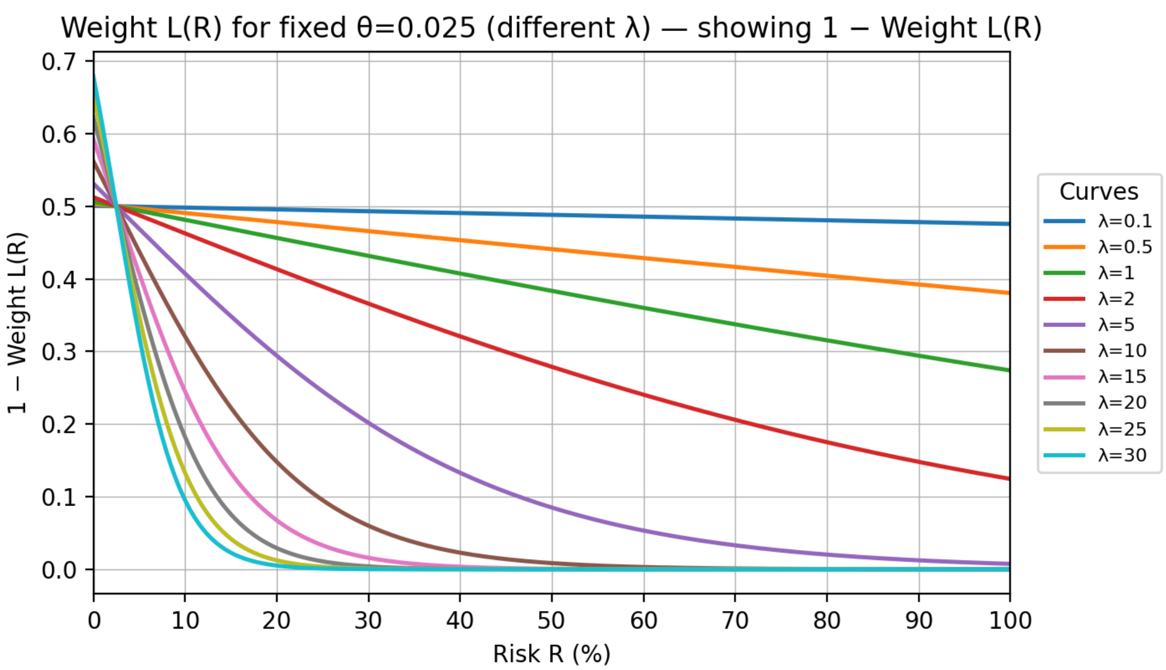
At high λ values, the transition is concentrated in a very narrow range around R= 5%. In this case, the safety factor transitions almost discretely from high values to a state of almost zero. Even a small exceedance of the threshold causes a marked drop in perceived safety, which means extremely low risk tolerance above the threshold.

A very low threshold θ = 0.05 means that the system detects the critical risk area very early on. In combination with high λ values, this leads to an extremely restrictive response mode, where the acceptable risk range is extremely limited. Conversely, low λ values, even at such a low threshold, allow for a more gradual reduction of the safety factor and thus greater robustness of the model in environments with high uncertainty or variability of input estimates.

3.2.7 Extremely restrictive threshold and limited acceptable risk interval (θ = 0.025)

The graph (seeGraph 60) shows the behavior of the safety factor $V(R)$=1−L (R) at a fixed risk threshold value θ = 0.025 and a changing sensitivity parameter λ. The x-axis shows the input risk R in the range from 0% to 100%, while the y-axis shows the value of the safety factor.

Graph 60: Effect of the λ parameter on the safety factor at a fixed threshold θ = 0.025.



Regardless of the value of λ, all curves intersect at the point R= 2.5%, where the safety factor takes the value $V(R)$=0.5. This point represents a uniform reference threshold for the system at which perceived safety and risk are balanced. The parameter λ does not affect the position of the threshold, but only the dynamics of the transition around it.

Due to the very low value of the threshold θ, the system detects the critical risk area even at very low values of R. At low values of λ, the decline in the safety factor is still gradual, but it begins almost immediately after the threshold is exceeded. This means that even with mild sensitivity, the system quickly transitions from the high safety range to the reduced safety range.

At medium λ values, the transition becomes significantly more pronounced. The safety factor decreases rapidly in a relatively narrow risk range after exceeding the threshold, which allows for a clear distinction between acceptable and unacceptable risk, while maintaining the continuity of the response.

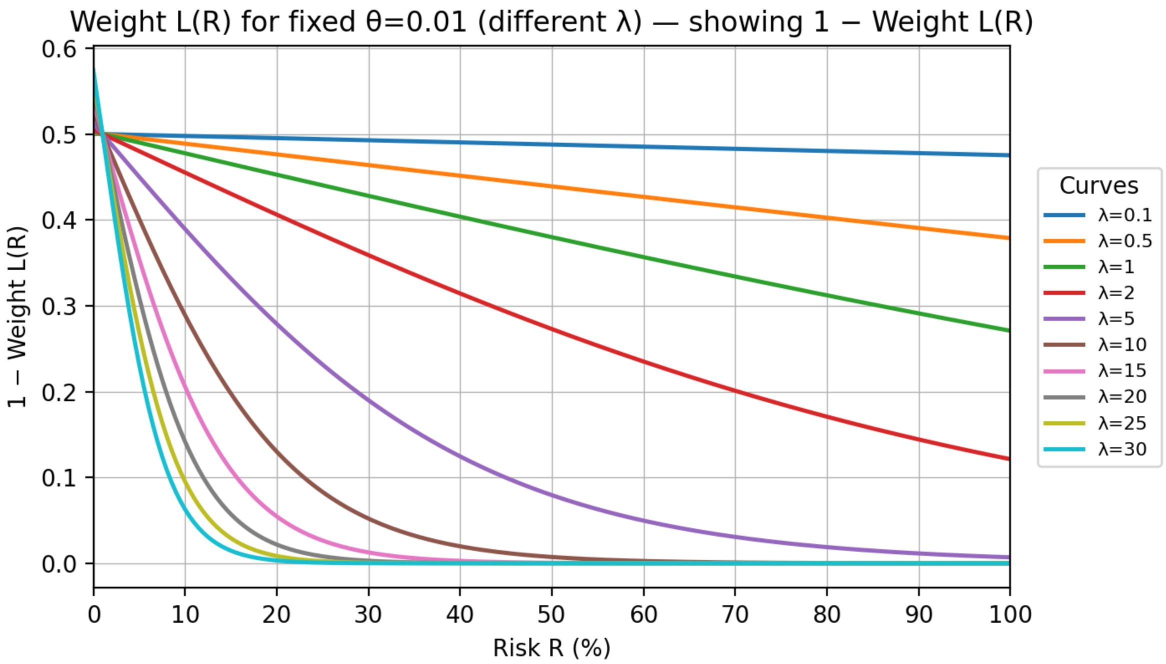
At high λ values, the behaviour of the model approaches an almost discrete threshold mechanism. Even a minimal exceedance of the threshold θ causes a very steep drop in the safety factor towards zero. The differences between the individual curves are concentrated almost exclusively in the immediate vicinity of the threshold, outside of which the safety factor quickly stabilizes at extreme values.

The combination of a very low threshold θ = 0.025 and high values of λ results in an extremely restrictive response regime. In this case, the system tolerates only a very small range of risk, which is appropriate for environments with extremely low tolerance for errors or high consequences of incidents. Conversely, lower λ values, even at such a low threshold, allow for a slightly more robust and gradual reduction in perceived security, which reduces the risk of model oversensitivity.

3.2.8 Near-zero risk tolerance and a threshold of 1% (θ = 0.01)

The graph (seeGraph 61) shows the behavior of the safety factor $V(R)$=1−L (R) at a fixed very low risk threshold value θ = 0.01 and changing sensitivity parameter λ. The x-axis shows the input risk R in the range from 0% to 100%, while the y-axis shows the value of the safety factor.

Graph 61 : Effect of the λ parameter on the safety factor at a fixed threshold θ = 0.01.



Regardless of the value of λ, all curves intersect at the point R=1%, where the safety factor takes the value $V(R)$=0.5. This point represents an extremely low threshold level at which the model transitions from the area of predominant safety to the area of increased risk. The parameter λ does not affect the position of this point, but only the steepness and speed of transition around it.

Due to the very low threshold value θ, the system detects the critical risk area even at minimal values R. At low values of λ, the transition of the safety factor is still relatively gradual, but nevertheless begins very early. The safety factor decreases continuously and gradually as the risk increases; because the threshold is very low, the transition begins early, but at low λ it remains spread over a wider risk interval.

At medium λ values, the decline in the safety factor accelerates significantly after the threshold is exceeded. The transition from the safe to the unsafe zone is concentrated in a narrower risk interval, which allows for a clearer differentiation between acceptable and unacceptable conditions, while the model still maintains the continuity of the response.

