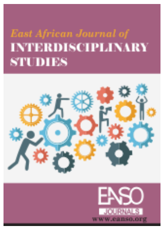

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Original Article

Extending the Subjective Dynamic Decision Model: A Heuristic and Meta-Cognitive Framework for Strategic Adaptation

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ABSTRACT

This paper introduces a novel extension of the Subjective Dynamic Decision Model (SDEM) by integrating multiple context-sensitive heuristics, adaptive decision thresholds, and a meta-cognitive uncertainty parameter. Unlike classical decision models, this enhanced framework explicitly captures feedback learning, subjective uncertainty, and self-reflective judgment, enabling a more realistic simulation of strategic behaviour under radical uncertainty. Traditional decision theories often rely on assumptions of rational agents, stable preferences, and complete information. However, in real-world contexts such as crises, complex markets, or adversarial environments, such conditions are rarely met. The enhanced SDEM integrates three core extensions to reflect cognitive and strategic diversity: (1) the availability of multiple context-sensitive heuristics, (2) a dynamic adjustment of the decision threshold based on experience, and (3) a meta-cognitive uncertainty parameter that regulates decision-making based on subjective confidence. These additions allow for the formal inclusion of adaptive learning, bounded rationality, and self-reflective judgement in decision processes. The paper presents the theoretical underpinnings of the model, discusses its implications for cognitive modelling and agent-based simulations, and illustrates its functionality through practical examples. Potential applications include cybersecurity, strategic intelligence, supply chain resilience, and energy markets. The proposed framework enables realistic modelling of heterogeneous behaviour in multi-agent environments and offers new insights into dynamic adaptation under uncertainty.

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INTRODUCTION

In an increasingly volatile, uncertain and complex world, decisions under uncertainty are gaining in theoretical and practical importance. Classical models of decision theory are based on the assumption of rational actors with stable preferences, complete information and well-defined probabilities. However, these assumptions are not fulfilled in many real-life contexts, for example, in geopolitical crises, dynamic markets or security-relevant situations. In such cases, human decision-making behaviour often relies on subjective assessments, intuitive heuristics and learning-based adaptation.

The Subjective Dynamic Decision Model (SDEM), introduced in 2025, represents an innovative attempt to map this reality, especially in decision-making contexts where data is incomplete and uncertainty is high. A real-world example is decision-making in cybersecurity, where organisations are often faced with incomplete threat data. The model enables decision makers to quantify their uncertainty and dynamically adjust their expectations to new threats. The focus is on heuristic decision-making under radical uncertainty, i.e. in situations where neither probabilities nor consequences can be objectively determined. The concept of radical uncertainty goes back to Frank H. Knight (1921) and describes situations in which neither probabilities nor possible events can be determined. More recently, the concept has been further developed by Kay and King (2020), among others, who argue that economic and political decisions are often made under conditions that cannot be modelled probabilistically.

The aim of this paper is to further develop the original SDEM conceptually. To this end, three extensions are introduced: the selection of context-dependent decision heuristics, the adaptive adjustment of the decision threshold and a metacognitive uncertainty parameter. These extensions enable the model to formally integrate cognitive diversity, feedback from experience and uncertainty awareness.

The work offers both theoretical and practical insights. Firstly, a theoretical deepening of the SDEM in terms of a more realistic decision logic and secondly, a practical applicability in cross-domain simulation scenarios. The following chapters first present the theoretical frame of reference, then explain the structure and extension of the SDEM, and finally discuss its implications, computational logic and limitations.

THEORETICAL BACKGROUND

Economic decision theory under uncertainty has historically developed along two central currents: rationalistic optimisation by means of expected utility theory and the behavioural science critique of this very assumption.

The classic subjective expected utility theory (SEU), according to Savage (1954), assumes that actors have consistent preferences and make decisions based on expected utility values resulting from subjectively weighted probabilities and outcomes. In practice, however, this model is often questioned in areas such as corporate planning, where decision-makers are confronted with uncertainties and incomplete information about future market developments. For example, a company operating in an unstable market might use a "take-the-best" heuristic, where it considers only the most important information to make quick decisions, while in a more stable market, it makes a more informed and risk-averse decision. In contrast

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to Prospect Theory (Kahneman & Tversky, 1979), which focuses on the description of systematic biases in the evaluation of losses and gains, the extended SDEM aims to map dynamic decision-making processes under uncertainty. The focus here is less on distortions in results and more on the underlying cognitive mechanisms, in particular, heuristic changes and uncertainty awareness.

