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Spice: a cognitive agent framework for computational crowd simulations in complex environments

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Abstract Pedestrian behavior is an omnipresent topic, but the underlying cognitive processes and the various influences on movement behavior are still not fully understood. Nonetheless, computational simulations that predict crowd behavior are essential for safety, economics, and transport. Contemporary approaches of pedestrian behavior modeling focus strongly on the movement aspects and seldom address the rich body of research from cognitive science. Similarly, general purpose cognitive architectures are not suitable for agents that can move in spatial domains because they do not consider the profound findings of pedestrian dynamics research. Thus, multi-agent simulations of crowd behavior that strongly incorporate both research domains have not yet been fully realized. Here, we propose the cognitive agent framework *Spice*. The framework provides an approach to structure pedestrian agent models by integrating concepts of pedestrian dynamics and cognition. Further, we provide a model that implements the framework. The model solves spatial sequential choice problems in sufficient detail, including movement and cognition aspects. We apply the model in a computer simulation and validate the *Spice* approach by means of data from an uncontrolled field study. The *Spice* framework is an important starting point for further research, as we believe that fostering interdisciplinary modeling approaches will be highly beneficial to the field of pedestrian dynamics.

Keywords Spatial sequential choice · Cognitive agent · Multi-agent simulation · Pedestrian dynamics · Crowd simulation

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1 Introduction

In the field of research on pedestrian dynamics, a profound understanding of both the pedestrians physical movement as well as their cognitive abilities is a necessary prerequisite for designing pedestrian behavioral models. If implemented in a software solution, these models help to forecast pedestrian movement behavior and to support human decision makers [101] in the context of events [1,3,21,48,63], emergencies [22,29,80,98], and urban design [27,45,74,96].

There are different simulation approaches in pedestrian dynamics [30], e.g. macroscopic concepts [44] or agent-based approaches [25]. In particular, multi-agent simulations [106] are highly suitable for pedestrian behavior forecasts because each pedestrian can be simulated by an individual agent. These approaches provide a risk-free methodology to predict pedestrian movement-related phenomena that emerge from the interactions of many individual agents [47].

However, a sole focus on movement aspects cannot describe pedestrian behavior exhaustively. This is especially true in complex environments in which pedestrians solve tempo-spatial problems with regards to activity planning. Typical examples of complex environments in which activity planning is relevant are shopping malls, city districts, public events, or transport hubs. Thus, complex behavior is present in all cases in which pedestrians can choose from a series of destinations to visit. In general, the destination choice task is known as spatial sequential choice [37] or strategic pedestrian behavior [53].

The integration of movement behavior and cognitive spatial choice planning is the basis of crowd simulations in the aforementioned complex environments. However, a well-grounded pedestrian-agent framework that fully integrates cognitive modeling approaches and pedestrian dynamics research for the use in multi-agent crowd simulation is still not within reach—although several researchers have approached this topic [50,81,102]. To close this research gap, we present the cognitive agent framework *Spice*, which serves as a theoretical basis for (Sp)atial sequent(i)al choi(ce) in multi-agent pedestrian dynamics simulations. The focus of *Spice* is therefore to connect pedestrian modeling approaches and cognitive findings in a framework by providing reasonable interfaces and components for agents in crowd simulations. Thus, the framework addresses cognitive processes on an abstract level and provides a general concept for interdisciplinary pedestrian behavior modeling.

The *Spice* framework defines guidelines to implement an artificial mind for pedestrian agents in crowd simulations. To validate our concept, we developed a model that follows the *Spice* framework's mechanisms. Thus, the model provides mathematical and algorithmic methods to implement the frameworks guidelines. Moreover, we implemented the model in a computer program that builds on the pedestrian multi-agent simulation framework MomenTUM [57] and we give evidence of the model's performance and feasibility by means of data from an uncontrolled field study, a student career fair. Figure 1 shows a simulation snapshot of the career fair scenario.[1] The presented snapshot provides a typical example situation in which spatial sequential choices are made and physical movement is omnipresent.

We structured the content of this paper as follows. First, we put the work in the context of related research. In Sect. 3, we describe the cognitive agent framework. The implementation of the framework is described in Sect. 4, while Sect. 5 covers the career fair case study to

[1] The term *scenario* defines the virtual environment in which the model is applied. Here, one has to differentiate between the environment and the model, because the model can be applied to diverse scenarios without changing the model's mathematical features.

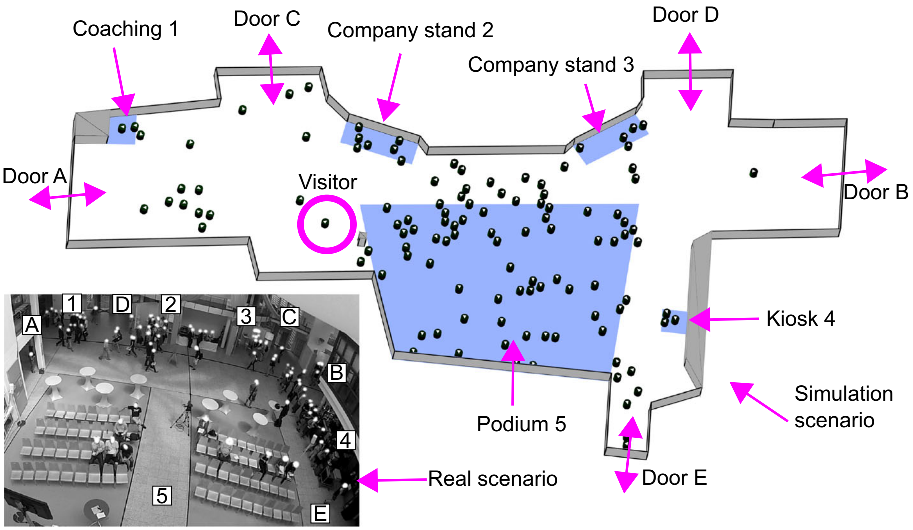

Fig. 1 A snapshot of a computer simulation of an area of a student career fair. The indicated visitor (cylinder with head-direction triangle) may choose to walk to the podium or buy a snack at the kiosk and finally leave the area through a doorway. The applied pedestrian behavior model that guides the virtual visitor is based on the *Spice* framework. The simulation was conducted in the simulation framework MomenTUM [57]. The left-bottom image shows the real-life environment of the study, recorded by a fish-eye camera

provide evidence that the *Spice* methodology correctly simulates crowd behavior in complex environments. In Sect. 6, we discuss the *Spice* approach. We conclude this paper in Sect. 7.

2 Related work

In this section, we put this paper in the research context of pedestrian behavior, spatial sequential choice, and cognitive architectures.

In pedestrian dynamics research, operational models serve to describe the pedestrian movement behavior. They can be implemented in multi-agent computer simulations to predict pedestrian walking aspects [17,46,77,82]. Following the layered modeling approach for pedestrian behavior [16,52,53], there is a tactical layer on top of the operational layer. Typically, the tactical layer models wayfinding behavior. Thus, routing models were developed to describe how pedestrian plan their routes in buildings and urban environments [49,58]. Nonetheless, wayfinding is only one of multiple spatial tasks pedestrians accomplish [41,100]. Based on the concept of [59], pedestrian behavior simulations have to implement multiple spatial task solving models, e.g. searching for an unknown location [97], wayfinding [43], or queuing [64]. The third and last modeling aspect of the three-layered behavior concept is the strategy layer. It describes decision making with regards to destination choices. Therefore, strategic models are clearly dedicated to spatial sequential choice, focusing on how pedestrians select destinations. The three layers are connected. Strategic models assign goals to the tactical layer. Similarly, tactical models provide walking targets to operational models.

In the context of pedestrian dynamics, some models consider strategic choice aspects [18,27,55,60,67,91] but there are only a few that address cognitive pedestrian agents in a broader sense [50,61,81,83,102]. Unfortunately, the reviewed models do not provide a generalized and comprehensive solution for the complex interplay of pedestrian movement behavior in association with high-level cognitive processes for spatial sequential choice in multi-agent pedestrian behavior simulations.

In a broader context, spatial sequential choice it also known as *trip chaining* [93], *action selection* [24], *location choice* [26], or *activity-based planning* [9]. In the transportation context, daily-trip and/or city-wide activity planning has been approached by multiple researchers, from early models [19] to highly sophisticated concepts [10,26,28,89]. Here, we address *trip planning*, focusing on travel by foot in complex but smaller environments such as transport hubs or public events.

From the viewpoint of the research on human-level cognition, spatial sequential choice is a complex interplay of multiple cognitive processes. Especially concerning the aspect of spatial choice planning, multiple researchers have carried out studies to explain the underlying cognitive processes [35,36,38–40,85,88]. It turned out that, for the aspect of destination choice, the fundamental factors for spatial choice plans are the distance to a destination, the waiting time at a destination, and the subjective priority of the offered activity at a certain destination.

The planning aspect is only one of multiple cognitive processes that must be realized by the artificial minds of pedestrian agents. The cognition of pedestrian agents should clearly follow the mechanisms of human cognition. Therefore, we analyzed the body of research on cognitive architectures [70]. We reviewed the ACT-R [7,92], the SOAR [68,69], and the EPIC [62] architectures and extracted the conceptual essentials to model a cognitive framework for intelligent pedestrian agents.

In summary, contemporary research misses a methodology that addresses spatial sequential choice in the context of cognitive modeling, pedestrian behavior dynamics, and feasible computational multi-agent-simulations.

3 Spice framework

We developed the *Spice* framework to approach the challenge of combining computational pedestrian behavior models and models of cognitive processes. Thus, the framework serves as a conceptual basis for elaborated pedestrian models that integrate cognitive constraints. These intelligent agents can be used to simulate pedestrian behavior in complex environments, e.g. large-scale public events.