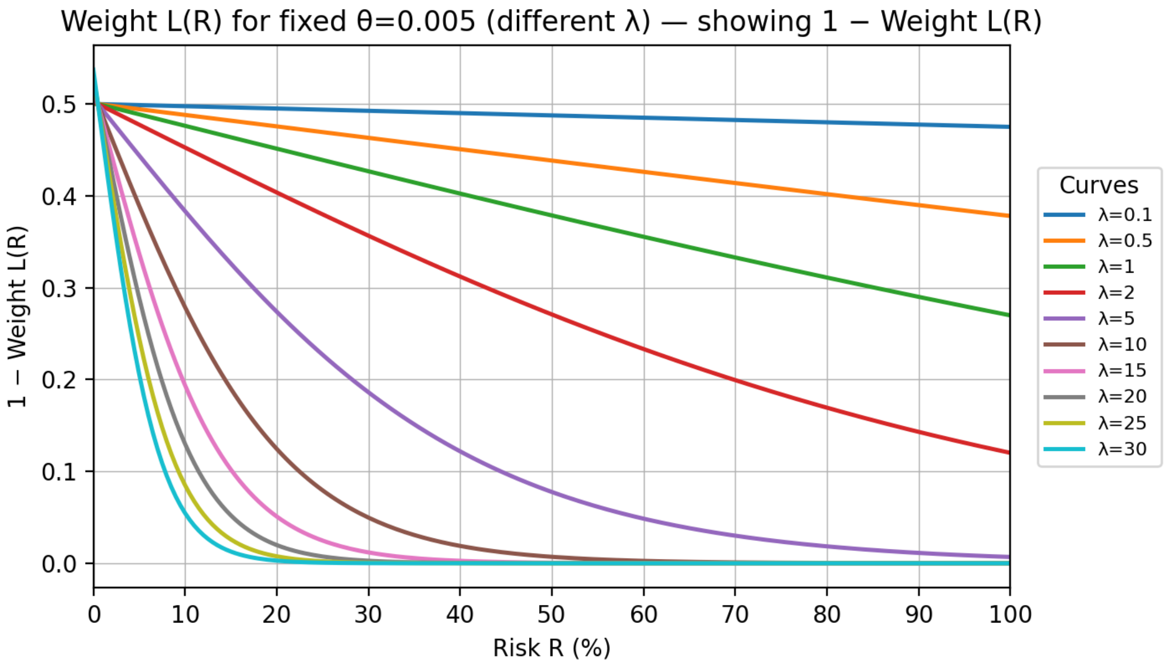
At high λ values, the behavior of the model approaches an almost discrete threshold mechanism. Even a very small exceedance of the threshold θ causes a steep and almost instantaneous drop in the safety factor towards zero. The differences between the individual curves are concentrated almost exclusively in the immediate vicinity of the threshold, outside of which the safety factor is practically constant.

The combination of a very low threshold θ = 0.01 and high values of λ results in an extremely restrictive response mode. In this case, the system tolerates only minimal risk deviations, which is appropriate for scenarios with very high consequences of errors or almost zero tolerance for incidents. On the other hand, such a setting significantly increases the sensitivity of the model to small changes in input data and can lead to overly rapid or overly harsh responses in operational environments.

3.2.9 Threshold at 0.5% and a highly conservative safety regime (θ = 0.005)

The graph (seeGraph 62) shows the behavior of the safety factor $V(R)$=1−L (R) at a very low risk threshold value θ = 0.005 and a changing sensitivity parameter λ. The x-axis shows the input risk R in the range from 0% to 100%, while the y-axis shows the value of the safety factor.

Graph 62 : Effect of the λ parameter on the safety factor at a fixed threshold θ = 0.005.



Since the threshold θ is set very low, all curves intersect at the point $R=$ 0.5%, where the safety factor reaches the value $V(R)$=0.5. This property confirms that the threshold θ determines the exact location of the breakpoint on the risk axis, regardless of the selected value of λ, while the parameter λ affects only the slope and spread of the transition between the safe and risky areas.

At low values of λ, the transition of the safety factor from higher to lower values is very gradual and spread over a wide risk interval. Although the threshold is set very low, the model still maintains a continuous and stable decrease in safety as risk increases. This behavior means that, despite the low threshold, the system does not react abruptly, but allows for a gradual adjustment of the assessment even when risks are detected early.

At medium λ values, the effect of the low threshold becomes more pronounced. The drop in the safety factor is concentrated in a narrower range around the threshold, with the model making a clearer distinction between risks below and above the threshold. The safety factor for very low risk values remains high, but even a small increase in risk causes it to decline more rapidly. In this mode, the system operates more selectively, but still maintains interpretability and a gradual response.

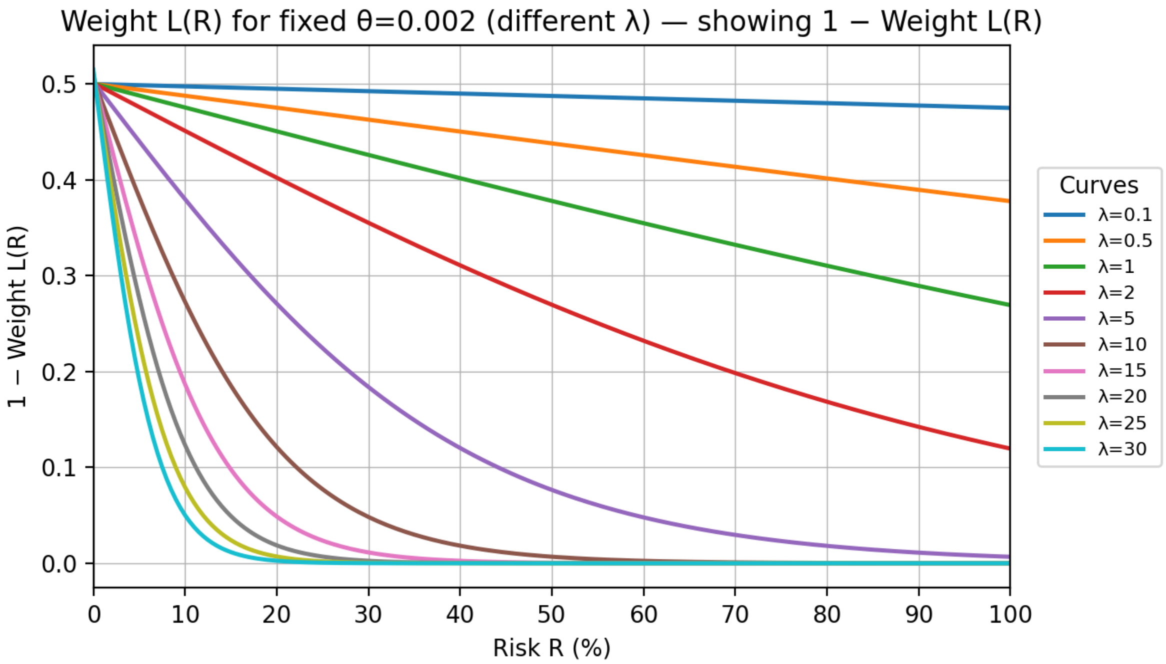
At high λ values, the transition becomes extremely steep and highly concentrated in the immediate vicinity of the threshold R=0.5%. The safety factor for risks below the threshold remains almost equal to 1, while even a minimal increase in risk above the threshold causes a rapid drop towards 0. In this range, the model approaches almost discrete decision-making, where the threshold θ, together with high sensitivity λ, acts as a sharp decision-making mechanism.

A very low threshold θ = 0.005 means that the system detects increased risk even at minimal risk values. In combination with higher λ values, this leads to an extremely restrictive safety regime, where risk tolerance is almost zero and responses are very rapid. Conversely, low λ values, even at such a low threshold, allow for more continuous and stable behavior, which is appropriate for environments with a high degree of uncertainty in input data or where it is important to prevent oversensitive and abrupt system reactions.

3.2.10 Threshold at 0.2% and very early switching to low security (θ = 0.002)

The graph (seeGraph 63) shows the behavior of the safety factor $V(R)$=1−L (R) at a fixed risk threshold value θ = 0.002 and varying sensitivity parameter λ. The x-axis shows the input risk R in the range from 0% to 100%, while the y-axis shows the value of the safety factor.

Graph 63 : Effect of the λ parameter on the safety factor at a fixed threshold θ = 0.002.



Since the threshold θ is set very low, all curves intersect at the point $R=$ 0.2%, where the safety factor reaches the value $V(R)$=0.5. This confirms the fundamental property of the logistic function: the threshold θ determines the position of the breakpoint on the risk axis independently of the value of λ, while the parameter λ regulates the steepness and spread of the transition.

At low values of λ, the transition of the safety factor from higher to lower values is very gradual. Even if the threshold is set extremely low, safety decreases slowly as risk increases, which means that even when the threshold is exceeded early on, the model still maintains relatively high values of the safety factor. This behavior is typical for environments where input data is uncertain and where continuous and stable risk assessment is desirable.

At medium values of λ, the decline in the safety factor around the threshold becomes much more pronounced. The model begins to distinguish more clearly between risks below and above the threshold, but the transition still takes place in an extended range, allowing for gradual adjustment of safety decisions.