In practice, however, this model is often challenged in areas such as corporate planning, where decision-makers are faced with uncertainty and incomplete information about future market developments. In such situations, companies resort to heuristic decision-making processes to reduce uncertainty and make quick decisions. Although this model is mathematically elegant, it assumes complete information, stable preferences and unrestricted rationality.

Bayesian models (e.g. inspired by Ramsey (1931) and later by de Finetti (1974)) extend this framework to include the ability to adjust expectations through Bayesian probability updates. However, they remain strongly normative in their formal structure and assume that agents have consistent prior distributions and can logically integrate new information - an assumption that often fails under real-world complexity. An alternative approach is the theory of bounded rationality, according to Herbert A. Simon (1955) emphasises that, due to limited information processing capacity, people do not make optimal decisions, but only satisficing ones. In this context, heuristic models have also been established that depict simplified decision-making rules, e.g. "take-the-best" or "fast-and-frugal trees" (Gigerenzer & Selten, 2002). Finally, agent-based approaches (ACE) have become established in modelling economics (Epstein, 2006), which simulate individual decision-making logic, learning processes and interaction in dynamic environments. These models are particularly suitable for the integration of subjective, dynamic decision-making processes.

Against this background, the Subjective Dynamic Decision Model (SDEM) positions itself as a hybrid solution. It combines subjective information processing, individual expectation formation and heuristic decision mechanisms in a dynamic, non-optimising framework. It thus addresses central deficits of the above-mentioned models, particularly with regard to real decision-making situations under uncertainty, ambiguity and complexity.

Table 1 compares the extended SDEM framework with established decision theories, highlighting its unique focus on radical uncertainty, bounded rationality, and metacognitive regulation. While SEU relies on probabilistic optimisation (Savage, 1954), and Prospect Theory emphasises reference-dependent biases (Kahneman & Tversky, 1979), the SDEM builds on bounded rationality (Simon, 1955), feedback learning, and metacognitive uncertainty (Fleming & Lau, 2014; Yeung & Summerfield, 2012).

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Table 1: Comparison of Theoretical Features Across SEU, Prospect Theory and SDEM.

Dimension	Subjective Expected Utility (SEU)	Prospect Theory	Subjective Dynamic Decision Model (SDEM)
Decision basis	Maximising expected utility	Value function with loss aversion	Heuristic evaluation based on subjective beliefs and expectations
Treatment of uncertainty	Probabilistic, assumed known	Framing of probabilities and outcomes	Radical uncertainty with subjective, incomplete, or conflicting information
Rationality assumption	Fully rational agents	Systematic cognitive biases	Bounded rationality and adaptive, reflective decision-making
Learning and adaptation	Static preferences	Limited updating via experience	Feedback-based learning from observed outcomes (Ot)
Metacognition / Self-awareness	Not included	Not formalized	Explicit parameter for uncertainty awareness (μ)
Context-sensitivity	Universal rule applies	Reference-dependent	Context-sensitive heuristic switching and threshold adaptation
Formal update mechanism	Bayesian updating	None	Dynamic update via h(Ut, Et, Bt)

ORIGINAL STRUCTURE OF THE SDEM

The Subjective Dynamic Decision Model (SDEM) describes strategic decisions under radical uncertainty based on subjectively interpreted information, individual convictions and experience-based expectations (Moch, 2025). At the centre is the so-called subjective decision state of an acting person at time t, formally represented as a combination of:

- subjectively perceived information It
- current beliefs Bt
- subjective expectations Et

The decision is made using a heuristic decision rule, not mathematical optimisation:

Decision = f(It, Bt, Et)

The threshold value Tt reflects individual motivation to act, attitude to risk or assessment of opportunity costs. If the expected benefit Ut remains below this threshold, no action is triggered:

Ut < Tt ⇒ no decision

Each action is followed by an observation Ot, from which the subjective decision-making state is actualised:

Update = g(Ot)

