Cognitive Modeling of Agents: Integrating Emotions, Goals, Needs, and Decision-Making

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Abstract

Traditional crowd simulations in complex environments like train stations often simplify human behavior by focusing solely on physical movement and neglecting psychological depth. This paper introduces a cognitive agent framework that integrates dynamic emotional states (e.g., valence, frustration) and physiological needs (thirst, hunger etc.) to model decision-making more realistically. Agents operate via a dual-mode architecture: during surplus time, they strategically pursue secondary goals using a utility-based mechanism that balances need intensity, spatial costs, and environmental opportunities; when needs exceed critical thresholds, they reactively prioritize urgent demands (e.g., finding a restroom). The framework also incorporates personalized factors (age, mobility, luggage) and agents' evolving knowledge of Points of Interest (POIs), enabling them to reason about unknown POIs and anticipate need fulfillment on trains. Implemented in a simulated train station environment, the model demonstrates how agents generate context-sensitive, heterogeneous behaviors such as interrupting travel plans for urgent needs or dynamically rerouting driven by internal state fluctuations. Results show that this approach captures a richness in decision-making absent in conventional rule-based simulations, offering improved realism for applications in crowd management and spatial design.

Keywords

Cognitive Modeling, Multi-agent Simulation, Crowd Simulation, Intuitive Decision Making, Naturalistic Decision Making

1. Introduction

In the complex socio-technical ecosystem of modern transportation hubs, understanding human behavior is critical for designing safer, more efficient spaces. Train stations, with their diverse populations (e.g., young, old, disabled, frequent, and first-time travelers), fluctuating crowding patterns (peak and off-peak hours), and multiple services (shops, ticketing), represent particularly challenging environments for both analysis and management. Identifying the main reasons for emotional changes that influence passenger behavior is especially complex within these settings.

Traditional approaches to crowd simulation are rooted in agent-based modeling and often rely on simplified representations that treat individuals as homogeneous entities responding primarily to physical stimuli, for example, modeling pedestrian flow through corridors or exits using basic rules of proximity and collision avoidance [1, 2]. Although effective in capturing large-scale movement patterns, such approaches frequently fail to reflect the rich interplay between cognitive states, emotional responses, and situational context that governs real human behavior.

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In reality, the actions of passengers are shaped by a variety of factors beyond physical space. Internal emotional states triggered by social interactions, personal urgency, or prior travel experiences play a significant role. These emotions are not static; they evolve in response to momentary events in the environment. Sometimes, even seemingly minor occurrences such as being blocked by another passenger or experiencing unexpected delays can lead to noticeable shifts in a person's emotional state, which in turn can shape the actions they subsequently take.

Yet, such subtleties are often overlooked in most simulations, which tend to prioritize mechanical rule-following and micro-level interactions while ignoring the psychological depth that drives human decisions. Consequently, these models may misrepresent crucial aspects of crowd dynamics, particularly during high-stress situations or emergencies, where panic, confusion, or urgency driven by emotional states can dramatically alter predicted behaviors of the crowd.

Contribution: In this paper, we present a cognitive agent framework for crowd simulation in train station environments that explicitly models the interaction between emotional states (valence and frustration) and physiological needs (including thirst, hunger, energy, and restroom urgency). Rather than treating behavior as a direct response to spatial constraints alone, our approach incorporates internal state dynamics and how they evolve in response to social and environmental stimuli. We demonstrate how fine-grained behavioral predictions can emerge from the continuous interplay between these internal states and external conditions, enabling agents to make context-sensitive decisions that go beyond deterministic rule-following.

To illustrate the effectiveness of our model, we follow the trajectory of a single agent through the simulation environment and visualize the evolution of its emotional and physiological states over time. The main contributions of this paper are as follows:

- We introduce a unified cognitive framework that integrates emotional states, physiological needs, knowledge base, and personal characteristics (persona) into agents' real-time decision-making processes in complex environments such as train stations.
- We then develop a dual-mode decision-making architecture that allows agents to dynamically shift between opportunistic and reactive behavior, guided by threshold-driven prioritization of needs.
- We demonstrate the effectiveness of our model by simulating the life span of a single agent and visualizing how internal state changes drive behavior over time, offering fine-grained behavioral predictions absent in conventional rule-based simulations.

Related Work: Modeling human behavior in complex public environments like train stations demands an interdisciplinary approach, drawing from cognitive science, artificial intelligence, and crowd simulation. Previous work [1, 2, 3] in this area has largely focused on agent-based modeling (ABM) frameworks (for an analysis of various comparable frameworks, refer to [4]) that simulate human decisions based on simplified assumptions typically reactive behaviors triggered by spatial constraints or crowd density. While effective for macro-level planning, such models lack the depth to capture simple but important human responses to stress, fatigue, or conflicting motivations.

Cognitive architectures such as Adaptive Control of Thought—Rational (ACT-R) and State, Operator, And Result (SOAR) have provided a more psychologically grounded framework, enabling simulations of memory, learning, and decision-making under controlled conditions [5, 6]. However, their applicability in dynamic, real-world scenarios remains limited. ACT-R excels in task based cognition but lacks support for modeling emotions or physiological drives factors critical in time-sensitive, high-stakes settings such as public transportation hubs [5]. SOAR supports strategic planning and learning but similarly underrepresents non-cognitive influences on behavior [6]. Recent work has attempted to bridge this gap by modeling individual naturalistic decision-making where expert agents must act under uncertainty and time pressure within cognitive architectures, demonstrating how recognition primed strategies can be operationalized computationally [7].

BDI (Belief-Desire-Intention) architectures have been widely used for modeling deliberative behavior, particularly where goal prioritization and intention formation are central [8]. Yet, many implementations abstract away from embodied experience and moment-to-moment affective states. The PECS (Physical, Emotional, Cognitive, Social) framework fills this gap by integrating emotion and physiology into agent models [9]. While conceptually rich, PECS often remains at the theoretical level, with few computationally tractable implementations suitable for large-scale simulations [10].

Parallel to these cognitive approaches, emotional modeling has evolved from categorical appraisals (as seen in the OCC model) [11, 12] to dynamic process models such as Scherer's Component Process Model (CPM) [13] and Frijda's theory of action tendencies [14]. These models underline the role of emotion as a core regulator of action, rather than a peripheral affect. Yet, their integration into agent simulations remains partial, often limited to discrete states or predefined reactions.

Several studies have explored agent behavior in transportation hubs. Many focus on evacuation scenarios or optimizing passenger flow, often using rule-based or reactive agents [15]. More recent work has begun to incorporate psychological factors like stress or social group behavior [16, 17] into simulations of crowd dynamics. However, few have attempted to create a unified framework where an agent's decisions emerge dynamically from the interplay between high-level goals (e.g., catching a train), evolving emotional states (e.g., stress, anger), and pressing physiological needs (e.g., thirst). In terms of needs and motivation, most prior work adopts static utility functions or rule-based thresholds for triggering needs-driven actions. Our proposed framework distinguishes itself by introducing a *priority-based utility mechanism* that enables dynamic negotiation between cognitive goals, emotional arousal, and physiological drives.