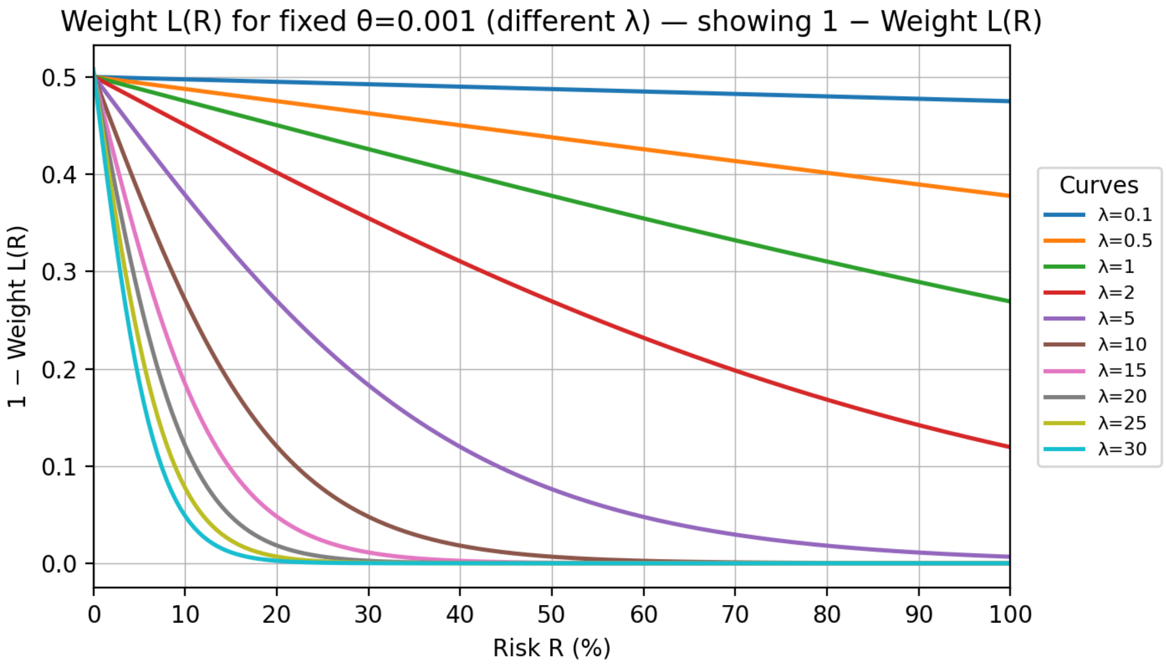
At high λ values, the transition narrows significantly and concentrates directly around $R=$ 0.2%. In this case, the safety factor for already very small risks quickly drops to zero, while for risks below the threshold it remains close to 1. The model behaves almost binary in this range, as even minimal changes in the input risk cause significant changes in the output estimate.

A very low threshold θ = 0.002 means that the system enters the area of increased response even with negligible perceived risks. In combination with higher values of λ, this leads to an extremely restrictive safety regime where risk tolerance is practically minimal. Conversely, low λ values, even at such a low threshold, allow for a continuous and less aggressive approach to risk, which is appropriate for scenarios with high measurement uncertainty or for the early stages of risk detection.

3.2.11 Threshold at 0.1% and almost zero tolerance for perceived risk (θ = 0.001)

The graph (seeGraph 64) shows the behavior of the safety factor $V(R)$=1−L (R) at an extremely low risk threshold value θ = 0.001 and a changing sensitivity parameter λ. The x-axis shows the input risk R in the range from 0% to 100%, while the y-axis shows the value of the safety factor.

Graph 64 : Effect of the λ parameter on the safety factor at a fixed threshold θ = 0.001.



Since the threshold θ is set very close to zero, all curves intersect at $R \approx 0.1\%$, where the safety factor reaches a value of $V(R)$=0.5. This confirms that the threshold θ directly determines the location of the breakpoint on the risk axis, regardless of the value of the parameter λ. Even a minimal perceived risk thus triggers a transition from a safe to a less safe area.

At low values of λ, the transition of the safety factor is relatively gradual despite the extremely low threshold. The safety factor decreases slowly as the risk increases, which means that even at a very early threshold, the model still maintains a certain continuity and tolerance. This behavior is appropriate for environments where risk measurements are subject to uncertainty or noise and where sudden responses are undesirable.

At medium values of λ, the drop in the safety factor becomes more pronounced in the immediate vicinity of the threshold. The model begins to distinguish very clearly between almost zero risk and all other values, with the transition still being extended but already markedly restrictive. Risks that only minimally exceed the threshold are quickly translated into low safety factor values.

At high values of λ, the transition narrows significantly and concentrates in an extremely narrow range just above $R \approx 0.1\%$. In this case, the safety factor for almost all risks above the threshold converges very quickly towards zero, while remaining close to 1 only in the almost zero risk range. In this mode, the model behaves almost binarily, which means that even a negligible change in the input risk causes a drastic drop in the safety rating.

A very low threshold θ = 0.001 represents an extremely conservative safety mode. The system is designed to allow virtually no perceived risk. In combination with high λ values, this leads to a distinctly rigid and restrictive response, suitable only for environments with extremely high safety requirements and highly reliable measurement data. Conversely, low λ values, even at such a low threshold, allow for a softer, more continuous transition, which reduces the risk of overly sensitive responses in real, dynamic environments.

3.2.12 The effect of λ sensitivity at a fixed threshold value θ for the safety factor

The graphs show the behavior of the safety factor $V(R)$=1−L (R) at a fixed risk threshold value θ and a changing sensitivity parameter λ. The x-axis shows the input risk R in the range from 0% to 100%, while the y-axis shows the value of the safety factor, which reflects the level of safety retained by the system in relation to the perceived risk.

At a fixed threshold value θ, all curves intersect at the same point $R=\theta\cdot$100%, where the safety factor reaches a value of $V(R)$=0.5. This property clearly shows that the threshold θ determines the position of the breakpoint on the risk axis, while the parameter λ does not affect its location, but only the shape of the transition around the threshold.

At low values of λ, the transition of the safety factor is very gradual. Safety decreases gradually as risk increases, without a pronounced break. This behavior means high tolerance to uncertainty and noise in the input data and ensures stable and continuous assessment even near the threshold. In this mode, the model operates smoothly and is suitable for environments where risk measurements are unreliable or where sudden responses are undesirable.

At medium values (λ), the drop in the safety factor near the threshold becomes more pronounced. The model begins to distinguish more clearly between the acceptable and unacceptable risk ranges, while still maintaining a certain degree of gradualness. This mode represents a compromise between stability and responsiveness and allows for interpretable and controlled adjustment of safety decisions.

At high values of λ, the transition of the safety factor narrows significantly and concentrates in a very narrow range around the threshold θ. The safety factor for risks below the threshold remains almost unchanged near 1, while for risks above the threshold it quickly converges towards 0. In this case, the model approaches discrete decision-making, where even small changes in risk near the threshold cause significant changes in the output estimate.

The safety significance of the parameter λ is therefore directly related to the selected operating mode. Low values of λ are suitable for systems where the emphasis is on robustness and resistance to fluctuations in risk assessments, while high values of λ support a restrictive and decisive safety mode in which the risk threshold is strictly enforced. In combination with a fixed threshold θ, the parameter λ thus allows for fine-tuning the responsiveness of the safety model without changing the acceptable risk limit itself.

3.2.13 Practical implications of choosing the safety parameter λ at a fixed threshold θ

An analysis of the impact of the sensitivity parameter λ at a fixed risk threshold value θ shows that, in practice, λ acts as a regulator of the response mode of the safety model rather than a determinant of the acceptable risk limit. The threshold θ always determines the transition point at which the safety factor is equal to 0.5, while λ shapes how quickly and how sharply the system responds to changes in risk in its environment.

At lower values of λ, the model operates with a distinctly continuous and gradual response. The safety factor decreases slowly as the risk increases, without a distinct break. In practice, this means greater tolerance to input data uncertainty, measurement noise, and minor short-term risk fluctuations. This setting is appropriate for environments where risk assessments are aggregated from multiple sources, where there is greater epistemological uncertainty, or where abrupt responses could have disproportionate operational consequences.

At moderate values of λ, a clearly recognizable transition zone forms around the threshold. The model begins to distinguish more clearly between lower and higher levels of risk, but still retains its gradualness and interpretability. In operational terms, this setting allows for a balanced approach where risks are treated neither too leniently nor too restrictively. This mode is suitable for most real-world security environments where it is necessary to simultaneously consider decision stability and reasonable system responsiveness.

At high values of λ, the transition of the safety factor narrows significantly and concentrates in a very narrow range around the threshold θ. The model begins to behave almost threshold-like, as even small changes in risk near the threshold cause large changes in the output estimate. In practice, this means high decision resolution and very low tolerance to risks above the threshold. Such a setting makes sense in environments with very high consequences of incidents or where the input data is very reliable, but at the same time increases the risk of system oversensitivity in the event of inaccurate or unstable risk estimates.

