VSM-ACT-R: Toward Using Cognitive Architecture For Manufacturing Solutions

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Abstract. The era of Industry 4.0 demands innovative solutions to produce high-quality products within tight lead times. This paper explores the integration of cognitive architectures (CAs) into manufacturing solutions, with a focus on using VSM-ACT-R, a cognitive architecture model built upon the ACT-R architecture. VSM-ACT-R aids in making informed decisions in smart scheduling that boosts productivity while ensuring consistent quality. The model stands out in three key aspects of decision-making in manufacturing: First, it executes tasks using decision-making algorithms and knowledge representations observed in human subjects, supported by declarative memories that reflect intuitive and domain-specific knowledge. Second, it mimics various levels of decision-making-from novice through to expert—using production rules and retrieval mechanisms that replicate variations of human behavior. Third, it simulates the learning processes of decision-makers, managed by a decision-choice control center that is driven by utility learning and reinforcement reward. We conclude by discussing an evaluation of this model, its applications, and its implications.

Keywords: Cognitive Architecture · Manufacturing · ACT-R

1 Introduction

Industry 4.0 aims to create "intelligent factories" where advanced manufacturing technologies enable smart decision-making through real-time communication and cooperation among humans, machines, and sensors [13]. Smart scheduling, which leverages advanced models and algorithms using sensor data, exemplifies one such solution [10].

A value stream map (VSM) is an essential tool in smart scheduling. It serves as a sophisticated flowchart that visualizes and controls the production line [8]. VSM meticulously tracks metrics like inputs, outputs, processes, overall equipment effectiveness (OEE), and cycle times-all crucial for quality and efficiency analysis in production control. However, plant managers face significant challenges in using VSM in production management. These challenges include difficulty applying VSM concepts to complex, real-world scenarios characterized by

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a high number of intertwined variables. This complexity consistently impedes plant decision-makers from making timely and optimal decisions regarding both time reduction and maintaining stable quality on the production lines.

This paper proposes a novel approach to address these challenges by integrating cognitive architectures into decision-making processes for manufacturing. Specifically, it employs a cognitive architecture to build models representing decisions and their process related to boosting productivity and ensuring consistent quality. This model leverages data derived from the VSM and decision-makers at Bosch plants.

Cognitive architectures (CAs) aim to create a unified model of the mind using invariant mechanisms to simulate and explain human behavior [1,5,7]. CAs use task-specific knowledge to generate behavior. They represent various types of knowledge, including declarative (factual), procedural (how-to), and in recent advancements, perception and motor skills. This knowledge allows CAs to not only simulate behavior but also explain it, both through direct examination and by tracing the reasoning steps involved in real-time (concurrent protocol).

This reports starts from prototypical decision processes distilled by plant managers of Bosch. Their insights, combined with a VSM tailored to their specific plant system, inform the build of our VSM-ACT-R model to enhance decision-making. It then introduces the developed VSM-ACT-R model[1], which stands out in decision-making tasks with three key strengths. First, the model can execute tasks using decision-making behaviors observed in humans and retrieve knowledge representations similarly. This capability is achieved through incorporating declarative memories that cater to intuition and professional knowledge from human subjects.

Second, the model integrates personas ranging from novice to intermediate and expert levels. This is achieved through developed sets of production rules that mimic the behavior of decision-makers at various expertise levels, coupled with retrieval mechanisms for full or partial knowledge representation.

Third, the model simulates the learning processes of decision-makers, transitioning from novice to expert. This simulation is facilitated by the decision-choice control center, which manages error-making, learning, and memory through utility learning and reinforcement rewards. This approach creates a realistic and dynamic decision-making simulation, making the VSM-ACT-R model a robust tool in cognitive architecture-facilitated decision-making in manufacturing.

The following sections discuss the task, the model, the model's performance evaluation, its application, and implications.

2 Related Work

In this section, we introduce ACT-R and its strengths to create a model that simulates human decision making behavior with learning.

There are currently primarily two kinds of knowledge representations in ACT-R: declarative and procedural knowledge. Declarative knowledge consists

[1] https://github.com/SiyuWu528/VSM-ACT-R.

of chunks of declarative memory (e.g., apple is a kind of fruit), while procedural knowledge performs basic operations, moves data among buffers, and identifies the next instructions to be executed (e.g., to submit your answer, you have to click the submit button). ACT-R has extensive applications across psychology and computer science, including professional development [4], military simulations [2], and autonomous driving simulations [11].

