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Decision overload in data-driven procurement: Designing organisational decision architectures

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Abstract

Increasing digitalisation has expanded the availability of data in operational procurement processes. Although data-driven systems are expected to improve decision-making, decision quality does not necessarily increase under conditions of high information density. Instead, decision-makers are confronted with multiple simultaneously plausible options, resulting in decision overload. This study analyses decision overload in data-driven ordering processes from an organisational perspective. Based on a structured literature review and theory-guided case analysis, the study identifies recurring mechanisms that impair decision-making capability. The findings show that decision overload does not primarily result from data availability, but from the absence of institutionalised selection mechanisms. Three core mechanisms are identified: lack of information selection, diffusion of decision responsibility, and absence of goal prioritisation. Building on these findings, a decision architecture framework is developed that translates these mechanisms into organisational design principles. The framework includes information filtering, clear assignment of responsibilities, temporal structuring, limitation of automated decision-making logic, and institutionalised goal prioritisation. The study shifts the focus of data-driven decision-making research from data and analytics to organisational decision structures, demonstrating that decision quality depends on the institutional design of selection mechanisms.

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1. Introduction

Operational procurement processes are being fundamentally changed by digitalisation. The availability of data and analytical tools is growing significantly (McAfee & Brynjolfsson, 2012; Waller & Fawcett, 2013). Companies are using data-based systems in a targeted manner. They forecast requirements, manage inventories and evaluate suppliers. This is associated with the expectation of making decision-making processes significantly more powerful and efficient (Provost & Fawcett, 2013; Westerman et al., 2014).

In data-intensive procurement contexts, however, this expectation is systematically missed. A growing database does not create clear decision-making structures. At the same time, several equally justifiable options for action arise (Mintzberg et al., 1976). Different key figures provide contradictory signals. Algorithmic systems supplement additional suggestions for action (Burrell, 2016; Provost & Fawcett, 2013). The situation remains ambiguous. Decisions require a choice between competing alternatives (Shrestha et al., 2019).

Research on bounded rationality illustrates the consequences. Decision-makers only have limited processing capacities (Simon, 1971).The quality of decisions does not automatically improve with increasing information density. Rather, the difficulty of distinguishing relevant from irrelevant information increases (Simon, 1971; McAfee & Brynjolfsson, 2012). Decision-making processes are therefore not limited by a lack of information, but constrained by problems of selection and weighting (Mintzberg et al., 1976).

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The use of algorithmic systems further exacerbates this dynamic. Models generate probabilistic forecasts whose validity does not emerge directly from the data, but must be interpreted depending on the context (Burrell, 2016; Provost & Fawcett, 2013). At the same time, studies on human-automation interaction show a clear pattern: technical recommendations are often adopted uncritically under time pressure or when responsibility is unclear (Parasuraman & Riley, 1997). This shifts the decision-making logic in favour of system-generated suggestions without systematically reflecting on their prerequisites and limitations (Shrestha et al., 2019).

In addition to cognitive and technological factors, organisational structures influence decision-making capacity. Digital platforms and integrated information systems structure access to information and determine the visibility of possible courses of action (Ritter et al., 2025; Westerman et al., 2014). At the same time, different organisational units pursue divergent objectives, such as cost optimisation, security of supply and flexibility (Simon, 1971; Shrestha et al., 2019). Decisions are thus shaped not only by information processing but also by coordination between competing goal systems (Mintzberg et al., 1976).

This constellation is referred to below as ‘decision overload’. Decision overload describes a situation in which several courses of action appear plausible at the same time, without there being a clear organisational selection logic that enables unambiguous prioritisation (Mintzberg et al., 1976; Simon, 1971). The problem therefore lies not primarily in the volume of available information, but in the lack of structure in decision-making processes (Power, 2002).

Research on data-based decision-making processes has a narrow focus, as it predominantly examines technological and analytical aspects, focusing in particular on forecasting models, increasing efficiency through data use and the development of decision support systems (Power, 2002; Provost & Fawcett, 2013; Waller & Fawcett, 2013), which means that the organisational dimension of decision-making processes is insufficiently captured (Shrestha et al, 2019); at the same time, the existing

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approaches remain separate from each other, as they either deal with cognitive limitations (Simon, 1971), analyse unstructured decision-making processes (Mintzberg et al, 1976) or investigate algorithmic decision support (Burrell, 2016; Parasuraman & Riley, 1997) without systematically integrating these perspectives (Shrestha et al., 2019), so that a central connection remains unclear, namely the explanation of decision overload as a result of the interplay of information density, algorithmic uncertainty and organisational structure (Moch et al., 2025), which means that the analysis remains fragmentary overall. It remains unclear through which specific mechanisms decision overload arises in data-driven processes and how this can be addressed institutionally (Moch, 2025a).