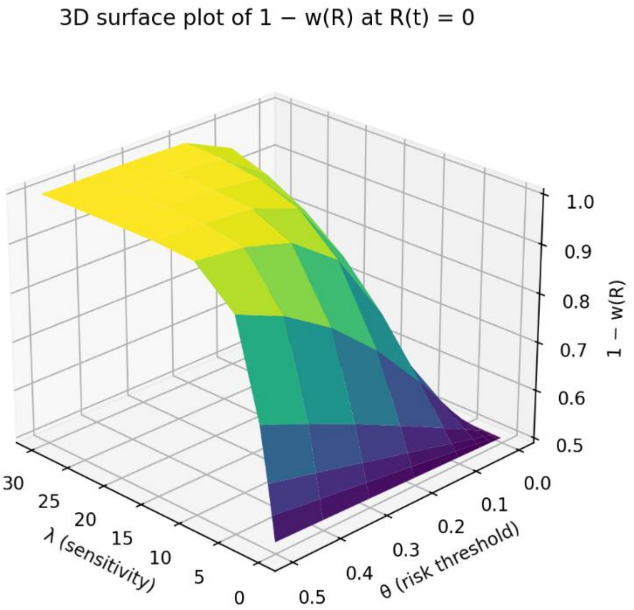
From the perspective of model application, it is important that the choice of the λ parameter is not considered in isolation, but in conjunction with the reliability of the input data, the operational context, and the purpose of the assessment. With a fixed threshold θ, the parameter λ allows for fine-tuning of the system's responsiveness without changing the acceptable risk limit itself. This allows the model to be adapted to different security regimes – from tolerant and robust to highly restrictive – while maintaining a uniform risk threshold concept.

3.3 The combined effect of the parameters λ and θ on the safety factor V(R)

3.3.1 Behavior of the safety factor at zero input risk (R(t) = 0)

The graph (seeGraph 65) shows the three-dimensional distribution of the safety factor $V(R)$ at zero input risk $R\ (t)$=0 as a function of the sensitivity parameter λ and the risk threshold θ. The safety factor is defined as the complement of the dynamic weight, $V(R)$=1− $w(R)$, so the graph directly reflects the inverse image of the behavior of the risk weight in the mode of complete absence of perceived risk.

Graph 65 : The effect of parameters λ and θ on the safety factor at zero input risk (R(t) = 0).



At low values of the parameter λ and low threshold values θ, the safety factor reaches its lowest values, which means that despite zero input risk, the model does not assign a high level of safety to the system. This reflects a very cautious or extremely preventive mode of operation, in which even minimal potential deviations cause a reduction in perceived safety. This behavior is a result of the input risk being to the left of the inflection point at low thresholds, where the logistic function still generates relatively high weights.

As the parameter λ increases, the safety factor increases rapidly and approaches the upper limit, indicating the model's greater ability to maintain a high safety rating under zero risk conditions. At medium and high values of λ, the influence of the θ threshold becomes less pronounced, as the system stabilizes in the high safety range regardless of the threshold setting. In this part of the parameter space, the logistic function operates in the low weight range, which is directly reflected in high values of $V(R)$.

The differences between individual threshold values θ are most noticeable at low and moderate values λ, where a change in the threshold significantly affects the perceived level of safety. Higher thresholds allow the model to maintain a relatively high safety rating even at low sensitivity, while low thresholds combined with low λ cause a rapid decrease in the safety factor. This confirms that the parameter θ acts as a basic detection filter in this mode, while λ determines the stability and robustness of the response.

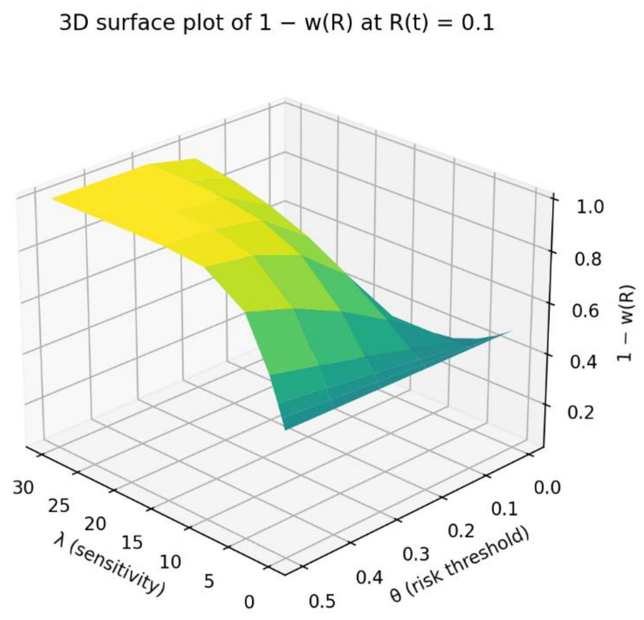
The range of safety factor values is relatively wide at $R\ (t)$=0, indicating that even in the absence of risk, the model allows for fine differentiation between more and less stable parameter configurations. In this mode, the model does not behave trivially or degenerately, but actively assesses the degree of confidence in the safety status of the system.

This graph clearly illustrates that the safety factor is not merely a mirror function of risk weighting, but rather an independent interpretative measure that reflects the relationship between perceived risk absence, threshold policy, and system sensitivity. The regime $R\ (t)$=0 thus represents the initial reference state of the model, in which it is verified whether the selected parameter values enable meaningful and stable safety assessment even under ideal conditions.

3.3.2 Behavior of the safety factor at low input risk (R(t) = 0.1)

The graph (seeGraph 66) shows the three-dimensional distribution of the safety factor $V(R)$ at a low but non-zero input risk value $R\ (t)$=0.1 depending on the sensitivity parameter λ and the risk threshold θ. Since the safety factor is defined as the complement of the dynamic weight, $V(R)$=1− $w(R)$, the graph reflects a gradual decrease in perceived safety even at low perceived risks and at the same time reveals how sensitivity and threshold settings affect this decrease.

Graph 66 : Influence of parameters λ and θ on the safety factor at low input risk (R(t) = 0.1).



At low values of the parameter λ and low threshold values θ, the safety factor decreases rapidly, which means that the model significantly reduces the perceived level of safety even at minimal risk. Such a response reflects a distinctly cautious operating mode, in which the system treats minimal deviations from the ideal state as relevant and potentially dangerous. In this range, the input risk is close to or to the right of the inflection point, causing a noticeable increase in weight and thus a decrease in the safety factor.

As the parameter λ increases, the high safety range expands, especially at higher threshold values θ. At medium and high values λ, the safety factor remains high in a wider part of the parameter space, indicating greater system robustness and greater tolerance to low risk levels. In this mode, threshold changes θ act primarily as a fine-tuning mechanism, while sensitivity determines the overall stability of the safety assessment.

The differences between individual threshold values θ are most pronounced at low and moderate values λ, where even small changes in the threshold significantly affect the perceived security. Higher thresholds allow for a higher safety rating to be maintained even when the risk is low but present, while lower thresholds cause a faster and more pronounced drop in the safety factor. This confirms that the parameter θ acts as a key distinguishing mechanism between negligible and relevant risk in this mode.

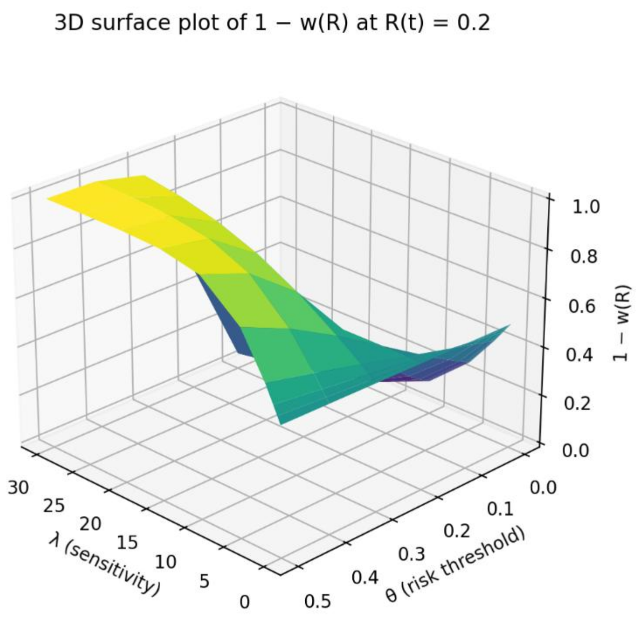
The range of safety factor values at $R\ (t)$=0.1 is already significantly wider than at zero risk, indicating increased differentiation between parameter configurations. In this mode, the model transitions from exclusively reference-based assessment to an active detection phase, in which it begins to clearly distinguish between more and less stable security settings.

This graph illustrates the transitional state of the model's operation, in which the security factor is not yet significantly compromised, but is already responding to the presence of risk. Combinations of a low threshold θ and low sensitivity λ lead to a rapid decline in security, while higher values of both parameters allow for a restrained and stable response. The mode $R\ (t)$=0.1 thus represents the first stage of active reduction of the security rating and clearly indicates the beginning of the transition from an ideal to a more stressed security state.

