Beaming market simulation to the future by combining agent-based modeling with scenario analysis

Appendix

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I Overview

This appendix is divided into eight sections. After the overview in the current section, Section II provides the pseudocode of the algorithms used for the agent-based market simulation that is introduced in Section 2.2 of the main paper. Then, Sections III–VI list the corresponding parameters, variables, functions, and indices. For the sake of readability and better distinction, the notation of parameters and indices follows a "single-letter" format (e.g., $a^{\text{true}}_{p,k}$ for the true performance value of product p regarding attribute k), while the notation of variables follows a "multiple-letter" format (e.g., $belief^{\text{attr}}_{i,p,k}$ for the current belief of consumer i regarding attribute k of product p). It should be noted that auxiliary variables—as indicated in the list of model variables—are used only in certain instances (e.g., during the initialization of a social network). Finally, Sections VII and VIII describe how the parameters were gathered and which parameters values have been used in the sample application being presented in Section 3 of the main paper.

II Algorithms

Figure II.1 illustrates the embedment of the seven main algorithms Alg. 1–7 in the theoretical framework by Rogers (2003), which distinguishes five phases of innovation adoption.

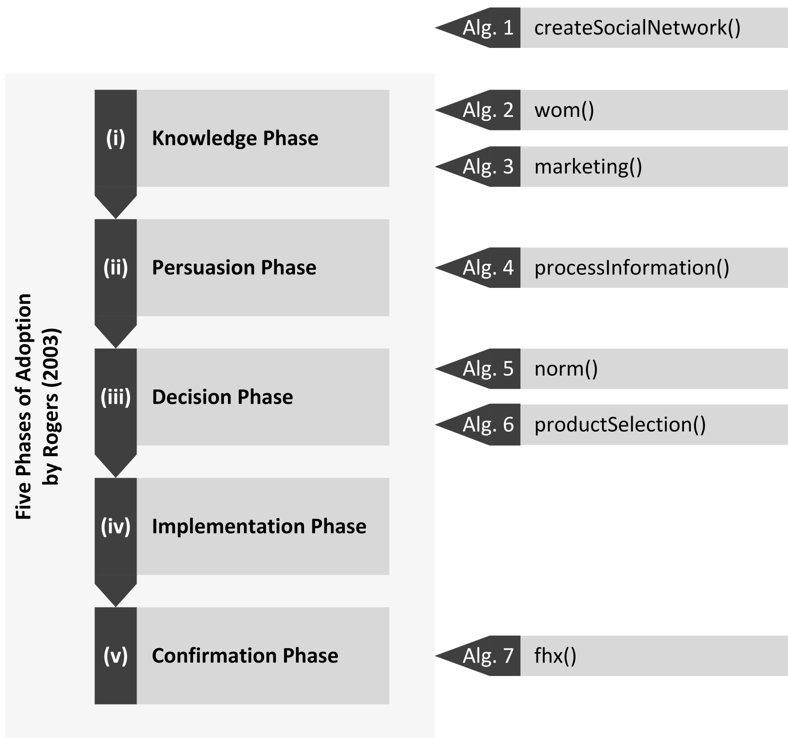

Figure II.1: Overview of algorithms

Algorithm 1 describes the initialization of the social network. Due to the fact that network structures may vary between markets and/or for certain products (Delre et al., 2010), different network generation algorithms were used in previous agent-based market models. The small-world network algorithm by Watts and Strogatz (1998) and the scale-free network algorithm by Barabási and Albert (1999) are the most prominent ones for that purpose. Both do not explicitly account for spatial proximity and, therefore, do not capture the effect that people living in close proximity are more likely to form bonds and, thus, influence each other (Latané et al., 1995). However, in our application case, it was important that the probability of two consumers being interconnected decrease with the spatial distance between these consumers—following a Newtonian-type inverse power law or a negative exponential function (cf., e.g., Morrill et al., 1988). We therefore utilized the network generation algorithm described and initially applied by Stummer et al. (2015), which is based on the Barabási and Albert (1999) network generating algorithm and extends it as suggested by Manna and Sen (2002) in order to create a Euclidean network that considers (i) the distance among nodes (spatial component) and (ii) the number of links of each node (clustering component). Thus, the probability that a new node is linked with an already existing one is driven by both a spatial (α) and a clustering exponent (β). For each new node n^{edges} links are generated. Apparently, a negative geodesic exponent α is likely to favor local links, while the parameter setting $\alpha = 0$ and $\beta = 1$ corresponds to the original Barabási and Albert (1999) network.