Against this background, this study analyses decision overload in data-driven ordering processes with the aim of identifying the underlying organisational mechanisms. Building on an integrated literature review and a theory-based reconstruction of real-world decision-making situations, a decision architecture is developed that addresses these mechanisms and stabilises decision-making capacity (Moch, 2025; Shrestha et al., 2019).

The research question is: Which organisational mechanisms generate decision overload in data-driven ordering processes, and how can decision architectures be derived from them?

This work makes three contributions. Firstly, decision overload is interpreted not as a consequence of a high volume of data, but as the result of a lack of organisational selection mechanisms. Secondly, different theoretical perspectives are integrated into a consistent explanation by analysing cognitive limitations, algorithmic uncertainty and organisational structures as interlinked elements of a decision-making process. Thirdly, the development of a decision architecture provides a structured approach that places the design of data-driven decision-making processes on an institutional footing.

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2. Literature review and theoretical framework

The increasing availability of data-based information systems has fundamentally changed the structure of organisational decision-making processes. Organisations use analytical methods to continuously monitor operational processes and derive courses of action on this basis (McAfee & Brynjolfsson, 2012; Provost & Fawcett, 2013). In procurement in particular, data-driven systems enable more precise planning of order timing, quantity decisions and supplier selection (Waller & Fawcett, 2013). However, the increasing integration of such systems not only leads to an expansion of the information base but also alters the requirements for organisational decision-making processes (Westerman et al., 2014; Shrestha et al., 2019).

A central theoretical reference point is the concept of bounded rationality. Decisions are made under conditions of incomplete information and limited cognitive processing capacities (Simon, 1971). As information density increases, it is not the comprehensive examination of all available options that increases, but rather the need for selective reduction (Simon, 1971; McAfee & Brynjolfsson, 2012). Organisational decision-making ability thus depends largely on the ability to prioritise relevant information and filter out irrelevant information (Power, 2002). Without such selection mechanisms, the likelihood increases that several courses of action will appear plausible at the same time (Mintzberg et al., 1976).

The structure of organisational decision-making processes exacerbates this problem. Empirical studies show that complex decision-making situations often do not proceed as clearly defined problem-solving processes, but are characterised by iterative coordination, interruptions and delayed decisions (Mintzberg et al., 1976). Decision-making processes are therefore not organised linearly, but develop incrementally alongside shifting problem definitions and courses of action (Simon, 1971; Mintzberg et al., 1976). With a high information density, the number of possible decision sequences also increases without a clear structure being specified (Shrestha et al., 2019).

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With the increasing use of algorithmic decision support, the problem situation shifts further. Data-based models generate forecasts based on statistical correlations that can serve as a basis for decision-making (Provost & Fawcett, 2013). At the same time, the functioning of these models often remains opaque to decision-makers, meaning that the results generated cannot be fully understood (Burrell, 2016). The resulting forecasts are not deterministic statements, but probabilistic patterns whose relevance must first be determined within the respective decision-making context (Burrell, 2016; Provost & Fawcett, 2013).

This uncertainty influences the interaction between humans and systems. Research on human-automation interaction shows that, under certain conditions, there is a tendency to adopt automated recommendations, particularly when under time pressure or where the allocation of responsibility is unclear (Parasuraman & Riley, 1997). The use of algorithmic systems thus not only leads to an expansion of the information base, but also alters the decision-making logic by partially delegating decision-making responsibility implicitly to technical systems (Shrestha et al., 2019).

In addition to cognitive and technological factors, organisational structures shape the processing of information and the selection of courses of action. Digital platforms and integrated information systems structure access to data and influence which options become visible in the first place (Ritter et al., 2025; Westerman et al., 2014). At the same time, organisational decisions are shaped by differing sets of objectives. Different units pursue different priorities, for example with regard to costs, delivery capability or flexibility (Simon, 1971; Shrestha et al., 2019). Decisions are therefore not to be understood exclusively as selection processes under uncertainty. They are also coordination processes between competing target systems (Mintzberg et al., 1976).