Furthermore, our goal is to provide a general guideline of how to integrate cognitive processes in the context of agent-based crowd simulations. The framework has to be carefully balanced regarding the introduced cognitive complexity, the simulation application domain, and the computational performance. These aspects impose restrictions on the framework and require to include contemporary pedestrian behavior modeling designs. Thus, we take a well-established methodology of pedestrian agent modeling into account: the three-layered concept of walking models,[2] tactical models, and strategic models. At the same time, we address a set of cognitive processes. We define placeholders and interfaces as well as required diverse behavior and cognitive mechanisms that have to be present in a model that implements the framework. This leads to the core challenge of mapping the cognitive processes to the pedestrian dynamics modeling design, and vice versa.

[2] In pedestrian dynamics, operational models describe movement/walking behavior. Throughout this paper, we will refer to operational models (in pedestrian dynamics sense) as walking or movement models.

3.1 Framework design

The *Spice* framework implements the three-layered approach of agent-based pedestrian modeling. Here, we break down the three layers into isolated cognitive concepts and reassemble these based on the principles of cognitive architectures.

As discussed before, strategic models provide a method to select destinations to visit. Thus, strategic models must consecutively create and revise spatial choice plans. A plan comprises a sequence of goals that are physically approachable destinations. Each goal is associated with a series of spatial sub-tasks that pedestrians have to solve to realize a goal. Therefore, a pedestrian that solves a plan decomposes the plan's current topmost goal into several sub-tasks. Tactical models are applied to solve sub-tasks by routing, queuing, and similar behavior modes. During sub-task solving, the tactical models create a series of walking targets. A walking target is physically reached by the agent via its movements.

Figure 2 describes the concept of decomposing a spatial choice plan into sub-tasks and walking targets with regards to the behavior layers. Figure 3 visualizes an example plan structure that was unfolded over time. Furthermore, Fig. 4 gives an example movement path to provide an impression of the realization of the plan in Fig. 3.

The three-layered approach of solving spatial choice plans in agent-based pedestrian behavior modeling is highly similar to a human problem-solving concept that is well-known as

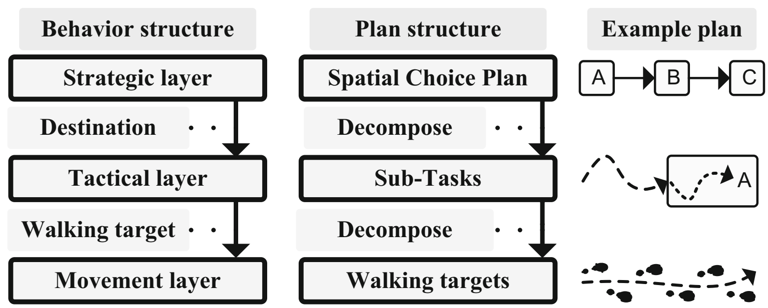

Fig. 2 An overview of the three hierarchical layers in pedestrian behavior modeling, the corresponding plan elements of a layer, and a visualization of an example plan. The hierarchical and piece-wise decomposition of a plan in goals, sub-tasks, and walking targets is omnipresent in pedestrian behavior

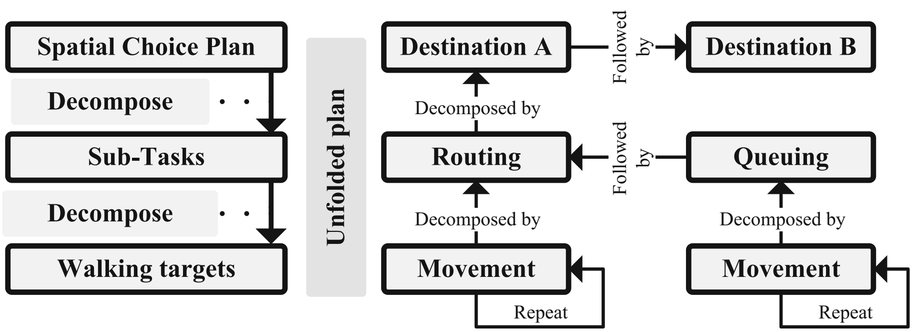

Fig. 3 An example plan that was implemented by a pedestrian agent. The composition relationships of the plan are shown. The spatial choice plan comprises the destination A and B. The goal A is unfolded and is based on a routing task followed by a queuing task. The pedestrian fulfills both tasks by a series of movements

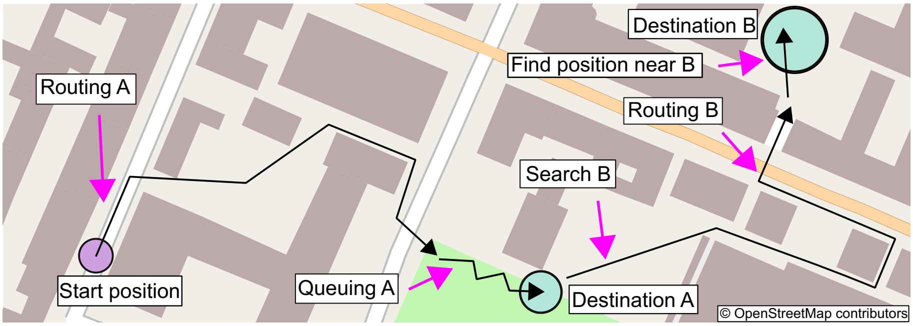

Fig. 4 An example trajectory of a pedestrian agent that realizes the spatial choice plan including all sub-tasks and movement behavior of Fig. 3

the *means-end problem-solving* approach [5,6,79,106]. The basis of the *means-end problem-solving* is to change the current state space stepwise to reach a solution state of a problem. Sub-goals and goals can be understood as *ends*, and the options of actions to reach the goals are *means*. Furthermore, people may revise the current plan because of some intrinsic or extrinsic change in the problem space. Such non-persistent plans demand an *open-minded commitment* towards the current *ends* [106].

We see that the typical pedestrian behavior modeling method and the basics of human-level problem-solving are identical concepts. The good agreement between the approaches is due to the fact that pedestrian cognition is a subset of the skills of human-level cognition. This serves as the theoretical basis of the *Spice* framework.

Based on this, we identify the mandatory cognitive processes that correspond to the pedestrian modeling layers. A review of the cognitive architecture literature, especially the ACT-R, gives us a good understanding of mandatory processes of a human-level cognitive system. The ACT-R defines an external world, perception, intention, motor, knowledge, and production rules [92]. Using this basis, we see that the three-layered pedestrian modeling approach is not optimal. The approach does not include a perception or memory module—and does not consider the modes of tactical behavior as separate behavior mechanisms. Thus, it is mandatory to extend the three-layered approach regarding three aspects: perception, memory, and operation.

Each behavior layer is connected to the perception model. For example, the movement procedures react directly to visible obstacles. To perform routing behavior, agents need to scan their environment to derive information for route choices. The same holds true for strategic behavior. The agents perceive their environment and gather information to generate or revise spatial plans. In summary, all layers need to be connected to a perception component.

A memory module holds information about facts, behavior and object relationships, and has to be connected to all pedestrian behavior layers. On the operational and tactical layers, the spatial knowledge and physical relationships of objects are most important. For example, pedestrians need to localize themselves in their cognitive maps beyond their perceivable environment [37]. Also, fact knowledge is applied in both layers. For example, an agent needs to identify social group members for social-based movement [84]. The strategic layer utilizes knowledge regarding destinations. For example, the type of actions that can be performed at a specific goal location is based on learned behavior [95]. In general, all layers use the memory to store and read manifold information regarding their respective tasks. In summary, all layers need to be connected to a memory component.

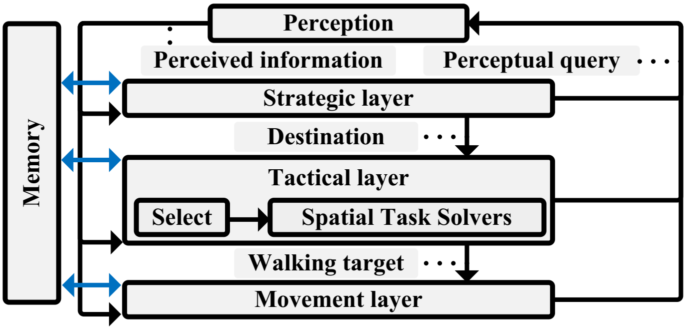

Fig. 5 The schema shows how we extended the original methodology of pedestrian behavior modeling [53] for the *Spice* framework. We explicitly added a perception and memory module and extended the tactical layer as a container for spatial task-solving mechanisms

The tactical models have to be understood as operations (*means*) of an agent. This requires an autonomous spatial decision making mechanism in the behavior modeling layer of pedestrians. The mechanism selects the correct operation to solve the strategic goal at hand [59]. This corresponds to the aforementioned sub-task generation by decomposing the current topmost goal of a plan.

We implemented all of the extensions in the original concept of pedestrian behavior modeling and provide the resulting structure in Fig. 5

The extended version of the pedestrian agent modeling layers enables us to set up a cognitive agent framework that includes the well-known cognitive components of human-level cognition.

The movement layer of pedestrian walking utilizes the perception and the memory processes. Thus, the movement model is the motor module of a cognitive framework because it ultimately changes the agent's position in the external world. The motor module—an independent and autonomous control loop within the agent—processes given walking targets.

