Simulation-based Business Process Evaluation in Home Health Care Logistics Management

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Abstract: *Home health care* (HHC) providers face an increasing demand in care services, while the labor market only offers a limited number of professionals. To cope with this challenge from a HHC provider's perspective, available resources must be deployed efficiently taking into account individual human needs and desires of employees as well as customers. On the one hand, corresponding *strategic* management questions arise, e.g., distribution or relocation of establishments or expansion of the vehicle fleet. On the other hand, logistical challenges such as the flexible and robust planning and scheduling of HHC service provision must be addressed by *operational* HHC management. This paper targets both perspectives by providing an integrated simulation-based framework for the evaluation of different business processes. Methods from *Agent-based Simulation*, *Dynamic Microsimulation*, and (*Distributed*) *Artificial Intelligence* are combined to investigate HHC service provision and to support practical decision-making. The presented approach aims to facilitate the reasonable development of the HHC provider's organization to ensure the sustainable delivery of required medical care.

1 INTRODUCTION

Many countries face challenges in coping with increasing demand for care services. In Germany, for example, the number of people in need of care will rise by approximately 32% by 2030, resulting in a growing shortage of care personnel (Rothgang et al., 2016). Besides stationary facilities and the support of relatives, *home health care* (HHC) is one possibility to receive essential care services. Here, caregivers are usually equipped with cars and render the required services at the patients' homes.

As the availability of qualified caregivers on the labor market is very limited, it is not feasible to hire additional caregivers for coping with the increasing demand in HHC. Thus, logistical optimization and managing of existing resources in HHC gains in relevance to enable efficient service delivery. At the same time, individual human needs and desires of employees as well as customers have to be taken into account. On the one hand, flexible and robust planning and scheduling of HHC service provision is a challenging logistical task for *operational* HHC management. On the other hand, corresponding *strategic* management questions arise, like the distribution or relocation of local establishments or the expansion the company's vehicle fleet. Testing and analyzing different strategies during daily operation can be time consuming, expensive, and thus economically harmful. To avoid negative consequences from such real-world investigations, the use of *simulation* is reasonable. Further, methods from the field of *Artificial Intelligence* can be applied to extend simulation technology and to increase the efficiency of operations by applying automated processes.

This paper combines these techniques and proposes a simulation-based framework for the evaluation and comparison of business processes in HHC logistics. It can serve as an assistance for HHC providers to facilitate the development of their orga-

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nization such that medical care can be ensured in the long term.

This paper is structured as follows: In Chapter 2, foundations of HHC and the state of the art in modeling, simulating, and assisting HHC processes are presented. In Chapter 3, the conceptual architecture of the framework is explained and its application is subject of Chapter 4. Finally, in Chapter 5, conclusions are drawn and an outlook on future work is provided.

2 BACKGROUND

This section terminologically introduces the domain of HHC as a combination of medical and non-medical care that is rendered by a mobile nursing service at the patients' homes. Additionally, this section presents the state of the art of two research areas that contribute to the development of the framework, i.e., forecast of care demand and assistance of operational HHC management.

2.1 Home Health Care

The provision of HHC services is usually part of the public health care system. There are national differences in HHC systems, yet, they have a common basis. Independent of a specific public health care system, populations can be divided by their individuals' care status, i.e., care-dependent or not care-dependent. Care-dependent individuals are referred to as *care recipients* and can be classified by different levels of care, e.g., depending on the required time of support. These levels may change, if the condition of the care recipient changes. Additionally, care recipients can be differentiated by their choice of care (*type of care*), that determines how they are treated. Typical choices are *family care*, where the care recipient will be taken care of at home by family or friends, *nursing care*, where the care recipient moves into a nursing facility, or *HHC*, where employees of an ambulatory care service provider (*HHC provider*) execute requested care services (*service requests*). In this work, HHC refers to "the provision of health care services to people of any age at home or in other noninstitutional settings" (Dieckmann, 2015, p. 3). To distinguish skilled medical services and non-skilled services (such as personal care routines, household maintenance, and social services), the non-skilled services are described using the term *home care*, in contrast to HHC, which also includes medical treatments, nursing services, and physical therapies (Prieto, 2008). Typically, one HHC provider employs several *caregivers* with different qualifications. Caregivers are equipped with diverse vehicles and render the service requests in the respective patients' homes according to their qualifications.