Research on digital transformation shows that data-driven systems can only develop their potential if they are embedded in suitable organisational structures (Westerman et al., 2014; Moch, 2025a). Technological efficiency gains are therefore linked to

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institutional adjustments that structure decision-making processes and clearly assign responsibilities (Moch et al., 2025). Without this structural embedding, the expansion of the information base does not lead to more stable decisions, but to an increase in complexity (McAfee & Brynjolfsson, 2012).

The literature thus suggests that decision overload cannot be understood as an isolated problem of the volume of information. Rather, decision overload arises from the interplay of several factors: the expansion of available courses of action through data (Waller & Fawcett, 2013), the uncertainty of algorithmic forecasts (Burrell, 2016), the limited cognitive processing capacity of decision-makers (Simon, 1971), and the institutional embedding of decision-making processes (Shrestha et al., 2019; Moch, 2025). Crucial here is the organisational ability to translate these factors into a consistent selection logic (Power, 2002).

From this perspective, decision overload can be understood as a structural problem in organisational decision-making processes. Decision overload arises when several courses of action appear plausible at the same time, without clear rules for prioritisation and selection being in place (Mintzberg et al., 1976; Simon, 1971). The central analytical question thus shifts from the quality of individual data or models to the design of decision-making structures that enable a reduction in complexity (Power, 2002; Moch, 2025). This theoretical framework forms the basis for the subsequent analysis of specific decision-making situations in data-driven ordering processes (Shrestha et al., 2019).

3. Methodological Approach

The study follows a qualitative, theory-driven research design with the aim of identifying mechanisms of decision overload in data-driven ordering processes (Mintzberg et al., 1976; Simon, 1971). The focus is not on measuring individual variables, but on analysing decision-making processes and their institutional structuring (Shrestha et al., 2019; Moch, 2025). The study aims to identify recurring

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patterns in complex decision-making situations and attribute these to underlying mechanisms (Mintzberg et al., 1976).

The literature review forms the basis of the study. It is based on a defined selection of relevant works from decision research, research on data-driven organisations and human-automation interaction (Provost & Fawcett, 2013; Parasuraman & Riley, 1997; Shrestha et al., 2019).

The selection is based on the relevance for three central areas of analysis. Firstly, the processing of information under conditions of high complexity (Simon, 1971). Secondly, the structure of organisational decision-making processes (Mintzberg et al., 1976). Thirdly, the effect of algorithmic decision support (Burrell, 2016; Parasuraman & Riley, 1997).The literature is evaluated not descriptively but analytically along these categories, with the aim of identifying recurring problem constellations and explanatory approaches (Provost & Fawcett, 2013; Power, 2002).

On this basis, an integrated theoretical framework is developed to serve as an analytical tool for the study (Moch, 2025; Shrestha et al., 2019). This framework describes the relationships between information density, algorithmic uncertainty, cognitive constraints and organisational structure (Simon, 1971; Burrell, 2016; Shrestha et al., 2019). It forms the basis for the subsequent reconstruction of specific decision-making situations (Mintzberg et al., 1976).

The empirical analysis takes the form of a theory-based reconstruction of cases. In this process, typical decision-making situations from data-driven procurement processes are systematically modelled on the basis of the literature (Waller & Fawcett, 2013; Power, 2002). These are not illustrative examples, but analytical distillations of empirically described contexts from supply chain research, decision support system research, and studies on algorithmic decision support (Provost & Fawcett, 2013; Parasuraman & Riley, 1997; Shrestha et al., 2019). The aim is to reconstruct decision-making processes under realistic conditions, without resorting to fictional scenarios (Mintzberg et al., 1976).

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The case analysis follows a standardised structure. For each reconstructed decision-making situation, the initial context, the sequence of decision-making processes, the actors involved, and the resulting decision-making behaviour are systematically recorded (Mintzberg et al., 1976; Shrestha et al., 2019). On this basis, the underlying mechanism that explains the observed decision-making dynamics is identified (Simon, 1971). The analysis thus focuses not on individual cases, but on identifying causal relationships (Moch, 2025).

The individual cases are then evaluated comparatively. The aim of the comparison is to identify recurring mechanisms that occur independently of specific contextual conditions (Shrestha et al., 2019; Mintzberg et al., 1976). This cross-case analysis reveals structural patterns that explain the emergence of decision overload (Simon, 1971; Burrell, 2016). The comparison thus serves to generalise observations and derive theoretically grounded mechanisms (Moch, 2025).