While significant progress has been made in modeling human behavior through various cognitive architectures and emotional/motivational theories, a persistent gap remains in their ability to holistically capture the dynamic, interwoven nature of human decision-making in complex, real-world environments. For instance, ACT-R, while highly effective for tasks involving precise cognitive activities like memory retrieval and attention shifts, often finds it challenging to account for the dynamic, affect-driven behaviors seen in spontaneous human interaction. For example, some work has explored how emotion can emerge within a cognitive architecture, yet it highlights that emotional responses are often treated as emergent properties or inferred rather than being naturally modeled as dynamic, driving forces within the core architecture [18].

Similarly, studies focusing on capturing dynamic performance in ACT-R centered on refining memory parameters for specific cognitive tasks, without addressing how evolving internal emotional states might dynamically alter goal pursuit or prompt unplanned actions in a crowded, high-stress public space [19]. Furthermore, Laird provides an analysis in [20] that extensively describes the limitations of both ACT-R and SOAR in this regard.

Regarding BDI architectures, while they provide an intuitive framework for goal oriented reasoning, they traditionally abstract away from the continuous, often subconscious influence of emotions and physical discomfort. For instance, a model combining BDI logic and temporal logics for decision-making in emergency situations focused on logical reasoning and planning under time constraints, but largely sidestepped the direct influence of dynamic emotional arousal (like panic or urgency) that can lead to non-rational but highly realistic behaviors in such high-stress situations [21].

These examples highlight a critical need: existing frameworks often treat emotions and physiological needs as secondary add-ons or external modulators, rather than fundamental, dynamically interacting components that can spontaneously alter an agent's goals and actions. Our proposed framework directly addresses this by introducing a unified cognitive architecture where an agent's decisions emerge dynamically from the continuous interplay between high-level goals, evolving emotional states, and pressing physiological drives.

Structure of the Paper The rest of this paper is structured as follows: Section 2 reviews theoretical foundations, including cognitive architectures, emotional modeling, and agent motivation theories. Section 3 presents our proposed cognitive modeling framework, detailing the agent architecture, internal states, and decision-making processes. Section 4 describes the simulation environment, configurations, and showcases results through a case study of a single agent's behavior. Section 5 discusses the implications, and its limitations. Finally, Section 6 concludes the paper and outlines future work.

2. Theoretical Foundations

2.1. Cognitive Architectures for Agents

The pursuit to create high-fidelity models of human behavior within complex, dynamic environments, such as major transportation hubs, has traditionally been grounded in theoretical frameworks of cognitive architectures [22]. Developed at the intersection of artificial intelligence and cognitive science, these architectures provide computational specifications of intelligent agents, laying out the fundamental structures and processes of cognition and action. Some of the more notable paradigms are the ACT-R, SOAR, BDI model, and the PECS framework. While each offers effective mechanisms for simulating goal oriented behavior, they differ significantly in their capacity to model the complex intertwinement of cognition, emotion, and physiological states considerations paramount to human decision-making in the high-stakes, high-density context of a train station [23]. In the following, we study these architectures.

ACT-R is a highly structured, hybrid cognitive architecture that attempts to provide a general theory of cognition in terms of modeling human thought processes as the interaction of independent modules [24]. It simulates human thought processes through symbolic rules and subsymbolic mechanisms. Essentially, ACT-R posits a core production system operating on information within two primary memory modules: a declarative module to store fact knowledge and a procedural module for storing production rules asserting skills and acquired procedures. The subsymbolic component of the architecture uses mathematical equations to gate cognitive processes, and is able to make quantitatively precise predictions about human performance on well-specified tasks [5].

As being modular and mechanistic, ACT-R is highly appropriate to simulate highly intense, goal-directed cognitive activity. For instance, an ACT-R passenger model is able to closely replicate the cognitive activities of searching for a platform number, including visual attention shifts and memory retrievals involved [25]. But its virtues in simulating circumscribed cognition establish its limitations in ecological validity too. Its emphasis on rational processing permits less room for spontaneous or affect-modulated behaviors characteristic of normal life. For example, while it can record a passenger's thoughtful search, it is less suited to record an emergent decision to help a misplaced traveler or to drastically divert based on a spontaneous increase in concern. Though extensions have sought to incorporate emotion, these are not part of the underlying architecture, thus limiting its application for simulation of the rich texture of agent interaction in open public spaces.

SOAR is a framework for problem solving and decision-making based on production rules and a goal-subgoal hierarchy [6]. All tasks in SOAR are formulated as attempts to solve problems within a "problem space," and all long-term knowledge is stored in a procedural memory of production rules. When an agent cannot immediately select its next action, an "impasse" occurs. SOAR resolves this by recursively creating a subgoal to figure out what to do next, a process known as universal subgoaling. The results of successfully resolving such impasses are cached as new production rules through a learning mechanism called "chunking," allowing the agent to improve its performance over time [26].

Its robust mechanisms for hierarchical planning and procedural learning make SOAR effective for modeling agents engaged in complex, strategic tasks. However, like ACT-R, SOAR was fundamentally designed as a model of the "cognitive band" of human behavior, with limited intrinsic support for affective or physiological processes. While researchers have developed extensions to incorporate emotions, these are often treated as secondary modulators of cognitive function rather than as integral components of the decision-making process itself [27]. Consequently, SOAR-based agents may struggle to realistically portray behaviors driven by stress, urgency, or physical discomfort states that are pervasive in crowded transit environments and profoundly influence human action.

BDI model is a framework for practical reasoning in agents with strong philosophical foundations in the work of Bratman on human planning [28]. Rather than focusing on low-level cognitive processes, BDI is specified at a higher level of abstraction. Agents possess three key mental attitudes: Beliefs (their representation of the world state), Desires (their long-term goals or objectives), and Intentions (the goals to which they have committed themselves to actively attempt to bring about). The architecture's main loop is to perceive the world to update beliefs, deliberate desires to generate new intentions, and execute plans to satisfy intentions [8]. Recent work has successfully used BDI to simulate context-sensitive energy regulation in vehicle-to-grid systems, demonstrating its utility in environments where multiple agents must coordinate based on shared goals and evolving beliefs [29].

This folk-psychological, intuitive approach makes BDI particularly well-suited for clear and interpretable modeling of deliberative reasoning and multi-agent negotiation. Traditional BDI implementations, however, model agents as purely rational agents, abstracting away from the ongoing, often subconscious influence of emotional and physiological states. This can result in behavior that is too logical or overlooks the certain sub-optimal decisions humans make under stressful circumstances. Whereas many have attempted to create "emotional BDI agents" by adding affective appraisals into the reasoning cycle [30], these models have a tendency to put emotion on top of an already existing rational framework rather than making it one of the fundamental building blocks of cognition.

PECS was developed in direct response to the cognitivist bias of earlier frameworks. The PECS reference model was developed to provide a more holistic conceptualization of human behavior [31]. It proposes that any realistic simulation of human action must take into account the tight interrelation among four interdependent dimensions: Physical (body of states, fatigue, physiological requirements), Emotional (affective states and effect), Cognitive (reasoning, memory, perception), and Social (relations, norms, group behavior).