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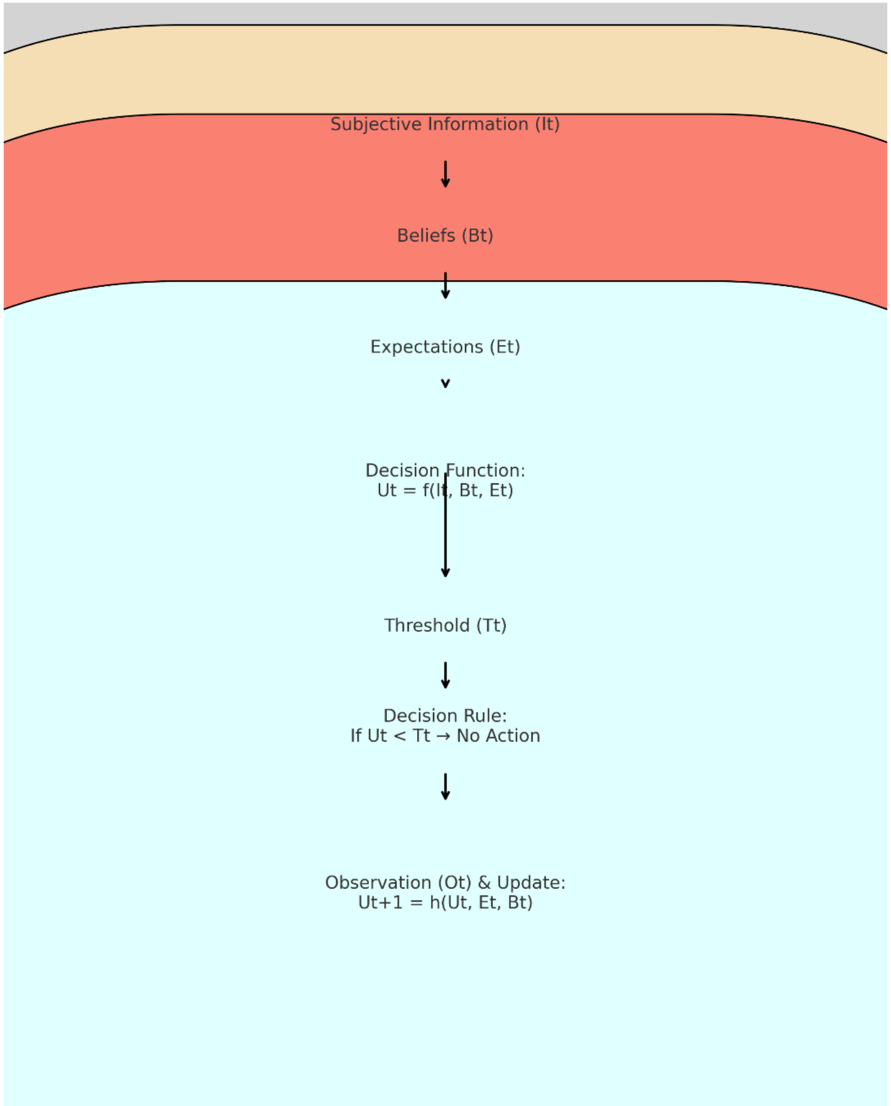
Figure 1: Visual Representation of the Original Subjective Dynamic Decision Model (SDEM)



The diagram illustrates the sequential structure of the original SDEM, highlighting how subjective inputs (It, Bt, Et) form a decision rule, which is then evaluated against a threshold Tt and adapted via learning from observations (Ot).

Updating takes place via an experience-based learning function U, which dynamically adapts feedback, expectations and beliefs:

Ut1 + = h(Ut, Et, Bt)

This mechanism makes it possible to formally model learning processes under uncertainty and with limited knowledge. Unlike classic optimisation models, the SDEM is based on subjective perception and takes cognitive limitations and heuristic behaviour into account. It is thus in the tradition of research on bounded rationality (cf. Simon, 1955) and is particularly suitable for volatile, data-poor or asymmetrically informed decision-making contexts.

MODEL EXTENSIONS

The original structure of the Subjective Dynamic Decision Model (SDEM) represents a basic heuristic that takes subjective information

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processing into account. To increase the model depth and realism, three central extensions are introduced in the following further development: (1) the selection of context-dependent heuristics, (2) the adaptive adjustment of the decision threshold and (3) the introduction of a metacognitive uncertainty parameter.

Selection of Multiple Heuristics

Instead of a fixed decision rule, a repertoire of heuristics should be available in the extended SDEM. Each heuristic represents a simplified rule for deciding how to act, which is activated individually and depending on the context. The selection is made via a context-sensitive activation mechanism that takes into account situational characteristics such as the level of uncertainty, time pressure or availability of information. A superordinate metacognitive control system that selects a suitable heuristic based on past experience is also conceivable.

Examples of heuristic decision rules are

- Minimalist rule: Act when a single critical signal is exceeded,
- Take-the-Best: Act if a dominant characteristic speaks in favour of an option,
- Cautious optimism: Only act when expectations are positive and negative indicators are absent.