ACT-R is effective in developing models to simulate human learning. Three key features distinguish the use of ACT-R in creating models that perform decision-making tasks with learning:

Self-configuration: ACT-R efficiently translates instructions into structured rules, forming the basis for task-specific production rules that enhance the efficiency of task execution.

Modular Design Mirroring Human Cognition: ACT-R's modules emulate human cognitive functions: perceptual modules update the system's view of the environment, a goal module tracks progress towards objectives, a declarative module uses past experiences for contextual understanding, and a central buffer system enables communication between modules. Additionally, the central production system recognizes patterns to initiate coordinated actions.

Subsymbolic Processes for Decision-making: ACT-R excels in its ability to reliably retrieve relevant memories and activate appropriate rules, ensuring both efficient and adaptive performance in decision-making tasks, such as skills training. It does so at a pace that mirrors human performance and offers the opportunity to model learning during this process.

3 The Task

This section details formulating a domain-specific decision problem for optimal production efficiency, leveraging VSM to define efficiency sectors and then abstracting the problem for mathematical modeling.

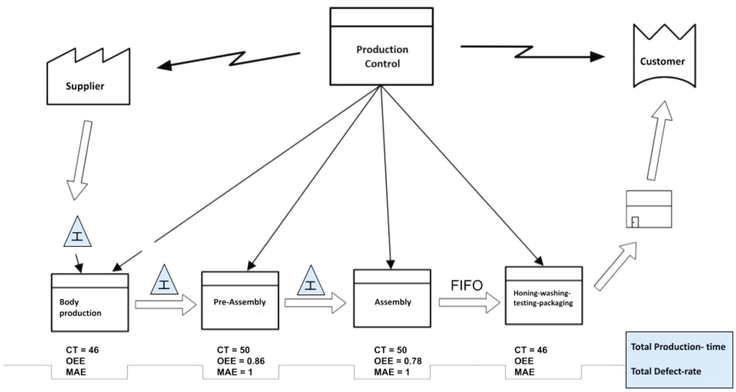


Fig. 1. An Example of Value Stream Map in a Plant Floor

The VSM (Fig. 1) depicts a prototypical manufacturing production line workflow from supplier to customer. Key components include Body Production, Pre-Assembly, Assembly, Honing, Washing, Testing, and Packaging. Later stages are interconnected via First-In-First-Out (FIFO) processes. Metrics displayed for each stage include Cycle Time (CT), Overall Equipment Effectiveness (OEE), and Mean Absolute Error (MAE). The flow progresses through each stage, aiming for efficient operation, performance monitoring, and error minimization to ensure high-quality production output and timely customer delivery.

Focusing on maintaining stable output for the plant, we consider the plant managers' feedback alongside the Value Stream Map (VSM) structure to develop a decision-making problem that aims to reduce total assembly time while minimizing the increase in defect rate. The task: Our manufacturing line has two sections with potential defect sources: pre-assembly and assembly. Pre-assembly takes 40 s with an OEE rate of 88%, while assembly takes 44 s with an OEE rate of 80.1%. To reduce total assembly time by 4 s, we need to identify which section can be shortened with minimal defect increase. There are two options: reduce pre-assembly time or reduce assembly time.

4 The Model

This section starts with capturing intuition and domain knowledge from decision makers, followed by the model structure and learning mechanism, and concludes by examining a model output snippet from one run of our VSM model.

4.1 Model Design

The model, built upon the prototypical decision process distilled by Bosch plant managers, incorporates how cognitive models are designed for different levels of expertise [3,6]. For novices, the model utilizes intuitive deliberative chunks to make decisions. For intermediates, it understands key metrics such as cycle time (CT) and Overall Equipment Effectiveness (OEE). However, intermediates often lack the ability to systematically analyze how these metrics interrelate and cumulatively impact efficiency and quality. Experts, on the other hand, make well-informed judgments based on a comprehensive view of all relevant metrics, obtained through Value Stream Mapping (VSM).

4.2 Declarative Chunks

We created chunks representing knowledge from intuitions to professional expertise. These representations are divided into three chunk types: decisions, decision merits, and goals. Decision chunk encodes six slots: reduction time, decision-making state (e.g., novice, intermediate, expert), OEE, and CT. The decision merits chunk holds knowledge on weights for sectors, defect increase for sectors, and the difference in defect rate increase between the two. The goal chunk encodes the initial production conditions and the ultimate goal of making the optimal decision.

4.3 Production Rules

Three sets of production rules represent the decision-making behaviors of novice, intermediate, and expert decision-makers. These sets comprise a total of 17 rules, each driven by goal-focused objectives across 14 states.