The primary strength of PECS lies in its conceptual integrity; it foregrounds the very elements embodiment, emotion, and social context that are often marginalized in other architectures. It serves as a valuable blueprint for designing more human-like agents. However, PECS is more of a high-level conceptual guideline than a detailed, computationally specified architecture. It describes what should be modeled but does not prescribe how to implement the complex interactions between its components. This lack of operational specificity has hindered its adoption for large-scale, spatially explicit simulations where precise behavioral rules and computational tractability are paramount.

Architecture	**Strengths**	**Limitations**
ACT-R	Detailed modeling of cognitive tasks, memory, and attention	Weak on emotional/physiological modeling, constrained in dynamic environments
SOAR	Strong problem-solving and planning capabilities	Limited emotion modeling, lacks bodily needs integration
BDI	Intuitive structure for goal-oriented reasoning	Often abstract; omits continuous emotional/physiological influences
PECS	Holistic framework integrating body, mind, and emotion	Conceptual; lacks detailed implementation standards

Table 1
Comparison of existing cognitive architectures

Table 1 shows the summary of the strengths and limitations of the architectures studied. Although each of them offers important insights into different facets of human behavior, none fully integrates dynamic emotional states with physiological drives in a way that is both behaviorally realistic and computationally tractable for use in simulating intelligent agents in a complex environment. This gap motivates the development of our proposed framework, which builds on these foundations but extends them to better reflect the richness and immediacy of human decision-making in crowded, high-stress environments like train stations.

2.2. Emotions in Cognitive Modeling

Accurate capture of emotion is crucial to the formation of cognitive models that accurately capture human behavior, particularly in dynamic, high-stakes situations. Various influential theories have shaped understanding and integration of emotions into cognitive modeling.

The **OCC model** [11] offers a tightly articulated, cognitive appraisal theory of emotions. It presumes that emotions are elicited by cognitive interpretations of situations, specifically focusing on how events, agents' actions, and objects relate to an individual's goals, standards, and preferences. The OCC model parses emotions into distinct categories (e.g., joy, distress, hope, fear, pride, shame) based on these appraisal dimensions and provides an open, rule-based framework for predicting emotional responses. Its rule-based and categorical structure renders it directly suitable for application in computational agent-based systems, enabling direct translation of environmental input into discrete states of emotion. Its focus on discrete, propositional appraisals, however, tends to limit its capacity to accommodate the smooth, subtle, and often ephemeral character of human emotional experience.

Another theory of emotion studied in the literature is the **Frijda's theory of emotions** [14]. It emphasizes the functional and motivational role of emotions. Frijda conceptualizes emotions primarily as "action tendencies" states of readiness to engage in specific behaviors aimed at coping with or responding to environmental changes. This view highlights that emotions are not merely internal states but powerful motivators that predispose individuals to act in particular ways (e.g., fear leads to flight or freezing, anger to attack). This perspective is particularly valuable for modeling real-time decision-making under stress, as it directly links emotional states to behavioral outputs, offering insights into how emotions facilitate adaptive responses in dynamic environments.

Furthermore, **Scherer's Component Process Model** [13] elaborates appraisal theory by proposing that emotions emerge from continuous, recursive stimulus evaluation over a series of appraisal dimensions, known as *Stimulus Evaluation Checks* (SECs). These are novelty, inherent pleasantness, goal relevance, coping potential, and norm compatibility. Unlike the OCC model's categorical output, Scherer's model suggests that the specific pattern of appraisals along these dimensions is what gives rise to the distinctive subjective experience and physiological response of an emotion. This model actually combines physiological response, expressive behavior, and subjective experience and offers a complete system for modeling emotion as a dynamic, multi-strata process. Its emphasis on continual assessment and the dynamic interplay of elements provides a more subtle description of emotional processes, and as such is particularly well-suited to capture the fluidity of human emotional reactions in dynamic socio-technical environments like train stations.

Together, these models offer complementary mechanisms for cognitive simulation: categorical appraisal (OCC), motivational readiness (Frijda), and dynamic multi-level processing (Scherer). Their integration offers more realistic agent action in simulations meant to simulate real-world emotional response and impact on decision-making in complex socio-technical environments.

2.3. Goals, Needs, and Motivation in Agents

Effective cognitive models of human behavior must account not only for decision-making and emotional responses but also for the underlying drivers of action namely, goals, needs, and motivational states. In intelligent agents, these constructs interact dynamically, shaping how individuals prioritize behaviors in response to both internal states and external stimuli.

Goals are typically conceptualized as mental representations of desired end states. In agent-based modeling, they are often structured hierarchically and can vary in abstraction, from long-term objectives (e.g., catching a specific train, arriving at a destination) to immediate subgoals (e.g., finding a restroom, purchasing a ticket). Cognitive architectures like BDI explicitly encode this hierarchical structure, allowing agents to adopt and revise intentions based on evolving beliefs and circumstances. However, real-world behavior is rarely governed by goals alone; other internal pressures frequently intervene.

Physiological needs —such as hunger, thirst, fatigue, the need for elimination, or the desire for comfort represent fundamental internal drives that can significantly modulate or even override cognitively defined goals. These needs introduce time-sensitive pressures that often lead to deviations from planned behavior, particularly in high-density, resource constrained environments like train stations. For instance, an agent whose main goal is to board a train may instead seek food or a restroom when physiological thresholds are reached, delaying or rerouting their planned trajectory. The urgency of these needs often correlates with their intensity, demanding immediate attention and influencing behavioral prioritization.

Motivation acts as the crucial bridge between needs, goals, and subsequent action. It refers to the processes that initiate, guide, and maintain goal oriented behaviors. Theories such as Maslow's hierarchy of needs [32] propose a hierarchical structure for human needs, suggesting that lower-level physiological needs must be met before higher-level psychological needs become primary motivators. More recent models, like the self-determination theory [33], highlight that human motivation is shaped by both biological imperatives and psychological factors, including autonomy, competence, and relatedness. In cognitive agent modeling, this translates into utility functions or dynamic weighting mechanisms that guide behavior selection based on the agent's internal state, the saliency of various needs and goals, and the contextual environment.

Crucially, the interplay between goals, needs, and motivation introduces variability and non-linearity into agent behavior. A fatigued agent under time pressure may opt to forego rest to pursue a high-priority goal, while another might re-prioritize their actions due to a sudden increase in stress or discomfort. This dynamic re-weighting of drives is central to generating realistic behavioral trajectories, especially under conditions of uncertainty, crowding, or resource scarcity. Existing models often simplify this interplay, leading to agents that are either overly rational or driven solely by basic urges.

In our framework (which will be discussed in the next section), we operationalize goals and needs as concurrent, interacting influences on agent decision-making. Each is modulated by a dynamically evolving motivational intensity and contextual salience. This approach allows for emergent behaviors that more closely mirror those of real humans navigating complex, high-stakes environments, where decisions are frequently a negotiation between immediate physical states, emotional responses, and longer-term objectives.

2.4. Decision-Making Framework for Agents

Decision-making systems within cognitive agents have conventionally been used to represent rational goal pursuit, usually by means of rule-based, utility-based, or planning deliberative systems. BDI architectures employ a deliberative loop where beliefs and desires are evaluated to construct intentions, which guide behavior by means of goal achievement and plan execution [8]. This approach is especially suited to reasoning on logical deduction, strategic planning, and social interactions in multi-agent systems as in applications ranging from logistics to automated negotiation. It has a tendency to downplay the broad effects of dynamic internal states like tiredness, urgency, or emotional excitement, which have profound implications in human decision-making in real applications.