2.2 Modeling and Simulation of Care Demand

The combination of *Dynamic Microsimulation* (DM) and *Agent-based Social Simulation* (ABSS) has been proposed as a hybrid approach for forecasting individual care demand (Lebherz et al., 2018). Seen individually, DM and ABSS are well known in the field of care demand analysis or for simulating care decisions. DM allows for simulating the developments of micro-units, e.g., persons or households, over time (Li and O'Donoghue, 2013). Here, statistical data and derived probabilities are used for the estimation of each micro-unit's potential future (Rutter et al., 2011). Decision-making analysis originated in Operations Research (OR). Usually, the target of OR approaches is the optimization of decision behavior, e.g., with multiple objectives (Azcárate et al., 2008). However, when reconstructing human decision-making, there is no need for such optimizations. Instead, sophisticated methods that include psychological and sociological theories are required for a realistic reconstruction of human decision behavior. ABSS enables the inclusion of such methods and thus seems more promising (Davidsson, 2002; Lorig et al., 2018).

Most ABSS approaches in health care pursue different goals and are suitable for strategic decision support (Liu and Wu, 2016) or process optimization (Moore et al., 2012), e.g., by simulating roles and activities in health care systems (Mustapha and Frayret, 2016). Yet, there are also approaches that focus on the forecast of care demand, e.g., Ma et al. (Ma et al., 2016). Other approaches combine existing methods in hybrid simulations, e.g., Bae et al. (Bae et al., 2016), who combine *Agent-based Modeling* and *Microsimulation* for studying population dynamics. However, for the forecast of individual care demand, there is no approach that combines methods for population forecasting, e.g., DM, with sophisticated methods for simulating individual human decision-making, e.g., ABSS. Yet, the combination of both methods seems promising to take individual decision behavior into account when forecasting future care demand.

2.3 Supporting Operational HHC Management

The support of operational management ranges from basic technologies for carrying out daily tasks to com-

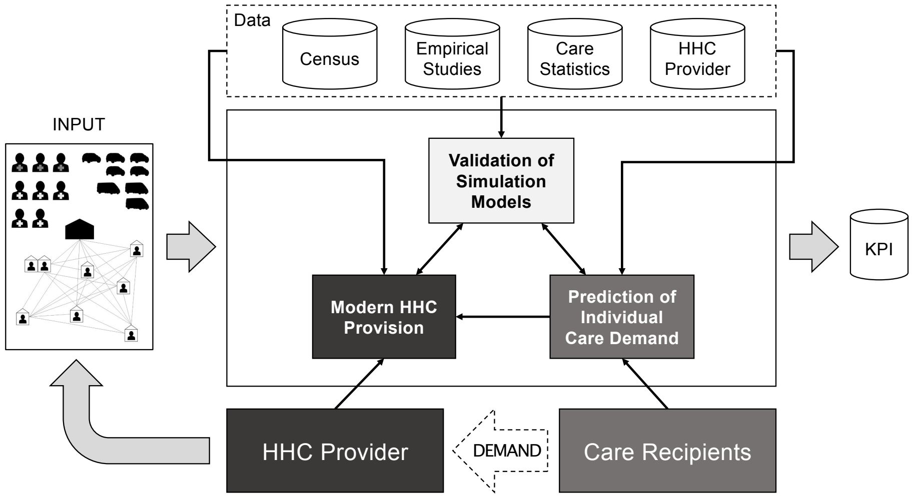

Figure 1: Conceptual Architecture of the Framework.

prehensive support for difficult decisions using sophisticated *Decision Support Systems* (DSS). Emiliano et al. (Emiliano et al., 2017) identified logistics problems in the domain of HHC and proposed a framework, which structures management tasks for the development of a DSS. An especially complex and recurring management task that is important for cost reduction is the scheduling and routing of available resources. Suitable methods for HHC scheduling and routing include *Variable Neighborhood Search* by means of a *Mixed-Integer Linear Programming* model (Mankowska et al., 2014) or the use of fuzzy models for more uncertain scenarios (Shi et al., 2017). A comprehensive overview on existing approaches is provided by Fikar and Hirsch (Fikar and Hirsch, 2017).