3.3.3 Behavior of the safety factor at moderately low input risk (R(t) = 0.2)

The graph (seeGraph 67) shows the three-dimensional distribution of the safety factor $V(R)$ at a moderately low input risk value $R\ (t)$=0.2 depending on the sensitivity parameter λ and the risk threshold θ. In this mode, the impact of input risk on the safety assessment is already clearly expressed, whereby the safety factor is no longer stable across the entire parameter space, but begins to decrease more significantly depending on the selected parameter settings.

Graph 67 : Influence of parameters λ and θ on the safety factor at moderately low input risk (R(t) = 0.2).



At low values of the parameter λ and low threshold values θ, the safety factor reaches low values, which means that even at a relatively low perceived risk, the model considers safety to be significantly reduced. This reflects the transition from a preventive to a stricter operating mode, in which the system begins to perceive risk as systemically relevant. In this area, the input risk is close to or to the right of the inflection point of the logistic function, so the risk weight increases rapidly, resulting in a significant decrease in the safety factor.

As the parameter λ increases, the range of higher safety factor values expands, especially at higher threshold values θ. At medium and high values of λ, the safety factor remains moderate to high in a wider part of the parameter space, indicating greater system robustness and greater tolerance to moderately low risk levels. In this mode, the λ parameter acts as a stabilizing mechanism that prevents premature lowering of the safety rating.

The impact of the threshold θ is more pronounced in this mode than at lower values of $R\ (t)$. Higher thresholds allow the system to maintain a relatively high perceived security, while lower thresholds cause a pronounced and rapid decline in the security factor. This confirms that the parameter θ in this range no longer acts solely as a filtering mechanism, but actively determines the boundary between acceptable and unacceptable security states.

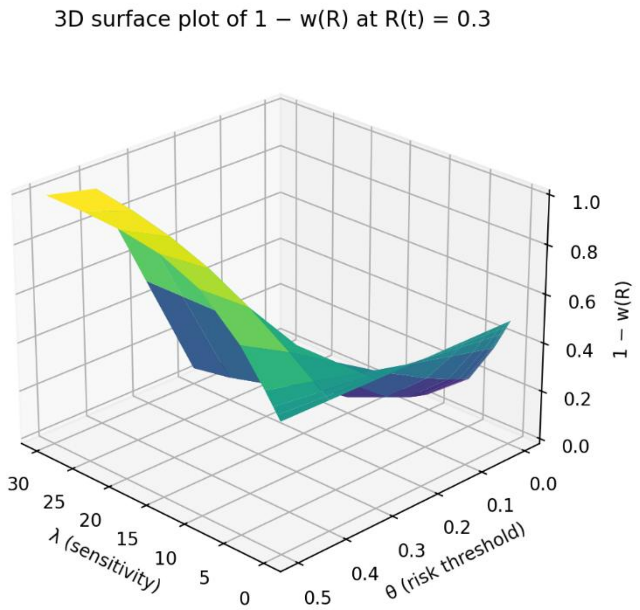
The range of safety factor values at $R\ (t)$=0.2 is already significantly wider than at lower input risk values, indicating increased differentiation between parameter configurations. In this mode, the model operates in a clearly transitional range where the safety factor begins to decrease systematically but does not yet reach complete collapse.

R e (t)=0.2 thus represents the second stage of active reduction of the safety assessment. In this state, the system still allows for balanced response adjustment, but requires a more careful selection of parameters, as inappropriate combinations can cause a rapid decline in perceived safety or, conversely, excessive tolerance to increasing risk.

3.3.4 Behavior of the safety factor at moderate input risk (R(t) = 0.3)

The graph (seeGraph 68) shows the three-dimensional distribution of the safety factor $V(R)$ at a moderate input risk value $R\ (t)$=0.3 depending on the sensitivity parameter λ and the risk threshold θ. This regime represents the central transition zone of the model's operation, in which the safety factor no longer reflects a stable or near-ideal state, but begins to systematically approach the zone of increased vulnerability.

Graph 68 : Influence of parameters λ and θ on the safety factor at moderate input risk (R(t) = 0.3).



At low values of the parameter λ and low threshold values θ, the safety factor reaches very low values, which means that the model perceives moderate risk as a significant safety problem. In this part of the parameter space, the input risk is clearly to the right of the inflection point of the logistic function, so the risk weight quickly saturates and the safety factor consequently drops sharply. This behavior corresponds to a restrictive and strictly preventive regime in which the system enters a low safety state even at medium risk values.

As the parameter λ increases, the low safety range gradually shrinks, while the safety factor remains moderate to high in most of the parameter space, especially at higher threshold values θ. This shows that increased sensitivity allows for a more differentiated response even at moderate risk, as the system no longer reacts in a binary manner but maintains a gradual decrease in the safety assessment. In this mode, the parameter λ acts as a key regulator of the transition slope, thus preventing premature saturation of the safety factor.

The influence of the threshold θ is pronounced and systemically important at $R\ (t)$=0.3. Higher thresholds allow moderate risk to still be considered manageable, while lower thresholds cause the model to quickly classify the safety status as unacceptable. In this mode, the parameter θ no longer acts merely as a boundary condition, but directly influences the perceived level of safety and thus potential response decisions.

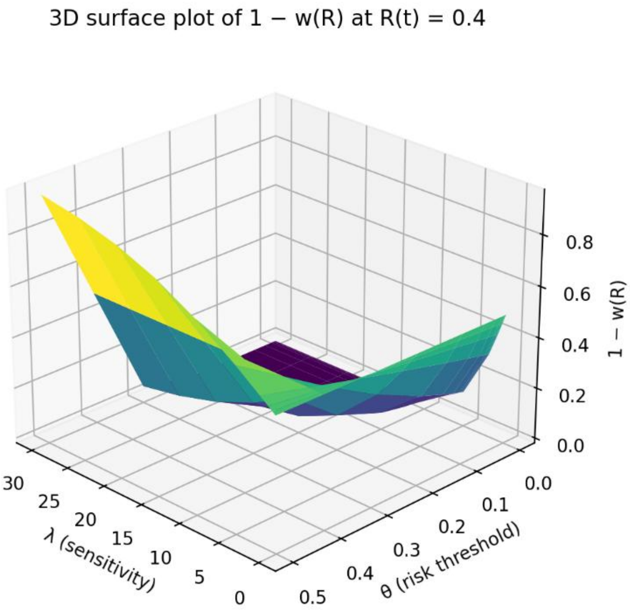
The range of safety factor values in this mode is very wide, indicating the model's high differentiation capability. Different combinations of parameters lead to significantly different safety assessments, ranging from relatively stable to highly endangered. The model is most informative in this range, as it allows a clear distinction between marginally acceptable and already problematic configurations.

The regime $R\ (t)$=0.3 thus represents a critical transitional phase in the operation of the safety factor. In this state, the choice of parameters λ and θ becomes decisive, as it directly determines whether the system will treat moderate risk as manageable or as a trigger for further protective or response measures. This graph therefore clearly illustrates the central role of parametric adjustment in balancing system stability and timely detection of increasing threats.

3.3.5 Behavior of the safety factor at a moderately increased input risk (R(t) = 0.4)

The graph (seeGraph 69) shows the three-dimensional distribution of the safety factor $V(R)$ at a moderately increased input risk value $R\ (t)$=0.4 depending on the sensitivity parameter λ and the risk threshold θ**.** This mode is already close to the central area of the logistic transition, so the safety factor no longer reaches high values in most of the parameter space and systematically moves towards the area of low perceived safety.

Graph 69 : Influence of parameters λ and θ on the safety factor at moderately increased input risk (R(t) = 0.4).



At low values of the parameter λ, the safety factor remains low regardless of the selected threshold value θ, which means that in this mode, the model treats moderately increased risk as unacceptable in terms of safety. In this case, the logistic function is located deep in the weight increase range, so the safety factor quickly decreases and loses stability. This behavior corresponds to a strictly protective mode in which the system operates with low tolerance to additional loads.

As the parameter λ increases, differentiation between individual threshold settings begins to appear. At higher values of θ, the safety factor can reach moderate values, indicating that the system still allows partial risk control when the parameters are set appropriately. The parameter λ in this range allows the transition to low security to occur gradually rather than suddenly, thereby maintaining a certain level of informativeness of the output assessment.

The effect of the threshold θ is pronounced and direct at $R\ (t)$=0.4. Higher thresholds shift the transition range towards higher risk values, which allows a moderate safety assessment to be maintained even under increased system load. Conversely, low thresholds cause the model to treat almost the entire range as safety-critical, bringing the safety factor closer to the lower values.