Other agent systems, particularly those used in crowd simulation, pedestrian flow, and emergency egress simulation, generally use simplified reactive strategies [34]. These are typically rule-based systems or threshold reasoning (e.g., “if local density is higher than x, reroute,” or "always move toward the nearest exit"). While computationally efficient and capable of generating macroscopic crowd behavior, these models typically exclude the richer complexities of human motivation and the subtle inter-trading of multiple desires and requirements made by individual agents. Reactive agents like these would not typically have the capacity for anticipation, dynamic re-evaluation of goals, or the refined behavioral modulation typical of human actors.

More recent hybrid approaches attempt to combine the reactive and deliberative approaches in an effort to build more sophisticated decision processes. For instance, dual-process models, that are founded on cognitive psychology, simulate rapid, intuitive (affective or heuristic) reactions alongside slower, more deliberative (rational) decision processes [35]. Dual-process models recognize that humans have a tendency to operate on numerous levels of cognition simultaneously, making rapid judgments in standard situations while developing lengthy reasoning for new or complex problems. The majority of uses of such dual-process models, though, do limit themselves to focusing on the interplay between cognition and affect and usually reject major physiological drives that predominate in actual time-limited situations such as train stations, where physical discomfort or tiredness can radically alter priorities for action.

These limitations point to the promise of a more integrated and comprehensive decision-making model one that can dynamically weigh a greater number of impactful factors, including physiological needs, affective states, and goal priority, to guide realistic, situational behavior. Current models are often seen to struggle with accounting for phenomena like interruption of behavior (e.g., deviating from a path to use a restroom), spontaneous generosity (e.g., helping a tourist despite personal goals), or breakdown under stress.

Our proposed model builds on these prior foundations with utility-based functionality to enable smooth prioritization, disruption of behavior, and emergent adaptation as a function of the interaction between internal (physiological and affective) and environmental (spatial, social, temporal) states. By offering dynamic utilities for potential actions in terms of the agent's current needs, emotions, and goals, we aim to implement a more diverse set of human-like behavior in complex, dynamic worlds. This technique allows for a more ecologically valid simulation, simulating the way people react and make choices with the multifaceted pressures present in high-density, high-stress public settings.

3. Cognitive Modelling of Agents

3.1. Proposed Decision-Making Framework

The proposed decision-making framework for agents operating in a train station environment is designed to emulate human-like reasoning under bounded rationality and fluctuating internal states. It integrates emotional dynamics, physiological needs, knowledge, and goals to produce adaptive and context aware behavior. At its core, the framework hinges on two primary modes of operation: opportunistic fulfillment during surplus time and reactive prioritization in response to urgent needs. Agents continually monitor their internal states including emotional valence and frustration, need levels, and temporal constraints and use this information to dynamically select actions. Their overarching behavior is driven by a hierarchical goal structure, where the main goal (e.g., boarding a train) may be temporarily overridden by urgent needs. The transition between these states is governed by predefined thresholds. When agents possess sufficient surplus time, they evaluate potential secondary actions using a utility-based mechanism. This involves computing the utility of visiting known Points of Interest (POIs), factoring in the intensity of each active need, the satisfaction potential of each POI, and personalized movement costs influenced by agent specific characteristics (e.g., age, mobility, emotional state). Needs are filtered using soft and hard thresholds to determine their eligibility for utility computation or immediate prioritization.

If no POIs meet the utility requirements or time constraints, agents suspend action selection until their internal or external conditions change such as discovering a new POI, receiving updated knowledge, or experiencing a shift in need urgency. When no known POI can satisfy an active need, agents consider "unknown POIs" using expected distance and uncertainty penalties to guide exploration behavior. In contrast, if any need exceeds its hard threshold, the agent's behavior transitions into a reactive mode: a temporary main goal is established to resolve the urgent condition. In this mode, agents forgo utility-based evaluation and instead seek the closest known POI capable of satisfying the urgent need, resuming regular goal processing only after the need falls below the hard threshold.

This dual-mode framework combining strategic opportunism with reactive prioritization enables agents to exhibit flexible, human-like behavior while remaining computationally tractable. The inclusion of anticipated post departure satisfaction (e.g., restroom or food availability on the train) and incomplete knowledge about the environment further enhances the realism of agent decision-making.

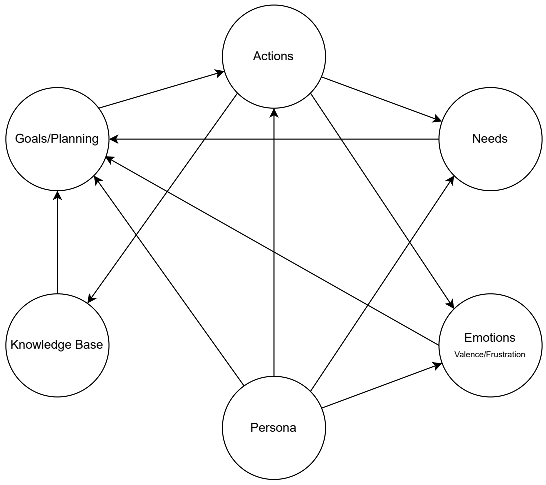

Figure 1: The figure illustrates how the internal states of an agent influence one another. Personal and agent-specific characteristics (persona) shape the evolution of emotions for example, by determining the rate at which emotions decay. These characteristics also affect the prioritization of needs through the definition of soft and hard thresholds. Additionally, they influence action planning via the spatial decay function, and directly impact physical actions, such as walking speed. Planning determines the actions an agent takes, while actions, in turn, influence both needs and emotions. Emotions also feed back into the planning process through their effect on spatial perception. This interconnected system highlights the dynamic and recursive nature of decision-making in agents.

3.2. Agents' Internal State

3.2.1. Emotions

Our emotional model focuses on two key dimensions: **Valence** and **Frustration**. Each emotion is represented as a continuous scalar value with a defined range and neutral point:

- **Valence** ranges from -1 (extremely negative affect) to 1 (extremely positive affect), with neutrality at 0.
- **Frustration** ranges from 0 (absence of emotion) to 1 (maximum intensity), with neutrality at 0.

A core property of the model is that emotional states tend to decay toward their respective neutral values over time. This behavior is modeled using the following exponential decay function:

$$E(t+1) = E(t) + \lambda \cdot (E_{\text{neutral}} - E(t)), \quad \text{where } 0 < \lambda < 1 \tag{1}$$

where:

- $E(t)$ is the current emotion value,
- E_{neutral} is the neutral point for the specific emotion,
- λ is the *Emotional Decay Quotient* (EDQ), a parameter defined per agent.