The tactical layer also applies the perception and memory processes. Furthermore, the tactical concept of selecting a spatial task solving mechanism (e.g. queuing or routing) is an autonomous and self-driven control loop within the agent. This can be explained by means of an example. If people have to queue up, they do so without activating high-level cognitive decision making. They implicitly learned to queue up by observing others [34]. Therefore, the tactical model layer corresponds to a set of self-guided operations and defines an operation module.

The strategic layer includes most of the cognitive capacities of an agent. The layer applies the perception, memory, preference, deduction, and planning processes. Here, the preference module models the intention module known from the ACT-R. The deduction and planning modules are a subset of the general purpose mechanisms of decision making module within traditional cognitive architectures.

In a cognitive architecture, the memory modules are often the center of the system and are connected to most of the other modules. The SOAR architecture is an excellent example of this type of design [68]. This memory centered approach is well-suited for a pedestrian agent cognitive framework. For example, the pedestrian behavior layers communicate by means of the spatial choice plan that resides in the memory.

We integrate all of the previous views into a single concept. The general design of the cognitive agent framework is shown in Fig. 6.

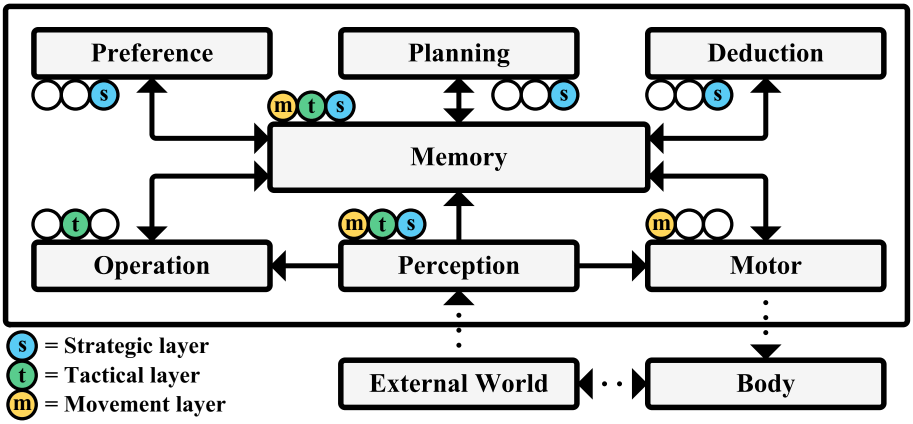

Fig. 6 The structural design of the *Spice* framework. The corresponding pedestrian behavior layers are indicated by symbols. The connectors define the information flow between the modules

Finally, we define the dynamic aspects of the *Spice* framework. Again, we analyze the three-layered pedestrian modeling concept. It includes three independent (but communicating) control loops, which correspond to the movement layer, tactical layer, and strategic layer. Communication between the control loops is realized by providing information regarding the current plan in a top-down manner by means of the memory.

The movement is an automatic motor action that is functionally independent of the tactical and strategic layer. The walking target is the primary goal of the motor module, and is the low-level part of the current spatial choice plan. The tactical layer derives the walking target and updates the motor's goal accordingly. Similar to the movement layer, the tactical layer operates functionally independent from the other layers. It finds solutions to the task of reaching a goal that was provided by the strategic layer via the memory. The strategic layer finds and adapts the current spatial plan and is the hierarchically topmost control loop. The next destination is the goal that is provided to the tactical layer. In general, the main interface between the controls is the memory, because each layer accesses a given part of the plan information.

Figure 7 provides the *Spice* framework's design of Fig. 6 from perspective of the control loops.

3.2 Module design

Up to here, the modules of the *Spice* framework are generic containers of cognitive processes. In the following, we will explain the functions of the processes in more detail, from a pedestrian dynamics point of view and, in order to keep the framework as lean as possible, we will focus explicitly on the components mandatory for spatial sequential choice in context of pedestrian behavior. This is of high importance because the framework will be implemented in a multi-agent simulation that should provide good computational performance. Nonetheless, we will not provide specific implementations of the models in this section, but will instead focus on explaining the modules with regard to pedestrian behavior simulations. An example implementation of the framework is given in Sect. 4.

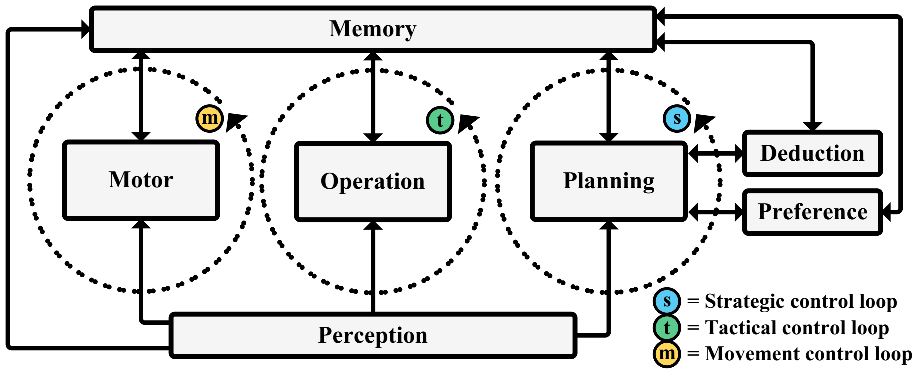

Fig. 7 A schema of the *Spice* framework with focus on the control loops. The dashed lines indicate independent control loops that exist for each pedestrian behavior layer. The solid connectors define the information flow between the modules. The memory is the interface between the control loops

In the previous section, we identified seven different and interconnected cognitive processes: preference, planning, deduction, memory, operation, perception, and motor. Each process has to fulfill one or multiple cognitive functions of a pedestrian agent.

The memory is the container of information regarding the dynamic and persistent facts, behaviors, and relationships of the agent, other pedestrians, and the environment [42,75,94]. The knowledge is structured and defined in an information network [6] in the sense of object-orientated design [86]. This leads to a fixed set of types and parts of the memory; thus, the agent cannot learn new categories of objects. This is a highly important performance aspect of pedestrian multi-agent-simulation. In such a simulation, all element types of the simulation are known to the simulation's agents. The pedestrian agents will never face objects from non-pedestrian application domains. Therefore, the agents do not need to alter their given memory structure. However, this does not neglect that the agents are able to learn within the context of their initial memory design. For example, a cognitive map can be modeled by a graph in the two-dimensional plane [58]. Pedestrians that have partial knowledge of the graph can learn the position and relations of objects in the environment by means of the perception process. Therefore, learning is directly coupled to the persistent aspects of the knowledge, which can be seen as the long-term memory. The persistent pieces of information of the simulation do not change over the course of a simulation, and they are already known or can be learned. In contrast, dynamic pieces of information can change at any moment of time, e.g. the availability of a goal or the current behavior of the agent. Hence, dynamic information are in flow regarding the tempo-spatial dynamics of the simulation; thus, dynamic knowledge can be understood as short-term memory information.

The memory also includes an information network regarding the behavior elements of an agent. It addresses the goals, the plan, and the agent's implemented behavior. In the framework, a goal is represented as a memory element that formalizes the properties of a specific destination. A plan defines a set of ordered goals. The first (topmost) goal is the current objective pursued by the agent. As discussed before, the topmost goal is decomposed into spatial sub-tasks. This requires the current tactical sub-task as well as the walking target to be stored as parts of the plan.

The visually perceived pieces of information are complex, and they are subject to ongoing changes due to the movement of the agent and other pedestrians in a crowd simulation. In order to keep the computational performance at a reasonable complexity, the perception process should not address complex pattern recognition tasks. Therefore, we focus only on the perceptual domains that have high relevance to spatial decision making [37] in the context of pedestrian simulations. We address the perception regarding visibility, distance, and crowd. The visibility perception checks whether destinations, areas, and other agents are visible to an agent. An important aspect of visibility perception is that it updates the spatial knowledge. Hence, the visibility perception is the main input for learning external information. Another perception concept is the distance and crowd perception. The distance perception provides an estimation of the traveling distances to destinations, other agents, and obstacles. Similarly, the crowd perception estimates the number of people at a location. We also refer to the crowd perception as occupancy perception, because it enables the agent to perceive the numerosity of crowds. In addition, the perception cooperates with the motor process to enable self-orientation in the simulation space. Thus, we assume that the perception process provides an automatic updating of the spatial memory [99].

The preference process provide functions that describe how the agent's desire, motivation, or interest in goals change over time. Thus, the preferences serve to model the spatial sequential choice aspect of priority [37]. Hence, each preference process describes the cognitive approach to a goal [33] and therefore an activity offered at a destination. Such activities are, for example: buying a train ticket, enjoying a music act at a festival, or visiting the restrooms. In general, multiple goals can serve to fulfill the same underlying preference. Each destination is linked to one or multiple preferences that model the drive to engage in the activity offered at the goal's location. Typically, subjective preference is driven by a multitude of factors, including external (e.g. advertisements) and internal stimuli (e.g. biological needs) However, the preference process has to abstract from such factors in order to stay within reasonable modeling complexity.

The deduction process is a mandatory process that we see as an expert system [13] with a focus on pedestrian simulations. Therefore, the agents can deduce a set of well-defined information. For example, the agent has to monitor if an activity can be performed at the moment or in the near future. Furthermore, the agent may check if the activity of the topmost goal of a plan is being performed, or if an activity can be performed multiple times. Such checks are of core relevance for agents in spatial sequential choice simulations and guide the planning process. The complexity of the checks can vary due to the deduction process implementation. Thus, the process has a significant impact on the complexity of the virtual world. Nonetheless, a complex deduction process implementation may be avoided at all times to ensure good multi-agent simulation performance.

