An Analysis of ACT-R and CLARION Representing Heuristic Strategies for Consumer Decision-Making

A Systematic Literature Review

Willem van de Sanden[1]
Supervisors: Bernd Dudzik[1]**, Chenxu Hao**[1]
[1]EEMCS, Delft University of Technology, The Netherlands

A Thesis Submitted to EEMCS Faculty Delft University of Technology,
In Partial Fulfilment of the Requirements
For the Bachelor of Computer Science and Engineering
June 22, 2025

Name of the student: Willem van de Sanden
Final project course: CSE3000 Research Project
Thesis committee: Bernd Dudzik, Chenxu Hao, Catharine Oertel

Abstract

Heuristic strategies are an integral part of consumer decision-making. Heuristics serve as mental shortcuts that reduce cognitive effort, simplifying consumer decisions. To go from qualitative insights into these heuristics to quantitative data, a cognitive architecture must represent these heuristic strategies to understand consumer behavior better. This study will focus on the cognitive architectures ACT-R and CLARION since there is an interesting distinction in how they structure symbolic (explicit) and subsymbolic (implicit) cognition, influencing how they represent heuristic behavior. Currently, there is no systematic overview and comparison of how ACT-R and CLARION represent heuristics relevant to consumer decision-making. This paper aims to fill this knowledge gap by performing a systematic literature review on papers that contain an ACT-R or CLARION representation of heuristics relevant to consumer decision-making. The review uses four databases for the literature search: Scopus, Web of Science, IEEE Xplore, and ACM Digital Library. In total, 58 records have been screened, and 12 records have been included in the review. The review shows that ACT-R's strength relies on representing heuristics by sequentially executing rule-based heuristics, while CLARION focuses on representing similarity-based heuristics by using bottom-up activation from its implicit layers. The results show a pattern in which the architectural structure mainly determines which heuristic strategies have been represented.

1 Introduction

It has long been a concern in cognitive science and behavioral economics to understand how people make decisions. Heuristics are efficient rules of thumb that people use to make decisions; they serve as mental shortcuts that reduce the cognitive effort required to solve problems [1]. Humans often rely on heuristic strategies to make efficient decisions. Heuristics are especially relevant in consumer decision-making, where people usually make decisions based on limited information or cognitive constraints [2]. For example, instead of comparing all aspects of a product before making a decision, a consumer chooses to buy the product they recognize (recognition heuristic).

Modeling such heuristic decision strategies is an essential goal of cognitive architectures. Cognitive architectures can be seen as a blueprint for intelligence, specifically, a proposal about the mental representations and procedures that enable intelligent behavior [3]. Cognitive architectures can be applied to tasks such as modeling human decision and choice, reproducing reaction time bottlenecks, and simulating autonomous agents [4]. The cognitive architectures Adaptive Control of Thought-Rational (ACT-R) and Connectionist Learning with Adaptive Rule Induction On-line (CLARION) were chosen for this study since they both show the highest competence in modeling psychological experiments compared to other architectures [5]. In addition, both ACT-R and CLARION are well-established cognitive architectures, which means there is a sufficient amount of literature on which to base this study. Each architecture offers a different approach to modeling cognitive decision-making. Both ACT-R and CLARION are fully integrated hybrid models. Previous research has been conducted on heuristic decision strategies represented in CLARION [6] and ACT-R [7].

In cognitive psychology, implicit and explicit thought distinguishes between cognitive processes that occur unconsciously and automatically (implicit) versus those that are conscious, deliberate, and controlled (explicit) [8]. This distinction is especially relevant in the context of consumer decision making, which is based on both explicit and implicit thinking. Cognitive psychology recognizes two major paradigms: one that integrates implicit activation with explicit thinking, exemplified by ACT-R, and another that treats implicit and explicit cognition as separate interacting systems, which is used in CLARION. ACT-R uses subsymbolic processes, such as an activation level, to support symbolic rules [9], while CLARION is a dual-process architecture that treats explicit (symbolic) and implicit (subsymbolic) components as separate but interacting cognitive systems [10]. This distinction between architectures creates an interesting difference in how heuristic strategies are represented.

Although both ACT-R and CLARION have been applied to various decision-making tasks, there is currently no systematic overview and comparison of how they represent heuristic strategies. This is important because consumer decision-making involves a combination of symbolic and subsymbolic processes [11], and it remains unclear which architecture better represents heuristic decision-making in a consumer context.

It is worth exploring this research gap since cognitive architectures are increasingly being used in applied domains. Knowing how ACT-R and CLARION represent heuristics used in consumer decision-making could inform researchers to make better design choices to model consumer behavior in the future. What is still missing is a systematic overview based on existing literature that shows how the heuristic strategies used in consumer decision-making are represented in ACT-R compared to CLARION. Addressing this knowledge gap through a systematic literature review will guide future research in cognitive modeling and applied consumer behavior. Modeling consumer heuristics in cognitive architectures would turn qualitative insights on consumer biases into quantitative data. This will further enable research to improve understanding and prediction of consumer behavior.

This research aims to provide a systematic overview of all aspects regarding ACT-R and CLARION representing heuristic strategies relevant to consumer decision-making, thereby answering the following research question:

How do ACT-R and CLARION represent heuristic strategies in consumer decision-making?

To answer the primary research question, the following sub-questions will be used:

- **SQ1:** *How are the heuristic strategies conceptually represented in ACT-R or CLARION, or both?* This question aims to analyze how these heuristic strategies are conceptually represented so that an overview can be created on how to represent these heuristic strategies in ACT-R and CLARION. This also enables comparisons between different heuristic representations and between ACT-R and CLARION. *Conceptually represented* means how the model elements (memory, buffers, layers) are used together to simulate a specific heuristic.

- **SQ2:** *Are there differences between ACT-R and CLARION in that they represent specific heuristics strategies and not the other, and if so, what is the motivation for this?* This question aims to answer whether certain heuristic strategies are represented only by one architecture and not the other, focusing on why this difference occurs in previous literature.

- **SQ3:** *What are the strengths and limitations reported in the literature regarding ACT-R and CLARION representing these heuristic strategies?* This question aims to create an overview of the strengths and weaknesses of using ACT-R or CLARION to represent heuristic strategies.

The remainder of this paper is organized as follows. In Section 2, an overview of ACT-R and CLARION is provided and background information on consumer decision-making is described. Furthermore, Section 4 describes the methodology used in this systematic review. Third, Section 5 presents the results of this review, followed by Section 6, where the results are discussed and limitations of this study are detailed. Next, Section 7 will provide a discussion of the ethical considerations and reproducibility, followed by Section 8, which answers the research questions and includes directions for future work.

2 Related Work

Surveys have provided an overview of the behavioral heuristic research landscape. One of the most prominent, e.g., Gigerenzer & Gaissmaier's overview of heuristic decision making, provides an abstract overview of a wide variety of heuristics and how they are used in decision making [1]. Here, the mechanisms behind the heuristics are only described in abstract terms without relation to any cognitive architecture.

There are also prominent architecture-specific papers, such as Marewski & Mehlhorn's specification of 39 decision processes represented in ACT-R, showing how ACT-R uses its interacting modules with production rules and response timing to simulate specific (non)compensatory heuristic decision strategies [7]. For CLARION, such a prominent review is Sun & Hélie's outline of reasoning with heuristics and induction. Here, it is shown how CLARION uses its modules to simulate similarity and availability-based heuristics, such as the representativeness heuristic [12].