Algorithm 2 describes the unidirectional word-of-mouth communication process that takes place between two directly connected consumers within the social network, when consumer j sends information and consumer i receives that information. The time span between two subsequent communication events initiated by a specific consumer is drawn from a triangular distribution $L_j^{\text{wom}} \sim \text{triang}(l_j^{\text{wom,min}}, l_j^{\text{wom,max}}, l_j^{\text{wom,mod}})$. When such a communication event occurs, the sending consumer j (randomly) selects an attribute k^* she is aware of ($awareness_{i,p,k^*}^{\text{attr}} = 1$). Then, she prepackages the relevant *Topics* for the communication event which contains the (current) beliefs $belief_{j,p,k^*}^{\text{attr}}$ regarding the selected attribute k^* of all products p that she is aware of. These beliefs are transmitted to the designated receiving consumer agent i, who processes this information in accordance with Algorithm 4.

Algorithm 3 describes the marketing activities, which allow for raising awareness and transfer product-specific information. They start at a specific time t_q^{mark} and target a predefined group of consumer agents being selected according to the marketing range m_q^{range}. Each marketing activity focuses on a specific attribute m_q^{attr} of product m_q^{prod} and broadcasts the content of the marketing message m_q^{cont} (i.e., the information regarding the performance level of the product attribute) which then is processed by the receiving consumer i (see Algorithm 4) considering the weighing factor w_i^{mark}. It should be noted that marketing efforts are necessary to raise awareness for new products and their associated (new) attributes.

Algorithm 4 describes how a consumer forms or alters the personal belief toward a product's attribute ($belief_{i,p,k}$). This information processing is performed whenever new information (*value*) is obtained by either (i) marketing, (ii) word of mouth, or (iii) first-hand experience. In the case of marketing, *value* equals m_q^{cont} (see Algorithm 3). When it comes to word of mouth, *value* equals the belief $belief_{j,p,k}$ of the communication partner j regarding one specific attribute k (see Algorithm 2). For first-hand experience, *value* is the true performance value $a_{p,k}^{\text{true}}$ (see Algorithm 7). The received information is weighted individually to represent the credibility of each information source (*weight*). Although inter-agent credibility might vary ($w_{i,j}^{\text{wom}}$), as a general rule, marketing has less impact (w_i^{mark}) on a consumer's belief compared to word of mouth (Day, 1971).

Algorithm 5 describes the normative social influence $norm_{i,p}$ on consumer i with regard to product p. The influence is exerted by this consumer's peers (i.e., consumers j for whom $connected_{i,j} = 1$). Similar to the approach used by van Eck et al. (2011), the strength of the influence results from dividing the number of peers owning the product ($own_{i,p}^{\text{peers}}$) by the number of peers (n_i^{edges}). Normative social influence plays a role in Algorithm 6 as part of the purchasing process.

Algorithm 6 describes the process of selecting and purchasing a new product. It is initiated when the current product reaches the end of its regular lifetime (drawn from a triangular distribution $L_{p,i}^{\text{life}} \sim \text{triang}(l_{p,i}^{\text{life,min}}, l_{p,i}^{\text{life,max}}, l_{p,i}^{\text{life,mod}})$), which might be shortened due to product failure (drawn from a triangular distribution $\Gamma_p \sim \text{triang}(\gamma_p^{\text{min}}, \gamma_p^{\text{max}}, \gamma_p^{\text{mod}})$). Then, all products p and corresponding attributes k a consumer i is aware of ($awareness_{i,p}^{\text{prod}} = 1$ and $awareness_{i,p,k}^{\text{attr}} = 1$) are evaluated. To this end, the expected utility $utility_{i,p}^{\text{prod}}$ of each (aware) attribute k is calculated with respect to (i) the individual and previously formed beliefs $belief_{i,p,k}^{\text{attr}}$ and the individual part-worth utility function $\mathrm{u}_{\mathrm{i,k}}^{\text{attr}}(\cdot)$, (ii) the normative social influence $norm_{i,p}$, which is exerted by this consumer's peers, and (iii) a (small) stochastic error term ε covering any further influencing factors that have not been explicitly considered. Ultimately, consumer i purchases—and, thenceforth, owns ($own_{i,p}^{\text{prod}} = 1$)—the product that offers the maximum utility value ($utility_i^{\text{max}}$).

Algorithm 7 describes how the beliefs of consumer i are influenced by first-hand experience with the newly purchased product after using it for a while. The time span between the purchase of the product and the corresponding first-hand experience is determined by a continuous uniform distribution $L^{\text{fhx}} \sim \text{uniform}(l^{\text{fhx,min}}, l^{\text{fhx,max}})$. When such an event occurs, consumer i receives information regarding the true performance value $a_{p,k}^{\text{true}}$ of attribute k of product p considering the weighting factor w_i^{fhx}, which determines the impact of first-hand experience on consumer i. The new information is processed according to Algorithm 4.