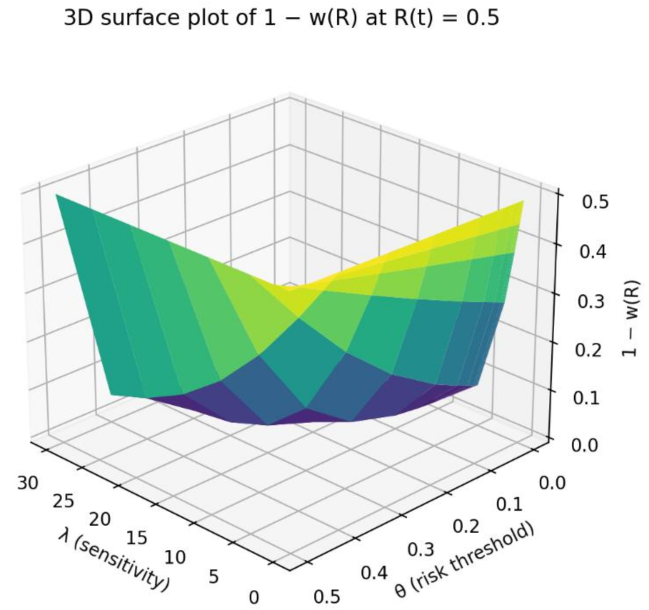
The range of safety factor values in this mode is still relatively wide, but most of the parameter space is already in the low to moderately low safety range. This means that the model is gradually losing the ability to interpret the state as stable and is approaching a phase where the safety factor begins to act as an indicator of impending collapse.

The mode $R\ (t)$=0.4 thus represents a transition from a balanced to a more pronouncedly endangered security situation. In this range, the choice of parameters λ and θ becomes particularly sensitive, as small changes can cause significant differences in perceived security. The graph clearly shows that at this stage, the model no longer responds purely preventively, but already signals the need for active risk management measures.

3.3.6 The marginal equilibrium between security and risk (R(t) = 0.5)

The graph (seeGraph 70) shows the three-dimensional distribution of the safety factor $V(R)$ at an input risk value $R\ (t)$=0.5. Mathematically, the turning point of the logistic function is at $R= \theta$; therefore, $R\ (t)$=0.5 is only a turning point in the case of θ =0.5, otherwise it is located to the left or right of the transition depending on the selected value of θ. At this value, the system is placed in a state where safety and risk are no longer clearly separated, but are in direct mutual equilibrium.

Graph 70: Influence of parameters λ and θ on the safety factor at the input risk threshold (R(t) = 0.5).



The graph area is distinctly symmetrical and shows a characteristic "saddle" shape, reflecting the fact that the effects of the parameters λ and θ balance each other out. A special feature of this regime is that at $R\ (t)$=0.5, the safety factor strongly diverges with respect to θ : at θ >0.5, $V(R)$ can remain high, while at θ <0.5, it generally transitions to lower values. The parameter λ mainly sharpens or smooths this stratification. This means that at this input risk value, the system can no longer generate stable high security ratings.

The impact of the threshold θ is direct and almost linear in this mode. Higher thresholds allow for a slight increase in the safety factor, as the transition point of the logistic function shifts above the current risk value. Conversely, lower thresholds cause an additional decrease in the safety rating, quickly pushing the system into the perceived risk zone.

In this mode, the parameter λ no longer acts as the primary trigger, but as an amplifier of the differences caused by the choice of threshold θ. At higher values of λ, the transition becomes more concentrated, so the differences between low and high thresholds are more pronounced in the value of the safety factor. At lower values λ, the surface remains flatter, which means that the system responds more cautiously, but at the same time loses resolution.

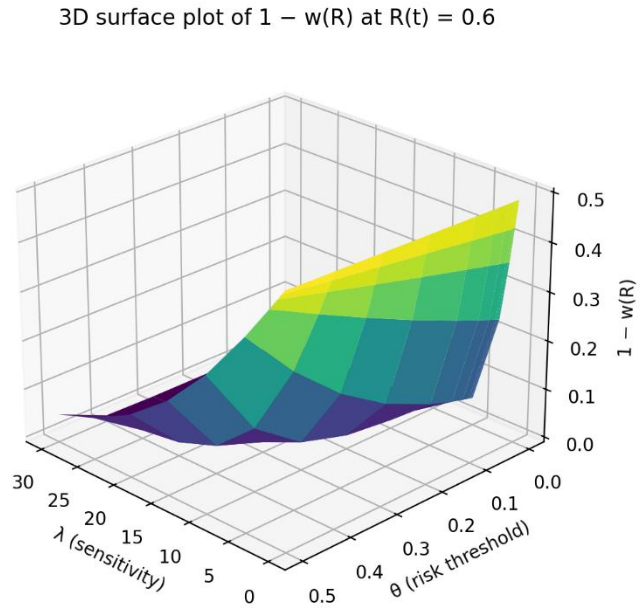
A special feature of this mode is that the safety factor does not reach high values in any combination of parameters. Even with a very favorable setting of θ and high values of λ, the upper limit of the safety assessment remains limited. This clearly shows that at $R\ (t)$=0.5, the system is already at the limit of its safety capacity and that a further increase in risk can no longer be compensated for by simply adjusting the parameters.

$R\ (t)$=0.5 therefore represents a critical turning point in the operation of the model. In practice, this means a situation in which the operator must make a strategic decision: either to reduce the input risk with additional protective measures or to accept the fact that the safety factor can no longer remain at an acceptable level. At this point, the model no longer functions as a preventive mechanism, but as a clear indicator that the limits of manageability have been reached.

3.3.7 Transition to the reduced safety zone (R(t) = 0.6)

The graph (seeGraph 71) shows the three-dimensional distribution of the safety factor $V(R)$ at an input risk value $R\ (t)$=0.6, which already exceeds the threshold of the logistic function's marginal equilibrium. This regime represents a state in which risk prevails over safety, so the safety factor is significantly reduced throughout the entire parameter space.

Graph 71: Influence of parameters λ and θ on the safety factor at an increased input risk value (R(t) = 0.6).



The graph area is significantly shifted towards low safety factor values. In most combinations of the parameters λ and θ, the value of $V(R)$ remains low, often close to the lower limit, which means that the system can no longer maintain a satisfactory safety rating. Unlike the limiting case $R\ (t)$=0.5, there is no longer a balance here, but a clear state of prevailing risk.

The effect of the threshold θ becomes significantly limited in this mode. Higher thresholds do allow for a slight increase in the safety factor, but this effect is limited and insufficient to achieve moderate or high safety values. This shows that the logistic transition has already been completely exceeded and that moving the threshold can no longer significantly change the risk-safety ratio.

The parameter λ loses its role as an effective regulator in this range. At low values of λ, the system response is very flat, so the safety factor remains low regardless of the threshold selected. At high values of λ, the transition becomes even more pronounced, but this does not lead to higher safety, only to faster saturation in the low value range. This confirms that greater sensitivity in conditions of already elevated risk does not improve the safety picture, but can even destabilize it.

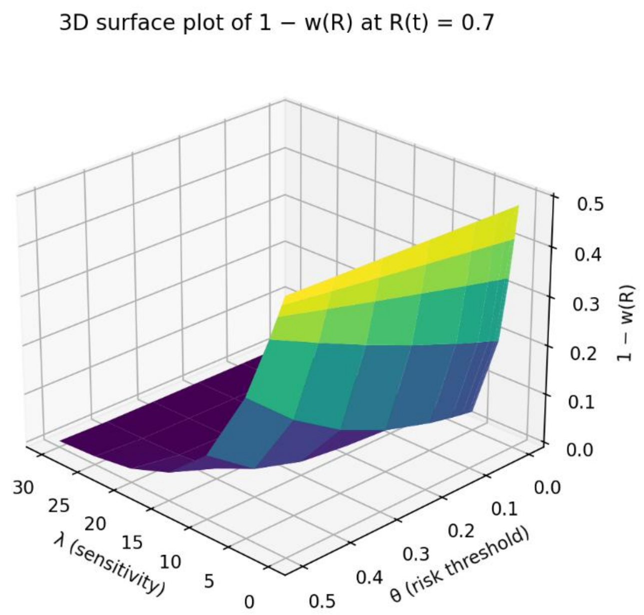
A special feature of this mode is that even with the most favorable combinations of parameters (high θ, moderate λ), the safety factor does not approach the average value. This means that the system is already in a state where internal parameter adjustment can no longer compensate for the increased input risk. In this mode, the safety factor acts primarily as an indicator of degradation and no longer as a fine-tuning mechanism.

The mode $R\ (t)$=0.6 thus marks the transition from a manageable to a less favorable state of system operation. In practical terms, this means that further reliance on parametric adjustment of the model is no longer sufficient. To restore acceptable safety, it is necessary to actively reduce the input risk or introduce additional external protective measures. At this stage, the model clearly signals that the limit of internal adaptability has been exceeded.

3.3.8 Stabilization of low safety at high risk (R(t) = 0.7)

The graph (seeGraph 72) shows the three-dimensional distribution of the safety factor $V(R)$ at an input risk value $R\ (t)$=0.7, where risk is clearly predominant. In this mode, the system enters a state of stable low safety, in which the internal parameters of the model no longer have a significant impact on the final outcome.

Graph 72 : Influence of parameters λ and θ on the safety factor at a high input risk value (R(t) = 0.7).



The graph area is almost entirely aligned in the low safety factor range. Regardless of the choice of threshold θ or sensitivity parameter λ, $V(R)$ remains limited to low values, indicating model saturation in the high-risk range. Compared to the case $R\ (t)$=0.6, the influence of the parameters is further weakened here, as the graph surface practically no longer responds to their changes.