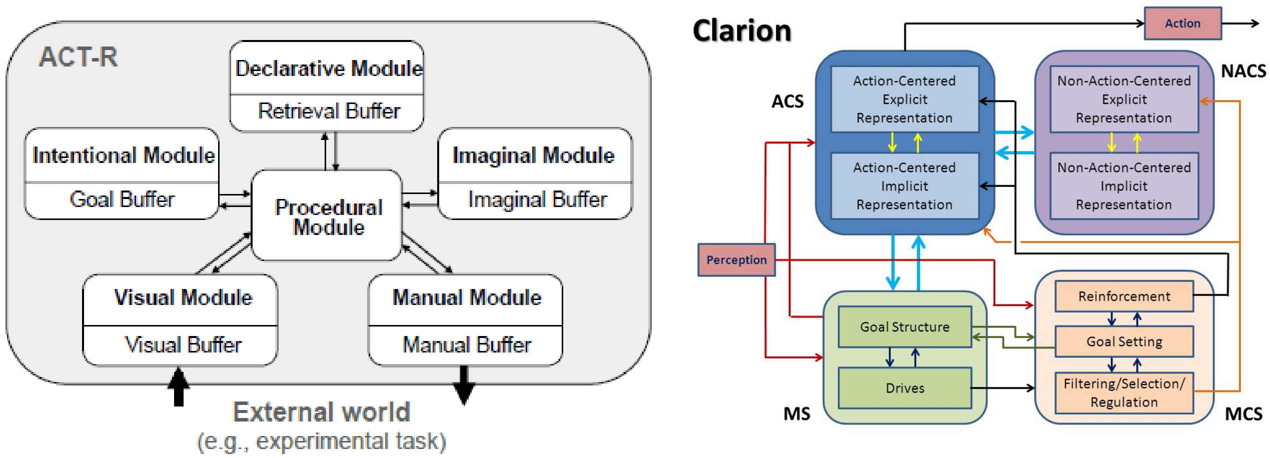
However, these studies on heuristic decision-making remain focused on either only abstract cognitive descriptions or focus solely on one architecture. In addition, no preceding survey has explored which consumer-relevant heuristics each architecture can or cannot represent and what the strengths and weaknesses are in these representations.

This review closes that gap by analyzing and comparing ACT-R and CLARION side by side, focusing on consumer decision strategies. This creates an overview of the consumer-relevant heuristic representations currently available in the literature, showing how architectural capabilities shape the distribution of heuristic representations in the literature.

Outside of the literature on cognitive architecture, macro-level agent-based models have examined consumer choice from a sociocultural perspective [13]. In contrast, this review focuses on micro-level consumer heuristic models in cognitive architectures (ACT-R and CLARION).

3 Background

This Section will provide a background overview of the research area. First, an overview of ACT-R's cognitive architecture will be given in Section 3.1, and an overview of CLARION in Section 3.2. Furthermore, background on the consumer decision-making process will be provided in Section 3.3, followed by a detailed list of heuristic strategies relevant to consumer decision-making in Section 3.4.



(a) An overview of ACT-R's default modules and buffers [7].

(b) The CLARION architecture contains: action-centered subsystem (ACS), non-action-centered subsystem (NACS), motivational subsystem (MS), and meta-cognitive subsystem (MCS).

Figure 1: Overview of two cognitive architectures: ACT-R and CLARION.

3.1 An overview of ACT-R

The ACT-R architecture consists of multiple independent modules that organize their interaction through a production system (Figure 1a). The procedural module containing the production system consists of If-Then production rules, in the form of "condition → action", where the conditions are checked against the modules, and if the condition is met, then the action will follow [9, 7].

While the production system coordinates the modules, it can only use the information stored in the modules' buffers. This can be seen as working memory, linking the module content to the rules of the production system, forming a processing bottleneck [7].

Different cognitive processes are represented within each independent module. Storage and retrieval of declarative memory are handled in the declarative module and retrieval buffer. Furthermore, the goals someone would like to achieve are tracked in the intentional module. In addition, the imaginal module handles information necessary to fulfill tasks. The manual module is used for motor actions, and the visual module is used for perception [7, 9].

Furthermore, ACT-R is a hybrid cognitive architecture, similar to CLARION, in that it distinguishes between symbolic and sub-symbolic systems: *Symbolic layer:* The modules and buffers, together with the production system, form the symbolic system. The symbolic system contains a serial flow since only one production rule can fire at a time [14]. *Sub-symbolic layer:* The sub-symbolic system coordinates the access to the information in the modules and buffers. This system consists of a set of equations and determines, for example, the timing of memory retrieval [15]. This is in contrast to the dual process theory, which is used to construct the CLARION architecture, where symbolic and subsymbolic systems are explicitly separated within each module [16].

3.2 An overview of CLARION

The CLARION architecture is based on a dual process theory. In every subsystem, the top level represents explicit knowledge (easily accessible but requires attentional resources), whereas the bottom level represents implicit knowledge (automatic but harder to access). The top and bottom-level processing results are integrated to simulate similar reasoning seen in humans [12, 16].

In addition, there is a difference in how explicit and implicit knowledge is represented at the top and bottom levels of the subsystems. The top level consists of chunk nodes, where each chunk node is represented by a set of features in the bottom level so that they may be activated together through bottom-up activation (when the features are activated first) and top-down activation (when the chunks are activated first). Bottom-level features are connected using a connectionist network, which is highly efficient [12, 16].

This dual process theory creates an intuitive approach to modeling implicit and explicit cognition [16], which is important in heuristic reasoning.

Furthermore, CLARION consists of four subsystems: the action-centered subsystem (ACS), the non-action-centered subsystem (NACS), the motivational subsystem, and the meta-cognitive subsystem. An overview of how CLARION is structured and how the subsystems interact can be seen in Figure 1b. This paper will focus on the ACS and NACS subsystems, as these are primarily involved in heuristic reasoning [6, 12].

The Action-Centered Subsystem (ACS)

The ACS is the primary subsystem of CLARION. In addition to containing procedural memory, the ACS can also control other subsystems. In its operations, the ACS receives input from the environment and will create action recommendations that are partly based on input from the other subsystems.

Top Level: The top level of the ACS represents explicit knowledge in the form of condition chunks and action chunks. Condition chunks can be activated by other subsystems or input from the environment. Action chunks can represent motor actions or commands to other subsystems. Condition and action chunks are linked, implementing explicit rules in the form of "Condition chunk → Action chunk."

Bottom Level: The bottom level contains implicit procedural knowledge represented using features linked to a top-level chunk node. These features are connected via nonlinear connectionist networks [6, 12].

The Non-Action-Centered Subsystem

The NACS is a "slave system" that captures declarative memory (both semantic and episodic). The inputs and outputs of the NACS mostly come from and go to the ACS, which uses action chunks to command the NACS. Many forms of reasoning are captured in the NACS.

Top Level: Explicit knowledge is represented in chunk nodes that represent concepts, which can be activated by an ACS query, another chunk node (associative), or its similarity to another chunk (similarity matching). This results, together with a base-level activation, in an activation level from which, when normalized, an internal confidence level is derived. This confidence level is used in the ACS when deriving recommended actions based on input from the NACS.

Bottom level: The features in the bottom level of the NACS are similarly structured compared to the ACS. In this way, connections between top-level chunks and their corresponding bottom-level connections allow for a natural computation of similarity, which is used for activation in the NACS [6, 12].

3.3 Consumer Decision-making

Consumer decision-making can be described following the process of the traditional "Five-stage model of the consumer buying process", which involves five steps consumers take when making decisions [17]. In the first stage, consumers identify a specific need for a product, followed by the second stage, where the consumer will search for information about the product. Thirdly, consumers will evaluate the different options that they can choose from. In the following stage, consumers will decide on their final purchase choice. Finally, consumers will exhibit post-purchase behavior in which they judge their purchase and share their experience with others.

Each stage in this decision-making process maps to different heuristic strategies consumers use. This mapping can be seen in Table 1. The heuristic strategies used in this mapping will be included in the eligibility criteria of this review and are discussed in detail in Section 3.4. The content in Table 1 is based on combining the information on the consumer stages [17] with the information on the heuristic strategies presented in Section 3.4.