Algorithm 1 – Creating the social network

function createSocialNetwork()
  repeat $(n^{\text{edges}}+1)$ **times**
    $Consumer^{\text{init}} \leftarrow Consumer^{\text{init}} \cup \text{randomConsumer}(C \notin Consumer^{\text{init}})$
  end repeat
  for all $C_i \in Consumer^{\text{init}}$ **do**
    for all $C_j \in (Consumer^{\text{init}} \setminus C_i)$ **do**
      $\text{connect}(C_i, C_j)$
    end for
    $consumer_i^{\text{edges}} \leftarrow n^{\text{edges}}$
  end for
  $Consumer^{\text{connected}} \leftarrow Consumer^{\text{init}}$
  for all $C_i \in (C \setminus Consumer^{\text{connected}})$ **do**
    $Consumer^{\text{connectable}} \leftarrow Consumer^{\text{connected}}$
    for all $C_j \in Consumer^{\text{connectable}}$ **do**
      $prob_j^{\text{consumer}} \leftarrow \text{distance}(c_i^{\text{pos}}, c_j^{\text{pos}})^{\alpha} \cdot (consumer_j^{\text{edges}})^{\beta}$
      $prob_i^{\text{sum}} \leftarrow prob_i^{\text{sum}} + prob_j^{\text{consumer}}$
    end for
    repeat n^{edges} **times**
      $prob^{\text{cutoffRW}} \leftarrow \text{random}(0, prob_i^{\text{sum}})$
      for all $C_j \in Consumer^{\text{connectable}}$ **do**
        $prob^{\text{sumRW}} \leftarrow prob^{\text{sumRW}} + prob_j^{\text{consumer}}$
        if $prob^{\text{sumRW}} \geq prob^{\text{cutoffRW}}$ **then**
          $\text{connect}(C_i, C_j)$
          $consumer_i^{\text{edges}} \leftarrow consumer_i^{\text{edges}} + 1$
          $consumer_j^{\text{edges}} \leftarrow consumer_j^{\text{edges}} + 1$
          $Consumer^{\text{connectable}} \leftarrow Consumer^{\text{connectable}} \setminus C_j$
          $prob_i^{\text{sum}} \leftarrow prob_i^{\text{sum}} - prob_j^{\text{consumer}}$
          $prob^{\text{sumRW}} \leftarrow 0$
          exit for
        end if
      end for
    end repeat
    $Consumer^{\text{connected}} \leftarrow Consumer^{\text{connected}} \cup C_i$
  end for
end function

Parameters:

C	Set of consumers (indexed by i)
c_i^{pos}	(Geographical) position of consumer i
n^{edges}	Number of edges set for each consumer during network generation
α	Spatial exponent used during network generation
β	Clustering exponent used during network generation

Variables:

$Consumer^{\text{connectable}}$	Set of connectable consumers
$Consumer^{\text{connected}}$	Set of already added consumers to the network
$Consumer^{\text{init}}$	Set of initially connected consumers
$consumer_i^{\text{edges}}$	Number of edges of consumer i
$prob_i^{\text{consumer}}$	Probability of connecting with consumer i
$prob^{\text{cutoffRW}}$	Random cutoff value for the summarized probabilities during the roulette wheel procedure
$prob^{\text{sumRW}}$	Sum of probabilities of connectable consumers considered so far in the roulette wheel procedure
$prob_i^{\text{sum}}$	Sum of probabilities of all connectable consumers with consumer i

Indices:

i, j	Index of consumer

Functions:

connect(C_i, C_j)	Connects consumer i with consumer j
distance$(c_i^{\text{pos}}, c_j^{\text{pos}})$	Returns the geodesic distance between the geographical positions of consumers i and j
random$(value1, value2)$	Returns a random number between *value1* and *value2* based on a continuous uniform distribution
randomConsumer(C)	Returns a random consumer from a set of consumers C

Algorithm 2 – Word of mouth

```
function wom(i, j)
    for all A_k ∈ A do
        for all P_p ∈ P do
            if awareness^attr_{j,p,k} = 1 then
                Attributes ← Attributes ∪ k,
                exit for
            end if
        end for
    end for
    k* ← randomAttribute(Attributes)
    for all P_p ∈ P do
        if awareness^attr_{j,p,k*} = 1 then
            Topics ← Topics ∪ (p, k*, belief^attr_{j,p,k*})
        end if
    end for
    for all (p, k, belief) ∈ Topics do
        processInformation(i, p, k, belief, w^wom_{i,j})
    end for
end function
```