The methodological approach thus combines a structured literature review with systematic case reconstruction and comparative analysis (Provost & Fawcett, 2013; Power, 2002). On this basis, it becomes possible to explain decision overload not as an isolated phenomenon but as the result of recurring organisational structures, and to derive conceptual starting points for the design of decision architectures (Moch et al., 2025; Shrestha et al., 2019).

4. Case studies: Decision-making problems in data-driven procurement processes

The following case studies reconstruct typical decision-making situations in data-driven procurement processes with the aim of identifying structural mechanisms of decision overload (Waller & Fawcett, 2013; Shrestha et al., 2019). The cases are not interpreted as isolated instances, but as analytical summaries of recurring decision-making constellations (Mintzberg et al., 1976).

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The first case describes a decision-making situation characterised by competing information signals. In data-driven procurement processes, forecast data, stock information and lead time indicators are available simultaneously, generating conflicting consequences for action (Waller & Fawcett, 2013; Provost & Fawcett, 2013). Rising demand forecasts, sufficient short-term stock levels and extended delivery times simultaneously generate several justifiable decision options (McAfee & Brynjolfsson, 2012). The decision sequence is therefore structurally open (Mintzberg et al., 1976). An organisational prioritisation of the signals is not defined (Simon, 1971). The decision-making process is characterised by the simultaneity of competing information sets without a selection rule (Power, 2002). The underlying mechanism consists of the lack of institutional selection of information (Simon, 1971). The weighting of indicators is situational and not rule-bound (Mintzberg et al., 1976). The result is an increased likelihood of delayed or inconsistent decisions (Shrestha et al., 2019).

The second case describes a decision-making situation characterised by the dominance of algorithmic recommendations for action. Data-driven systems generate specific proposals for order quantities and timing based on historical data (Provost & Fawcett, 2013; Power, 2002). These proposals structure the decision-making process without the underlying assumptions being fully understood (Burrell, 2016). The decision-making sequence is reduced to the evaluation of a central system recommendation (Shrestha et al., 2019). Alternative options are not systematically examined (Mintzberg et al., 1976). Under conditions of time pressure or unclear responsibility, critical reflection on the recommendation is omitted (Parasuraman & Riley, 1997). The decision-making process is characterised by an implicit delegation to the system (Shrestha et al., 2019). The underlying mechanism consists of the diffusion of decision-making responsibility in conjunction with systemic dominance (Parasuraman & Riley, 1997; Shrestha et al., 2019). Decisions are no longer structured as independent selection processes, but rather as the adoption of pre-

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structured proposals (Burrell, 2016). The result is a context-independent application of algorithmic decisions (Moch et al., 2025).

The third case describes a decision-making situation determined by competing organisational goal systems. In integrated procurement systems, cost indicators, delivery capability metrics and risk assessments become visible simultaneously (Ritter et al., 2025; Waller & Fawcett, 2013). These indicators are assigned to different organisational units, each of which follows its own independent evaluation logic (Shrestha et al., 2019). The decision sequence is characterised by the simultaneous validity of multiple goal systems without an overarching prioritisation rule (Simon, 1971; Mintzberg et al., 1976). Decisions require coordination between units with incompatible decision-making logics (Shrestha et al., 2019). The decision-making process is thus structured not by selection but by coordination (Mintzberg et al., 1976). The underlying mechanism consists of the lack of institutional prioritisation of organisational goals (Simon, 1971). Conflicts of interest are negotiated on a situational basis and not resolved according to fixed rules (Mintzberg et al., 1976). The result is structural delay and inconsistent decision outcomes (Moch, 2025).

Analysis of the three cases shows that decision overload does not arise from a lack of information, but from the simultaneous availability of several structured yet incompatible decision options (Simon, 1971; Shrestha et al., 2019). In all cases, there is a lack of an institutionalised selection logic that reduces the decision-making situation (Power, 2002). As a result, decision-making processes remain open-ended, ambiguous and not conclusively structured (Mintzberg et al., 1976). Decision overload should therefore be understood as the result of a lack of selection mechanisms in information-rich, algorithmically supported and organisationally differentiated decision-making environments (Moch, 2025; Burrell, 2016).