Table 1: Mapping consumer heuristics onto the five-stage consumer decision process

Decision-making stage	Key heuristics
Need recognition (I need/want something)	• Fluency / Availability (easily recalled cues trigger need) • Social (peer adoption signals need)
Information search (search information about the alternatives)	• Fluency / Availability (ease-of-recall guides internal search) • Anchoring (first price/attribute encountered becomes an anchoring reference) • Social (spoken communication, reviews)
Evaluation of alternatives (compare options and narrow them down)	• Representativeness (match to the mental image of what an ideal item in the category looks like) • Recognition (choose the recognized brand/product) • Attribute-substitution (simplify the evaluation by asking an easier question) • Non-compensatory cue rules (one decisive cue suffices) • Compensatory weighting/adding (integrate all cues and weigh them) • Anchoring (reference from initial anchor) • Satisficing (if it satisfies a certain threshold) • Social (imitate-the-majority, default)
Purchase decision (final choice)	• Anchoring (anchor-based promotions can influence the quantity of a purchase) • Recognition (grab the known label on a shelf) • Satisficing (first acceptable option purchased) • Social (default choice, reciprocity offers)
Post-purchase behavior (evaluate satisfaction and share experience)	• Fluency / Availability (most easy-to-remember memories shape word-of-mouth) • Representativeness (experience judged against mental image) • Social (reciprocity and conformity in reviews/sharing)

3.4 Consumer Decision-making Heuristics

In consumer decision-making, a combination of heuristics and preferences are used with varying degrees of intensity to come to a decision [18]. An extensive list of heuristic strategies related to consumer decision-making is shown below. This list will be used in the eligibility criteria to assess the relevance of the papers in the review.

Memory-based heuristics

Heuristics based on recognition or recognition fluency/availability:

- Fluency/Availability heuristic: Consumers can make judgments based on ease of recall. Therefore, more recent experiences have a greater influence on decisions [18, 19]. An example is when people choose a certain product based on the fluency with which it comes to mind.

- Recognition heuristic: The person considers all the options and chooses the one they recognize at first glance [18]. For two alternatives, the recognition heuristic is defined as: "If one of two alternatives is recognized and the other is not, then infer that the recognized alternative has the higher value with respect to the criterion" [20].

Cue-based heuristics (non-compensatory)

Heuristics based on cues/attributes (non-compensatory): These heuristics are called "non-compensatory" because a cue cannot be outweighed by any combination of less valid cues [21]. This category holds heuristics such as one-good-reason heuristics, elimination-by-aspects [22, 23], acceptance by aspects [23], take-the-first heuristic, take-the-best heuristic and lexicographic rule [18]. For example, a lexicographic heuristic would prefer a product that is superior to another product on the most important cue for which the two options discriminate [21].

Additive (compensatory)

Heuristics involving weighting and adding (compensatory): The attributes of the different alternatives are compared based on their utility value, and then the consumer can choose the one that has the highest value for them [18]. For example, the Equal-Weight/Tallying heuristic can be used [22, 24], in which the value of a cue is either +1 or -1, simplifying the decision process.

Similarity-Based

Representativeness heuristic: consumers make judgments based on similarity to products or brands that fit the consumer's mental image of a category as preferred. This heuristic can lead to over-reliance on surface-level characteristics of a product [19]. For example, when making sequential food choices, people can create a representativeness heuristic for certain products. For consumers, healthy-looking food labels can cue them to make biased choices. Due to the mental representation related to this label, consumers assume that this product is healthy, while that may not be the case [25].

General heuristics

- Anchoring: Consumers rely heavily on the initial piece of information (the anchor) when making decisions. Product judgments are adjusted from the anchor subsequently (estimating product value based on the first price seen); in this process, an initial price, product attribute, or recommendation can serve as an anchor. Even irrelevant anchors can influence consumer judgments [19]. An example is the purchase behavior of consumers when they decide how much they would like to buy. Here, the anchoring heuristic plays an important role, where consumers can make biased decisions due to anchor-based promotions [26].
- Attribute Substitution: For example, in purchase decisions, substitution can be used to replace a complicated question with an easier one. This results in easier decision-making. For example, when making purchase decisions, people may, instead of investigating all aspects of a decision, ask the question, "Which brand do I like best?" [27].
- Sufficient Satisfaction: People explore all options in no particular order until one satisfies them sufficiently, given their goals and preferences [18].
- Social: Individuals decide by the rule of reciprocity or by imitating others [18], such as the heuristic of the default choice, the imitate-the-majority heuristic, and the reciprocity heuristic. All these social heuristics are commonly used in consumer decisions.

4 Methodology

The research method used is a systematic literature review, described in detail in the book [28]. Furthermore, the report will adhere to the PRISMA guidelines [29]. Zotero[1] (version 7.0.15) has been used to organize the collected data. In addition, the systematic review process will be visualized via a PRISMA flow diagram. The entire review is done by one reviewer.

Firstly, the inclusion and exclusion criteria were constructed from the research questions, which are discussed in Section 4.1. Secondly, the search engines used in this review are shown in Section 4.2. Furthermore, in Section 4.3, the search strategy is elaborated on. Additionally, the screening and selection methods in this review are discussed in Section 4.4. After that, the methods of data extraction and synthesis are discussed in Section 4.5.

4.1 Eligibility criteria

Eligibility criteria are used to assess whether a paper should be included or excluded in a systematic review. In this study, the following inclusion/exclusion criteria have been used:

[1] www.zotero.org

- Architecture focus: The study must include ACT-R and/or CLARION as the primary cognitive architecture(s).
- Heuristic Strategies: The study must include one or more relevant representations of consumer decision-making heuristics. See the list of relevant consumer heuristics that are included in this study in Section 3.4. Therefore, studies that solely address irrelevant heuristics to consumer decision-making are excluded.
- Peer-reviewed literature: The literature must be published in a peer-reviewed journal, conference proceeding, or book chapter from an academic publisher.
- Language and Accessibility: The paper must be written in English and must be accessible in full text.

4.2 Search Engines

The papers for the review are collected on Monday, 12 May 2025. The database search engines used for this literature search are Scopus[2], Web of Science[3] (all databases), ACM Digital Library[4] and IEEE Xplore[5]. These four databases have been chosen for this review to incorporate a complete view of the available literature. The first two databases, Scopus and Web of Science contain a wider range of topics. In contrast, ACM Digital Library and IEEE Xplore focus more on technical papers, for example, in the field of Computer Science.

4.3 Search Strategy

This review has searched literature that contains information on ACT-R or CLARION with a specific link to how they represent decision-making with heuristic strategies.

To search for these papers, three key terms are identified in Table 2, specifically **heuristic*** (and related words), **decision*** and the cognitive architecture **ACT-R** or **CLARION** or both.

Table 2: Key search terms and their synonyms for this review

Term	Related words
Heuristic strategies	heuristic*, rule of thumb, bounded-rationality, fast-and-frugal, intuitive
Decision-making	decision*
Cognitive Architecture	ACT-R, CLARION

Queries have been constructed for this literature search. See Appendix A for the full queries of the literature search. The specific search query contains a search on the title, abstract, and keywords of the literature so that the literature found focuses primarily on the search keywords in contrast to when the entire text is used in the search. The saying "clarion call" has been excluded with an AND NOT operator from the query results related to CLARION since it was not related to the study.

4.4 Screening and Selection

For the screening and selection phase of the review, a checklist has been constructed, which can be seen in Appendix B, following the method described in “Doing a Systematic Review” [28]. Based on the eligibility criteria (Section 4.1), which have been structurally displayed in the checklist, a record is either included or excluded in the screening and selection phase. At first, the papers were screened on title and abstract, after the papers were screened on full text.

4.5 Data extraction and synthesis

The literature resulting from the screening and selection will be used in the data extraction and synthesis. The information items selected to be extracted from the papers can be seen in Table 3.