The planning process comprises three mechanisms: goal evaluation, scheduling, and re-planning check. In the evaluation phase, the distance, the occupancy, and the priority of each goal are mathematically combined to the goals' valences as a basis for the planning. This approach should be based on the explanations of [37], who describes that it is highly likely that people perform spatial sequential choices by intra-alternative and not by intra-attribute evaluation. Intra-attribute evaluation means that each single attribute of alternatives is compared individually, e.g. first the distance, then the occupancy. Intra-alternative evaluation describes that the attributes of alternatives are compared jointly; thus, an abstract valence is created for all attributes per alternative. The scheduling mechanism makes use of the valence of each goal, perception information, and deduced information to construct a plan that comprises an ordered set of goals. Planning is a wide research field, and many different methodologies might be used here. However, the findings of [37] regarding spatial sequential choice provide the core assumptions for the implementation of the planning process. The re-planning mechanism monitors the goals' valences and indicates the need of a plan revision. Here, the reactivity dilemma need to be solved [87].

Humans learn behavior operations and operation sequences that can be applied in different situation [6,104]. In spatial sequential choice, there are also typical behavior operations that are applied to solve spatial tasks in a pedestrian simulation context. The operation process analyzes the topmost goal of a plan and selects the appropriate tactical behavior model that serves to reach the goal. Thus, the operation process switches between tactical models (*means*) based on the current task (*ends*) and the agent-environment situation. All tactical behavior models solve spatial tasks by repetitively determining walking targets in the agent's field of view.

The movement is typically the single motor action pedestrians are capable of in pedestrian simulation. Hence, the motor process moves, accelerates, and rotates the agent to change its position in the simulation environment. The motor actions are guided by walking targets provided by the operation process. If a pedestrian is supposed to stand still, the motor switches to a standing mode that enables the agent to maintain its position despite physical interaction with other agents. Thus, standing is used to model the interaction with a destination, e.g. buying a newspaper at the head of a queue.

The *Spice* framework comprises multiple functions that can be implemented in varying detail. This means that models that implement the framework may differ heavily in their complexity. In the next section, we provide an example model that builds on the principle of the framework. The model shows a clear trade-off between computational complexity and mandatory cognitive functionality.

4 Spice example model

Pedestrian dynamics is a research field in which the behavior of pedestrian is studied, modeled, and simulated [16,30,74]. Multi-agent crowd simulations build upon these pedestrian behavior models to forecast the crowd's movement in different spatial situations [63,96].

In the previous section, we described the *Spice* framework, which integrates the modeling concepts of pedestrian behavior, research on spatial sequential choice, and cognitive architectures. Here, we propose a simulation model that is based on the *Spice* framework. The model can be seen as the example implementation of the framework—but also as a highly capable pedestrian behavior model that is used to simulate spatial sequential choices and the agents' movement in multi-agent pedestrian simulations in complex environments.

It is important to note that the *Spice* framework introduces cognitive constraints for the model via the frameworks dynamic and static structure. However, the framework does not demand that all of the model's components are per se cognitive concepts. This tolerant view of the framework enables researchers to include models that are not yet fully grounded in cognitive sciences but are well-known in pedestrian dynamics, e.g. the social force model [46]. We believe that this approach fosters interdisciplinary research. Consequently, we also integrate some pedestrian models in the example implementation of *Spice* which are functionally highly valuable in pedestrian simulations but are still not fully grounded in cognitive sciences.

In the subsequent sections, we will briefly describe the implementations of the model's processes. However, we will explain the planning process in more detail because it is highly valuable regarding the aspects of spatial sequential choice. Figure 8 provides an overview of the nested models of the *Spice* framework implementation.

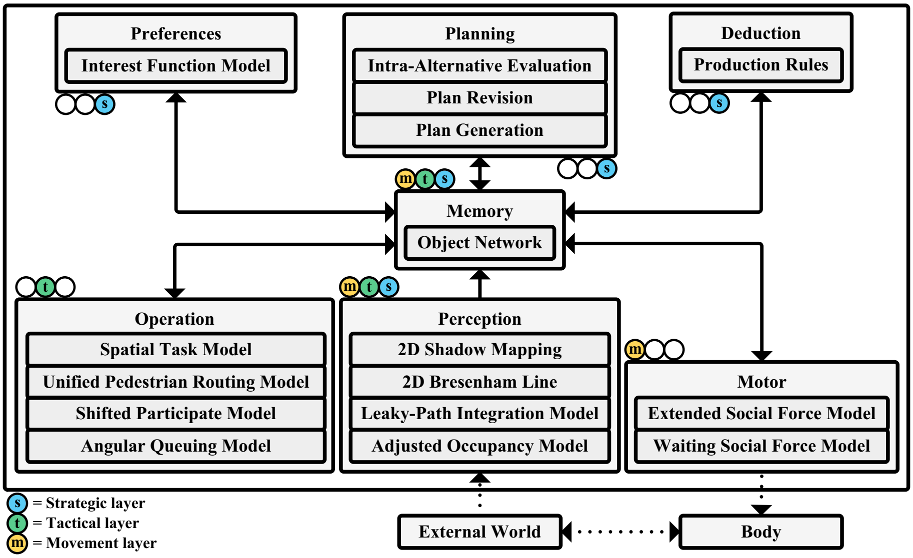

Fig. 8 The schema gives an overview of the nested models that are implemented in the proposed *Spice*-based model

4.1 Memory implementation

The memory implementation is a network structure that models the environment and individual information of a pedestrian agent. The knowledge-representation covers a static but complete subset of the information of the pedestrian behavior domain. The memory is dynamic in the sense that every environment provides different contents for the definitions, and that the agents may only have access to a subset of all pieces of information of a scenario. Learning effects enable the agents to enrich their own memory with information concerning the scenario. Furthermore, the memory provides access to the knowledge for all other cognitive processes of the model.

The memory is strictly modeled applying object-orientated analysis and design methods. This provides sufficient detail and flexibility for a pedestrian simulation. In Fig. 9, we depict the memory elements and their relations on an abstract level.

The environment network comprises other pedestrians, the topology as a graph abstraction, areas, and obstacles. These elements define a scenario. The environment memory does not solely address spatial properties but also further information, which are strictly related to the scenario elements. For example, a destination area may have opening hours. Thus, information like these are part of the area's element. The environment information can be learned by an agent via exposure. For example, the agent might only have little prior knowledge about the scenario, but will get to know details about the destinations by means of exploration and thanks to its perception process.

The agent has memory elements that describe its physical information, plan, social context, and preferences. The plan of an agent comprises goals, a current tactical operation, and a walking target. The social context of an agent has influence on the realization of the mechanisms of the strategical, tactical, and operational layers. For example, a social group leader can change the goals of the social group members and, thus, their behavior. We model

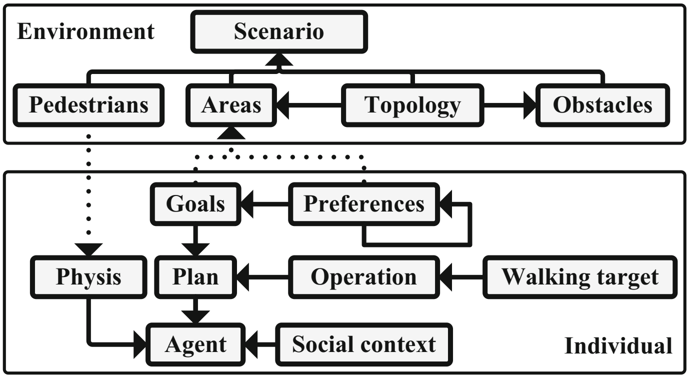

Fig. 9 The schema of the agent's memory. The dotted arrows indicate an *is associated with* and the solid arrows a *is part of* relationship. The environment part integrates all information objects that exist in the scenario. The content of an agent's memory primarily consists of a subset of the environment information, which serves to model partial knowledge and to enable learning effects. The internal part models all agent information that are associated with behavior, physical information, and social context

the social context as a fundamental fact that does not have to be learned by an agent. The physical element models the agent's body properties.

There are connections between and within the environmental and individual memory elements. These connections model direct relations of information. For example, a pedestrian can perceive other agents and capture their physical information. Another example is the connection between the preferences and the areas. Thus, the agent can associate that some areas provide activities that satisfy individual preferences.

4.2 Perception implementation

For the perception process, we include models of distance, visibility, and occupancy perception. We make use of the leaky path integration model for distance estimation [71], and we extended the method to provide a scaling factor for environments of different sizes. In order to estimate the number of pedestrians at a location, we use a variant of the occupancy model [2]. Here, we distinguish the occupancy at queues, e.g. at a counter, and the occupancy at locations to stay at, e.g. standing in front of a stage. For location visibility checks, we apply shadow mapping [103]. The map provides visibility polygons that can be understood as an isovist [15] based on the perspectives of all goal locations. For agent and obstacle visibility checks, the Bresenham's line algorithm [20] is applied on a grid that covers the simulation plane. The line reaches from the perceiving agent to another object—and if the line is blocked by an obstacle on the grid, this means that the object is not visible.