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5. Comparison of cases and mechanisms of decision overload

The comparative analysis of the reconstructed cases shows that decision overload does not result from isolated decision-making situations, but from recurring structural patterns in organisational decision-making processes (Mintzberg et al., 1976; Shrestha et al., 2019). The cases differ in their specific manifestations but exhibit consistent mechanisms that occur independently of the respective context (Simon, 1971). The focus of the analysis is therefore not on the cases themselves, but on the underlying decision-making structures (Moch, 2025).

A first mechanism lies in the lack of organisational selection of information. In data-driven decision-making environments, several valid but contradictory signals are generated simultaneously (McAfee & Brynjolfsson, 2012; Provost & Fawcett, 2013). Forecasts, inventory data and other indicators each provide plausible recommendations for action without a clear prioritisation being specified (Waller & Fawcett, 2013). The decision-making situation is thus characterised by the simultaneity and competition of options (Mintzberg et al., 1976). Without institutionalised selection rules, the weighting of information is shifted to the individual decision-maker (Simon, 1971). The result is increased cognitive load and a rising likelihood of delayed or inconsistent decisions (Simon, 1971; Shrestha et al., 2019). In this case, decision overload arises from the lack of structure in information processing (Power, 2002).

A second mechanism involves the diffusion of decision-making responsibility in conjunction with the dominance of algorithmic systems. The cases analysed show that system-generated recommendations for action frequently serve as the central basis for decision-making (Provost & Fawcett, 2013; Power, 2002). At the same time, responsibility for the decision remains unclear or is implicitly transferred to the system (Shrestha et al., 2019). As a result, the decision-making structure is no longer clearly assigned to a single actor (Simon, 1971). Under conditions of time pressure or complexity, critical scrutiny of the proposals is reduced, and decisions are increasingly

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determined by the logic of the system (Parasuraman & Riley, 1997; Burrell, 2016). Decision overload manifests itself here not in a multitude of actively weighed alternatives, but in the reduction of the decision to an unquestioned option (Shrestha et al., 2019).

A third mechanism lies in the lack of institutional prioritisation of organisational goals. The cases show that decisions are frequently shaped by competing sets of goals that are simultaneously legitimate (Shrestha et al., 2019; Simon, 1971). Different organisational units follow different evaluation logics without there being an overarching prioritisation rule (Mintzberg et al., 1976). The decision-making structure forces the actors involved to resolve conflicting goals on a case-by-case basis (Shrestha et al., 2019). This results in coordination efforts and delays that impair decision-making capacity (Moch, 2025). In this case, decision overload arises from the impossibility of clearly weighing several equally valid objectives (Simon, 1971).

The three identified mechanisms share a common structure. In all cases, decision overload arises from the lack of institutionalised rules for reducing complexity (Power, 2002; Moch, 2025). The number of simultaneously plausible options for action increases systematically due to the diversity of information, algorithmic support and organisational differentiation (McAfee & Brynjolfsson, 2012; Burrell, 2016; Shrestha et al., 2019). Without binding selection mechanisms, the decision-making situation remains structurally open and ambiguous (Mintzberg et al., 1976). The cause of decision overload therefore does not lie in the amount of information, but in the lack of institutional organisation of decision-making processes (Simon, 1971; Power, 2002).

The analysis forces a shift in the definition of the problem. Decision overload is not a cognitive deficit of individual decision-makers, but an expression of structural deficits in organisational decision-making architectures (Shrestha et al., 2019; Moch, 2025). Decision overload arises where organisations do not establish stable rules for selection, prioritisation and clear assignment of responsibility (Simon, 1971; Mintzberg et al., 1976). The identified mechanisms form the basis for the subsequent