Excel is used to extract the data. In Excel, a data extraction table has been created, where each individual heuristic strategy researched in a study is documented in a separate row and where the information items are structured in columns.

[2] www.scopus.com
[3] https://webofscience.com
[4] https://dl.acm.org/
[5] https://ieeexplore.ieee.org/

To answer the research question, the extracted data must be processed to obtain the needed information via data synthesis. For example, for SQ1, the heuristic strategies need to be grouped per heuristic and architecture, and then the variants of representations need to be taken into account to answer the question.

Table 3: Mapping of each data extraction item to the review's three sub-questions.

Information item extracted	**Sub-question(s)**
Study characteristics	
Architecture used (ACT-R, CLARION, both)	**SQ1, SQ2**
Study design (Simulation, Experiment + Simulation, Conceptual etc.)	**SQ1**
Study aim (aim of this research)	**SQ1**
Architecture version details (modules, parameters)	**SQ1**
Heuristic strategies	
Heuristic(s) represented	**SQ1**, **SQ2**
Heuristic type (memory-based, cue-based, similarity-based, additive, and hybrid)	**SQ2**
Definition of the heuristic	**SQ1**, **SQ2**
Model-elements mapping (buffers, layers, productions)	**SQ1**, **SQ2**
Input information assumed (attributes, cues, priors)	**SQ1**
Decision rule (verbal rule)	**SQ1**
Strengths and limitations	
Strengths reported	**SQ3**
Limitations reported	**SQ3**
Results	
Key quantitative findings	**SQ3**
Key qualitative findings	**SQ3**
Comparative results (between ACT-R and CLARION, or between heuristics)	**SQ2**, **SQ3**

5 Results

This Section contains the results of this study. Section 5.1 provides an overview of the review process. Furthermore, in Section 5.2, the distribution of heuristic strategies is displayed per architecture, followed by Section 5.3, where the description of the heuristic representations is discussed.

5.1 Review Process

A PRISMA flow diagram [30] for the literature review is visualized in Figure 2. In this figure, the systematic review process is documented. The application of this review protocol resulted in the inclusion of the following reviewed papers: [7, 15, 12, 31, 32, 33, 34, 35, 36, 37, 38, 39].

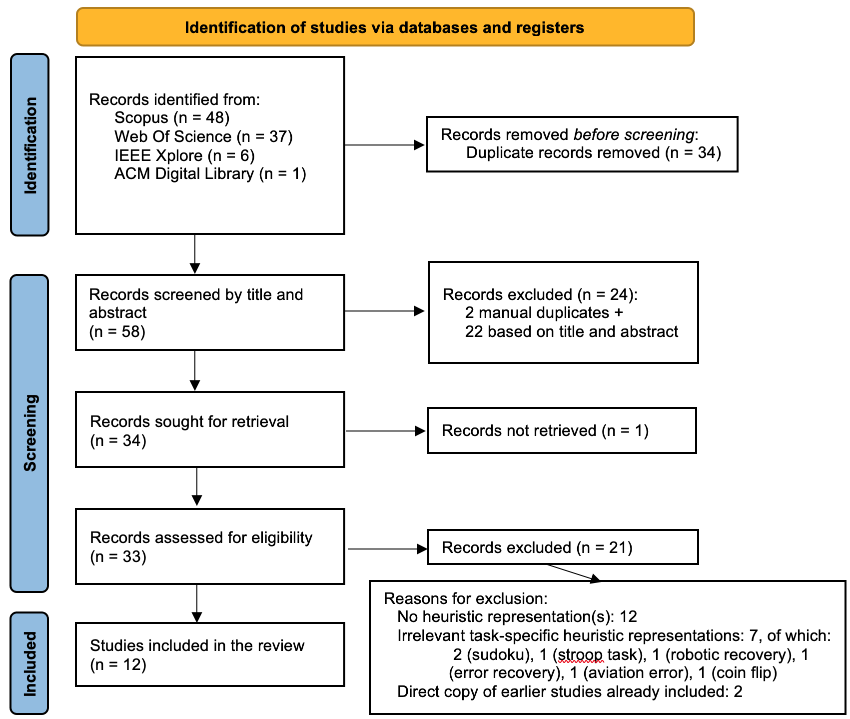


Figure 2: PRISMA flow diagram of this study.

5.2 Which heuristics are represented?

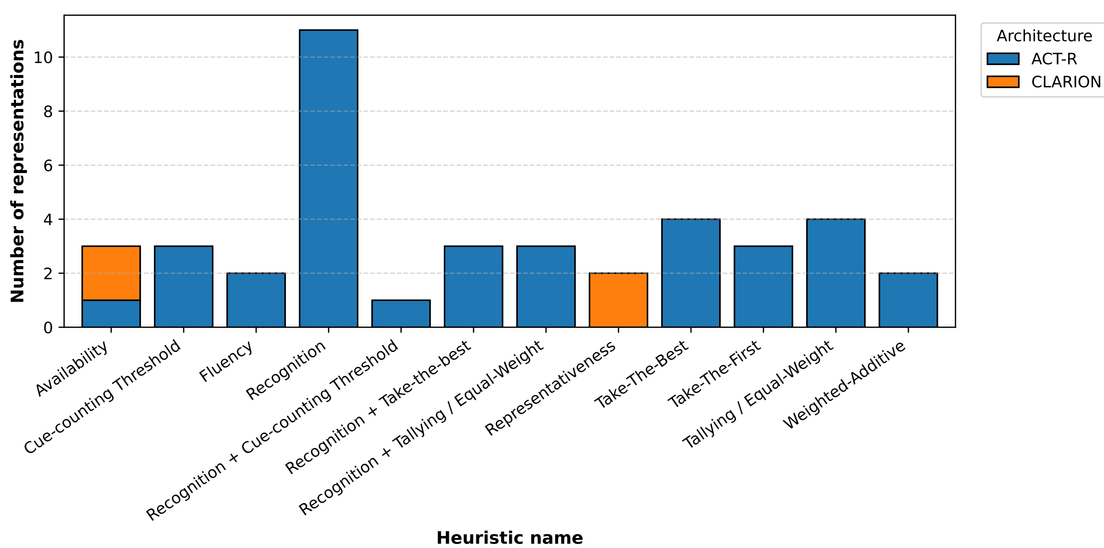
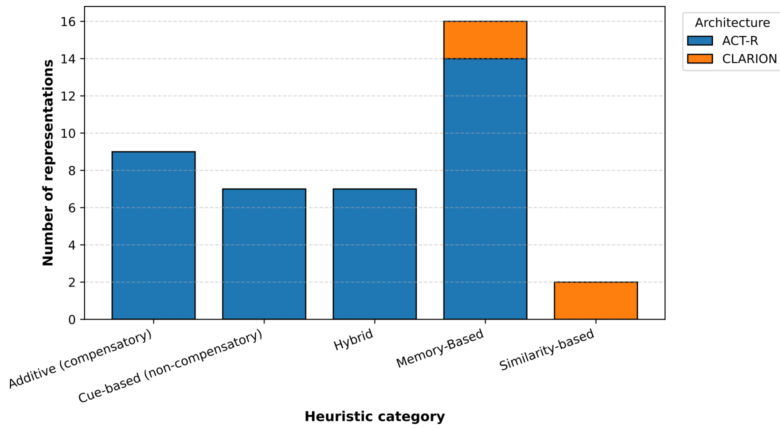
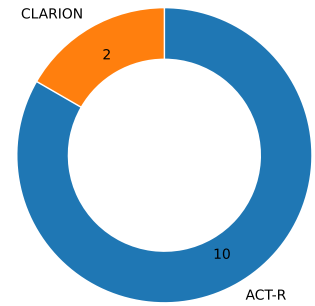


Figure 3: distribution of heuristic strategies represented by ACT-R and CLARION.



(a) Heuristic categories represented by ACT-R and CLARION.



(b) The distribution of papers per architecture.