We use the expert production rule set as an example, as shown in Fig. 2. Once the decision-choice center decides to activate this set of expert decision productions, it starts by perceiving the problem and retrieving related decision-making metrics from chunks. The imaginal buffer then acts as a temporary workspace, holding and manipulating relevant information during decision-making. It allows the model to build new mental representations or modify existing ones based on incoming data or problem-solving needs. This involves using the imaginal buffer to assess the relationships between the decision target and decision metrics, particularly considering the impact of each sector's weight on the defect rate change, and determining the final defect rate increase for each sector. These results are stored in the imaginal buffer and later retrieved for comparison. This then allows the model to select the sector with the lowest defect increase.

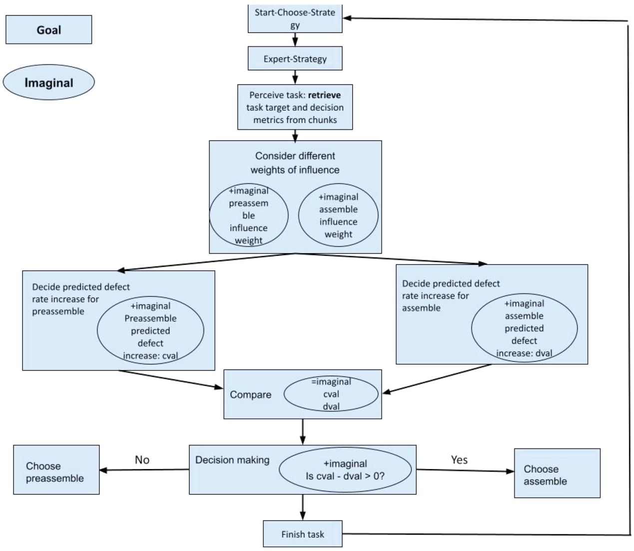


Fig. 2. Production rules control structure for expert decision making and their use of the ACT-R Goal and Imaginal buffers

4.4 Level of Expertise Mechanism

The model can learn while performing tasks through two mechanisms leading to varying levels of expertise, as shown in Fig. 3.

The model mimics human decision-making behavior through differentiating knowledge representations. **Declarative Memories**: These memories store

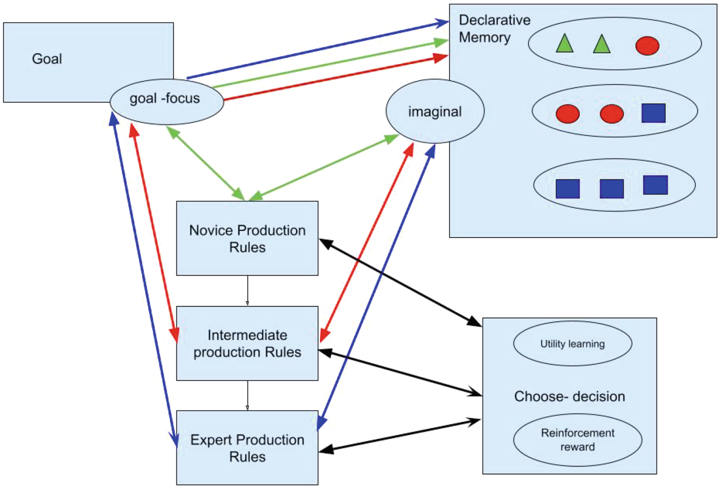


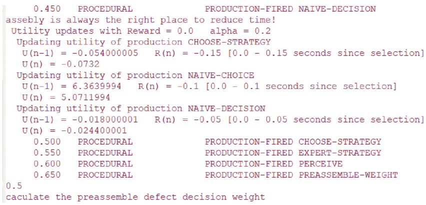
Fig. 3. Level of expertise mechanism in VSM-ACT-R

knowledge that aligns with human intuition and expertise gained from the VSM. For example, the green triangles in the figure represents a portion of the intuition used by novice decision-makers. **Production Rules**: These rules capture the rational decision-making processes observed in human subjects. The green (lighter) lines illustrate how the imaginal buffer retrieves relevant portions of the novice declarative memory and feeds them to the novice production rule set. Intermediate and expert decision-making levels follow the same principle. Red and blue shapes represent their respective declarative memory chunks, and the corresponding (darker) colored arrows show the flow of information through their production rule sets. Finally, the goal buffer utilizes the "goal focus" command to manipulate the different phases of the task.

Beyond mimicking human behavior, the model also simulates the learning progress achieved by the **Decision-Choice Control**, which manages errors, learning, and memory through utility learning and reinforcement rewards. Novice decision-making starts with a utility base and includes a noise setting. The intermediate and expert production rules receive rewards when the corresponding decision-making results are achieved. The utility of these production rules updates is based on the rewards received and the retention of memory, which depends on the time passed since the rule last fired.