To make such approaches usable for the operations manager, Begur et al. (Begur et al., 1997), for instance, developed a tool to support scheduling and routing decisions of caregivers. To facilitate capacity planning, Zhang et al. (Zhang et al., 2012) developed a DSS using *optimization* and *Discrete Event Simulation* with demographic data. Besides this, the use of methods from the field of Artificial Intelligence is an increasing trend in practical applications. Becker et al. (Becker et al., 2019) surveyed the use of multiagent systems and agent-based simulations to support automated planning and scheduling in operational HHC logistics management. Discovered approaches mostly focus on the evaluation of specific aspects of HHC logistics management systems, yet, the study revealed shortcomings in end user provision, evaluation of developed concepts, and in dealing with a shortage of qualified workers. Comprehensive approaches that include both demand and supply modeling were not identified.

3 EVALUATION FRAMEWORK FOR HHC BUSINESS PROCESSES

The framework proposed in this paper conceptualizes and enables the evaluation of different business processes in HHC logistics by means of simulation. It allows for the long-term evaluation of strategies for potential future scenarios while taking the possible influences of the customers into account. The framework consists of two components: a simulation that predicts the care demand of individuals and an approach for the planning and provision of HHC services. This section presents a conceptual architecture in which all required components as well as their interactions are introduced. Moreover, it outlines how the simulation-based prediction of individual care demand and the approach for modern HHC provision facilitate the evaluation of business processes of HHC providers.

3.1 Conceptual Architecture of the Framework

To evaluate whether or not a specific business process for the delivery of HHC services is economically viable and satisfactory for care recipients and caregivers, its present and future suitability must be systematically assessed under a variety of potential cir-

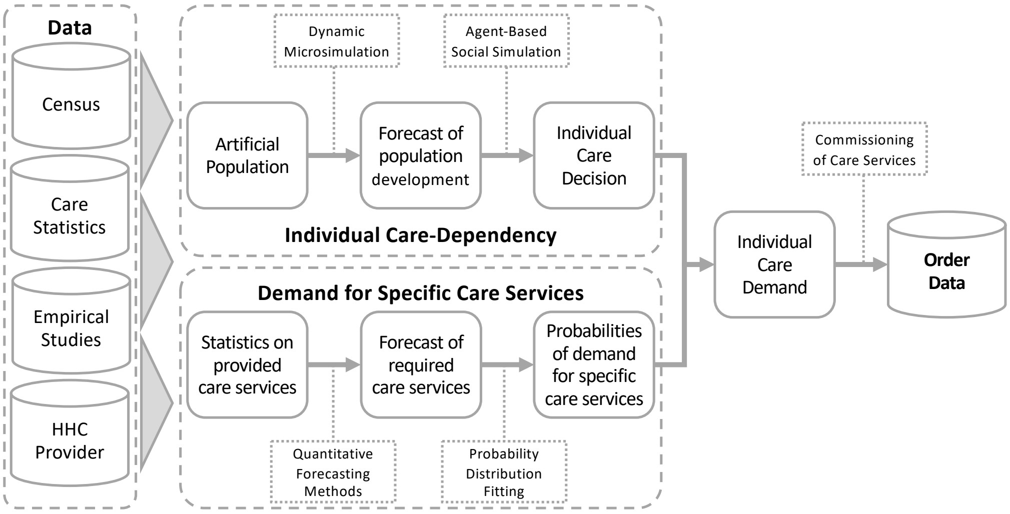

Figure 2: Forecasting Individual Care Demand.

cumstances. To achieve this, the presented framework (cf. Figure 1) models real-world care recipients, their demand for care services, and HHC providers that fulfill such services. This enables the simulation-based evaluation of care provision approaches and serves as an assistance system for HHC providers.