Figure 4: Overview of coverage in the reviewed literature.

5.3 How are the heuristics represented?

5.3.1 Memory-Based

Recognition [7, 31, 32, 37, 34]
Core Mechanism: If one option is recognized and the other is not, choose the recognized one.
In ACT-R, the recognition heuristic is represented as follows:

- Declarative memory: holds the declarative information chunks on the alternatives to choose from.
- Retrieval buffer: holds the information on whether the alternative is recognized or not.
- Procedural memory: holds the rule "choose recognized."

In addition, the imaginal buffer can be used:

- Imaginal buffer: first encode the cue chunks inside the imaginal buffer, then proceed to the variant above.

Availability/Fluency [12, 32, 33, 34, 35]
Core Mechanism: Estimate frequency from the ease of retrieving instances, so if easier recall → higher utility value; therefore, if two alternatives are recognized, pick the faster retrieved one.
ACT-R [32, 33, 34]
In ACT-R, the availability/fluency heuristic is represented as follows:

- Declarative Memory: Holds chunks on the options with their learned base-level activation. A higher base-level activation results in a shorter chunk retrieval time.
- The Procedural Module fires two retrieval requests.
- In the Retrieval Buffer, the latencies of the requests are timed and compared on their retrieval fluency. If the retrieval fluency is noticeably different, then pick the fastest one.

CLARION [12, 35]
In CLARION, the availability/fluency heuristic is represented as follows:

- Bottom level NACS (implicit declarative memory): every time a name is seen or used, it is (re)learned in the bottom-level attractor neural network inside the NACS. Therefore, attractors representing frequently recalled names have large attractor fields → higher chunk node activation in the top level (bottom-up activation).
- Top level NACS (explicit declarative memory): In the top level, the explicit knowledge is represented as a chunk with a corresponding Boltzmann distributed activation level.
- ACS (procedural memory): When the ACS probes the NACS, one of these chunk nodes is chosen stochastically (Boltzmann). Therefore, a higher chunk node activation results in easier recall of that chunk (higher accessibility) because it has a higher probability of being chosen.

5.3.2 Cue-based (non-compensatory)

Take-The-Best [15, 34, 36, 38]

Core Mechanism: Evaluate cues of two alternatives sequentially in cue validity order (ecological validity); stop and decide based on the first discriminating cue.

In ACT-R, the take-the-best heuristic is represented as follows:

- Goal buffer: this buffer holds the pointers to the two alternatives and the next cue in the validity list
- Declarative memory: this holds the value of the cues paired with the corresponding alternatives.
- Retrieval buffer: holds the latest cue value chunk (used by the procedural module).
- Procedural memory: functions as a stack of production rules corresponding to a fixed ordering of "check cue 1" at the top of the stack (highest validity). When both cue values of the alternatives for the first cue are retrieved, then, if the cue is discriminating, write the choice to the goal buffer and fire the "make choice" rule in the production system else, increment the cue pointer (goal buffer) and fire "check cue 2" rule in production.

Take-The-First [34]

Core Mechanism: Evaluate cues of two alternatives sequentially in retrieval fluency order (accessibility); decide based on the first discriminating cue.

In ACT-R, the take-the-first heuristic uses the same steps as detailed above in the take-the-best heuristic. The difference is that the take-the-first heuristic does not need a fixed ranked validity list. The used cue order is decided dynamically by the retrieval latencies of the cue value alternative pairs. Here, the fastest cue chunk will be compared first on the cue value between alternatives.

5.3.3 Additive (compensatory)

Weighted-Additive [15, 37]

Core Mechanism: Multiply each cue value by its validity weight and then sum all values; choose the alternative with the highest summed total.

In ACT-R, the weighted-additive heuristic is represented as follows:

- Declarative memory: in the declarative memory, all cue-weight chunks and cue-value chunks are stored. Together, the weight and value per cue are used for the sum computation.
- Procedural memory: performs the rules (in order): retrieve weight → retrieve value → update sum → next cue, until all cues have been processed. When all cues have been processed, the action "compare sums" fires, and the decision to choose a certain alternative is made.
- Imaginal buffer: holds the updated value for the current sums computed in the weighted additive process.
- Goal buffer: updates the pointers to the next cue to evaluate.

Tallying/Equal-Weight [15, 31, 34]

Core Mechanism: for each alternative, count the number of positive cue values and subtract the number of negative cue values; choose the one with the largest count.

In ACT-R, the Tallying/Equal-Weight heuristic is represented as follows:

- Declarative memory: holds a cue value chunk per option, in which the value is either "+" or "-" (+1 or -1).
- Procedural memory: holds three production rules: retrieve cue, update sum, decide. First, all cues will be retrieved sequentially, and the sum will be updated accordingly. In the end, a decision will be made based on the final sum.
- Imaginal buffer: holds the value of the current sum of positives and negatives.
- Goal buffer: holds the pointer to the next cue to evaluate.

Other variants on this heuristic in reviewed studies:

- Only count positive values, so if a negative value is encountered, do not update the sum and base the final decision only on the number of positive cues.
- See the next Section on the cue-counting threshold heuristic.

Cue-Counting Threshold [7, 31]
Core Mechanism: retrieve cues until a threshold positive/negative cues is reached; If positive minus negative cues $\geq C$*, then choose recognized, else choose unrecognized*

In ACT-R, the cue-counting threshold heuristic is represented similarly to the tallying/equal-weight heuristic (see above). The difference is that if the current sum (in the imaginal buffer) is above a specific threshold C (stored in the goal buffer), then the decision fires to stop early and choose the recognized alternative.

5.3.4 Similarity based

Representativeness [12, 35]
Core Mechanism: Estimate the probability from the similarity between the instance and prototypes; choose the category with the highest normalized activation.

In CLARION, the representativeness heuristic is represented as follows:

- Bottom level NACS (implicit declarative memory): stores micro-feature vectors for every category prototype and the target instance. This connection-less bottom level is linked to top level chunks. Through this connection-less bottom level of CLARION, similarity is converted into activation of top-level concept chunks.
- Top level NACS (explicit declarative memory): this holds symbolic category chunks. The activation level of these category chunks is determined through bottom-up activation from the bottom level NACS. This results in a Boltzmann-distributed activation value per category.
- ACS (procedural memory): This module receives the chunks from probing the NACS module. In the ACS, Boltzmann normalization will be used to extract probability from the activation levels attached to the chunks. This probability value represents the probability that the target belongs to the category.
- Procedural rule: choose the category that has the highest probability that the target belongs to it.

5.3.5 Hybrid heuristic strategies

Racing strategies [7, 31]
Core Mechanism: racing strategies combine multiple heuristic strategies, such that the fastest retrieved result from a strategy decides.

For ACT-R, different racing combinations of memory-based heuristics vs. additive (compensatory) heuristics have been encountered in the reviewed studies: the race between Recognition vs. Tallying/Equal-Weight heuristic and the race between Recognition vs. Cue-counting threshold heuristic. In these representations of the heuristic strategy races, both heuristics will be executed in parallel, and time will be recorded. The heuristic that fastest provides a decisive result wins. See the above Sections for a representation of these individual heuristics.

Sequential combination strategies [37]
Core Mechanism: first use the recognition heuristic, then, if recognition is indecisive, use a lexicographic heuristic assessing cues in validity order to decide.

For ACT-R, this form of sequentially combining two heuristics has been encountered. First, use the recognition heuristic; if indecisive, decide via the take-the-best heuristic. In this variant, different lengths of validity cue lists have been tested when representing the take-the-best heuristic. The variant that contained a medium validity cue list (LRK50), so a list only containing high and medium valid cues, resulted in a right balance between accuracy and performance.

6 Discussion

This section discusses the results presented in Section 5. Firstly, the difference in heuristic representations between ACT-R and CLARION is discussed, followed by an analysis of the strengths and weaknesses of the architectures representing the heuristics. Third, the motivation behind the heuristic coverage gaps is discussed. Finally, the limitations of this study are detailed.