Parameters:

A	Set of attributes (indexed by k)
P	Set of products (indexed by p)
$w_{i,j}^{\text{wom}}$	Weighting factor determining the impact of information received via word of mouth by consumer i from consumer j

Variables:

$Attributes$	Set of attributes k a sending consumer j is aware off
$awareness_{i,p,k}^{\text{attr}}$	Awareness of consumer i regarding attribute k of product p
$belief_{i,p,k}^{\text{attr}}$	Belief of consumer i regarding attribute k of product p
$Topics$	Set of topics in a communication event between consumers

Indices:

i, j	Index of consumer
k	Index of attribute
k^*	Index of selected attribute
p	Index of product

Functions:

processInformation$(i, p, k, value, weight)$	Function that processes the performance information *value* (here: $belief^{\text{attr}}_{j,p,k^*}$) received (here: via word of mouth) by consumer i for attribute k of product p considering a *weight* factor (here: $w^{\text{wom}}_{i,j}$). Function is further specified in Algorithm 4.
randomAttribute$(Attributes)$	Returns a random attribute index from a set of attributes

Algorithm 3 – Marketing

function marketing(q)
  for all $C_i \in C$ **do**
    if random$(0,1) \leq m_q^{\text{range}}$ **then**
      processInformation$(i, m_q^{\text{prod}}, m_q^{\text{attr}}, m_q^{\text{cont}}, w_i^{\text{mark}})$
    end if
  end for
end function

Parameters:

C	Set of consumers (indexed by i)
m_q^{attr}	Attribute targeted by marketing activity q
m_q^{cont}	Content (performance level) communicated by marketing activity q
m_q^{prod}	Product targeted by marketing activity q
m_q^{range}	Range of marketing activity q (probability that a consumer is exposed to marketing activity q)
w_i^{mark}	Weighting factor determining the impact of a marketing activity on consumer i

Indices:

i	Index of consumer
k	Index of attribute
p	Index of product
q	Index of marketing activity

Functions:

random$(value1, value2)$	Returns a random number between *value1* and *value2* based on a continuous uniform distribution
processInformation$(i, p, k, value, weight)$	Function that processes the performance information *value* (here: m_q^{cont}) received (here: via marketing) by consumer i for attribute k of product p considering a *weight* factor (here: w_i^{mark}). Function is further specified in Algorithm 4.

Algorithm 4 – Information processing

function processInformation$(i, p, k, value, weight)$

$awareness^{\text{prod}}_{i,p} \leftarrow 1$

$awareness^{\text{attr}}_{i,p,k} \leftarrow 1$

$belief^{\text{attr}}_{i,p,k} \leftarrow \frac{belief^{\text{attr}}_{i,p,k} + value \cdot weight}{weights_{i,p,k} + weight}$

$weights_{i,p,k} \leftarrow weights_{i,p,k} + weight$

end function

Variables:

$awareness^{\text{attr}}_{i,p,k}$	Awareness of consumer i regarding attribute k of product p
$awareness^{\text{prod}}_{i,p}$	Awareness of consumer i regarding product p
$belief^{\text{attr}}_{i,p,k}$	Belief of consumer i regarding attribute k of product p
value	Attribute's performance value of the received information (by marketing activities, word of mouth, or first-hand experience)
weight	Weighting factor for the received information (by marketing activities, word of mouth, or first-hand experience)
$weights_{i,p,k}$	Sum of weights for attribute k of product p obtained by consumer i

Indices:

i	Index of consumer
k	Index of attribute
p	Index of product

Algorithm 5 – Normative social influence

function $\mathrm{norm}(i, p)$
    for all $C_j \in C$ **do**
        if $connected_{i,j} = 1$ **then**
            $own^{\text{peers}}_{i,p} \leftarrow own^{\text{peers}}_{i,p} + own^{\text{prod}}_{j,p}$
        end if
    end for
    $norm_{i,p} \leftarrow \frac{own^{\text{peers}}_{i,p}}{n^{\text{edges}}_{i}}$
end function

Variables:

$connected_{i,j}$	Indicates whether consumer i and consumer j are directly linked in the social network
n^{edges}_{i}	Number of peers of consumer i
$norm_{i,p}$	Normative social influence on consumer i concerning product p
$own^{\text{peers}}_{i,p}$	Number of peers of consumer i owning product p
$own^{\text{prod}}_{i,p}$	Indicates whether consumer i owns product p