To allow for the investigation and comparison of different business processes that serve as input of the proposed framework, their performance must be quantified. For this purpose, the framework returns KPIs, e.g., adherence to schedules or the ratio between travel and service provision times. By this means, a more profound decision-making basis is created for the management. Yet, more advanced KPIs such as customer satisfaction must be gathered and evaluated after implementing the business process in the real-world system.

Business processes of HHC providers may be discriminated into three hierarchical layers depending on the goal they pursue and how they define and structure the process. On the highest level, the *strategic layer* defines business process based on future developments. Such strategic decisions might include investment decisions such as the recruitment of new staff. The practical implementation of such strategies is achieved by the *tactical layer*. Here, the achievement of the business goal is addressed by algorithms that, e.g., solve problems of staff allocation. Finally, the lowest layer can be defined as *operational layer* where the business process specifies the short-term operational control. Such processes, for example, define weekly schedules that assign each caregiver to render specific services for multiple care recipients.

The hierarchical order of these layers also represents the stepwise implementation and evaluation of business processes. Management decisions take place of the strategic layer. Here, the structured and thorough investigation of such processes might for instance require the top-down application of different scheduling algorithms as well as the simulation-based analysis of multiple schedules by the framework.

The presented framework pursues an approach where the individual care demand of a specific population is predicted by DM and ABSS. Based on this demand, specific order data is generated that serves as input for the provision of the requested services. The fulfillment of the services is then simulated and different KPIs are gathered. As both components require real-world data, sociodemographic and empirical data sources are integrated by the framework, e.g., census data and operational data from the care provider. To ensure the generation of reproducible and credible simulation results, a data-based validation of the simulation models is also an inherent part of the proposed framework.

3.2 Prediction of Individual Care Demand

The prediction of individual care demand, as implemented by the framework, includes the determination of recent care demand as well as the realistic prediction of future care demand for reliable and sustainable planning (cf. Figure 2). This includes the forecast of the number of care-dependent individuals as well as information about their location and the requested type of care. In previous work, *Agent-Based Microsimulation* (ABMS) has been proposed for predicting future care demand (Lebherz et al., 2018).

This approach can be used to generate synthetic information on the amount of HHC-demanding people and potential service requests (order data) and allows for the transformation of individual care demand into specific service requests for HHC providers. For the prediction of care demand, two perspectives need to be considered: The forecast of individual care-dependency, i.e., the prediction of the amount and location of all HHC-demanding people in the investigated area, and forecasts of the demand for specific care services, i.e., the prediction of potentially requested services. The combination of both perspectives allows for the determination of the individual care demand.

Forecasting Individual Care-dependency. This perspective allows for determining the number of care recipients that choose HHC services for their care support at an arbitrary (future) point in time. Here, ABMS generates location, level of care, and further information about the care recipient's family situation. ABMS is an iterative approach and consists of three steps. The first step is the generation of an artificial population. Sociodemographic and care statistic data are used to generate an artificial population that matches all required structural characteristics of the real population, e.g., age structure. Furthermore, the combination of map data, census data, and geo-referencing approaches allows for the allocation of the artificial population to real-world households (Lebherz et al., 2018). In the second step, DM is used to predict the stepwise development of this population into the future (Li and O'Donoghue, 2013). This allows for the investigation of the demographic development as well as of each individuals' care status, level of care, and family situation. In the third step, ABSS is used to simulate individual care decisions and the preferred type of care for every care dependent person. A simulative decision-making process based on objective and subjective criteria is used for analyzing care decisions. Influences that potentially affect this decision are implemented as different functions, e.g., saving of cost or social steadiness, which are objectively interpreted depending on each individuals' situation. By this means, data about the individual care level or living situation can be integrated into the decision-making process. Finally, an individual subjective assessment of these results allows for deriving unique decisions based on the individual person's characteristics (Lebherz et al., 2018). After a determined number of iterations, the output is a set containing information on every care recipient, its demographic characteristics, and its choice of care. For the application in the presented framework only those recipients choosing HHC are considered.