These simplified rules are examples of fast-and-frugal heuristics, which have proven effective in complex, uncertain environments such as construction and infrastructure planning (Love, Ika, & Pinto, 2023). This extension allows a more realistic modelling of individual differences in decision-making behaviour.

Adaptive Adjustment of the Threshold Value

In the basic model, the decision threshold T is static. In the extended version, this is dynamically adjusted depending on the deviation feedback between expected and actually observed results. The parameter α (learning parameter) describes the sensitivity of the adjustment. A high discrepancy between expectation Et and result Ot leads to an increase or decrease in the action threshold, depending on the direction of the feedback:

$$T_{t+1} = T_t + \alpha(E_t - O_t)$$

In this way, empirical values are systematically integrated into the individual's willingness to act.

Metacognitive Uncertainty Parameter

To take internal conditions into account, an uncertainty parameter μ is introduced, which expresses the perceived clarity or ambiguity of one's assessment. If there is a high level of uncertainty, the decision threshold is increased in order to avoid rash or error-prone behaviour. The parameter μ can be interpreted either as a stable individual risk propensity type or as a situational variable that dynamically adapts to current information clarity, signal noise or decision conflicts. The metacognitive uncertainty parameter μ can be linked to psychological concepts of confidence calibration and self-evaluation (Fleming & Lau, 2014; Yeung & Summerfield, 2012). These studies show that people are able to systematically assess their sense of uncertainty and derive action adjustments from this - a process that is formally modelled in the SDEM. Empirically, μ could be operationalised via self-reports (confidence ratings), response times or dispersion in probability assessments. This extension of the model makes it possible to incorporate uncertainty awareness directly into the willingness to make decisions:

$$T_{t+1} = T_t + \mu$$

THEORETICAL AND PRACTICAL IMPLICATIONS

The extensions of the SDEM enable a more realistic and differentiated representation of decision-making behaviour under uncertainty. They have both theoretical significance for the further development of decision theory and practical relevance in complex fields of application.

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Theoretical Implications

The formal integration of multiple heuristics breaks with the ideal of a universal decision rule. Instead, it is recognised that individuals switch between different evaluation strategies in a context-sensitive manner, a concept that corresponds to the psychological and behavioural decision-making literature (cf. Gigerenzer & Selten, 2002). The adaptive adjustment of the threshold value removes the boundary between evaluation and the learning process. Decisions are not only made on the basis of static preferences, but also depending on the course of previous experiences. This allows dynamic modelling of adaptation processes, as discussed in the literature on "adaptive expectations". The integration of the metacognitive parameter μ bridges the gap between formal modelling and cognitive psychology. The model thus opens up new approaches to the operationalisation of uncertainty perception and self-reflection in quantitative decision-making systems.

Practical Implications

In practice, the extended SDEM can be used to simulate decision-making processes in areas that are characterised by unstable information, subjective assessments and strategic uncertainty. Areas of application include

- **Cybersecurity**, where attackers and defenders make decisions based on fragmented, distorted signals,
- **Global supply chains** in which companies make location decisions and diversify risk under geopolitical risks,
- **Intelligent energy markets** in which suppliers react to volatile price developments and continuously adjust their expectations,
- **Strategic information work** in politics, the military and intelligence services, in which decisions on action are based on subjective interpretations of enemy intentions.

Particularly noteworthy is the model's ability to generate heterogeneous behaviour in simulated multi-actor systems that cannot be derived from a rational-homogeneous basic model. The SDEM can therefore be used not only for analysis purposes but also for developing resilient strategies in volatile environments.

PRACTICAL CALCULATION EXAMPLES FOR EXTENDED SDEM

Subjective Expected Utility

The subjective expected utility E is the central decision criterion of the original SDEM. It results from the weighted sum of all possible action outcomes, taking into account their individual probabilities of occurrence.

The basic formula is:

$$E = \sum_{i=1}^{n} P_i \cdot U_i$$

This refers to:

- Pi: subjectively assessed probability of scenario iii occurring,
- Ui: subjective benefit associated with scenario iii,
- n: Number of scenarios considered.

A concrete example:

Let's assume a decision-maker evaluates three scenarios:

- Scenario 1: with probability 0.40 and benefit +10,
- Scenario 2: with probability 0.30 and benefit 0,
- Scenario 3: with probability 0.30 and benefit -8.