As we have only considered valence and frustration and 0.0 is considered to be the neutral point for these emotions, the equation is simplified to :

$$E(t+1) = (1-\lambda) \cdot E(t), \quad \text{where } 0 < \lambda < 1 \tag{2}$$

This formulation ensures that emotional states gradually stabilize in the absence of external stimuli. For example, a strongly negative valence (e.g., -0.8) will decay toward 0 (neutral mood), while high frustration (e.g., 0.9) will decay toward 0 over time. To maintain emotional realism and numerical stability, both emotional values are **clamped to their defined bounds** after each update step:

- Valence: $[-1, 1]$
- Frustration: $[0, 1]$

This prevents overshooting caused by decay dynamics or numerical artifacts. The decay mechanism allows emotions to serve as temporally extended signals that modulate agent behavior without growing unbounded.

3.2.2. Needs

An agent's needs are categorized into two groups: **physiological requirements** and **informational needs**. Each physiological need is represented on a continuous scale from 0 to 1, where the interpretation depends on the type of need.

- **Physiological Needs:** Thirst, Hunger, Nicotine, Restroom, and Energy.
- **Informational Need:** A binary value where 1 indicates that the agent requires information and 0 means that the need is satisfied.

Each physiological need is governed by two thresholds:

- A *soft threshold*, beyond which the need becomes a candidate for the agent's decision-making process.
- A *hard threshold*, which forces the agent to temporarily abandon the *main goals* and prioritize satisfying the need.

3.2.3. Goals

The goal system is structured hierarchically to manage agent objectives:

→ **Main goal:** The primary objective for agents in the train station environment is either boarding a train or departing the station after disembarking. While other motivations for visiting a train station exist, they are considered less common and are not explicitly modeled.

→ **Secondary Goal:** These represent secondary objectives that agents may pursue concurrently with their main goal. For example, an agent with 20 minutes before train departure may choose to drink a cup of coffee.

→ **Temporary main goal:** When a physiological need surpasses its hard threshold, addressing that need becomes the agent's temporary main goal. Temporary main goals override the main goal until the need is sufficiently satisfied.

3.2.4. Knowledge Base

The agent's knowledge base is represented as a vector, where each element corresponds to a POI and contains a pair of values: $(A_{\text{Location}}, A_{\text{State}})$. The first value, A_{Location}, indicates whether the agent knows the POI's location (1 for known, 0 for unknown). The second value, A_{State}, represents the POI's operational status (1 for open, 0 for closed).

Initially, the agent assumes all known POIs are open. As the agent explores the environment, it updates the state of each POI based on its interactions, ensuring that the knowledge base reflects the current open/closed status of each POI.

3.2.5. Persona

This component encapsulates attributes of an agent. This includes age, basic mobility (representing physical fitness), EDQ, and luggage. Attributes of persona influence the agent's movement speed and decision-making.

3.3. Actions

Agents are equipped with a set of predefined actions that they can execute within the environment, such as sitting on a bench, purchasing coffee, or navigating toward a platform. Each action modifies the agent's internal state. For example, the action of 'eating a sandwich' reduces the agent's hunger and energy need.

Figure 1 provides a conceptual overview of how an agent's internal states, including emotions, needs, and actions, interact and influence one another. It illustrates how personal characteristics (persona), such as the EDQ, shape the evolution of emotions, affecting the rate at which they decay and the prioritization of needs. The figure also highlights the feedback loop between emotions, action planning, and physical actions, such as walking speed. These dynamic relationships underscore the complex and recursive nature of decision-making in agents, laying the groundwork for the detailed discussions on needs, goals, and planning that follow.

3.4. Decision Making

The decision-making process in agents is generally divided into two situations. When they have excess time on their hands and if they have urgent needs. In the first case, an agent realizes that they can use the time in their hands to address some of their needs that are not urgent. In the second case, a need has passed the hard threshold, and that need has become so important to the agent that they decide to postpone acting on main goal and rather take addressing the urgent need as a temporary main goal and try to address it. The decision-making process is illustrated in Figure 2.

3.4.1. Case: Surplus Time in Hand

When agents have surplus time in hand, and they might be able to address some of their needs that have exceeded soft threshold, they employ a utility-based mechanism to rank and select which need to address at each decision point. This mechanism integrates the agent's internal state and spatial context.

Need Filtering and Priority Escalation Each need is associated with a soft threshold and a hard threshold. Needs exceeding the soft threshold are considered in the utility evaluation. Needs exceeding the hard threshold immediately become temporary main goals and they do not follow the same process as the needs between soft and hard threshold.

Utility Function for Needs and POIs The utility $U_i(POI)$ of a POI for need i is defined as:

$$U_i(POI) = n_i \cdot s_i(POI) \cdot f(d) \tag{3}$$

where:

- n_i is the current need level for i.
- $s_i(POI)$ is the satisfaction potential of the POI for need i.
- $f(d)$ is a spatial decay function based on perceived distance d.