Forecasting the Demand for Specific Care Services. The second perspective pursues two different goals. The first one is a realistic assessment of specific services that are offered by HHC providers based on the care recipient's level of care. To this end, data of service providers is required about the types of services that are requested by care recipients depending on their level of care. In a following step, quantitative forecasting methods are used for the prediction of future service requests. Based on this forecast, methods for probability distribution fitting can be used to calculate probabilities of the demand for every specific care service (n) combined with every possible level of care (m). Hence, the first result is a $n \times m$ matrix consisting of probabilities for requesting a service.

The second goal is to determine which services are usually provided by family members or friends based on the assumption that even if a care recipient chooses HHC, some tasks are performed by family members or friends. Such information must be gathered through empirical studies, e.g., interviews. Hence, as a second result of this perspective, probabilities about the professional and non-professional provision of services must be collected. In summary, this perspective provides two different results, which can be combined as probability matrices.

Forecasting Individual Care Demand and Order Data. The set of HHC recipients combined with the calculated probability matrices enables the forecast of individual care demands. A random process is used to assign possible services to the recipients based on the provided probabilities. The probabilities regarding the professional or non-professional provision of services are used in a second random process, which transforms the demand forecast into realistic order data for potential HHC providers. Here, randomly chosen services are requested from the service provider. Final order data consists of a list of HHC recipients with all data provided by ABMS and two individual sets of services: HHC provider requests and services provided by family or friends.

3.3 Modern Home Health Care Logistics Management

Some management tasks in HHC are highly complex or require great coordination effort. The idea of modern HHC logistics management is to reduce the range of such tasks by means of innovative information systems, to create more space for social-related tasks concerning customers and employees, like sensitive human-to-human interaction in leading a team. The vision comprises an *Intelligent Assistance System* for decision support and a *Multiagent Control*

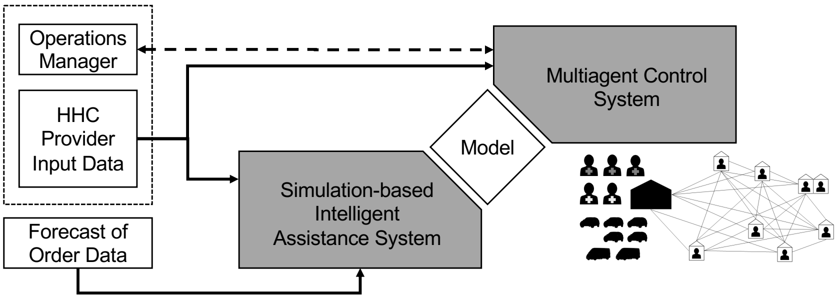

Figure 3: Modern HHC Logistics Management.

System for managing employees' operational activities during execution. Both parts can be understood as a mutual complement in practice (cf. Figure 3). First, the intelligent assistance system is applied for defining and planning the execution of HHC services. Afterwards, the multiagent system is used to control the execution of the planned activities and to adapt the execution if necessary.

Intelligent Assistance System. The system focuses on adapting the current way of providing HHC services to increase efficiency. It can be described as a comprehensive model-driven DSS with an *Intelligent User Interface*. According to Power (Power, 2008), a model-driven DSS has access to a financial, optimization, or simulation model, is able to manipulate this model, and to analyze the new situation to support decision makers. The system presented in this work is based on an agent-based simulation and provides support by the means of automated simulation studies. The suggested simulation model consists of care recipients in their homes and caregivers performing HHC services using vehicles in an abstract environment. To describe individual entities, the model is capable of representing individual behavior of employees and customers.