4.3 Preference implementation

The preference process is based on the interest function model [60]. The model describes the changes in preference over time in form of a sigmoid function. The model includes re-occurring preference by stringing together multiple varying sigmoid curves over time. One-time preferences can be described by a single sigmoid curve. Furthermore, multiple goals can serve to fulfill the same underlying preference. Consequently, each goal is linked to a preference process that models the internal drive to engage in the activity offered at one or

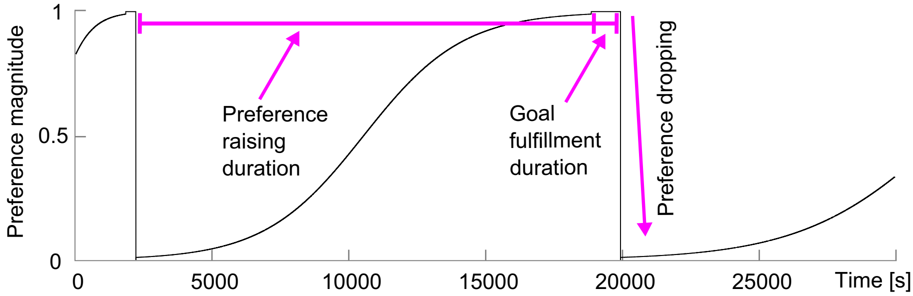

Fig. 10 An example plot of a re-occurring preference function. The phases are preference raising, preference fulfilling, and, if the goal is not a one-time activity, raising again after dropping. The duration for the preference raising is estimated based on the interest function [60]. The duration for the fulfillment of an activity is estimated by a Gamma distribution. A goal can only be fulfilled if the agent is physically present at the location of the respective goal. This indicates that agents can perform activities before and after the function reaches its peak

more goal locations. Social groups share the same preferences. This supports the simulation of homogeneous behavior within pedestrian groups (see Sect. 4.8).

The interest function model is grounded in the cognitive concept of goal-related memory accessibility [4,6,8] and in the idea of the cognitive approach to goals [32,33], brought together in a study regarding widespread interest [76].

Figure 10 provides an example plot of the course of an interest function.

An important aspect for the usage of the model is that every area that is a destination can be associated with a set of activities. Each activity type is associated with a preference. Thus, the preference models the priority aspect of destinations in the context of spatial sequential choice [37].

4.4 Deduction implementation

For the deduction process, we implemented static production rules in form of an expert system [13] to provide a fast deduction method. The main task of the deduction process is to translate known information to new facts. We focus on the two most important aspects in the pedestrian context. The deduction process checks whether an activity offered at a goal location can be performed and whether the activity related to the current topmost goal is in the state of being performed.

To evaluate if an activity is available, the model checks the preconditions of the activity. Thus, each goal is associated to the preferences of the destinations predecessors and to information concerning the temporal availability.

For the realization check, each goal is associated with a state that is based on the agent's behavior, including proximity to the goal's location. The realization state can only be changed for the top goal of the current plan.

These two mechanisms are usually sufficient for pedestrian simulations, but can be extended if further information is provided. For example, it is possible to introduce the aspect of time pressure to physically reach an activity location (due to availability times) by means of the deduction process.

4.5 Planning implementation

The planning process implementation is the core component of the agent's activity planning. The process integrates an ongoing evaluation of internal and external stimuli to adapt the agent's plan if necessary. Because we aim to describe a spatial sequential plan, we decided to focus on the main attributes of destinations [37]: distance, occupancy, and priority. The distances and occupancies are given by the perception process, and the priorities are given by the preference processes. Additionally, the planning process applies goal-related information provided by the deduction process. The planning process has three phases: goal evaluation, re-planning, and scheduling.

In the evaluation phase, the attributes of each goal are mathematically combined to the goal's valence as the basis for the planning. As discussed above, [37] provides strong evidence that it is highly likely that people perform spatial sequential choice by intra-alternative and not by intra-attribute evaluation. Thus, the goals are primarily ranked by a combined value based on the attributes of each goal. However, [37] states that "[...] it is not clear how subjects accomplished this." (p. 97). Therefore, we examined different attribute combination methods and found that the most reasonable agent behavior is provided if the attributes are sigmoid scaled and dynamically weighted. In the evaluation phase of the planning process, we combine the attributes k of a goal j, which have a distance $d_{j,t}$, an occupancy $o_{j,t}$, and a priority $p_{j,t,i}$ of preference type i, to calculate the valence $v_{j,t}$ at time t as given in Eq. 1 for an agent. It is important to note that the attributes are already normalized in a scale between zero and one by the other processes.

$$v_{j,t} = \Upsilon(1 - 2 \cdot d_{j,t}) \cdot \Lambda_d + \Upsilon(1 - 2 \cdot o_{j,t}) \cdot \Lambda_q + p_{j,t,i} \cdot \Lambda_p \tag{1}$$

Here, we first scale the values of the distance and the occupancy attribute from [0, 1] to [− 1, 1] and apply the sigmoid function Υ on both. The priority attribute is already sigmoid scaled, because the interest function model utilizes sigmoid curves. The sigmoid approach emphases the non-linear attribute evaluation of stimuli regarding psychological proximity, an idea that originates from field theory [73] and is used in connection with decision making models in economics [56]. The sigmoid function Υ is defined by:

$$\Upsilon(y) = \left(1 + e^{(-y \cdot z)}\right)^{-1} \tag{2}$$

The parameter $z > 0$ defines the strength of the scaling. Most commonly, we apply the value of $z = 10$. The higher the value of z, the lesser the agent's sensibility to changes of the attribute, e.g. if $z = 50$, an attribute value lower than 0.4 will be seen as nearly zero, and a value larger than 0.6 is interpreted as nearly one.

Before combining the sigmoid-scaled attributes in Eq. 1, each attribute is weighted by Λ. The Λ approach enables to handle indistinguishable attribute sets, e.g. if all locations are in the same proximity. Thus, other attribute types provide more impact in the final valence of each goal if another attribute type is indistinguishable. The value of Λ_k, k stands for the attributes d, o, or p, is computed by the maximal difference $k_{max} - k_{min}$ of the attribute k of all goals j divided by the sum of the perceivable differences of all attributes. In simulations studies, we found that the Λ concept is superior to linear or other concepts of weighting regarding the comprehensibility of the agents behavior. It is important to note that the Λ method does not contradict the intra-alternative concept of [37], but adds an evaluation layer.

$$\Lambda_k = (k_{max} - k_{min}) / \sum_{c}^{d,o,p} (c_{max} - c_{min}) \tag{3}$$

In pedestrian behavior simulations, a single spatial space is used a as simulation scenario, e.g. a building, a room, a district, or a city. Therefore, every simulation scenario is connected to other spatial systems via entrances and exits, e.g. doorways. We understand these as transit goals, which hide more complex goal structures. Thus, each complex goal structure describes a complex spatial environment, e.g. a complete building in which multiple further unknown goals may reside. This leads to the problem that the occupancy and distance properties for the hidden goals are unknown. As a consequence, $v_{j,t}$ cannot be computed based on Eq. 1 for transit goals. However, the value of $p_{j,t,i}$ integrates all goals accumulated by the complex goal and provides sufficient information to compute a valence. Hence, $v_{j,t} = p_{j,t,i}$ is a valid valence of a transit goal j. This view provides an interface to embed the spatial plan of an agent in a more complex hierarchical schedule [75].

For the scheduling phase, the number of goals to schedule is limited by the plan size n, which is drawn from a Gamma distribution every time a plan is created. The mean of the distribution is 4 and has a standard deviation of 2. These values were applied to follow the general guideline of the working memory capacity [12,23]. The study of [40] highly supports the mean and standard deviation assumptions. They showed that forcing participants to make plans using long-term memory cues will increase the planning duration in the case of multiple goals. This indicates a natural plan-size threshold in spatial sequential choice.

The planning duration is simulated via an exponential function based on the data from experiment 3 of [40]. In the study, people defined activity plans based on the goals' distances. We chose experiment 3 because the task presented is highly similar and clearly refers to spatial sequential choice. Therefore, the mean schedule duration ψ for scheduling n goals can be described by:

$$\psi(n) = 8.403 \cdot n^{0.6038} - 8.403 \tag{4}$$

The schedule phase is defined as bringing n goals in a sequential order regarding their current valences $v_{j,t}$ and deduced information. Thus, the task is to sort out goals and to put the goals in a certain order to determine the schedule Ω.

Initially, the procedure checks whether hierarchical planning takes place and evaluates whether the next goal is in the current spatial scale or if a transit destination has to be visited. This is done by computing the median valence $m_{j,t}$ of all non-transit goals and comparing it to the best valence $b_{j,t}$ of all transit goals. If $m_{j,t} < b_{j,t}$, the corresponding transit goal is set as the topmost goal—and if $m_{j,t} \geq b_{j,t}$, the topmost goal of the plan is within the current spatial domain.

If no hierarchical planning is given, a set of operations is executed to bring the plan in a rational goal order. Figure 11 provides the different operation by example.

At the beginning, the goals are ordered regarding their valence $v_{j,t}$.

In the next two steps, the deduction information is used to change the plan. If a goal was performed already (Fig. 11a) or if a goal is unavailable (Fig. 11b), it is removed from the plan.

In the next processing steps, all goals with the same underlying preference are evaluated. If the valence of a goal is less than that of another goal, it is removed, provided that the preferences are identical (Fig. 11c).

Another important operation is to swap the position of the top goal and the second goal if the top goal is a transit area from which the pedestrian entered the scenario (Fig. 11d). This is done only for the first-ever computed plan of an agent, substantiating the assumption that a pedestrian entering the simulation area had the topmost goal of visiting this area, which contradicts leaving the area immediately.

Goals that are currently not performable due to preference dependencies will still be scheduled but put behind available predecessor goals (Fig. 11e). This mechanism ensures logically correct plans, e.g. buying a ticket before entering the train can be planned without re-planning in between, even if the task of buying a ticket was not performed yet.