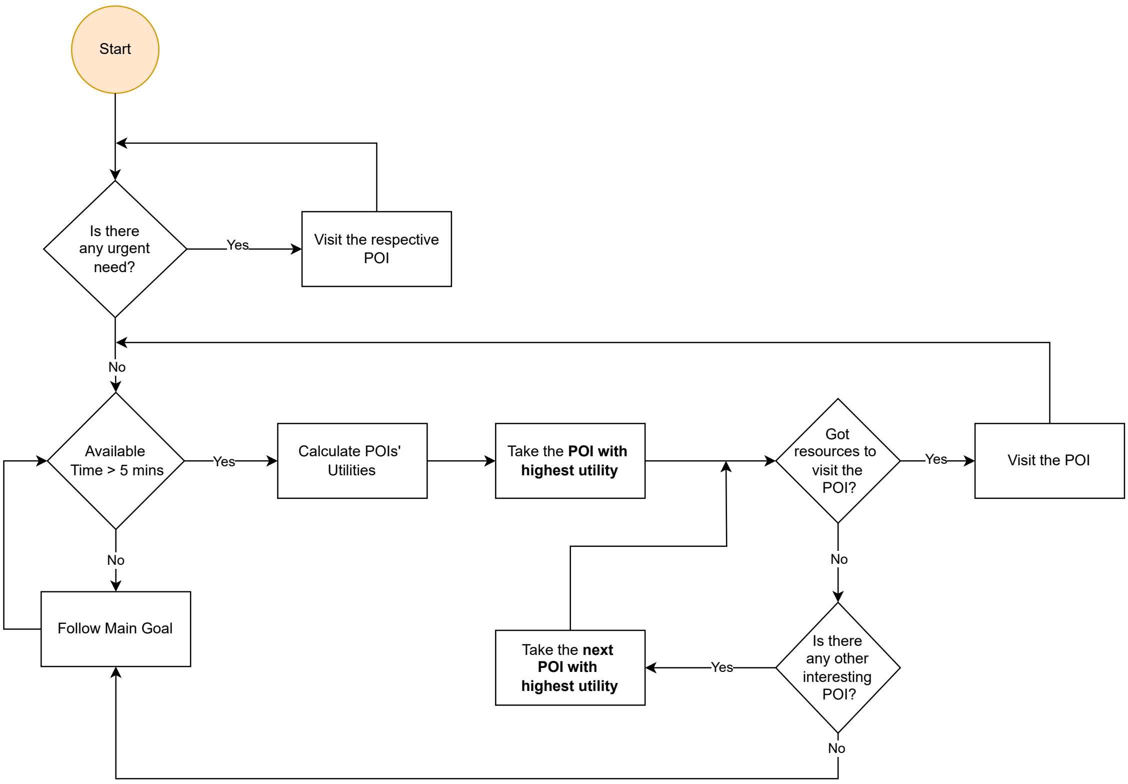

Figure 2: The figure illustrates the decision-making process of an agent considering whether to visit a POI before a scheduled train departure. The process begins by checking whether the agent has any urgent needs whose priority exceeds that of the main goal (i.e., catching the train). If no such urgent needs are present, the agent evaluates whether they have sufficient surplus time defined here as more than five minutes to address less critical needs. These are needs whose priority falls between predefined soft and hard thresholds. If surplus time is available, the agent considers fulfilling one or more of these intermediate priority needs. The five minute threshold is configurable and can be tailored per agent. The agent then evaluates the utility of all candidate POIs, ranking them from highest to lowest. They assess each POI in turn to determine whether they have the necessary resources (time) to visit it. If none are deemed feasible, the agent follows the path that prioritizes the main goal proceeding directly toward catching the train.

Example Consider an agent with the following need levels:

- Thirst: $n_{\text{thirst}} = 0.6$
- Hunger: $n_{\text{hunger}} = 0.7$
- Restroom: $n_{\text{restroom}} = 0.8$
- Nicotine: $n_{\text{nicotine}} = 0.5$
- Energy: $n_{\text{energy}} = 0.9$

Assume the agent is aware of the following POIs, each characterized by a satisfaction potential $s_i(POI)$ for the different needs and the distance from the agent:

Given a mobility factor $m = 1.5$, the spatial decay factor $f(d)$ for each POI is calculated using the following formula:

$$f(d) = \frac{1}{1 + m \cdot d}$$

The computed values of $f(d)$ for each POI are as follows:

- Vending Machine: $f(20) = \frac{1}{1+1.5\cdot 20} = \frac{1}{31} \approx 0.03226$

POI	Distance (m)	s_{thirst}	s_{hunger}	s_{Restroom}	s_{nicotine}	s_{energy}
Vending Machine	20	0.5	0.3	0.0	0.0	0.1
Shop	50	0.8	0.8	0.0	0.0	0.2
Restroom	100	0.0	0.0	1.0	0.0	0.0
Smoking Area	50	0.0	0.0	0.0	1.0	0.1

Table 2
Example POI characteristics

- Shop: $f(50) = \frac{1}{1+1.5\cdot 50} = \frac{1}{76} \approx 0.01316$
- Restroom: $f(100) = \frac{1}{1+1.5\cdot 100} = \frac{1}{151} \approx 0.00662$
- Smoking Area: $f(50) = \frac{1}{1+1.5\cdot 50} = \frac{1}{76} \approx 0.01316$

The utilities $U_i(POI)$ for each need per POI are then computed as the product of the satisfaction potential and the spatial decay factor:

POI	U_{thirst}	U_{hunger}	U_{restroom}	U_{nicotine}	U_{energy}	Total Utility
Vending Machine	0.00968	0.00677	0	0	0.00290	**0.01935**
Shop	0.00632	0.00737	0	0	0.00237	**0.01606**
Restroom	0	0	0.00530	0	0	**0.00530**
Smoking Area	0	0	0	0.00658	0.00118	**0.00776**

Table 3
Computed utilities per need per POI (with $m = 1.5$)

Interpretation In this example, the agent would prioritize visiting the **Vending Machine** first, as it has the highest total utility (0.01935), driven by the thirst, hunger and energy needs and proximity. After addressing the restroom need, the agent would re-evaluate the updated utilities. In a subsequent evaluation, the **Shop** would be the next most attractive POI, as it offers a good combined utility for thirst, hunger, and energy simultaneously too.

This example highlights how the utility-based mechanism enables agents to dynamically balance multiple needs and adapt their decisions based on both internal state and environmental constraints, including perceived movement effort through the personalized mobility factor.

Personalized Distance Cost The perceived cost of distance varies across agents. To model this, we introduce an agent-specific mobility cost factor m:

$$f(d) = \frac{1}{1 + m \cdot d} \tag{4}$$

$$m = m_0 \cdot f_{age}(Age) \cdot f_{mob}(Basic\,Mobility) \cdot f_{need}(Energy) \cdot f_{luggage}(Luggage) \cdot f_{emotion}(Frustration) \tag{5}$$

- $f_{age}(Age) = 1 + \alpha_{age} \cdot \left(\frac{Age-30}{30}\right)$
- $f_{mob}(Basic\,Mobility) = \frac{1}{Basic\,Mobility}$
- $f_{need}(Energy) = 1 + \alpha_{energy} \cdot Energy$
- $f_{luggage}(Luggage) = 1 + \alpha_{luggage} \cdot Luggage$
- $f_{emotion}(Frustration) = 1 + \alpha_{Frustration} \cdot Frustration$

Agent	Age	Basic Mobility	Energy(Need)	Luggage	Frustration	Resulting m
Young, fit	25	1.2	0.1	0	0.0	1.2012
Middle-aged, sedentary	40	0.3	0.7	1	0.2	9.9984
Elderly, tired	70	0.8	0.6	2	0.2	6.5220
Stressed commuter	35	1.0	0.2	1	0.6	2.9165
Relaxed tourist	50	1.0	0.0	0	0.0	2.0000

Table 4
Example agent profiles and resulting mobility cost factor m. The calculation are done, considering these parameter values: $\alpha_{age} = 0.5$, $\alpha_{energy} = 0.5$, $\alpha_{luggage} = 0.3$, $\alpha_{frustration} = 0.4$, $m_0 = 1.5$

Aggregated POI Utility and Decision Process The total utility of a POI is computed as:

$$Total\_Utility(POI) = \sum_i U_i(POI) \tag{6}$$

Agents rank POIs by total utility and select the POI with the highest value as their next action target. This mechanism enables agents to exhibit adaptive, heterogeneous behavior, dynamically balancing need urgency, movement costs, and environmental constraints.

Reasoning About Unknown POIs Agents are aware that certain types of POIs (e.g., Restrooms, Shops) are highly likely to exist in a train station, even if they do not know their precise location. To model this, we introduce "Unknown POI" entries for each such POI type. These entries are included in the utility evaluation with an expected distance d_{expected} and an additional uncertainty cost $C_{\text{uncertainty}}$:

$$f(d_{\text{unknown}}) = \frac{1}{1 + m \cdot d_{\text{expected}} + C_{\text{uncertainty}}}$$

The uncertainty cost discourages agents from preferring unknown POIs when known alternatives are available, while still allowing agents to actively explore when no known POIs satisfy a given need. If the agent discovers the actual location of the POI during exploration, the entry is updated in the Knowledge Base, and the uncertainty cost is removed. This mechanism enables agents to exhibit realistic exploratory behavior and reason about incomplete knowledge in the environment.

Suggested Parameter Values for Unknown POIs Table 4.2 provides suggested initial values for d_{expected} and $C_{\text{uncertainty}}$ for typical POI types. These values can be tuned empirically to reflect specific station layouts or agent behavior patterns.