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Table 2: Subjective Probability and Associated Utility of Decision Scenarios

Scenario	Probability (Pi)	Benefit (Ui)
Positive	0.4	+10
Neutral	0.3	0
Negative	0.3	-8

The subjective expectation (E) results in:

$E = 0.4 \cdot 10 + 0.3 \cdot 0 + 0.3 \cdot (-8) = 4 + 0 -2.4 = 1.6$

The formula for the subjective expected utility E shows how the average expected utility is calculated, taking into account the probabilities for each scenario. In this case, the benefit from the positive scenario is weighted with its probability (0.4), as are the benefits from the neutral (0.3) and negative scenarios (0.3). This results in a weighted average expectation of 1.6.

If the decision threshold is T = 2, no action is taken because E<TE.

Adjustment of the Threshold Value After Feedback

After negative feedback (observed utility O, expected utility E), the actor dynamically adjusts its threshold value. With a learning parameter α, this results in

$T_{t+1} = Tt + \alpha(Et-Ot)$

The adjustment of the threshold value T_{t+1} is based on the difference between the expected benefit Et and the actual observed result Ot. The parameter α controls how strongly the threshold value is adjusted. A high value of α indicates a rapid adjustment of the threshold value, while a low value of α indicates a slow or conservative adjustment. This parameter could, for example, be determined by empirical studies or by empirical values from previous decisions. One way to determine α could be to adjust it to the uncertainty and frequency of the discrepancy between expectation and outcome.

The threshold for action falls as a result of negative experience; the actor will be more willing to take risks next time.

In practice, the parameter α could be determined based on empirical data from real decision-making processes or through simulations. One way to estimate the value of α would be to conduct a series of experiments in which the actor repeatedly makes decisions and the feedback (outcome) is observed. The adjustment of the threshold could then be modelled in a way that reflects the actor's ability to learn and adapt to new information.

Effect of the Uncertainty Parameter

A metacognitive uncertainty value μ is assumed. The decision rule is:

$T_{t+1} = Tt + \mu$

This extension makes it possible to incorporate uncertainty awareness directly into the willingness to make decisions and to model cautious behaviour.

Case Study: Strategic Product Decision in the Automotive Market

A European car manufacturer is faced with the decision of whether to launch a new electric model in a price-intensive, technologically uncertain market segment. The decision is fraught with uncertainty: On the one hand, the model promises access to a growing urban market with state subsidies; on the other hand, there are considerable risks due to fluctuating raw material prices, technological upheavals and an unclear charging infrastructure.

Decision Heuristics

The company initially uses a "cautious optimism" heuristic. This states: only launch a new model on the market if the average expectation of success is positive AND there are no serious negative indicators (e.g. technological instability).

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The decision rule is:

"Act when the weighted benefit expectation is positive AND there are no warning signals."

Subjective expectation (E): Based on market research:

- Probability of high market penetration: 0.4 with benefit +14
- Probability of moderate acceptance: 0.4 with benefit +5
- Probability of flop or recall: 0.2 with benefit -12

The probabilities and benefit values were estimated using a combination of internal market expertise, qualitative scenario analyses and quantitative surveys. The scenarios (high, moderate and low market penetration) were defined with the help of structured expert surveys and market analyses. The probabilities of occurrence are derived from historical comparative data and industry-specific forecasts. The subjective benefits were operationalised as part of internal planning processes, taking into account strategic targets and economic expectations. This results in a weighted expected value that serves as a basis for decision-making.

$E = 0.4\cdot 14 + 0.4\cdot 5 + 0.2\cdot (-12) = 5.6 + 2 - 2.4 = 5.2$

Decision threshold (T): Initial threshold: $T0 = 6$

Since $E=5.2<T = 6$, the model is not introduced.

Feedback and Threshold Adjustment

One month later, it becomes apparent that a competitor has introduced a comparable model with great success. The subjective expectation rises to $Et=6.8$, the observed result is $Ot=11$.

With learning parameter $\alpha=0.2$, the result is

$T_{t+1}= Tt+ \alpha(Et-Ot) = 6+ 0.2\cdot (6.8-11) = 6-0.84= 5.16$

Uncertainty Parameter (μ)

New uncertainties in the battery raw materials market increase the internal uncertainty. The uncertainty parameter is set to $\mu=0.7$:

$T_{t+1}= 5.16+0.7= 5.86$

New Valuation

The expected value $E=6.8$ is now above $T=5.86$, but the decision is still postponed until further information on the charging infrastructure and subsidy policy is available. The new electric model is not introduced until $E=7.8$.

Conclusion

This case study illustrates how the extended SDEM:

- flexible heuristics,
- learning-based threshold adjustments and
- metacognitive uncertainty parameters

In order to model realistic decision-making dynamics in the context of technological market uncertainty.