6.1 Differences in heuristic coverage between ACT-R and CLARION

As described in Figure 3 and Figure 4a, there are differences in the distribution of representations of the heuristic strategies per architecture. ACT-R papers represent nine distinct heuristic strategies (37 individual models), whereas the literature on CLARION only covers two distinct strategies (4 individual models).

The overlap in representations between architectures is the representation of the Availability/Fluency heuristic. In this heuristic strategy, both architectures are able to map the latency of retrieval to a probability value. However, both architectures use different methods to achieve this. CLARION uses bottom-up activation through the NACS implicit memory to simulate the cognitive accessibility effect. This activation level is then used to create a probability in the ACS, and a higher probability represents easier retrieval. In contrast, ACT-R uses chunks in the declarative module with an activation level, and a higher activation lever means a shorter retrieval time. This retrieval time for a retrieval request is timed and compared in the Retrieval Buffer.

Representation gaps occur per architecture of specific heuristics. Literature on CLARION lacks representations of the recognition heuristic, cue-based heuristics, and additive heuristics. On the other hand, papers on ACT-R lack representation of similarity-based heuristics such as the representativeness heuristic.

The findings of this study extend claims in previous work of ACT-R's focus on rule-based heuristics and CLARION's focus on similarity-based heuristics by demonstrating that the heuristic coverage gaps in the literature are systematic.

6.2 Strengths and weaknesses

The cognitive architectures ACT-R and CLARION both contain architectural strengths and weaknesses with respect to the representation of heuristic strategies. An overview of these strengths and weaknesses is shown in Table 4.

Table 4: Strengths and weaknesses of ACT-R and CLARION for representing heuristic strategies.

Architecture	**Key strengths for representing heuristics**	**Main weaknesses**
ACT-R	• Sequentially chained production rules, which create an intuitive representation of cue-based (non-compensatory) heuristics and additive (compensatory) heuristics. • Explicit latency timing provides a quantitative response fluency per retrieval. Providing easy comparison for Take-the-first and availability/fluency heuristics. • Races and accumulators, needed for some heuristic types, only need a minimal number of extra production rules.	• There is no intuitive method to simulate similarity. Simulating heuristics, such as representativeness, is complex in ACT-R's current structure. • ACT-R contains the constraint of only serial execution of productions. This restricts cue-based heuristics, which people often execute in parallel.
CLARION	• The implicit layer provides similarity and fluency intuitively, which is ideal for heuristics such as representativeness and availability. • The dual process structure, simulating implicit/explicit processes, shows how sub-symbolic similarity influences symbolic choice. • The Boltzmann activation level provides probability values after normalization.	• Lacks a sequential production system, which is needed for the step-by-step execution of cue-based and additive heuristics. • There is no dedicated system that has the capability to execute explicit response timing.

6.3 Motivation behind the heuristic coverage gaps

As discussed in Section 6.1, there are specific research gaps in the representation of heuristic strategies per architecture. The motivation for these heuristic research gaps could be the following:

- Architectural structure:
  - ACT-R contains serial procedural rules, ideal for cue-based and additive heuristics that sequentially perform steps to reach a decision. In addition, ACT-R contains explicit retrieval latency timing. This response timing is ideal for the Take-the-first heuristic and memory-based heuristics.
  - CLARION contains implicit similarity and Boltzmann choice, which is ideal for similarity-based heuristics, such as the representativeness heuristic, which relies on these mechanisms.
  - Performing a similarity function, such as the representativeness heuristic, in ACT-R would require individually retrieving all category chunks and looping through them. This means a substantial amount of retrievals, which is complex and inefficient. In CLARION, similarity is built-in and low-effort. However, sequential simulation of cue-based and additive heuristics in CLARION would require an additional production layer to coordinate this process.

- Research Coverage: The number of papers on heuristic representations involving ACT-R (10 papers) is significantly larger than those involving CLARION (2 papers) (Figure 4b). This skewed literature distribution can cause ACT-R to represent more heuristic strategies than CLARION in the literature.

6.4 Limitations

There are some potential limitations to this study. Firstly, the number of papers that met all eligibility criteria is small, e.g., 10 papers for ACT-R and 2 for CLARION. Therefore, since the sample size on CLARION is especially small, the statistical power of comparison between the architectures is limited.

Secondly, many heuristic representations in the literature use simple tasks for modeling, for example, choosing the largest city between two cities rather than real consumer scenarios, such as deciding on two alternatives to purchase. Therefore, generalizing their fit to real consumer behavior may overstate external validity.

Furthermore, there is a publication bias in the included papers since poorly fitting heuristics are likely not to be included in a published paper. Therefore, only the successfully modeled heuristics are represented in the literature.

Finally, since this study focuses on consumer-relevant heuristics, not all papers containing heuristic representations were included (see Figure 2). However, the only papers excluded based on this criteria focused on very task-specific heuristics, such as rules for doing a Sudoku or recovering from an error. Therefore, excluding these papers should not lose valuable information for this study.

7 Responsible Research

7.1 Ethical considerations

All papers analyzed in this study had already anonymized their behavioral data. In addition, no new personal data was collected in this study, thus minimizing the risk to privacy.

There could be ethical risks related to modeling and predicting human heuristic behavior in the future since heuristic models can be embedded into persuasive systems. These systems could possibly influence people's behavior for purposes such as marketing. In addition, algorithmic bias in these heuristic models must be taken into account. To detect and prevent algorithmic bias at an early stage, a test should be performed using a bias and fairness audit toolkit to reveal whether the heuristic model shows patterns of systematic bias.

In the future, it is necessary to assess the risks and unintended effects before deploying such heuristic models. Therefore, an independent ethics review board should be mandated to evaluate the system before deploying any behavioral models to minimize ethical risks. In addition, transparency by design is essential. Therefore, any system using a heuristic model should disclose that, for example, a particular recommendation is generated by a behavior model.

Furthermore, this systematic literature review has been performed by a single BSc Computer Science student, which can present a number of risks. Usually, a review study is performed by multiple researchers to reduce mistakes and bias. Mistakes can be made in the screening and selection phase as well as in the data extraction phase. This risk has been reduced as much as possible by creating structured methods to execute those phases, such as the screening/selection checklist (Appendix B) and the data extraction table created in Excel (Section 4.5).

7.2 Reproducibility

The full systematic review procedure can be reiterated to verify the results. In the methodology, the PRISMA guidelines were used to ensure reproducibility. All necessary information to repeat the search phase is provided (Section 4.2 and 4.3), including the full-text queries (Appendix A). The Screening and Selection phase (Section 4.4) is structured by using a constructed checklist (Appendix B), following all information items extracted in the data extraction phase are listed (Section 4.5). In addition, a complete overview of the systematic review process is provided in a PRISMA flow diagram (Section 5.1).

8 Conclusion and Future Work

8.1 Conclusion

In this study, a systematic literature review has been performed on how the cognitive architectures ACT-R and CLARION represent heuristic strategies in consumer decision-making. In this review, the heuristic types, heuristic categories, and strengths/limitations of these representations in ACT-R and CLARION are explored.

Papers on ACT-R represent nine distinct types of heuristics, namely recognition, availability/fluency, take-the-best, take-the-first, weighted-additive, tallying/equal-weight, cue-counting threshold, racing strategies, and sequential combinations strategies. Whereas the literature on CLARION only covers two distinct heuristic strategies: the availability/fluency and representativeness heuristic(memory/similarity-based). ACT-R represents these heuristics by using production rules and buffer operations sequentially, while CLARION mainly relies on implicit similarity and Boltzmann activation levels.

The main strengths of ACT-R lie in explicit latency timing and sequentially chained production rules. The weaknesses are the lack of a system to represent similarity and the constraint on parallel execution of multiple productions.