The threshold θ no longer has a regulatory role in this mode. Moving the threshold has only a marginal effect on the shape of the surface, but does not allow a transition to higher safety values. This means that the risk has completely exceeded the threshold settings and that the model can no longer transform the safety outcome through internal adjustment.

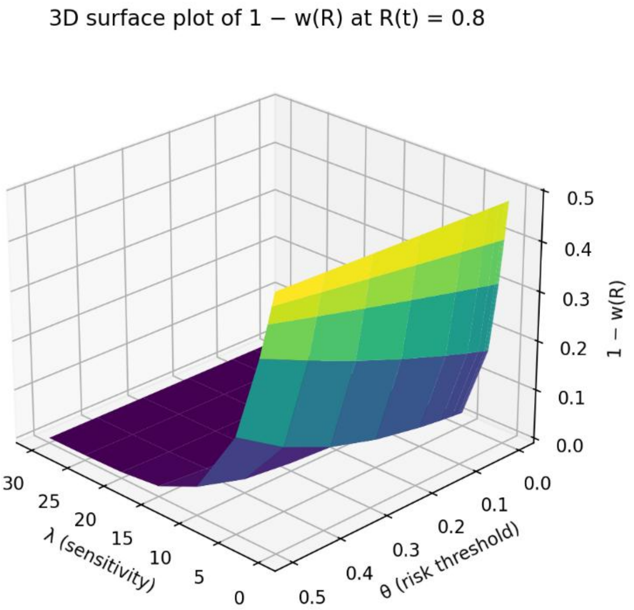
Similarly, the parameter λ loses its function as a responsiveness regulator. Increasing sensitivity does cause a slightly sharper transition to the low safety range, but this has no practical effect on improving the safety factor. The model thus confirms that, under conditions of significantly increased risk, greater sensitivity does not contribute to greater safety, but merely reinforces the existing situation.

The regime $R\ (t)$=0.7 thus represents a stable state of degraded safety in which the system is functionally determined by the input risk. In this range, the safety factor acts primarily as an indicator of an unfavorable state and no longer as an adaptive assessment mechanism. The model clearly shows that without external interventions to reduce the input risk, it is practically impossible to improve safety through internal parameter settings.

3.3.9 Almost complete saturation of low safety at very high risk (R(t) = 0.8)

The graph (seeGraph 73) shows the three-dimensional distribution of the safety factor $V(R)$ at an input risk value $R\ (t)$=0.8. This level of risk represents a very unfavorable starting point, in which the model almost completely loses its ability to adjust the safety outcome with internal parameters.

Graph 73: Influence of parameters λ and θ on the safety factor at a very high input risk value (R(t) = 0.8).



The graph area is markedly flattened in the range of very low safety factor values, indicating almost complete saturation of the logistic function. In most of the (λ, θ) combination space, remains $V(R)$ close to the lower limit, which means that the system perceives the safety state as permanently unfavorable. Changes in the threshold θ no longer have a noticeable effect on the increase in the safety factor, but only minimally reshape the edge parts of the surface.

The sensitivity parameter λ no longer acts as a responsiveness regulator in this mode, but merely accelerates the transition to a low safety state. At higher values of λ, this transition is even more pronounced, but the final result remains unchanged: the safety factor remains low regardless of the sensitivity level. This confirms that, with such a high input risk, increasing sensitivity does not bring any safety benefits, but merely reinforces the negative assessment.

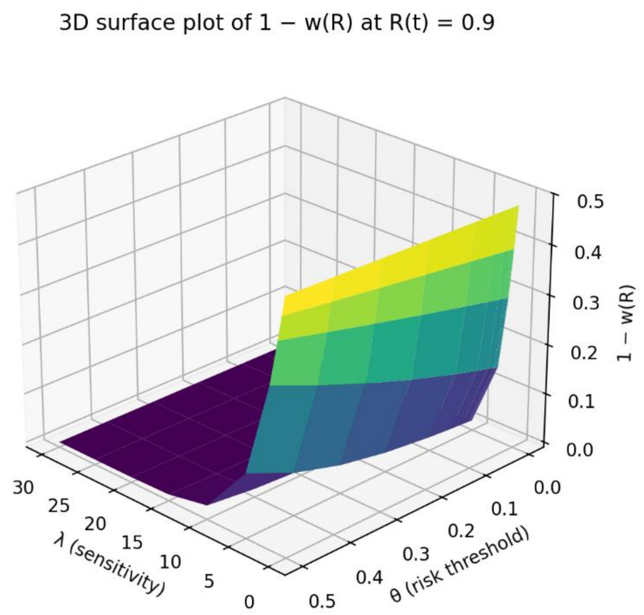
It is particularly noticeable that even at relatively high thresholds (θ), the system is no longer able to maintain moderate values (V) (R). The safety factor decreases even at moderate values of λ, which means that risk completely prevails over the threshold logic of the model. In this mode, the threshold no longer represents a meaningful decision limit, but becomes a mathematically irrelevant setting with no practical impact.

The mode R (t)=0.8 thus indicates an almost complete phase of safety degradation. In this range, the model functions primarily as a diagnostic indicator of a critical state and no longer as a tool for fine-tuning or optimization. The analysis clearly shows that, with such a high risk, the only effective way to improve safety is through external intervention that reduces the input risk, as the internal configuration of parameters can no longer significantly influence the result.

3.3.10 Complete dominance of risk and elimination of the influence of parameters (R(t) = 0.9)

The graph (seeGraph 74) shows the three-dimensional distribution of the safety factor $V(R)$ at an input risk value R (t)=0.9. This level of risk represents an extremely unfavorable situation, which is already very close to the upper limit of the model domain and in which the logistic function is practically completely saturated.

Graph 74 : The influence of parameters λ and θ on the safety factor at a very high input risk value (R(t) = 0.9).



The graph area is almost entirely aligned with very low safety factor values, which means that $V(R)$ remains close to zero in most parameter combinations. This clearly shows that the input risk in this mode completely dominates the internal settings of the model. Regardless of the selected threshold value θ or sensitivity parameter λ, the system perceives the safety status as extremely unfavorable.

The influence of the threshold θ is almost completely eliminated in this mode. Changes in the threshold do not cause a noticeable shift or expansion of the higher safety areas, but only minimal deformations of the surface at the edges of the graph. The threshold thus loses its role as an operational decision boundary and becomes merely a mathematical parameter with no practical effect.

The same applies to the sensitivity parameter λ. Increasing sensitivity does not lead to an improvement in the safety factor, but merely accelerates the transition to the area of complete degradation. At higher λ values, the drop in the safety factor is even more pronounced, but the end result remains the same: the safety factor remains at low values and no longer allows differentiation between different configurations.

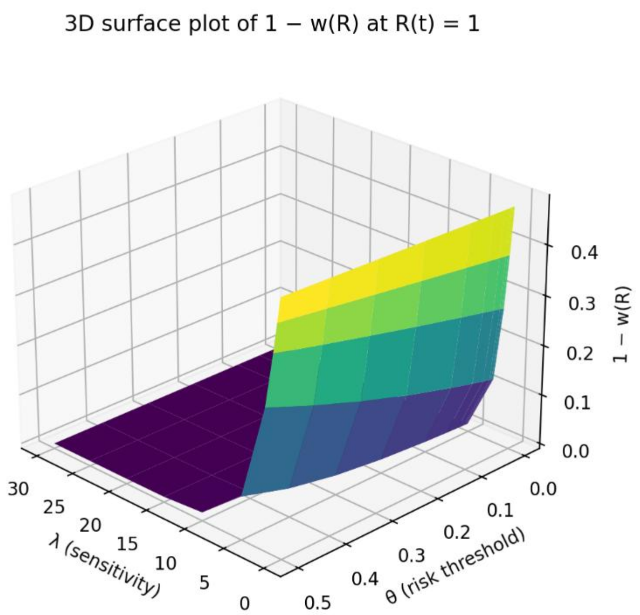
The $R\ (t)$=0.9 mode thus represents a practically completed phase of the model's operation in terms of safety assessment. In this range, the model no longer functions as a regulatory or optimization mechanism, but exclusively as an indicator of a critical state in which internal parameter adjustment cannot compensate for excessive input risk.

This graph clearly confirms the conceptual limit of the model: when the input risk exceeds a certain level, the influence of second-order parameters becomes negligible, and the safety outcome is entirely determined by the input value R. This further justifies the need for preventive risk management and early intervention, as mathematical adjustment mechanisms can no longer ensure an effective response in the late stages of escalation.

3.3.11 Formal extreme limit of the model and complete security degradation (R(t) = 1.0)

The graph (seeGraph 75) shows the three-dimensional distribution of the safety factor $V(R)$ at the maximum value of the input risk $R\ (t)$=1.0. This value represents the formal upper limit of the model's input space and, at the same time, the mathematical and conceptual extreme case of the system under consideration.

Graph 75 : Influence of parameters λ and θ on the safety factor at the maximum input risk value (R(t) = 1.0).



The area of the graph is almost entirely aligned with the zero plane of the safety factor, which means that $V(R)$ is very close to zero across the entire range of parameters. In this mode, the model consistently and unambiguously signals a complete loss of safety, regardless of the selected values of the threshold θ or sensitivity λ.