Example: Tactical Decision in Cybersecurity

A security organisation must decide in real time whether suspicious data activity should be classified as a threat and countermeasures initiated. The heuristic decision rule is: "Act immediately if the threat signal is high, unless uncertainties regarding source and relevance prevail." The subjective expected value is based on the probabilities of a genuine attack, a false alarm and system malfunction. The appearance of additional uncertainties (e.g. new forms of attack or signal distortion) increases μ significantly, which raises the threshold value T. As a result, the initially planned intervention is not carried out. The action is only triggered after further information validation and reduction of μ by new context data.

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This example shows how the combination of heuristics, learning values and uncertainty parameters creates a dynamic, context-sensitive decision-making process.

Table 3 summarises the differences between the two case studies, highlighting how the extended SDEM adapts to context-specific features such as feedback, uncertainty and heuristic logic.

Figure 3: Differences Between the Two Case Studies, Highlighting how the Extended SDEM Adapts to Context-Specific Features

Dimension	Automotive Market	Cybersecurity
Decision context	Strategic product launch under technological and regulatory uncertainty	Real-time classification of data activity under adversarial and signal distortion risks
Heuristic applied	Cautious Optimism: act only if expectations are positive and no warning signals exist	Threat-Conditional Rule: act only if signal is high and uncertainty is low
Threshold (T)	Initially set at 6, adjusted based on competitive feedback and μ	Adaptively increased with rise in μ (uncertainty), delaying immediate action
Learning mechanism (α)	Feedback from market observation modifies T over time	Feedback from contextual signal clarity modifies T indirectly via μ
Uncertainty parameter (μ)	Increased due to market instability (raw materials, infrastructure)	Increased due to unknown threat patterns and signal noise
Action outcome	Postponed until E > T, final launch triggered after updated evaluation	Action deferred until uncertainty reduces and confidence increases
Illustrated feature	Heuristic switching, dynamic thresholding, metacognitive hesitation	Metacognitive regulation, context-driven delay, adaptive readiness

DISCUSSION

While many decision models deal with uncertainty through probabilistic inference or bias correction, the extended SDEM stands out by embedding the perception of uncertainty and strategic self-adjustment directly into its structure. It reflects not only what agents believe, but also how confident they are in these beliefs, a dimension that is largely missing in existing formal models. Some scholars even suggest that under extreme uncertainty, decision-making can shift from heuristic to eristic modes, where actions are driven more by identity, emotion or urgency than by cognition (Kurdoglu, Ates, & Lerner, 2023).

The proposed extensions of the SDEM enable a more differentiated representation of real decision-making processes under uncertainty. In particular, the integration of multiple heuristics, adaptive thresholds and a metacognitive uncertainty parameter shifts the focus of the model from a static decision situation to a recursive, subject-centred learning and evaluation process. It is important to emphasise that the SDEM is not a forecasting tool in the narrower sense, but an analytical framework for the systematic description and simulation of decision-making logic under uncertainty. Modelling is used to better understand dynamic adaptations and strategic reactions, not to accurately predict individual actions.

The introduction of several decision heuristics reflects the empirically proven heterogeneity of cognitive strategies. Individuals use different decision rules depending on the context, such as quick rules of thumb, rule-based elimination processes or intuitive judgements. Modelling this diversity increases the descriptive validity of the SDEM compared to real-world decision patterns, which have been widely documented in

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psychological studies (cf. Gigerenzer & Selten, 2002; Berthet, 2021). The dynamic adjustment of the threshold value T reacts to feedback effects between expectation and result. This reflects a crucial aspect of real decisions: Learning processes are not continuous, but erratic, characterised by surprises, disappointments or confirmations. The model, therefore, takes into account the fact that actors recalibrate their willingness to act depending on the situation. The introduction of a metacognitive uncertainty parameter μ is particularly innovative. This makes it possible to model not only expectations in terms of content, but also the quality of one's own assessment. Uncertainty is therefore not viewed as an exogenous disturbance, but as a subjectively perceived state that is actively incorporated into the decision-making logic. This builds a bridge between formal decision modelling and psychological reflexivity. The metacognitive parameter μ can be calibrated on the basis of confidence ratings, information dispersion or reaction times. Qualitative assessments of uncertainty by decision-makers, for example, in the context of standardised decision protocols, can also contribute to operationalisation. Compared to the original SDEM, the extended model increases both the complexity-processing capacity and the connectivity to empirical decision research. The application to volatile systems, for example in the field of strategic early intelligence or adaptive simulation scenarios, promises new insights into non-linear behavioural patterns, emergent dynamics and the role of subjective perception in uncertain decision-making situations.