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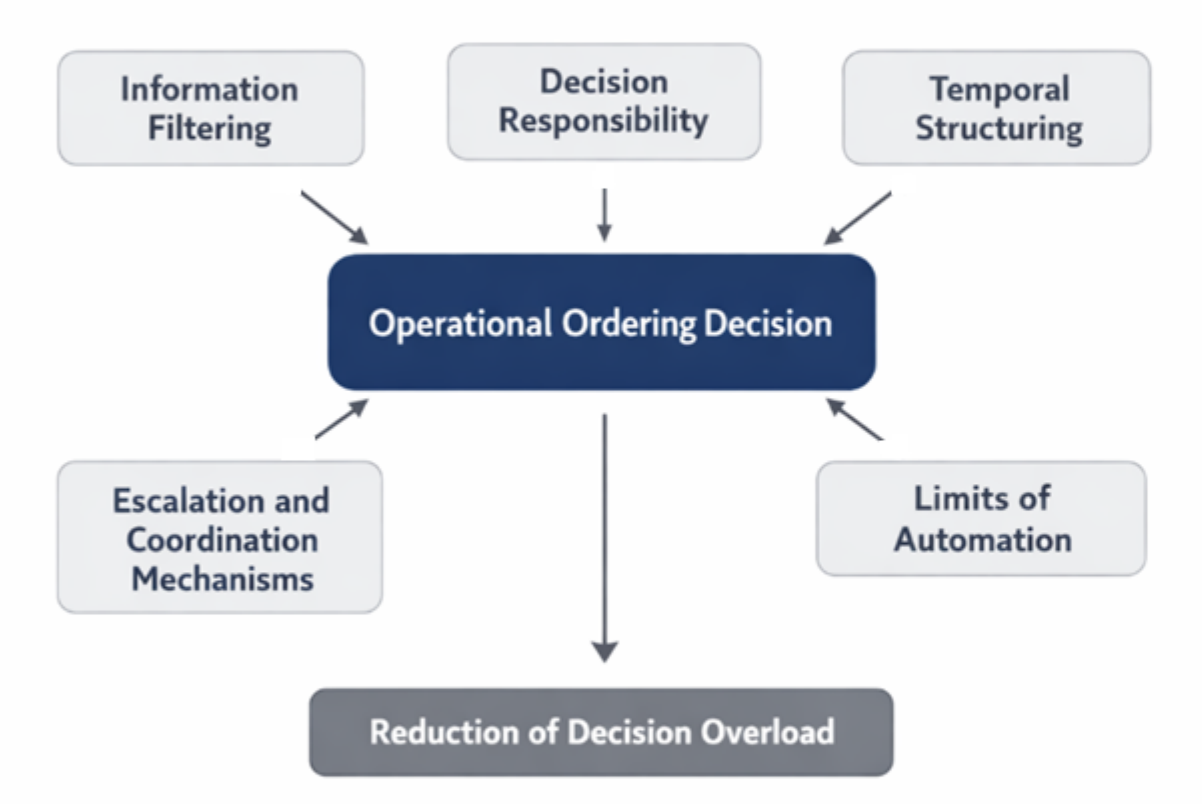
development of a decision architecture that systematically addresses these structural deficits (Moch et al., 2025).

6. Development of a decision-making architecture

The results make it clear that decision overload results from the lack of institutionalised selection mechanisms (Simon, 1971; Mintzberg et al., 1976; Power, 2002). The development of a decision architecture therefore aims not at expanding the information base, but at the structural reduction of decision options (McAfee & Brynjolfsson, 2012; Shrestha et al., 2019). In this context, decision architectures are to be understood as institutional arrangements that determine how information is selected, responsibilities are assigned and decision-making processes are coordinated (Shrestha et al., 2019; Moch, 2025).



Source: Author's own conceptual framework.

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Based on the identified mechanisms, the decision architecture can be reconstructed as a bundle of complementary structuring dimensions (Moch, 2025; Shrestha et al., 2019). Each dimension addresses a specific mechanism of decision overload and transforms it into a stable decision rule (Simon, 1971; Power, 2002).

The first dimension concerns institutionalised information filtering. This is based on the lack of selection of competing information signals (McAfee & Brynjolfsson, 2012; Provost & Fawcett, 2013). In data-driven decision-making environments, the simultaneous availability of several plausible indicators creates structurally open decision-making situations (Waller & Fawcett, 2013). Information filtering limits this openness by determining which information is considered primarily relevant in specific decision-making contexts (Simon, 1971). Decisions are thus no longer based on the totality of available data, but on a pre-structured selection of indicators (Power, 2002).

A second dimension concerns the clear allocation of decision-making responsibility. The underlying mechanism is the diffusion of responsibility in conjunction with the dominance of algorithmic systems (Parasuraman & Riley, 1997; Shrestha et al., 2019). Decision architectures determine which actor is responsible for which decision and how algorithmic recommendations are integrated into the decision-making process (Shrestha et al., 2019). This prevents decisions from being implicitly delegated to technical systems (Burrell, 2016). The decision remains structured as the action of a clearly identifiable actor (Simon, 1971).