In this case, the effect of the risk threshold is completely negated. Since the input risk exceeds all reasonable thresholds, the threshold can no longer act as a dividing line between safe and unsafe states. Mathematically, this manifests itself as complete saturation of the logistic function, and in practice as the inability of the system to mitigate the perceived risk in any way through internal parameterization.

The same applies to the sensitivity parameter λ. Regardless of whether the transition of the function is very steep or very flat, the output safety factor has already reached its lower limit. Changes in λ therefore do not cause a qualitatively different response, but only negligible numerical differences that have no operational significance.

The mode $R\ (t)$=1.0 thus represents the terminal state of the model, in which the evaluation and control functions completely fail and the model functions exclusively as an alarm indicator of complete degradation. This state is no longer intended for optimization or adjustment, but rather to confirm that the system has exceeded the limit of manageable risk.

This graph has primarily a methodological and validation role. It confirms that the model is mathematically consistent even at the edges of the domain, that it behaves monotonically and predictably, and that it does not generate artificial or misleading safety signals under extreme conditions. At the same time, it clearly emphasizes the fundamental assumption of the model: safety cannot be reconstructed solely by setting parameters when the input risk is absolute.

3.3.12 The combined effect of the parameters λ, θ, and the input risk R(t) on the safety factor V(R)=1−w(R)

An analysis of the surface graphs of the safety factor $V(R)$=1− $w(R)$ shows that the effects of the parameters λ and θ are basically the same as for the weight $w(R)$, but with the opposite sign of the effect: everything that increases the weight $w(R)$ decreases the safety factor $V(R)$, and vice versa. Therefore, $V(R)$ directly reflects the "residual security" in terms of how strongly the weighting mechanism activates risk perception for a given $R\ (t)$.

The input risk $R\ (t)$ determines the basic starting point for security. At low values of $R\ (t)$, $V(R)$ remains high in most parameter combinations because the weight $w(R)$ is still relatively low. As $R\ (t)$ increases, $w(R)$ approaches saturation towards 1, and as a result, $V(R)$ falls towards 0. This demonstrates the natural monotonic logic of the model: higher input risk systematically reduces the safety factor, with the greatest differentiation between configurations occurring at medium values of $R\ (t)$ and saturation prevailing at extreme values.

The risk threshold θ determines the level of input risk at which the safety factor begins to degrade more rapidly. A higher θ means that the system "maintains" higher safety for a longer period of time, because the transition of the weight $w(R)$ towards high values is shifted to a higher $R\ (t)$. A lower θ shifts the transition range to the left, causing $V(R)$ to start decreasing at lower risk levels. In practice, this means the difference between a more cautious interpretation of risk (higher θ) and a more preventive interpretation (lower θ), where the safety factor loses value more quickly.

The sensitivity parameter λ determines the dynamics of the transition, i.e., how quickly $V(R)$ collapses around the threshold. At low λ, the transition is extended, so safety decreases gradually and smoothly. At high λ, the transition from high safety to low safety occurs in a narrow band around $R \approx \theta$, while outside this band, $V(R)$ quickly saturates towards 1 (if $R\ (t)$ is well below the threshold) or towards 0 (if $R\ (t)$ is well above the threshold). Such parameterization is very sensitive to small changes in input risk near the threshold: a minimal change in $R\ (t)$ can cause a pronounced jump in the safety factor.

The interaction between $R\ (t)$, θ, and λ is most informative in the transition zone, when $R\ (t)$ is approximately comparable to the threshold. At that point, the model most clearly distinguishes between "safer" and "less safe" configurations, as the range of values for $V(R)$ widens significantly. When $R\ (t)$ is very low (close to 0), the differences are less pronounced because security remains high for most settings. When $R\ (t)$ is very high (close to 1), the differences decrease again because the security factor drops towards zero for most settings.

The graphs as a whole therefore confirm that $V(R)$=1− $w(R)$ is not merely an "inverted weight," but rather an interpretable measure that combines three aspects: (1) the current risk pressure via $R\ (t)$, (2) the threshold at which the system begins to consider risk unacceptable via θ, and (3) the speed and sharpness of response via λ. The safety factor thus shows whether the model is operating in a stable safe state, in a transitional degradation state, or in a saturated low-safety state, where parameterization can no longer significantly change the output state, but rather confirms that risk has already prevailed over safety.

3.3.13 Practical implications of the combined influence of parameters λ, θ, and input risk on the safety factor V(R)=1−w(R)

The practical value of the safety factor analysis $V(R)$=1− $w(R)$ lies primarily in the fact that the model does not merely provide an abstract risk assessment, but directly expresses the available level of system safety based on the detected environmental conditions and selected parameter settings. This allows $V(R)$ to be used as an operational quantity to support decision-making, not just as an intermediate mathematical term.

In environments with low or intermittent risk, a combination of a moderately higher threshold θ and a lower to medium value λ proves to be sensible. This setting causes the safety factor to remain stable and high and to decrease gradually, even if there are minor fluctuations in the input risk. In practice, this means fewer false alarms, greater tolerance to uncertain or noisy input data, and more predictable system behavior, which is important in logistics and organizational environments where excessive sensitivity leads to inefficiency or unjustified operational restrictions.

In transitional or unstable environments where risk can change rapidly, the use of mean values (λ) and a realistically set threshold (θ) is most useful operationally. In this mode, the risk level (V) (R) begins to decrease noticeably with a relevant increase in the risk level (R) (t), but without sudden jumps. This enables timely detection of a deterioration in the security situation and the gradual activation of additional measures, such as enhanced monitoring, additional supplier verifications, or access restrictions, before the system enters a low security state.

In high-risk or crisis scenarios, it makes sense to use higher values for λ and a lower threshold for θ, as this combination causes a rapid and significant drop in the security factor even when the threshold is only slightly exceeded. Operationally, this means a clear signal that the security space has been exhausted and that immediate responses are needed. In this mode, the model acts as a decision trigger rather than a continuous evaluator, which is appropriate in situations where response speed is more important than subtle differences between risk levels.

At the same time, the analysis points out the limitations of extreme settings. If the threshold θ is set too low, the safety factor loses its discriminatory power, as $V(R)$ quickly drops to zero even at low values R (t). This can lead to a state of constant low security detection, where the model no longer provides information to distinguish between moderate and very high risk. Similarly, at very low values of λ, $V(R)$ remains in a wide range close to medium or high values, which can obscure actual changes in risk and reduce the responsiveness of the system.

From the perspective of its use in supply chain cybersecurity management models, this means that $V(R)$ is not a universal constant, but a contextually adaptable measure. The parameter θ must represent the real limit of risk acceptability in a specific operational environment, while the parameter λ is used to adjust the speed and sharpness of the response depending on the reliability of the input data and the dynamics of the threats. The input risk R (t) then acts as a trigger that moves the system between states of high security, transitional degradation, and low security.

The practical implication of the entire set of graphs is therefore clear: the model allows for a distinction between strategic tolerance setting (via θ and λ) and tactical response to actual perceived risk (via R (t)). This allows the security factor $V(R)$ to be used as a transparent and explainable indicator that links mathematical formalization with real decisions on control, restrictions, or tightening of security measures at different stages of system operation.

4 CONCLUSION

The appendix provides a comprehensive graphical and interpretative insight into the functioning of the risk weighting mechanism and the security response derived from it. Through a systematic analysis of the influence of the sensitivity parameters λ, the risk threshold θ, and the input risk R, it was shown how the logistical risk assessment$L$ (R), the dynamic weight $w(R)$, and the security factor $V(R)$=1− $w(R)$ change throughout the entire interval of possible input values and in different parametric regimes.

The analysis clearly showed that the parameters λ and θ have different but interdependent roles. The threshold θ determines the location of the transition or the level of risk at which the model changes its assessment, while the parameter λ shapes the dynamics of this transition – from a continuous and gradual response at low values to an almost discrete, threshold behaviour at high values. This confirms that no parameter alone determines the behavior of the model, but rather that the significance of individual settings is established only in their combination.

Surface displays and heat maps at fixed input risk values provided additional insight into the synergistic effect of parameters at different stages of risk perception—from the latent regime at R (t)=0, through transitional areas, to states of near-complete saturation at high values of R. It was found that as the input risk increases, the differentiation ability of the model gradually decreases, while the weight stabilizes in the high range, reflecting the transition to alarm and quasi-binary modes of operation. Similarly, at a safety factor of , a symmetrical but substantively reversed pattern emerges, where increasing risk leads to a systematic reduction in the safety reserve and, ultimately, to an almost complete degradation of the safety status.

The appendix does not introduce new methodological elements, but serves as a validation and explanatory supplement to the main text of the dissertation. Its value lies in the transparent and repeatable presentation of the model's behavior across the entire parameter domain, clearly showing the limits of meaningful application, transitional regimes, and the consequences of extreme parameter settings. In this way, the appendix supports the understanding of the model not only at an abstract mathematical level, but also in the context of practical application, where the choice of parameters directly reflects the organization's risk tolerance, the relationship between stability and responsiveness, and the method of decision support.