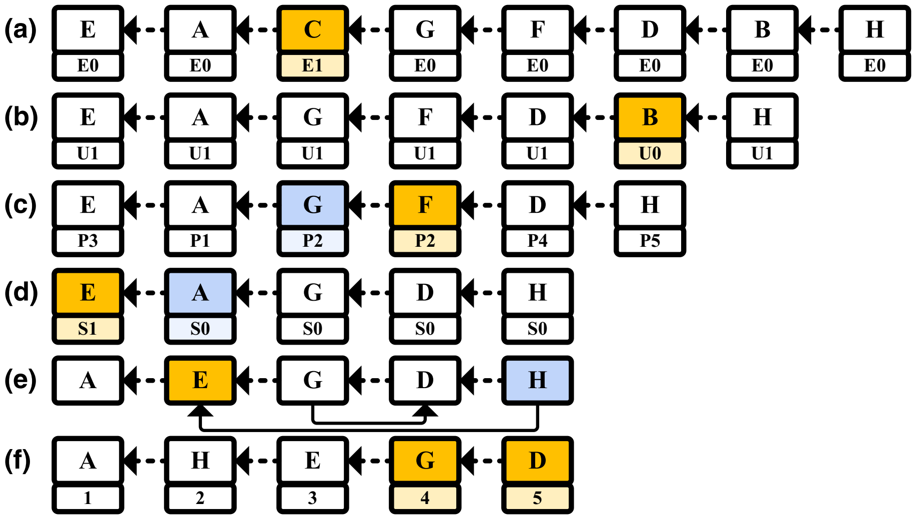

Fig. 11 An example plan generation that shows the processing steps by example: **a** remove *C* because it was already performed; **b** remove *B* because it is unavailable; **c** remove *F* because it has the same preference as *G*, but has a smaller valence; **d** swap *E* and *A* if it is the first-time planning and if *A* is the entrance area of the agent; **e** put *H* before *E* because it is *E*'s predecessor preference; **f** remove *G* and *D* because the plan's length is $n = 3$

Finally, the plan size is reduced to n elements (Fig. 11f).

After scheduling, the $v_{j,t}$ values of the currently created plan are stored in the memory in the form of *as planned valences* $v_{j,r}$. Furthermore, the current topmost goal can now be used by other processes. The deduction process performs realization checks, and the operation process selects appropriate behavior based on the topmost goal's properties.

In many situations, re-planning is mandatory. Clearly, re-planning is activated every time a plan is empty. This situation is present if a pedestrian is put into the simulation as a new agent, and during longer simulations.

$$\Omega = \emptyset \tag{5}$$

However, re-planning is also required if the top goal of the current plan changes its availability state. Eq. 6 determines whether the topmost goal is currently available, using an availability check ava, or whether the goal is performable, applying the performable check $perf$ regarding predecessors.

$$\neg ava(t, \Omega_1) \text{ or } \neg perf(\Omega_s, \Omega_1) \tag{6}$$

Here, Ω_1 is the top goal.

The last condition for re-planning is if the valence of a goal with a higher planning position changed significantly compared to the next lower goal's valence. The pedestrian agent evaluates these conditions only for visible goals; thus, we simulate reactive and situative re-planning [51]. An agent creates a new plan if the following logical expression is valid:

$$\exists j \in \Omega_s | perf(\Omega_s, \Omega_{j-1}) \wedge ((v_{j,r} - v_{j-1,r}) - (v_{j,t} - v_{j-1,t})) \geq j \cdot \zeta \tag{7}$$

Here, Ω_s defines the goals of Ω that the agent can perceive. Eq. 7 describes that re-planning is required if the current valence $v_{j-1,t}$ of a visible goal $\Omega_{j-1} \in \Omega_s$ is smaller than the valence $v_{j,t}$ of the next lower visible goal $j \in \Omega_s$. Hereby, the difference in valence is related to the *as planned* valences $v_{j-1,r}$ and $v_{j,r}$, including the position of a next higher goal in the plan $j \cdot \zeta$ as tolerance. Thus, every time the *as planned* valences are in discrepancy regarding the perceived valences, re-planning is performed to adapt the agent's behavior to changing environments. The parameter $\zeta \in]0, 2]$ defines the reactivity of the agent's re-planning. If ζ is near zero, the agent is extremely reactive—and if $\zeta = 2$, the agent is immune to valence changes. Furthermore, re-planning cannot be activated during scheduling.

In general, planning is a huge field, e.g. shown by research in artificial intelligence [87] and agent-based modeling [106]. Thus, one can easily identify multiple more aspects that can be added to the planning procedure to increase the capabilities of the agents. However, our goal was to create a lean model and to include the most influential planning components for spatial sequential choice in pedestrians. Our approach keeps the concept as concise as possible to ensure reproducibility of the introduced cause-and-effect relations.

4.6 Operation implementation

The operation process selects behavior models of pedestrian dynamics in order to fulfill the sub-tasks of the current top goal of a spatial plan.

We implemented the operation process by applying the spatial task model of [59]. The spatial task model is a generic concept that is designed to handle multiple tactical behavior models. For the *Spice* example model, we implemented a wayfinding, a queuing, and a staying model. In order to solve wayfinding behavior, we use the unified pedestrian routing model [58], which operates on routing graphs [11,65]. The model describes the routing behavior of pedestrians based on survey-based and route-based spatial knowledge [105]. For the queuing behavior, we apply a variant of the angular queuing model [59,64]. For the staying behavior, we apply the shifted participating model [59]. The model describes how pedestrians find a position to remain and stand at in an open space, as part of a crowd, in front of an object of interest. This is done by a two-dimensional computational gamble experiment.

Each of these tactical models repetitively finds a walking target that is a position in the agent's visual field to guide the motor process.

4.7 Motor implementation

The movement model uses the walking target as a spatial goal, e.g. the next position in the queue or the next street junction to head to. For movement, we apply the social force model [46], which was improved regarding numerical stability [66]. In the case that pedestrians stand still, we apply a second variant of the social force model for standing pedestrians [54].

4.8 Social group implementation

In pedestrian dynamics simulations, social groups are an important factor that influences the overall behavior of crowds. If social groups are ignored, this will often lead to erroneous forecasts of pedestrian behavior. This is a direct consequence of research on the complex behavior of social groups [14,78,84,90]. However, we do not include group decision making or similar mechanisms, which could account for group-based spatial sequential choice. Still, we apply the social group concept of following the leader [31]. We added specific social properties to the agent memory element: the social group affiliation and the social group leader. Both are mandatory to simulate leader-follower behavior of groups and to describe the dependencies between social group members. In our case, a single pedestrian agent is the leader of the social group, and all social group members apply the same behavior operations as the leader. This approach enables groups of people to stay together and to interact with the environment in a similar manner.

5 Field study

In the previous section, we described a model that implements the *Spice* framework. In this section, we validate the model and, thus, also the framework.

We conducted an uncontrolled field study and measured various data in order to apply the *Spice*-based model on this scenario. The goal was to evaluate that the concepts of the *Spice* framework are suitable to accurately simulate pedestrian behavior - and there is evidence that the *Spice* framework is an appropriate methodology to model artificial minds of pedestrian agents for crowd simulations in complex environments.

The uncontrolled field study is a student career fair. In Sect. 5.1, we give details of the scenario and the simulation input data. The measured validation data is described in Sect. 5.2. Based on the validation data, we conducted a macroscopic analysis and parameter tuning—discussed in Sect. 5.3. A macroscopic analysis evaluates whether the emerging multi-agent patterns correspond to the measured data. A microscopic analysis of the simulation results is given in Sect. 5.4. If the behavior of individual pedestrians is quantitatively identical to the real visitors of the career fair, the agents' decision making is correct. Both methods will show that the *Spice* approach can accurately forecast the spatial sequential choices of individual pedestrians and the related emerging crowd behavior patterns.

It is important to note that we apply the career fair scenario for parameter tuning and validation. This is, however, a mandatory preliminary validation step to evaluate whether the *Spice* method is general capable of simulating pedestrian behavior correctly. This implies that, in the course of future research, several more validation studies will have to be carried out to prove that the approach is generalizable for different scenarios.

We implemented the *Spice* model in the pedestrian multi-agent simulation framework MomenTUM[3] [57]. The framework follows the three-layered concept of pedestrian behavior modeling, which includes strategic behavior, tactical behavior, and walking behavior. Hence, we implemented each part of the model in the corresponding components of MomenTUM.

For an initial impression, Fig. 12 shows a snapshot of the simulation's visualization.

5.1 Career fair scenario

We scientifically observed a student career fair with cameras and used that data for our validation simulations. A snapshot of the area of the uncontrolled field study is shown in Fig. 1. The scenario is a part of a large career fair. It provides multiple locations the students can interact with as well as multiple entrances and exits. In the validation scenario, the locations the pedestrians can perform activities at are labeled coaching (1), company stands (2), company (3), kiosk (4) and podium (5). The entrances and exits are numbered (A) to (E). (A) and (B) are the entrances and exits that exhibited heavy pedestrian traffic. All locations were visible and comprehensible in the video footage; thus, we extracted their locations based on the floor plans and on-sight adjustments.

We used approximately 33 min of the video material to accurately measure the necessary simulation input data. The video footage was annotated by three human reviewers who had identical guidelines:

[3] https://github.com/tumcms/MomenTUM.