Through manipulation of the modeled (artificial) world, different scenarios can be evaluated and the gained knowledge can be applied to improve real-world processes. Examined scenarios include different possibilities for performing services and the consideration of potential future circumstances, which are realized by using forecast order data. To manage data and to control the DSS, an intelligent user interface is applied. Here, the model's input data and the higher-level system are administered by a software agent, which is able to communicate with the operations manager (user) via different channels. Since not all employees are familiar with information technology, this interface is to be understood as an intuitive connection to a virtual employee. Accordingly, the core computational application of the intelligent assistance system is controlled and conducted by the software agent. It comprises the design and conducting of simulation experiments as well as output data analysis as defined in *Hypothesis-Driven Simulation Studies* (Lorig et al., 2017). Based on the forecasted order data and the available resources as input data, multiple simulation experiments are systematically designed and executed to identify the most efficient provision of HHC services. To this end, the simulation model is modified accordingly and several alternatives of service provision are evaluated. For instance, specific combinations of skilled and non-skilled workers that form a set of teams can be tested in the artificial world and KPIs can be measured to assess their suitability. Furthermore, corresponding planning data for order fulfillment and routing is generated, aggregated, and structured in a schedule, which can be treated as a separate output of the system. Besides the generation of daily schedules, real-world processes can benefit from using insights from simulation output data analysis to adapt schedule patterns or adjust involved long-term resources. The latter, for instance, can be realized by hiring professionals with specific skills according to the analysis results.

Multiagent Control System. To link the described model with the real world, the multiagent control system uses the model to create a cyber-physical relation: real-world entities (like employees) are represented by virtual surrogates in the simulation model and communication is directed in both ways. Similar to the application of the model by the intelligent assistance system, the control system creates a virtual world in a non-terminating simulation run representing the real world. Defined properties (like geographical location) of the modeled entities are continuously synchronized with the values of the real world. Based on the current simulation state, unavoidable deviations from the schedule can be handled by computing several opportunities in parallel simulation runs. These start from the current simulation state, and by selecting the best alternative to change the current schedule for the remaining tasks. Because of information exchange and coordination on the virtual level between the representatives, the respective real-world participants can reduce communication efforts and are provided with necessary data and instructions. While the operations manager is the user of the intelligent assistance system in the first step, he or she is now part of the multiagent control system itself and represented by a virtual surrogate, which initiates coordination tasks like auctions and votes.

This also enables, for instance, the real-time processing of urgent customer service requests, which require the coordination of the consultation with caregivers. Moreover, customers with an affinity for technology can be connected to the system by using personal devices, which eases the sending of such requests. Wearable technologies on the customer side allow for emergency requests, which can be handled automatically by the multiagent control system. Changing preferences of the employees (caregivers) can also trigger coordination processes in a similar way. In summary, the multiagent control system offers two main functions regarding disturbances of the previously planned execution of HHC services: On the one hand, the current real-world status is transferred to the simulation and can be used for (short-term) experiments to compute a well-suited solution to change the current schedule. On the other hand, coordination and communication between the real-world participants is carried out by virtual representatives and reduces time and effort among the employees of the HHC provider.

4 APPLICATION AND VALIDATION OF THE FRAMEWORK

To demonstrate the feasibility of the proposed framework, its application is presented in this section. This includes the identification and acquisition of a data basis, the application of the introduced models for care demand and decision support, as well as the presentation of a frame for validating the models.

4.1 Data Basis

Data required for the model application and validation comes from four sources. Census data represents sociodemographic data and contains information, e.g., about financial aspects or residential situations. Care statistics of the respective regions include information on, e.g., the number of care recipients and their level of care. To produce reliable results, we use empirical studies to generate and validate the model behavior. A first study is concerned with care recipients and contains information about different motives to choose a specific type of care as well as subjectively perceived individual conditions. A second study focuses on care recipients that make use of HHC and the services they request. HHC provider data contains information such as average duration of different services, travel times, and demand for various services depending on the level of care. Since the created population is projected into the future, collected data must be updated using validated statistical methods and trend analyses.