4.5 Model Output

The partial trace in Fig. 4 shows how the model transitions from naive to more expert-like behaviors. Each production rule's utility is updated based on the reward received and the time since the last selection. For example, the NAIVE-CHOICE rule's utility decreased from 6.36 to 5.07 due to a reward of –0.1 for the time passed since the last selection. As the utility of naive strategies decreases, the likelihood of the EXPERT-STRATEGY being fired increases.



```
    0.450   PROCEDURAL              PRODUCTION-FIRED NAIVE-DECISION
assebly is always the right place to reduce time!
 Utility updates with Reward = 0.0   alpha = 0.2
  Updating utility of production CHOOSE-STRATEGY
   U(n-1) = -0.054000005   R(n) = -0.15 [0.0 - 0.15 seconds since selection]
   U(n) = -0.0732
  Updating utility of production NAIVE-CHOICE
   U(n-1) = 6.3639994   R(n) = -0.1 [0.0 - 0.1 seconds since selection]
   U(n) = 5.0711994
  Updating utility of production NAIVE-DECISION
   U(n-1) = -0.018000001   R(n) = -0.05 [0.0 - 0.05 seconds since selection]
   U(n) = -0.024400001
    0.500   PROCEDURAL              PRODUCTION-FIRED CHOOSE-STRATEGY
    0.550   PROCEDURAL              PRODUCTION-FIRED EXPERT-STRATEGY
    0.600   PROCEDURAL              PRODUCTION-FIRED PERCEIVE
    0.650   PROCEDURAL              PRODUCTION-FIRED PREASSEMBLE-WEIGHT
0.5
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Fig. 4. VSM-ACT-R Model Output

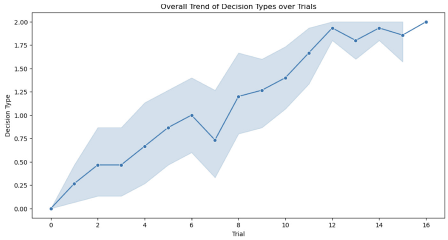

Fig. 5. Trend of Decision Types over Trials with SD shown as gray fill (Color figure online)

5 Model Evaluation

To answer the question of whether this model learns and how it simulates learning progression and captures individual differences, we first use descriptive statistics and linear regression to show the average progression of decision types across 16 trials. We then use a mixed linear model to assess and illustrate the effects of trials on decision types across ACT-R model personas, with repeated measures of trials, and random effects to account for individual differences. Last but not least, we use an ordered logistic regression to analyze and understand the relationship between the number of trials and an ordinal dependent variable of learning progress from novice to expert.[2]

5.1 Analyzing Learning Rate

We ran the ACT-R model 15 times to understood its behavior [9]. Each time, we asked it to run 15–16 trials until the model achieved stable expert behavior. We collected data with decision types encoded as 0, 1, and 2 for novice, intermediate, and expert strategies.

The decision-making data for the runs, acting as ACT-R personas, are shown in Fig. 5. the average progression of decision types from novice (0) to expert (2) across 16 trials. Starting at approximately 0 in trial 0, the mean decision type rises to about 0.75 by trial 4 and reaches around 1.25 by trial 8. Despite slight fluctuations, the trend continues upward, with the mean decision type approaching 1.75 by trial 12 and around 1.9 by trial 16. The narrowing 95% confidence intervals, ranging from approximately 0.5 to 2.0 initially to 1.5 to 2.0 in later trials, indicate increasing consistency among participants' decision-making abilities.

The learning rate, defined as the rate at which decision type progresses from novice (0) to expert (2) across trials, is modeled using a linear regression. This

[2] Notebook and data can be accessed at https://github.com/SiyuWu528/VSM-ACT-R/tree/main/Brims_data_analysis.

model assumes a constant learning rate across all trials shown in Eqn. 1.

$$Eqn.\,1:\; y = \beta \times x + \alpha$$

where y is the mean of decision type, x is the trial number, and β (the slope) represents the learning rate. The learning rate for the ACT-R personas is 0.111 with variance of the residuals of 0.026.

5.2 Analyzing Individual Differences

We then use a mixed linear model that includes both fixed and random effects, to assess the effects of trials on decision types, and random effects to account for individual differences. This analysis allows to handling data with nested structures (e.g., multiple trials per personas). In addition, it accounts for the correlation of responses within the same participant and allows for the inclusion of random effects due to individual differences (Table 1).

Table 1. Mixed Linear Model Regression Results

Dependent Variable:			decision_type			
No. Observations:	227		**Method:**	REML		
No. Groups:	15		**Scale:**	0.4014		
Min. group size:	15		**Log-Likelihood:**	-232.9159		
Max. group size:	16		**Converged:**	Yes		
Mean group size:	15.1					
	Coef.	**Std.Err.**	**z**	**P>|z|**	**[.025**	**.975]**
Intercept	0.151	0.112	1.340	.180	-0.070	0.371
Trial	0.127	0.010	13.198	.000	0.108	0.146
Group Var	0.076	0.063				