CLARION's strength is its implicit layer, which represents similarity intuitively by using implicit bottom-up activation. This dual process system, where symbolic processes are separated from subsymbolic, shows how implicit cognition influences explicit choice. The main weaknesses of CLARION are the lack of a procedural layer that is able to simulate sequential procedural rules and the lack of a dedicated module that handles explicit response timing.

Taken together, the results confirm that the architectural affordances mainly determine which heuristic strategies have been represented. Therefore, CLARION focuses primarily on similarity-based heuristics, and ACT-R on rule-based strategies.

8.2 Future work

In the future, more research needs to be performed to fill the research gaps identified in this study.

For ACT-R, a system needs to be constructed to model similarity-based cognition, such as the representativeness heuristic. In addition, research should explore how to enable the parallel execution of production rules in ACT-R.

For CLARION, a procedural layer should be constructed that is able to use sequentially chained production rules to simulate step-by-step cue-based and additive heuristics. In addition, a dedicated system that can handle response timing would be a beneficial addition to the CLARION architecture in the future.

References

[1] G. Gigerenzer and W. Gaissmaier. "Heuristic decision making". In: *Annu. Rev. Psychol.* 62 (2011), pp. 451–482. DOI: 10.1146/annurev-psych-120709-145346.

[2] J. R. Bettman, M. F. Luce, and J. W. Payne. "Constructive consumer choice processes". In: *J. Consum. Res.* 25.3 (Dec. 1998), pp. 187–217. DOI: 10.1086/209535.

[3] P. Thagard. "Cognitive architectures". In: *The Cambridge Handbook of Cognitive Science*. Ed. by K. Frankish and W. Ramsey. Cambridge, U.K.: Cambridge Univ. Press, 2012, pp. 50–70.

[4] P. Langley, J. E. Laird, and S. Rogers. "Cognitive architectures: Research issues and challenges". In: *Cognitive Systems Research* 10.2 (2009), pp. 141–160. DOI: 10.1016/j.cogsys.2006.07.004.

[5] I. Kotseruba and J. K. Tsotsos. "40 years of cognitive architectures: Core cognitive abilities and practical applications". In: *Artif. Intell. Rev.* 53.1 (Jan. 2020), pp. 17–94. DOI: 10.1007/s10462-018-9646-y.

[6] S. Helie and R. Sun. "How the core theory of CLARION captures human decision-making". In: *Proc. Int. Joint Conf. Neural Netw. (IJCNN)*. San Jose, CA, USA, July 2011, pp. 173–180. DOI: 10.1109/IJCNN.2011.6033218.

[7] J. N. Marewski and K. Mehlhorn. "Using the ACT–R architecture to specify 39 quantitative process models of decision making". In: *Judgm. Decis. Mak.* 6.6 (2011), pp. 439–519. DOI: 10.1017/S1930297500002473.

[8] F. Van Overwalle and M. Vandekerckhove. "Implicit and explicit social mentalizing: Dual processes driven by a shared neural network". In: *Front. Hum. Neurosci.* 7 (Sept. 2013), p. 560. DOI: 10.3389/fnhum.2013.00560.

[9] F. E. Ritter, F. Tehranchi, and J. D. Oury. "ACT-R: A cognitive architecture for modeling cognition". In: *WIREs Cogn. Sci.* 10.3 (2019), e1488. DOI: 10.1002/wcs.1488.

[10] R. Sun. "The CLARION cognitive architecture: Extending cognitive modelling to social simulation". In: *Cognition and Multi-Agent Interaction: From Cognitive Modelling to Social Simulation*. Ed. by R. Sun. Cambridge, U.K.: Cambridge Univ. Press, 2005, pp. 79–100. DOI: 10.1017/CBO9780511610721.005.

[11] L. A. Bolos, C. J. Lagerkvist, and M. M. Kulesz. "Complementarity of implicit and explicit attitudes in predicting the purchase likelihood of visually sub-optimal or optimal apples". In: *Food Qual. Prefer.* 75 (2019), pp. 87–96. DOI: 10.1016/j.foodqual.2019.02.011.

[12] R. Sun and S. Helie. "Reasoning with heuristics and induction: An account based on the CLARION cognitive architecture". In: *Proc. Int. Joint Conf. Neural Netw. (IJCNN)*. Brisbane, Australia, June 2012, pp. 1–8. DOI: 10.1109/IJCNN.2012.6252552.

[13] O. Roozmand et al. "Agent-based modeling of consumer decision making process based on power distance and personality". In: *Knowl.-Based Syst.* 24.7 (2011), pp. 1075–1095. DOI: 10.1016/j.knosys.2011.05.001.

[14] F. Ritter et al. "Modeling the range of performance on the serial subtraction task". In: *Proc. Int. Conf. Cogn. Model. (ICCM)*. Ann Arbor, MI, USA, 2007, pp. 299–304.

[15] C. M. Dimov, J. N. Marewski, and L. J. Schooler. "Constraining ACT–R models of decision strategies: An experimental paradigm". In: *Proc. Annu. Meeting Cogn. Sci. Soc. (CogSci)*. Berlin, Germany, July 2013, pp. 2201–2206.

[16] R. Sun. "Interpreting psychological notions: A dual-process computational theory". In: *J. Appl. Res. Mem. Cogn.* 4.3 (2015), pp. 191–196. DOI: 10.1016/j.jarmac.2014.09.001.

[17] A. Stankevich. "Explaining the consumer decision-making process: Critical literature review". In: *J. Int. Bus. Res. Mark.* 2.6 (Sept. 2017), pp. 7–14. DOI: 10.18775/jibrm.1849-8558.2015.26.3001.

[18] P. Mir-Artigues. "Combining preferences and heuristics in analysing consumer behaviour". In: *Evol. Inst. Econ. Rev.* 19.2 (Sept. 2022), pp. 523–543. DOI: 10.1007/s40844-022-00234-8.

[19] Fiveable. *Heuristics and decision rules in consumer choice.* https://library.fiveable.me/consumer-behavior/unit-13/heuristics-decision-rules-consumer-choice/study-guide/xC5sozZMTenx3XvC. Accessed: 2025-05-20. July 2024.

[20] D. G. Goldstein and G. Gigerenzer. "Models of ecological rationality: The recognition heuristic". In: *Psychol. Rev.* 109.1 (2002), pp. 75–90. DOI: 10.1037/0033-295X.109.1.75.

[21] A. Dieckmann, K. Dippold, and H. Dietrich. "Compensatory versus noncompensatory models for predicting consumer preferences". In: *Judgm. Decis. Mak.* 4.3 (2009), pp. 200–213. DOI: 10.1017/S193029750000173X.

[22] H. Willman-Iivarinen. "The future of consumer decision making". In: *Eur. J. Futures Res.* 5.1 (Dec. 2017), p. 14. DOI: 10.1007/s40309-017-0125-5.

[23] L. Bremer, M. Heitmann, and T. F. Schreiner. "When and how to infer heuristic consideration set rules of consumers". In: *Int. J. Res. Mark.* 34.2 (2017), pp. 516–535. DOI: 10.1016/j.ijresmar.2016.10.001.

[24] J. F. Bonnefon et al. "Qualitative heuristics for balancing the pros and cons". In: *Theory Decis.* 65.1 (May 2007), pp. 71–95. DOI: 10.1007/s11238-007-9050-6.

[25] A. Fagerstrøm et al. "An explorative study on heuristic effects of healthy food labels in an online shopping situation". In: *Procedia Comput. Sci.* 181 (2021). CENTERIS 2020 / ProjMAN 2020 / HCist 2020, pp. 709–715. DOI: 10.1016/j.procs.2021.01.222.

[26] B. Wansink, R. Kent, and S. Hoch. "An anchoring and adjustment model of purchase quantity decisions". In: *J. Mark. Res.* 35.1 (Feb. 1998), pp. 71–81. DOI: 10.2307/3151931.