4.2 Application of the Care Demand Model

The care demand model starts with the generation of an artificial population. For this purpose, all available data (e.g., census, land register, or map data) is used to create a population that matches the real-world population on all required characteristics (e.g., care status and level of care). The iterative ABMS process is initialized with this population. First, DM projects the population one year into the future. During this step, the care level of individuals might change so it is necessary to adapt their type of care. ABSS is then used to simulate a new care decision for each individual.

First, the given situational context is evaluated and all objective decisive factors (e.g., monetary or social criteria) are determined with rating functions for each potential decision. Following this, an assessment is performed to derive a reasonable decision depending on each care recipients objective situation according to census data. Income or family members living in the same household can influence the decision. Here, the same objective situation leads to the same decision. Hereafter, a subjective assessment is made based on the care recipient's individual constitution. Every care recipient is characterized by an individual configuration of four motives, represented by social actor types, i.e., *homo economicus*, *homo sociologicus*, *identity keeper*, *emotional man*. This allows for different preferences and interests in decisive factors (Lorig et al., 2018). For instance, homo economicus tries to save money and to reduce efforts, while homo sociologicus lays emphasize on a steady social environment and cares less about money.

At the end of this phase, an individual assessment is made that interprets the objective assessment based on the recipient's individual constitution and generates an updated population. After a predefined number of iterations, a subset consisting of all care recipients that have HHC as type of care is used for further process. Now, every person of this set is assessed regarding different HHC services, based on a random process and explored probabilities. A subsequent second random process is used for choosing a subset of these services that will be requested at a professional HHC provider. Finally, each person of the artificial population who choses HHC demands a set of services as a set of order data.

4.3 Application of the HHC Model

The order data determines which customer requests which service during which time interval. The HHC provider has the option to read in a duty roster for the considered period of time, so further planning algorithms can use information of employees' availability. Both serve as input data for the intelligent assistance system. Furthermore, overtime hours of employees, customer geolocation data, and type and quantity of available vehicles are also required. Before using a state of the art algorithm for temporal planning, the system retrieves current or predicted traffic data. As a first step, the algorithm creates a schedule and related routing data on the basis of the input data. After that, a simulation run is executed for evaluation using the agent-based simulation model.

Depending on the HHC provider's questions, the design of experiments is conducted which includes planning of further simulation runs to answer what-if questions. In addition, experiments can be conducted to find efficient solutions of service delivery. For example, an HHC provider wants to examine the impact of buying an additional vehicle. Another example is that the operational manager wants to know if current processes of service provision are able to cope with an increasing demand in 5 years, and if not what are possible adaptions to handle the situation. Finally, methods of output data analysis are applied to provide knowledge on a significant level. Key performance indicators can be defined and measured data is aggregated accordingly. If the simulation model represents the real world with sufficient accuracy, conclusions for real processes can be drawn.

4.4 Empirical Validation of the Models

Finally, the validity of the simulation framework must be ensured. Since the models are developed and evaluated independently of each other, verification and internal validation are not considered here. To ensure credible results, the validity of the models and some respective results have to be determined. Therefore, this paper examines the individual components of the framework, i.e., the decision-making model and the HHC model, and investigate them for validity using empirical data. The used data basis consists of the conducted empirical studies and HHC data as described in Section 4.1.

The validity of models can be ensured in various ways. For example, face validation is a method in which experts evaluate the model (Sargent, 2013). They determine whether the assumptions made during concept development are correct and whether the model is suitable for solving the problem. Furthermore, the model output is checked for appropriateness for the application area. These methods are subjective, since the assessment of the model depends on an expert and his domain knowledge. Objective validation includes, for example, sensitivity analysis, which tests the effects of changes in the values of the input variables on the model output. The framework validation presented here focuses on comparing the model output with data of the real world in order to approximate the model output to it and validate the model (empirical or historical validation). The system output is compared with the test data to determine differences, e.g. using statistical methods. This type of validation is independent of experts or assessments by third parties and therefore objective (Sargent, 2013).