A third dimension concerns the temporal structuring of decision-making processes. The underlying mechanism lies in the delay caused by unstructured decision sequences (Mintzberg et al., 1976). In the absence of clearly defined decision sequences, iterative coordination processes arise without a clear conclusion (Mintzberg et al., 1976; Simon, 1971). Temporal structuring defines decision cycles, deadlines and escalation rules that limit and stabilise the decision-making process (Power, 2002). Decisions are thus embedded in a binding temporal order (Moch, 2025).

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A fourth dimension concerns the limitations of automated decision-making logic. The underlying mechanism is the uncritical adoption of system-generated recommendations for action (Parasuraman & Riley, 1997; Burrell, 2016). Decision architectures define thresholds and conditions under which algorithmic suggestions must be reviewed or adjusted (Shrestha et al., 2019). This integrates the use of automated systems into a controlled decision-making structure (Moch et al., 2025). The decision is not based exclusively on algorithmic logic, but on a combination of system-generated information and context-based evaluation (Provost & Fawcett, 2013).

A fifth dimension concerns the institutionalised prioritisation of organisational goals. The underlying mechanism is the simultaneous existence of competing, equally valid goal systems (Shrestha et al., 2019; Simon, 1971). Decision architectures determine the criteria by which conflicting goals are resolved (Mintzberg et al., 1976). These prioritisation rules reduce the need for situational coordination and enable consistent decisions across different organisational units (Moch, 2025).

The decision architecture should not be understood as an additive collection of individual measures, but rather as an integrated system of selection rules (Power, 2002; Moch, 2025). The individual dimensions act complementarily by addressing different sources of decision overload (Shrestha et al., 2019). Information filtering reduces the number of relevant options, the assignment of responsibility stabilises decision-making authority, temporal structuring limits decision-making processes, the limitation of automation prevents system dominance, and goal prioritisation reduces coordination conflicts (Simon, 1971; Burrell, 2016).

Taken as a whole, the decision architecture enables the transformation of an open, ambiguous decision-making situation into a structured decision-making environment (Mintzberg et al., 1976; Shrestha et al., 2019). Decision overload is thus not reduced by additional information, but by the institutional limitation and ordering of decision-making processes (Power, 2002; Moch, 2025). The decision-making capacity of

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organisational units thus derives from the stability of the underlying decision architecture (Moch et al., 2025).

7. Discussion

The present analysis shows that decision overload in data-driven procurement processes does not primarily result from the availability of large amounts of data, but from the lack of institutional structuring of decision-making processes (Simon, 1971; Mintzberg et al., 1976; Shrestha et al., 2019). This finding shifts the problem definition from an information-related to an organisation-related explanatory approach (Moch, 2025). Whilst existing research regards the expansion of data and analytical capabilities as the central driver of efficiency gains (McAfee & Brynjolfsson, 2012; Waller & Fawcett, 2013), the analysis makes it clear that decision-making capacity cannot be stabilised without appropriate selection mechanisms (Power, 2002).

The findings can be situated within existing theoretical frameworks, yet systematically extend them. The concept of bounded rationality describes the necessity of selective information processing, but remains confined to the level of individual decision-making capacity (Simon, 1971). This study shows that this selection capability must be institutionally organised to be effective under data-driven conditions (Shrestha et al., 2019). Decision overload is thus not merely a consequence of cognitive limitations, but an expression of a lack of organisational selection structures (Moch, 2025).

Approaches to unstructured decision-making processes also provide an important foundation by describing decision-making processes as non-linear, iterative sequences (Mintzberg et al., 1976). The present analysis extends this perspective by showing that such unstructured processes with high information density systematically lead to overload if there are no stable decision rules (Simon, 1971; Shrestha et al., 2019). Unstructured decision-making is thus not merely a description of decision-making processes, but a central mechanism of decision overload (Mintzberg et al., 1976).

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The integration of algorithmic decision support is discussed in the existing literature primarily in terms of efficiency potential and transparency issues (Burrell, 2016; Parasuraman & Riley, 1997). This study shows that algorithmic systems also alter the structure of decision-making processes by shifting responsibilities and influencing decision-making logic (Shrestha et al., 2019; Moch et al., 2025). The use of such systems not only leads to an expansion of the information base but also alters the institutional conditions of decision-making (Provost & Fawcett, 2013).