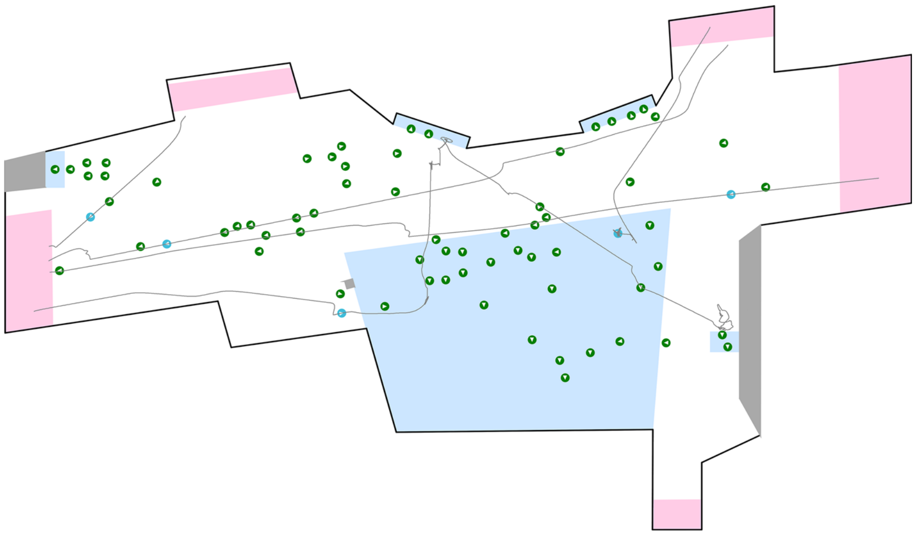

Fig. 12 A snapshot of the career fair simulation. The green circles are pedestrians. The blue areas are service points of queues and areas where pedestrians can stay to interact with the location. The pink areas are exits and entrances. The movement trajectories of five different pedestrians (marked in blue) are shown as gray paths (Color figure online)

- Count people as part of a queue if they actually queue up for at least 1 s.
- Count people as participants of the podium or the company stands if they direct their attention and body to the area for at least 1 s.
- Use predefined lines on the floor that describe the spatial boundary of the scenario. The moment a person crosses that line is used to define whether a person leaves or enters the scenario.
- Select random persons that were able to walk through the scenario in an unimpeded and linear manner, and measure their velocity.
- Select random social groups and count the members of the groups. The groups have to enter and leave the scenario together.
- Select random social groups and count the number of interactions with the goal areas of the scenario.

We annotated the video supported by a MATLAB tool[4] that enables the user to step through the video frame by frame and to add annotations to the images. The annotations can be extracted as a file for automatic analyses.

We were able to extract the following input data sets my means of the video analysis:

- The in-flow distributions of the pedestrians for all entrances (A–E). The in-flow models the number of pedestrians that enter the area over time. This data is an important input to realistically add pedestrian agents into the simulation.
- The social group size distribution of the people. The social group size is the basis for the number of pedestrian agents that follow the plan of a group's leader within a social group. This data is an important property of the agents' social context.

[4] The tool was provided by Prof. Köster and her team, University of Applied Sciences Munich.

- The free-flow velocity distribution of the people. The free-flow velocity defines the unimpeded walking speed of pedestrians and is an important parameter of movement models and is a fundamental property of the pedestrians.
- The activity service time distributions of the locations (1–5). The service time helps to identify the period of how long people interact with locations. The data is an important input data for the preference module and the deduction process.
- The interarrival time distribution of the locations (1–5, A–E). These distributions describe the duration between the arrival of pedestrians at exits, at queues, and at areas where pedestrians stay for a certain time, e.g. to listen to a lecture at the podium. The data is an important input data for the preference module.
- The 2D coordinates of obstacles and destinations. This data models the physical environment of the simulation. The geometric reconstruction is based on a 3D building information model, a computer aided design model, and on-site observations of the building.

The simulation input data provides all information to generate an agent population and the environment features.

Apart from the input data, we measured validation data that will be compared to the simulation output data to check whether the model provides realistic behavior. Details concerning this data are provided in the next section.

5.2 Validation data

Here, we provide the macroscopic and microscopic validation data. The data served to validate the model and, thus, the *Spice* framework. If the simulated effects correspond to the aggregated behavior in the video data, we can expect that a macroscopic validity is given.

The macroscopic validation data is based on the emerging phenomena of a pedestrian multi-agent simulation that includes spatial sequential choice. We look at two macroscopic patterns. The first phenomenon is the number of pedestrians that visit and interact with destinations. In the career fair scenario, the destinations that provide activities are numbered (1)–(5). Similarly, the second phenomenon describes the number of pedestrians that leave the scenario through doorways. The exits are identified by the letters (A)–(E).

We analyzed the 33 min of video material (see Sect. 5.1) and extracted the out-flows (A–E) and the number of pedestrians' interactions with locations (1–5). This data is aggregated over the 33 min and provides a mean value of the number of people at interaction areas and the

Table 1 Here, the measured macroscopic validation data from the career fair is shown

Type	Area	Mean
Queuing	Coaching 1	9.45
Staying	Company 2	3.24
Staying	Company 3	1.90
Queuing	Kiosk 4	3.86
Staying	Podium 5	40.01
Exit	Door A	0.337
Exit	Door B	0.400
Exit	Door C	0.0265
Exit	Door D	0.0180
Exit	Door E	0.0515

The data is based on a 33 min video footage. The values provide the aggregated number of pedestrian that interact with the locations over time in [pedestrian/s] and leave the area at exits in [pedestrian/s]

Table 2 Here, the measured number of interaction of social groups of visitors are given in different categories

Number of interactions	1	2	3	4	5
Number of pedestrians	342	96	5	1	3

The data is based on 33 min of video footage

number of people leaving the scenario over time. Table 1 provides the macroscopic validation data.

The microscopic validation gives an account of the individual decisions of the real visitors of the fair. Thus, we randomly selected pedestrian groups and measured the planning behavior of 447 groups of visitors by means of the 33 min of video footage. A core problem of the video analysis is that we cannot identify the re-planning procedures of pedestrians. Nonetheless, we can quantify the length of the activity sequences of the visitors by accurately observing their interaction behaviors.

Table 2 provides the number of interactions of the observed people. It is important to note that if a visitor stayed at the scenario until after the 33 min, we assumed that this visitor would leave the scenario and increase the number of interactions by 1.

5.3 Macroscopic validation

It is quite common that models that explain real life phenomena contain a set of free parameters. The choice of the parameters has impact on the mathematical behavior of the models and on the results of computational simulations that build upon the model. The given model of Sect. 3 comprises 5 free parameters in total. One of these free parameters was explained in Sect. 4.5, the reactivity ζ of the re-planning component.

Here, we identify the parameters of the model by means of a grid-search [72]. This method needs some optimal criteria that can be compared to simulation results to find an optimal parameter choice. The existence of an optimal parameter set provides crucial evidence that the model is able to simulate the pedestrians' spatial sequential choice and movement behavior. If it were impossible to find such an optimal parameter set, we would have to discard the hypothesis that the *Spice* framework can provide a valid abstraction of the cognitive processes of pedestrians.

We computed the grid-search by testing 1296 parameter combinations and using the data of Table 1 as optimality criteria. For each combination, we ran 12 simulations to calculate average results. A single simulation generates microscopic agent behavior and emergent macroscopic data, which is structured in the same manner as in Table 1. To identify the parameter set that provides the most accurate simulation results, we computed the weighted mean error in regards to the data of Table 1.

We found a set of optimal parameters for the free parameter and run 297 simulations to evaluate the quantitative accuracy of the simulation. The error distribution of the simulations is shown in Fig. 13. The x-axis gives the error in percent of a simulation regarding the macroscopic validation data. The plots refer to the mean error regarding the number of people that interact with areas (a) and doors (b). Here, a value of 5 describes that the error in a simulation is 5 % with regards to the measured data of Table 1. The y-axis gives the relative likelihood of the errors to occur. We estimated that the errors follow Gamma distributions and successfully tested this hypothesis by means of the Kolmogorov-Smirnov goodness-of-fit test.

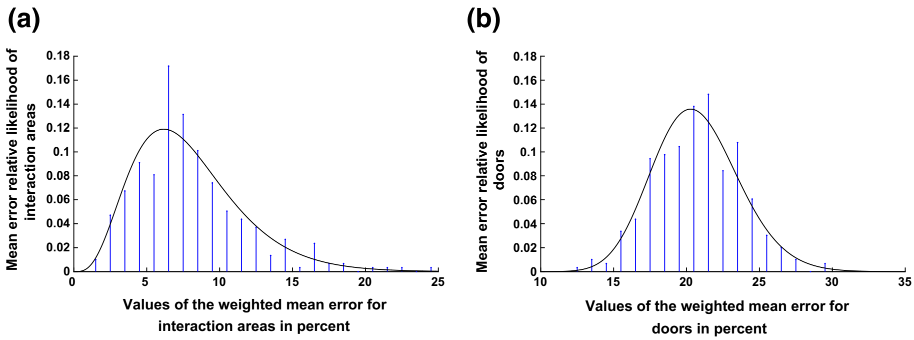

Fig. 13 Here, the error distributions based on 297 simulations with optimal parameters are shown. The plots indicate the variability of the model's accuracy for the weighted mean error of the interaction areas (**a**) and doors (**b**) in percent. We also added the estimated Gamma distributions to the plots

The error distribution of Fig. 13 show some variance. However, the results give evidence that the simulation predicts the number of pedestrians over time at interaction areas with a mean accuracy of 92.1 % and the out-flow of pedestrians over time at the doors with a mean accuracy of 79.3 %. These results are extraordinarily accurate in the context of pedestrian behavior simulation. The reasons is that pedestrian behavior and decision making are generally extremely dynamic. Thus, highly similar situations in real life will always provide different macroscopic validation data.

5.4 Microscopic validation

The microscopic validation focuses on the evaluation of the behavior of individual pedestrians. This analysis is a mandatory addition to the macroscopic analysis. The reason is that there is the possibility of simulating the emerging patterns without a proper simulation of individual behavior. If the model were to function without simulating correct individual planning decision, we would assume that the good macroscopic simulation results (see Sect. 5.3) were found by pure chance. Thus, we also checked the individual decision making of pedestrians to approach this concern.