[27] A. Stephenson. *Heuristics and shopper behavior in market research – Part 1.* https://explorerresearch.com/heuristics-and-shopper-behavior/. Accessed: 2025-05-20. Nov. 2024.

[28] A. Boland, M. G. Cherry, and R. Dickson. *Doing a Systematic Review: A Student's Guide.* London, U.K.: SAGE, 2014.

[29] M. J. Page et al. "The PRISMA 2020 statement: An updated guideline for reporting systematic reviews". In: *BMJ* 372 (2021), n71. DOI: 10.1136/bmj.n71.

[30] PRISMA. *PRISMA 2020 flow diagram.* https://www.prisma-statement.org/prisma-2020-flow-diagram. 2020.

[31] K. Mehlhorn and J. N. Marewski. "Racing for the city: The recognition heuristic and compensatory alternatives". In: *Proc. Annu. Meeting Cogn. Sci. Soc. (CogSci)*. Boston, MA, USA, July 2011, pp. 360–365.

[32] W. Gaissmaier, L. J. Schooler, and R. Mata. "An ecological perspective to cognitive limits: Modeling environment–mind interactions with ACT–R". In: *Judgm. Decis. Mak.* 3.3 (2008), pp. 278–291. DOI: 10.1017/S1930297500002461.

[33] U. Drewitz and M. Thüring. "Modeling the confidence of predictions: A time-based approach". In: *Proc. Int. Conf. Cogn. Model. (ICCM)*. Manchester, U.K., July 2009, pp. 228–233.

[34] J. N. Marewski and L. J. Schooler. "Cognitive niches: An ecological model of strategy selection". In: *Psychol. Rev.* 118.3 (2011), pp. 393–437. DOI: 10.1037/a0024143.

[35] S. Hélie and R. Sun. "An integrative account of memory and reasoning phenomena". In: *New Ideas Psychol.* 35.1 (2014), pp. 36–52. DOI: 10.1016/j.newideapsych.2014.06.004.

[36] C. Dimov et al. "How to model the neurocognitive dynamics of decision making: A methodological primer with ACT–R". In: *Behav. Res. Methods* 52.2 (2020), pp. 857–880. DOI: 10.3758/s13428-019-01286-2.

[37] H. B. Fechner et al. "Strategies for memory-based decision making: Modeling behavioral and neural signatures within a cognitive architecture". In: *Cognition* 157 (2016), pp. 77–99. DOI: 10.1016/j.cognition.2016.08.011.

[38] C. M. Dimov and J. N. Marewski. "Cognitive architectures as scaffolding for risky choice models". In: *Psychological Perspectives on Risk and Risk Analysis: Theory, Models, and Applications*. Cham, Switzerland: Springer, 2018, pp. 201–216. DOI: 10.1007/978-3-319-92478-6_9.

[39] H. B. Fechner, L. J. Schooler, and T. Pachur. "Cognitive costs of decision-making strategies: A resource demand decomposition analysis with a cognitive architecture". In: *Cognition* 170 (2018), pp. 102–122. DOI: 10.1016/j.cognition.2017.09.003.

A Syntax Search Queries

Table 5: Full-text query syntax used in each database engine.

Database engine	Full-text query
Scopus	TITLE-ABS-KEY ((heuristic* OR ("rule-of-thumb" AND decision*) OR ("bounded-rationality" AND decision*) OR ("fast-and-frugal" AND decision*) OR "intuitive decision*") AND "ACT-R") OR TITLE-ABS-KEY ((heuristic* OR ("rule-of-thumb" AND decision*) OR ("bounded-rationality" AND decision*) OR ("fast-and-frugal" AND decision*) OR "intuitive decision*") AND "CLARION" AND NOT "clarion call")
IEEE Xplore	((("All Metadata":heuristic* OR ("All Metadata":"rule-of-thumb" AND "All Metadata":decision*) OR ("All Metadata":"bounded-rationality" AND "All Metadata":decision*) OR ("All Metadata":"fast-and-frugal" AND "All Metadata":decision*) OR "All Metadata":"intuitive decision*") AND "All Metadata":"ACT-R") OR (("All Metadata":heuristic* OR ("All Metadata":"rule-of-thumb" AND "All Metadata":decision*) OR ("All Metadata":"bounded-rationality" AND "All Metadata":decision*) OR ("All Metadata":"fast-and-frugal" AND "All Metadata":decision*) OR "All Metadata":"intuitive decision*") AND "All Metadata":clarion AND NOT "All Metadata":"clarion call"))
ACM Digital Library	(((Title:(heuristic* OR ("rule-of-thumb" AND decision*) OR ("bounded-rationality" AND decision*) OR ("fast-and-frugal" AND decision*) OR "intuitive decision*") OR Abstract:(heuristic* OR ("rule-of-thumb" AND decision*) OR ("bounded-rationality" AND decision*) OR ("fast-and-frugal" AND decision*) OR "intuitive decision*") OR Keyword:(heuristic* OR ("rule-of-thumb" AND decision*) OR ("bounded-rationality" AND decision*) OR ("fast-and-frugal" AND decision*) OR "intuitive decision*")) AND (Title:("ACT-R") OR Abstract:("ACT-R") OR Keyword:("ACT-R"))) OR ((Title:(heuristic* OR ("rule-of-thumb" AND decision*) OR ("bounded-rationality" AND decision*) OR ("fast-and-frugal" AND decision*) OR "intuitive decision*") OR Abstract:(heuristic* OR ("rule-of-thumb" AND decision*) OR ("bounded-rationality" AND decision*) OR ("fast-and-frugal" AND decision*) OR "intuitive decision*") OR Keyword:(heuristic* OR ("rule-of-thumb" AND decision*) OR ("bounded-rationality" AND decision*) OR ("fast-and-frugal" AND decision*) OR "intuitive decision*")) AND ((Title:(clarion) OR Abstract:(clarion) OR Keyword:(clarion)) AND NOT (Title:("clarion call") OR Abstract:("clarion call") OR Keyword:("clarion call")))))
Web of Science	((TS=(heuristic* OR ("rule-of-thumb" AND decision*) OR ("bounded-rationality" AND decision*) OR ("fast-and-frugal" AND decision*) OR ("intuitive decision*")) AND TS=("act-r")) OR (TS=(heuristic* OR ("rule-of-thumb" AND decision*) OR ("bounded-rationality" AND decision*) OR ("fast-and-frugal" AND decision*) OR ("intuitive decision*")) AND TS=(clarion NOT "clarion call")))

B Screening and Selection checklist

Table 6: Screening and selection checklist for the systematic review

Reviewer name:	________________
Author name / Study ID:	________________
Title:	________________
Journal:	________________
Day: ____ Year: ____	

Domain	**Include (☐ each that applies)**	**Exclude (☐ each that applies)**
Architecture focus	☐ ACT-R ☐ CLARION	☐ Only other architectures (e.g. Soar, EPIC) without meaningful comparison to ACT-R or CLARION
Heuristic strategies	☐ Addresses one or more consumer heuristics from the consumer decision-making heuristics section 2.4	☐ Focuses either on heuristics not relevant to consumer decision-making or on no heuristics at all
Decision-making focus	☐ Explicit link to decision-making aspects	☐ No relevant link to decision-making aspects
Publication type	☐ Peer-reviewed journal article ☐ Peer-reviewed conference paper ☐ Academic book chapter	☐ Grey literature (thesis, report, blog, technical note)
Language & access	☐ English full text available	☐ Non-English and no high-quality translation ☐ Full text not obtainable
Overall decision	☐ **INCLUDED**	☐ **EXCLUDED**
Notes		

C Use of tools

Zotero (version 7.0.15) has been used to record the literature review process. The paper has been written in LaTeX using Overleaf. Both ChatGPT o3 and Grammarly have been used to assist in writing style, grammar, and LaTeX code used in this paper.