POI Type	d_{expected} (meters)	$C_{\text{uncertainty}}$
Restroom	20	0.5
Shop	25	0.7
Smoking Area	30	0.3
Vending Machine	20	0.6
Bench	15	0.3

Table 5
Example of initial parameters for unknown POIs

3.4.2. Incorporating Anticipated Need Fulfillment on the Train

Some needs such as restroom use or hunger can be fulfilled either in the station or on the train. To model rational anticipation, agents are penalized for addressing such *deferrable* needs in the station when they could instead be satisfied later on the train.

To implement this, we introduce an **indicator addressability** $a_i \in \{0, 1\}$ for each need i, where $a_i = 1$ if the need can also be satisfied on the train, and $a_i = 0$ if it must be satisfied in the station. The utility function for visiting a POI is modified as follows:

$$U_i(\mathrm{POI}) = n_i \cdot s_i(\mathrm{POI}) \cdot f(d) \cdot (1 + \gamma \cdot (1 - a_i))$$

Here:

- n_i is the current intensity of need i
- $s_i(\mathrm{POI})$ is the POI's suitability for satisfying need i
- $f(d)$ is a distance-based decay function
- γ is a scaling parameter that increases the relative utility of station only needs

This formulation ensures that agents strategically prioritize needs that cannot be deferred, while still considering deferrable needs if convenient.

3.4.3. Case: Agent Has an Urgent Need

When a need exceeds its predefined hard threshold, the agent immediately designates addressing that need as a *temporary main goal*. In this situation, the agent's cognitive and decision-making processes prioritize satisfying the urgent need over all other objectives, including the main goal and *temporary main goal*. Unlike the surplus time scenario, where multiple needs may be weighed and ranked using a utility-based mechanism, the presence of an urgent need triggers a focused behavior pattern. The agent does not evaluate competing needs or optimize across multiple POIs. Instead, the agent identifies the nearest available and known POI that satisfies the urgent need and navigates directly toward it.

This reactive behavior continues until the need is sufficiently addressed either by fully or partially lowering the need level below the hard threshold at which point the agent resumes normal goal processing. If the original main goal remains time-sensitive (e.g., catching a train), the agent assesses whether sufficient time remains to continue pursuing it or adjusts its priorities accordingly.

This mechanism ensures that highly urgent physiological needs are treated with appropriate behavioral dominance, mirroring real-world human prioritization in similar contexts.

4. Implementation and Results

4.1. Modeling Basis of the Simulation

The cognitive modeling framework is embedded within a 3D agent-based simulation designed to capture realistic passenger behaviour in train station environments [36]. The simulation replicates Hamburg-Harburg station and enables controlled evaluations of human decision-making, emotional dynamics, and environmental interaction under dynamic constraints.

Simulation Framework The extensible architecture of the simulation supports 3D visualisation, agent cognition, and multi-layered behavioral modeling. Agents' behaviour is driven by a state-based logic system that governs the selection of primary goals (e.g., catching a train) and the pursuit of secondary needs (e.g., rest, food, or information). Their behavior dynamically adapts to environmental inputs, internal needs, and time constraints. The simulation and thus the cognitive modelling framework are implemented with the GoDot Engine v4.4.

Environment and Points of Interest (POIs) The station environment is modeled with segmented navigation zones and manually placed POIs, including restrooms, vending machines, seating areas, shops and information panels. Agents may interact with these POIs depending on their physiological or informational needs. Queue dynamics and POI-specific capacities are modeled to support crowding behaviour.

Agent Cognition and Behavior Agents are initialized with distinct persona traits that influence mobility, knowledge levels and decision-making preferences. Cognitive behaviour emerges from a utility-based mechanism that evaluates potential actions based on internal (e.g., thirst, hunger) and external conditions (e.g., POI location, crowding). When needs exceed soft thresholds and the agents have more than 5 minutes of time until train departure, agents may fulfill them if they get the opportunity to do so; above hard thresholds, behaviour will change to prioritise satisfying the urgent condition. Emotional state influence both behaviour and path planning.

Model Parameters Key parameters of the model include:

- Agent population sizes derived from real-world train schedules with subject to external factors (day of week, time of day, weather, events in the area).
- Various POIs, each with configurable capacity and satisfaction values.
- Persona-based attributes (e.g., mobility and luggage burden).
- Soft and hard threshold for needs.
- Initial distribution/values of need and emotion values

Evaluation and Logging The system logs individual and global metrics including movement paths, goal success rates, queue times, segment-specific density distributions and state transitions. This data enables detailed analysis of flow patterns and system-wide effects of interventions.

4.2. Configurations

Due to the complex interaction between physiological and emotional needs, as well as the rich environment, the framework can be adjusted to fit a variety of scenarios. In the following section, we will introduce the parameters for the scenarios specified later on.

Utility Calculation The utility function of POIs can be adjusted by tweaking its parameters to have more realistic modeling. The satisfaction potentials of POIs were used as presented in Table 3.4.1. The $\alpha-$values for personalized distance cost were used as in the example provided in Table 3.4.1

Table 4.2 shows different types of trains and the types of needs they can fulfill for an agent. Regarding γ, the scaling parameter that increases the relative utility of station-only needs, we use a value of 0.5.

Train Type	a_{thirst}	a_{hunger}	a_{restroom}	a_{nicotine}	a_{energy}
ICE	1	1	1	0	1
ME/FLX	0	0	1	0	1
City Train/S-Bahn	0	0	0	0	1
Unknown	0	0	0	0	0

Table 6
Train types and the types of need they can satisfy. ($a_{\text{need}} = 1$ indicates the possibility of fulfilling the need)

Needs and Emotions The aforementioned needs are implemented and the soft and hard threshold are set to 0.4 and 0.9 respectively. They are increased every 20 seconds by $\epsilon \backsim \mathcal{N}(0.0625, 0.01)$. This corresponds to an increase of the needs from 0 to 0.9 in 8 hours. Through interaction with various POIs, such as vending machines or restrooms, the needs can also change. Furthermore, the emotions valence and frustration are implemented. Both emotions decay every 20 seconds with the rate of the EDQ to their neutral point of 0.

Different events can trigger a change of emotions. This includes for valence: completing a secondary goal $(+0.2)$, reaching the primary goal $(+0.1)$, getting useful information from other agent or information board $(+0.1)$, reaching the soft/urgent threshold of a need $(-0.1/-0.3)$ or missing their train (-0.3).

The frustration emotion changes with the following events: sitting on a bench (-0.2), missing train ($+0.3$), POI queue full ($+0.2$), finishing their navigation without reaching their goal ($+0.1$) and waiting for elevator/train doors ($1e^{-5}$ every physic tick).

Points of Interest (POIs) Multiple POIs are placed in the 3D model of the Hamburg-Harburg train station. This includes a total of 47 benches, 8 vending machines, 5 smoking area, 4 shops and 1 restroom area. The following table presents a breakdown of the usage time and capacity of POIs. The capacity of the POI is defined as the maximum number of individuals who can utilise the POI concurrently. In the event of maximum capacity, the agent can begin queuing at the most of the POIs.