We analyzed the number of interactions of simulated pedestrians in contrast to the measured number of interactions from Table 2. Furthermore, we evaluated the individual behavior of four pedestrian groups to provide evidence that the integration of the cognitive processes and pedestrian dynamics models operates smoothly.

We executed 11 simulations. Each simulation applied the optimal parameter combination as described in the previous section. The number of pedestrian groups within these 11 simulations is 9832. In Table 3, we compared the length of the simulated and the measured activity sequence (see Table 2). The similarities of the planning between simulation and real data are 96.05 %, a highly accurate result. This gives promising evidence that the planning module was designed with the correct cognitive assumptions.

Finally, we evaluate the behavior of four pedestrian groups in detail and show microscopic and macroscopic dynamics that built upon the individual pedestrian movement. Therefore, Fig. 14 provides four annotated snapshots of the simulation.

Figure 14a highlights a pedestrian that uses the scenario as a transit area, moving from door (B) to door (A). Furthermore, the areas of Company (1), Company (2), and the Podium

Table 3 Here, we compare the relative frequency of the 447 measured and 9832 simulated activity sequences of pedestrians at the career fair scenario

Interactions	Measured (%)	Simulated (%)	Error (%)
1	76.51	74.105	2.405
2	21.477	19.935	1.542
3	1.119	3.234	– 2.115
4	0.224	1.831	– 1.607
5	0.671	0.895	– 0.224

The given error describes the difference between measured and simulated in percentage

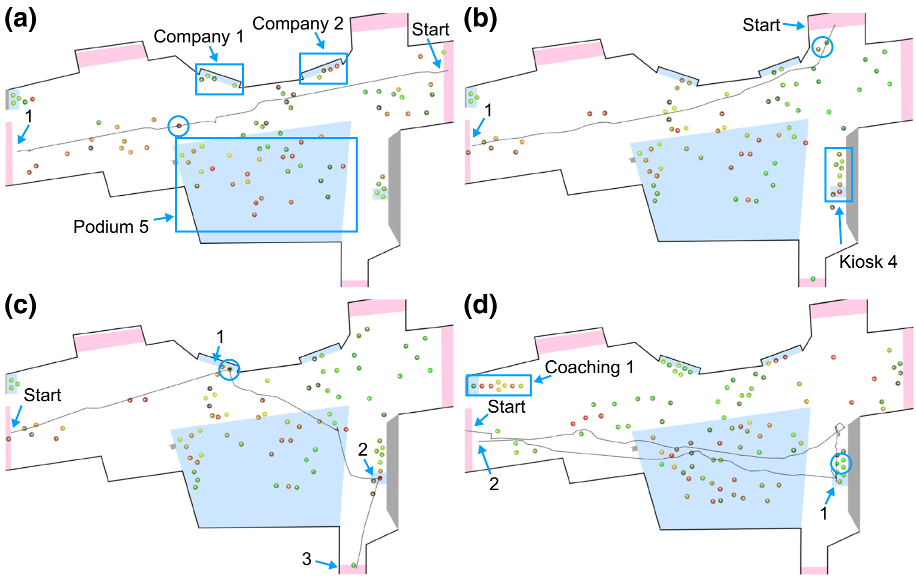

Fig. 14 Here, annotated snapshots of the career fair simulation are shown. In (**a**–**d**), the trajectories of the pedestrians are shown as black paths, and the respective pedestrian group under observation is highlighted with a blue circle. Furthermore, all pedestrian groups are color coded. The given numbers provide the number of interactions of a pedestrian group. **a** Shows a pedestrian that uses the scenario as a transit area. Also, the three areas where pedestrians create patterns by staying are highlighted. **b** Shows a pedestrian group that enters the scenario from a side entrance. The kiosk queue is highlighted. **c** Shows a pedestrian that visits two different location before leaving the scenario. **d** Shows a pedestrian group in a queue. Also, the coaching queue is highlighted (Color figure online)

(5) are highlighted. Here, the pedestrians perform staying behavior. This behavior describes that a pedestrian finds a position at the areas to pause and stay.

Figure 14b shows two pedestrians of a social group. They enter the area from the side door (D) and follow the main corridor to door (A). Furthermore, the Kiosk (4) queue is highlighted. The queue grows alongside the east obstacle to the north and has a short (mean) service duration. Thus, the queue emerges and clears in intervals.

Figure 14c highlights a pedestrian that enters the scenario from door (A), visits the Company (1), the Kiosk (4) and leaves the area at door (E). Three interactions are quite seldom in this scenario (see Table 3)

Figure 14c shows three pedestrians of a social group that visit the Kiosk (4) and leave at door (A). Furthermore, the Coaching (1) queue is highlighted. The queue grows alongside the north obstacle to the east. The queue has a long (mean) service duration and grows slowly but steady.

Each pedestrian group of Fig. 14 shows realistic and plausible behavior patterns. This indicates that the cognitive processes and the behavior models integrate smoothly.

6 Discussion

Here, we will discuss the *Spice* frameworks and the model limitations as well as the validation results.

The *Spice* framework describes the dynamic and static structures of an artificial mind of intelligent pedestrian agents. The important cognitive processes for spatial sequential choice are addressed and are connected to existing pedestrian behavior modeling paradigms. In general, the framework is a guideline to implement a model of pedestrian behavior with cognitive constrains that provides placeholders and interfaces for the model to realize. However, we still miss three important influences categories on pedestrian spatial sequential choice that should be integrated into the framework: the social, attention, and emotional factors. Social aspects—including speech—create an interface for the agents to interact directly. This mechanism provides a basis of social group-based planning behavior. Attention guides the perception processes and, therefore, has influence on the information processing in general. This factor will provide a methodology for integrating high dynamics regarding personal and environmental interactions. Emotions will give a method to dynamically change characteristics of pedestrians' behaviors.

The described model that builds on the framework comprises multiple nested and interrelated models. We showed that the interplay of the models enables complex multi-agent pedestrian simulations with cognitive constraints. However, we still have to improve specific models of the *Spice*-based model implementation. For example, the visibility methods utilize most of the simulation's computation-time. Furthermore, the literature on spatial sequential choice and similar topics describes diverse influences on destination choice in pedestrians, e.g. time-pressure. One additional and important aspect is to integrate a state-of-the-art memory model that can be directly applied to the pedestrian dynamics context. We will integrate these aspects in extensions of the model.

We applied the model on an uncontrolled field study, a student career fair. Thereby, we compared the measured validation data to the simulation results. This gave evidence that the *Spice* concept is suitable for practical application. Furthermore, we showed that the implementation of the *Spice* framework can simulate complex pedestrian behavior accurately. If the validation of the simulations were to provide highly inaccurate results, we would have to revise the underlying concept of the framework and the model. However, the validation of the model gives remarkable evidence that the proposed methodology simulates a multi-agent pedestrian system of spatial sequential choice with high accuracy. Nonetheless, we will conduct more validation studies in the future to show that the model can be applied to a wide range of scenarios without a prior parameter tuning.

7 Conclusion

In pedestrian dynamics, simulations help to forecast the spatial behavior of individual pedestrians and crowds. Such predictions are able to provide support to crowd managers and decision makers to improve pedestrian safety and comfort. Unfortunately, many pedestrian behavior models do not address the complex interplay of cognitive processes and movement behavior. This is especially true for complex environments in which pedestrian behavior is highly dependent on the interplay of personal and environmental interactions. Here, pedestrians show complex tempo-spatial behavior with regards to activity planning. We realized that there is no profound cognitive framework that addresses cognition and pedestrian movement concepts for crowd simulations in complex environments and that is based on the fundamental paradigms of pedestrian behavior modeling.

We approached this issue by presenting the *Spice* framework. It integrates and extends the three-layered agent-based pedestrian modeling methodology, which addresses strategic models of destination choice, tactical models of spatial task solving, and movement models of walking behavior. The framework associates different cognitive processes to the three-layered pedestrian modeling concept. We include the cognitive processes of planning, deduction, perception, preference, memory, and operation. These processes are placeholders that provide interfaces which define the dynamic and static structure of the framework.

The *Spice* framework provides guidelines to design artificial minds of pedestrian agents for crowd simulations based on pedestrian behavior and cognitive models. Thus, researchers can implement a model based on the framework. At the same time, the framework is flexible—and it enables researchers to integrate models which are fully or partially grounded on cognition. In all cases, the framework will provide cognitive constraints to the overall pedestrian behavior model.

We gave evidence that the framework can be used as a tool to model intelligent pedestrian agents by developing an example model. The model uses the framework as a starting point and implements the framework's components by sub-models. Therefore, we gave an overview on the model's mechanisms and explained the planning process in more detail.

We validated the *Spice* methodology and showed that the method is suitable for multi-agent simulations of pedestrian crowds in which spatial sequential choice is a core aspect of the scenario. For the validation, we used data from an uncontrolled field study. The data was compared to the model's simulation results to assess the quality of the simulated microscopic and macroscopic behavior phenomena. The comparisons showed—quantitatively and qualitatively—that the *Spice* approach simulates pedestrian behavior in complex environments accurately. Hence, we provided evidence that the model is able to simulate the individual decision making and behavior of pedestrians, as well as the resulting crowd phenomena. Considering the results, it appears that we applied valid assumptions when designing the *Spice* framework

In future research, we will improved the *Spice* framework regarding multiple new cognitive processes. This will further improve the interdisciplinary research and collaborations involving cognitive sciences and pedestrian dynamics. Similarly, we will refine the model that is build upon the framework by integrating further aspects of spatial sequential choice.

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