The arrows from the empirical data basis in Figure 4 point to the components of the framework to be validated. First, the decision-making model and the results that require empirical validation are examined. Therefore, Section 4.1 presents two empirical studies. The generation of the initial population and its projection one year into the future are based on valid inputs (e.g., census data) and models (cf. Section 3.2). Therefore, the decision-making model is the first starting point of an empirical validation. A decision is made using objective and subjective factors of the agents regarding the type of care. Objective factors are derived from census data. The subjective factors are compared with empirical data, so that the effect of motivations defined in the model can be validated against reality through target-oriented questioning. Furthermore, the waiting functions, whose validity cannot be guaranteed by statistical methods alone, have to be validated against empirical data. This concerns functions that work upon subjective perceptions of care recipients, such as social pressure based on the experience of the individual. The resulting updated population can be validated by comparison with estimation models of health statistics.

The next step of the model that has to be valid is the mapping of services to the agents on the list of HHC recipients. Here, the second empirical study, which contains information about services requested by care recipients, is used. The same applies to the

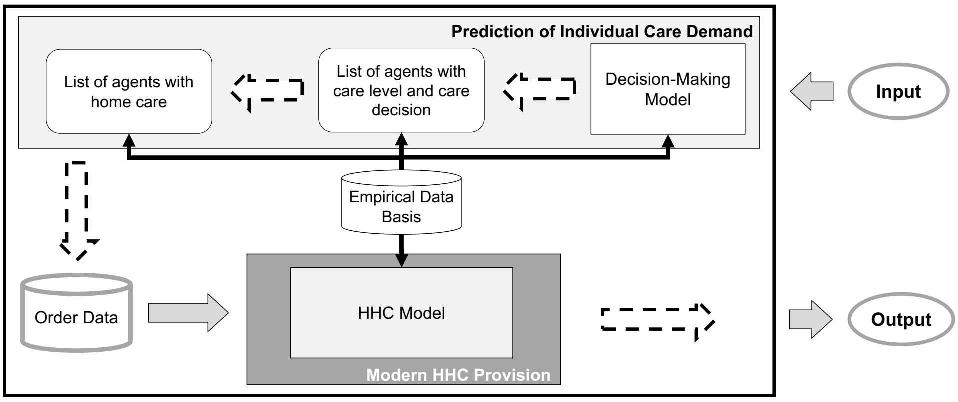

Figure 4: Empirical Validation of the Framework.

next step in the framework which reduces the list of services which are not rendered by family members but requested at HHC providers. For these two lists, both their generation and validation are based on the same data of the empirical study. This means that the data is divided into a training set for generation and a test set for validation. The final output of the model is the order data, which is transferred to the HHC simulation model. Here, the model itself has to be validated, in order to produce a reliable output. Therefore, internal documentation data of the HHC provider is used. Caregivers use hand-sized devices to enable electronic documentation while executing daily tasks. The corresponding data is stored in the HHC providers' database. In addition to this, the corresponding order data, and the used schedule serve as model input in order to compare the model output and the real world documentation data. According to this, the corresponding time recording is defined as measuring points in the simulation run. If the artificial output data matches the gathered real data, the model is considered to be sufficiently valid.

5 CONCLUSIONS AND OUTLOOK

In this paper, we introduced a framework that allows HHC agencies to systematically analyze and optimize business processes with respect to current and future care demand. To this end, methods from the fields of Agent-based Simulation, Dynamic Microsimulation, and (Distributed) Artificial Intelligence were combined. Questions ranging from strategic to operational logistics management were addressed and the approach's results can help to increase the efficiency of HHC business processes while at the same time taking human needs into account.

In future work, we will extend the modeling and simulation of service provision to IoT-, robotics-, and qualification-based innovations to allow for preinvestment analysis. In long term research, we are working on combining micro- and agent-based simulation for validated care demand prognosis. Also, we will further elaborate on aspects of AI planning for the practical application in a multiagent setting as well as on refining knowledge generation and processing. This includes the development of a system for the automated design and conducting of simulation experiments of HHC scenarios.

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