At the same time, the extension of the model raises new methodological questions: How can the choice of heuristics be empirically identified? Which function realistically describes the metacognitive uncertainty parameter? How can a calibrated learning parameter be determined depending on the context? These open issues are the subject of the following limitations. To situate the SDEM within the broader landscape of adaptive decision models, it is helpful to contrast it briefly with reinforcement learning approaches.

While the SDEM integrates feedback learning and dynamic adaptation, it differs fundamentally from models based on reinforcement learning (RL). RL frameworks rely on reward maximisation through value iteration or policy learning, assuming repeated interactions and stable state-action mappings. In contrast, the SDEM does not seek optimality but captures subjective uncertainty, context-specific heuristics, and self-regulatory thresholds. Rather than optimising rewards, it formalises bounded rationality in non-ergodic and non-stationary environments, where goals, beliefs and evaluation standards may shift unpredictably. This makes the SDEM more suitable for modelling one-off or high-stakes decisions under radical uncertainty.

EMPIRICAL VALIDATION AND APPLICATION PERSPECTIVES

The components formulated in the model offer broad connectivity to empirical research and simulation-based applications. Three perspectives are particularly relevant for the validation of the extended SDEM: firstly, the experimental recording of subjective expectation formation under uncertainty, secondly, the observation of adaptive heuristics over time, and thirdly, the simulation of decision-making processes in agent-based models.

One possible area of application is crisis response research, for example, in cybersecurity or geopolitical risk scenarios. Here, different groups of actors with different uncertainty parameters could be simulated against each other. Structured decision-making protocols in companies or strategic organisations can also be analysed for empirical substantiation in order to extract patterns of heuristic action and metacognitive calibration.

LIMITATIONS

Despite the theoretical extension and increased model plausibility, the extended Subjective

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Dynamic Decision Model (SDEM) has several limiting factors that affect both its application and empirical validation.

Firstly, the operationalisation of subjective decision-making states poses a methodological challenge. Although the components μ and α are conceptually separable, they are difficult to quantify in empirical studies or to capture through direct observation. Subjective beliefs and expectations are often implicit and unstable, making model calibration difficult. Secondly, the choice and weighting of heuristics is highly context-dependent. While the model allows for a variety of heuristic decision rules, it is unclear how this selection can be systematically controlled in an empirical or simulative setting. Without a theory of heuristic choice, the application remains limited to specific decision situations or strongly bound to assumptions. Thirdly, a standardised function for integrating the metacognitive parameter μ is still missing. Although its theoretical significance is plausible, there are considerable uncertainties regarding its empirical measurement, its dynamics and its influence on decision-making logic. The question of whether μ is consciously perceived or has a more implicit effect also remains unanswered. Finally, the model remains largely simulation-based and requires sound empirical validation. The theoretical modelling to date is coherent, but concrete applications are required to verify its validity, for example in the decision analysis of crisis teams, corporate strategies or risk awareness systems. At the same time, these limitations open up productive connection points for future research. In particular, the empirical foundation, algorithmic implementation and interdisciplinary embedding of the model form central perspectives for its further development.

One possible form of empirical validation is to carry out controlled decision-making experiments in which test subjects repeatedly make decisions under controlled uncertainty. The measured decision thresholds, expectation corrections and self-uncertainty data could then be compared with the model parameters α and μ. Alternatively, the extended SDEM could be implemented in an agent-based simulation environment and compared with real behavioural data, for example, in energy or supply security crisis scenarios.

Several avenues for future research emerge from the current extension of the Subjective Dynamic Decision Model (SDEM). First, empirical validation of the model's key components, particularly the calibration of the metacognitive uncertainty parameter (μ) and the learning rate (α), remains a central task. Experimental protocols involving confidence ratings, reaction times or scenario-based assessments may help identify robust proxies for these constructs.

Second, a systematic investigation of heuristic selection mechanisms is needed. Although the model provides for multiple heuristics, the empirical foundation for their activation, switching and contextual dependency has not yet been formalised. Interdisciplinary studies that combine behavioural decision research and computational modelling could contribute to a deeper understanding of these dynamics.

Third, the integration of the SDEM into agent-based simulation environments (ABM) should be explored in more detail. Specifically, heterogeneous agent populations with individualised uncertainty profiles and context-sensitive decision logic could offer more realistic representations of collective behaviour in stress scenarios or complex adaptive systems.