POI Type	Usage time	Capacity
Restroom	4 min	9
Shop	5 min	4
Smoking Area	5 min	9
Vending Machine	2 min	1
Bench	7 min	2-6

Table 7
Configuration of POIs in the simulation model; For each type of POI, a usage time and a capacity is set in the model.

4.3. Scenarios

In order to showcase the implementation and evolution of the agent's internal state, we have looked into some agents' lifespans in the model. In the following, we have looked at these data more precisely. At the start of the simulation, we have set the initial values for needs, emotions, knowledge base, persona, and the train they want to catch. They decide the rest themselves, based on their needs. All of the scenarios take place at 30th October of 2024.

4.3.1. A tourist's visit to the train station

The agent is spawned with these initial values:

- Needs: Thirst, Hunger, Nicotine, Restroom, Energy, Information respectively 0.44, 0.20, 0.25, 0.30, 0.37, True(1)
- Emotions: Valence and frustration, respectively -0.10 and 0.20
- Persona: Luggage, Age, Basic Mobility, EDQ, Smoker: No luggage, 50, 1, 0.0039, True(1)
- Knowledge base : He is a tourist and totally new to the station, therefore he does not know about the POIs in the station.
- Goal: Taking the ICE 881 to Munich train station at 14:13
- Spawn time and planned departure: 13:43 and 14:13 respectively

The agent arrives at the station at 13:43. His primary objective is to catch train 881, scheduled to depart at 14:13. Shortly after arrival, the agent retrieves platform information from a display board. Recognizing that he has sufficient time before departure, he begins addressing secondary needs. At 13:45, he notices a vending machine and quenches his thirst, reducing his thirst level to zero. He then proceeds to a platform but realizes it is incorrect. After consulting the information board again, he navigates to the correct platform. Given the combination of initial physiological states and recent fluid intake, he visits a restroom at 14:00. At 14:08, he rests briefly on a bench before successfully boarding the train at 14:13. The agent's valence level fluctuates throughout the episode due to various factors such as acquiring needed information, achieving secondary goals, or encountering obstacles (e.g., discovering the incorrect platform). Frustration levels increase in response to negative experiences in the environment but, like valence, tend to decay over time toward a neutral baseline. This work

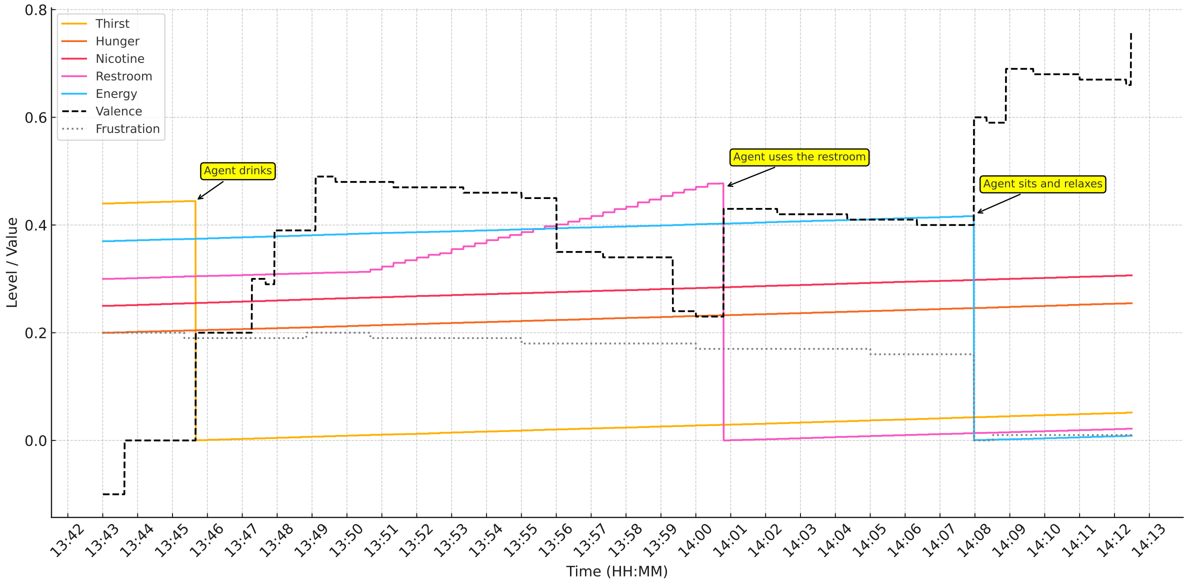

Figure 3: Temporal evolution of emotion and need levels for an agent in the simulation model. The figure illustrates how the agent's internal states emotions and physiological needs dynamically change in response to situational factors and decision-making processes within a goal-oriented scenario.

also models agent interactions, including behaviors such as requesting information from other agents, which happens at the first minute of the scenario, and exhibiting increased frustration when obstructed by them. The latter did not occur during this particular agent's run, as the station was not crowded at the time.

5. Discussion

In this paper, we proposed an approach to cognitive modeling of agents in a train station environment, incorporating both emotional states and individual needs. Each agent is assigned a persona that differentiates it from others. Agents begin with a baseline understanding of their environment, and their knowledge base is updated as they explore the simulated environment. Building on this foundation, we introduced a decision-making mechanism that allows agents to make choices based on both their internal states and external factors, such as the availability of POIs. This cognitive modeling approach was implemented in a simulation environment, where it demonstrated realistic and coherent agent behavior. Validating cognitive models remains a complex challenge due to the inherently intricate and variable nature of human cognition, as well as the unpredictability of external conditions. Our work represents an effort to rationally approximate a basic decision-making process that accounts for both internal and external influences. There is significant room for future improvement, including enhanced detail in agent modeling, parameter optimization, and refinement of the decision-making algorithms.

We believe our approach offers a foundational step toward more realistic cognitive modeling of agents in simulations. Accurate modeling of this kind can enhance our understanding of human behavior in complex environments like train stations, enabling better prediction and planning. Potential applications are wide-ranging, including disaster preparedness, crowd management, and architectural or environmental planning.

6. Conclusion & Future Work

In this work, we presented a cognitive modeling framework for simulating agents in a train station environment, incorporating individual personas, emotional states, and evolving knowledge bases. By designing a decision-making mechanism sensitive to both internal factors (such as needs and emotions) and external stimuli (such as environmental dynamics and POI availability), we aimed to move toward more realistic agent-based simulations. Our implementation demonstrated that cognitively informed agents can exhibit believable and diverse behaviors within a dynamic environment. While the model simplifies many aspects of real human cognition, it serves as a promising foundation for more complex and robust simulations of human-like decision-making.

Looking ahead, there are several promising directions for future work: (i) enhancing agent complexity by incorporating richer emotional models, social dynamics, and learning mechanisms; (ii) refining the decision-making process through more advanced heuristics or probabilistic reasoning models; (iii) parameter optimization and calibration, possibly using empirical data or machine learning techniques; and (iv) validation against real-world behavior, such as through observational studies or crowd simulation benchmarks.

Furthermore, applying this framework to more diverse environments such as airports, shopping centers, or emergency evacuation scenarios could broaden its applicability and test its generalizability. Ultimately, we hope that continued development in this area can contribute to more accurate, interpretable, and useful simulations for planning, design, and emergency preparedness.

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Declaration on Generative AI

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