The results suggest that decision overload should be understood as a structural problem of organisational decision-making architectures (Shrestha et al., 2019; Moch, 2025). This interpretation contrasts with alternative explanations that view decision overload primarily as an individual problem (Simon, 1971). Such a perspective would attribute decision overload to limited cognitive capacities or a lack of competence on the part of decision-makers (Simon, 1971). However, the cross-case analysis shows that comparable patterns of problems occur independently of individual characteristics (Mintzberg et al., 1976). The cause therefore lies in the structure of decision-making processes and not in the characteristics of individual actors (Shrestha et al., 2019).

Another alternative explanation could interpret decision overload as a temporary adjustment problem that is reduced in the course of organisational learning processes (Westerman et al., 2014). This perspective assumes that organisations develop suitable routines over time to cope with increased information density (McAfee & Brynjolfsson, 2012). However, the analysis shows that the identified mechanisms do not occur as transitional phenomena, but are structurally determined (Moch, 2025). Without targeted institutional adjustments, the problem patterns are reproduced regardless of experience and learning processes (Shrestha et al., 2019).

This study thus contributes to the integration of technological and organisational perspectives on decision-making processes. It demonstrates that the impact of data-driven systems cannot be viewed in isolation, but depends on their embedding within organisational decision-making structures (Shrestha et al., 2019; Moch et al., 2025).

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Decision quality is not solely a function of data availability or model quality, but the result of institutionally structured selection processes (Power, 2002; Provost & Fawcett, 2013).

The validity of the results is limited by the chosen methodology. The analysis is based on a theory-driven reconstruction of decision-making situations rather than on primary data from specific organisations (Mintzberg et al., 1976). The identified mechanisms should therefore be understood as analytical generalisations, the empirical manifestation of which may vary depending on the context (Shrestha et al., 2019). Future research could build on this and investigate how decision architectures are implemented in different organisational environments and what effects result from this (Moch, 2025a).

Despite these limitations, the analysis provides a precise explanation of decision overload as a structural phenomenon. It shows that the central challenge of data-driven decision-making processes lies not in the increase in the volume of information, but in the design of decision-making structures that enable a stable reduction in complexity (Simon, 1971; Power, 2002; Moch, 2025).

8. Conclusion

The analysis shows a clear mechanism. Decision overload in data-based ordering processes is not caused by data availability. It is caused by the lack of institutionalised selection mechanisms (Simon, 1971; Mintzberg et al., 1976; Shrestha et al., 2019). Several simultaneously plausible options for action do not automatically lead to overload. They only generate it if there are no stable rules for prioritisation, responsibility allocation and coordination (Power, 2002; Moch, 2025). Decision overload is therefore a structural problem of organisational decision-making processes (Shrestha et al., 2019). The explanation thus shifts from an information-related to an institutional perspective (Moch, 2025).

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The decisive factors are not the amount of data, models or individual decision-making ability (McAfee & Brynjolfsson, 2012; Provost & Fawcett, 2013). The decisive factor is the structure of the decision-making processes (Simon, 1971; Mintzberg et al., 1976). Decision-making ability arises through selection. It is created by converting information into stable rules (Power, 2002; Shrestha et al., 2019). Based on this, a decision architecture is developed (Moch et al., 2025; Shrestha et al., 2019). This addresses the identified mechanism. Central elements are information filtering and clear assignment of responsibilities. In addition, there is time structuring and the limitation of automated decision-making logic. Institutionalised goal prioritisation also plays a role (Simon, 1971; Burrell, 2016; Parasuraman & Riley, 1997). These elements do not reduce the complexity of the environment. They limit the complexity of the decision-making process (Mintzberg et al., 1976; Power, 2002). The contribution lies in the explanation of decision overload as a consequence of a lack of institutional order (Moch, 2025).

This results in a new perspective on data-based decision-making processes. Technological progress alone does not increase the ability to make decisions (Westerman et al., 2014; McAfee & Brynjolfsson, 2012). The design of organisational structures is crucial. It enables a permanent limitation of complexity (Shrestha et al., 2019; Power, 2002). The digitalisation of procurement processes should therefore be understood as a design problem (Waller & Fawcett, 2013; Westerman et al., 2014). Organisations do not need to integrate as much data as possible. They need to structure decision-making processes. The aim is to generate actionable decisions from data (Provost & Fawcett, 2013; Moch, 2025). Decision architectures are the central starting point for this (Shrestha et al., 2019).

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