Finally, the application of the SDEM in real-world domains such as strategic intelligence, energy resilience or cybersecurity presents a valuable opportunity for empirical refinement. Joint research initiatives with academic institutions, government actors or private-sector partners may facilitate the development of operational decision-support frameworks based on the model.

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CONCLUSION AND OUTLOOK

The extended Subjective Dynamic Decision Model (SDEM) offers a promising approach to modelling strategic decisions under radical uncertainty. By integrating multiple heuristics, adaptive thresholds and a metacognitive uncertainty parameter, a decision-theoretic framework is created that explicitly accounts for both cognitive constraints and subjective perception. Thus, the model contributes to closing a significant gap between normative theory and real decision behaviour. The theoretical foundation and exemplary application show that the SDEM not only allows a differentiated description of individual action logics, but can also be used in simulated multi-actor systems to map complex dynamics and emergent behaviour. The extensions increase the connectivity to empirical research in psychology, economics and the social and security sciences. There are several perspectives for future research. Firstly, empirical validation of the model is required, particularly with regard to the operationalisation of subjective states, the selection of heuristics and the effect of metacognitive factors. Secondly, the algorithmic implementation of the model offers the possibility of realising adaptive decision agents in simulation-based early warning systems or strategic planning instruments. Thirdly, the SDEM opens up new approaches for interdisciplinary cooperation, for example, for the development of cognitively informed decision support systems.

Overall, the extended SDEM represents a theoretically sound and practically applicable contribution to the further development of decision theory under uncertainty. It forms a robust basis for future empirical, methodological and application-oriented research. The key innovation of the extended SDEM lies in its synthesis of adaptive learning, heuristic flexibility, and metacognitive awareness within a unified formal model. By moving beyond both rational optimisation and static heuristic models, it offers a dynamic and psychologically grounded alternative for modelling real-world decisions under radical uncertainty. This framework fills a critical gap between normative theory and observed strategic behaviour.

REFERENCES

Berthet, V. (2021). The impact of cognitive biases on professionals' decision-making: A review of four occupational areas. *Frontiers in Psychology*, *12*, 802439. https://doi.org/10.3389/fpsyg.2021.802439

de Finetti, B. (1974). *Theory of probability* (Vol. 1). Wiley.

Epstein, J. M. (2006). *Generative social science: Studies in agent-based computational modelling*. Princeton University Press.

Fleming, S. M., & Lau, H. C. (2014). How to measure metacognition. *Frontiers in Human Neuroscience*, *8*, 443. https://doi.org/10.3389/fnhum.2014.00443

Gigerenzer, G., & Selten, R. (Eds.). (2002). *Bounded rationality: The adaptive toolbox*. MIT Press.

Kay, J., & King, M. (2020). *Radical uncertainty: Decision-making for an unknowable future*. The Bridge Street Press.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*(2), 263-291. https://doi.org/10.2307/1914185

Knight, F. H. (1921). *Risk, uncertainty and profit*. Houghton Mifflin.

Kurdoglu, R. S., Ates, N. Y., & Lerner, D. A. (2023). Decision-making under extreme uncertainty: Eristic rather than heuristic. *International Journal of Entrepreneurial Behavior & Research*. https://doi.org/10.1108/IJEBR-07-2022-0587

Love, P. E. D., Ika, L. A., & Pinto, J. K. (2023). Fast-and-frugal heuristics for decision-making

Article DOI: https://doi.org/10.37284/eajis.8.1.3022

in uncertain and complex settings in construction. *Developments in the Built Environment, 14,* Article 100129. https://doi.org/10.1016/j.dibe.2023.100129

Moch, E. (2025). The Subjective Dynamic Decision Model (SDEM): A new approach to decision-making under radical uncertainty. *East African Journal of Arts and Social Sciences*, *8*(2), 27-40. https://doi.org/10.37284/eajass.8.2.2948

Ramsey, F. P. (1931). *The foundations of mathematics and other logical essays*. Routledge.

Savage, L. J. (1954). *The foundations of statistics*. Wiley.

Simon, H. A. (1955). A behavioural model of rational choice. *The Quarterly Journal of Economics, 69*(1), 99-118. https://doi.org/10.2307/1884852

Yeung, N., & Summerfield, C. (2012). Metacognition in human decision-making: Confidence and error monitoring. *Philosophical Transactions of the Royal Society B: Biological Sciences, 367*(1594), 1310-1321. https://doi.org/10.1098/rstb.2011.0416