Significant Effect of Trial on Decision Type. The coefficient for the trial is 0.127 with a p-value of $<.05$, indicating a highly significant positive effect of trial on decision type. This suggests that experience or exposure to more trials positively influences the decision-making process, resulting in higher decision type scores. Participants learn or adapt their decision-making strategies over time, becoming more proficient or confident with each subsequent trial.

Individual Differences Among Participants. The random effects component of the model shows a variance of 0.076 for participants, indicating variability in the intercepts across different participants. This variability suggests that while the overall trend shows an increase in decision-type scores with more trials, individual participants start from different baseline levels. In humans, some participants may naturally have higher or lower decision-type scores due to personal characteristics, prior experience, or other unmeasured factors.

5.3 Analyzing Learning Progress

We then use an ordered logistic regression model without considering individual differences, to analyze the relationship between the number of trials and an ordinal dependent variable of learning progress from novice to expert. This aims to look deeper into how changes in the predictor influence the likelihood of different levels of the ordered outcome in decision-making.

Table 2. Ordered Model Regression Results

Dep. Variable:	decision_type			**Log-Likelihood:**		-182.40
Model:	OrderedModel			**AIC:**		370.8
Method:	Maximum Likelihood			**BIC:**		381.1
No. Observations:				227		
Df Residuals:				224		
Df Model:				1		

	coef	**std err**	**z**	**P>|z|**	**[.025**	**.975]**
Trial	0.3545	0.040	8.802	.000	0.276	0.433
0/1	1.6906	0.310	5.447	.000	1.082	2.299
1/2	0.2262	0.139	1.631	.103	-0.046	0.498

Table 2 shows that the threshold 0/1 (1.69) with p-value < 0.05 indicates a significant cut-off between novice and intermediate categories. The threshold 1/2 (0.23) is not statistically significant (p-value = .103), suggesting that the model does not provide strong evidence for a clear separation between intermediate and expert decision types over just 15 trials.

ACT-R personas tend to move to higher decision categories as they undergo more trials, with a significant transition between novice and intermediate, but not as clear a transition between intermediate and expert. The initial learning curve is steep, however, once personas reach an intermediate level, further improvements become subtler.

6 Conclusion and Discussion

This study towards using cognitive architecture to enhance manufacturing efficiencies by creating VSM-ACT-R, created a model that incorporates learning and behavior differentiation in a decision-making task aimed at optimizing a manufacturing production line. The model simulates three types of behavior-novice, intermediate, and expert-mirroring human decision-making rationales. The model learns over the course of trials and exhibits individual differences. It demonstrates a human-like learning progression, showing a steep learning curve at the beginning and gradual improvements later on.

It is worth noting that the subtle and gradual progression of the model from intermediate to expert levels may be inherent to the model itself. It is possible that the differentiation between the expert and intermediate decision-making levels is not distinct enough. Additionally, the incentives provided to the expert strategy may be significantly higher than those given to the intermediate strategy and could lead the model to have a smooth learning curve later on. Therefore, it could be worthwhile to adjust the model based on real-world scenarios.

VSM-ACT-R could be extended to teach novice decision-makers not only optimized strategies but also highlight common mistakes they might make, guiding them through a learning trajectory. It will be able to serve as a tutor in manufacturing decision-making, not just by providing the right answers but by guiding them on how to achieve those answers, akin to a peer.

We are particularly excited about the model's potential for further deployment with open-source large language models [12]. In manufacturing decision-making, off-the-shelf generative models often struggle to deliver accurate results and learning behavior exhibited by cognitive models. We can leverage VSM-ACT-R's ability to simulate tens of thousands of ACT-R participants in decision-making tasks to generate target data that incorporate learning and optimized decisions. This generated data will be used as the target to fine-tune large language models, aiming to align their decision-making with the ACT-R agents we will develop, The fine-tuned language model not only predicts human decisions for new problems but also provides important insights into the learning and correction rates in these tasks.

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