Indices:

i, j	Index of consumer
k	Index of attribute
p	Index of product

Algorithm 6 – Product selection

function productSelection(i)
    for all $P_p \in P$ **for which** $awareness^{\text{prod}}_{i,p} = 1$ **do**
        $own^{\text{prod}}_{i,p} \leftarrow 0$
        for all $A_k \in A$ **for which** $awareness^{\text{attr}}_{i,p,k} = 1$ **do**
            $utility^{\text{prod}}_{i,p} \leftarrow utility^{\text{prod}}_{i,p} + \mathrm{u}^{\text{attr}}_{\text{i,k}}(belief^{\text{attr}}_{i,p,k})$
        end for
        $utility^{\text{prod}}_{i,p} \leftarrow utility^{\text{prod}}_{i,p} + norm_{i,p} \cdot w^{\text{norm}}_{i} + \varepsilon$
        if $utility^{\text{prod}}_{i,p} > utility^{\text{max}}_{i}$ **then**
            $utility^{\text{max}}_{i} \leftarrow utility^{\text{prod}}_{i,p}$
            $p^* \leftarrow p$
        end if
    end for
    $own^{\text{prod}}_{i,p^*} \leftarrow 1$
end function

Parameters:

A	Set of attributes (indexed by k)
P	Set of products (indexed by p)
ε	Stochastic utility evaluation error term

Variables:

$awareness^{\text{attr}}_{i,p,k}$	Awareness of consumer i regarding attribute k of product p
$awareness^{\text{prod}}_{i,p}$	Awareness of consumer i regarding product p
$belief^{\text{attr}}_{i,p,k}$	Belief of consumer i regarding attribute k of product p
$own^{\text{prod}}_{i,p}$	Indicates whether consumer i owns product p
$utility^{\text{max}}_{i}$	(Current) maximum utility of consumer i during the decision phase
$utility^{\text{prod}}_{i,p}$	Expected utility of product p by consumer i

Indices:

i	Index of consumer
k	Index of attribute
p	Index of product
p^*	(Current) preferred product

Function:

$\mathrm{u}^{\text{attr}}_{\text{i,k}}(value)$	Returns the part-worth utility of consumer i for attribute k and value $value$

Algorithm 7 – First-hand experience

function fhx(i, p)

  for all $A_k \in A$ **for which** $awareness^{\text{attr}}_{i,p,k} = 1$ **do**

    processInformation$(i, p, k, a^{\text{true}}_{p,k}, w^{\text{fhx}}_i)$

  end for

end function

Parameters:

A	Set of attributes (indexed by k)
$a^{\text{true}}_{p,k}$	True performance value of product p regarding attribute k
w^{fhx}_i	Weighting factor determining the impact of first-hand experience on consumer i

Variables:

$awareness^{\text{attr}}_{i,p,k}$	Awareness of consumer i regarding attribute k of product p

Indices:

i	Index of consumer
k	Index of attribute
p	Index of product

Function:

processInformation$(i, p, k, value, weight)$	Function that processes the performance information *value* (here: $a^{\text{true}}_{p,k}$) received (here: first-hand experience) by consumer i for attribute k of owned product p considering a *weight* factor (here: w^{fhx}_i). Function is further specified in Algorithm 4.

III Model parameters

Parameter	Explanation
A	Set of attributes (indexed by k)
$a_{p,k}^{\text{true}}$	True performance value of product p regarding attribute k
C	Set of consumers (indexed by i)
c_i^{pos}	(Geographical) position of consumer i
$L_{p,i}^{\text{life}}$	Triangular distribution $L_{p,i}^{\text{life}} \sim \text{triang}(l_{p,i}^{\text{life,min}}, l_{p,i}^{\text{life,max}}, l_{p,i}^{\text{life,mod}})$ used for determining the product lifetime of product p purchased by consumer i
L_i^{wom}	Triangular distribution $L_i^{\text{wom}} \sim \text{triang}(l_i^{\text{wom,min}}, l_i^{\text{wom,max}}, l_i^{\text{wom,mod}})$ used for determining the length between two communication events of consumer i
m_q^{attr}	Attribute targeted by marketing activity q
m_q^{cont}	Content (performance level) communicated by marketing activity q
m_q^{prod}	Product targeted by marketing activity q
m_q^{range}	Range of marketing activity q (probability that a consumer is exposed to marketing activity q)
N	Number of consumer agents
n^{edges}	Number of edges set for each consumer during network generation
P	Set of products (indexed by p)
w_i^{fhx}	Weighting factor determining the impact of first-hand experience on consumer i
w_i^{mark}	Weighting factor determining the impact of a marketing activity on consumer i
$w_{i,j}^{\text{wom}}$	Weighting factor determining the impact of information received via word of mouth by consumer i from consumer j
α	Spatial exponent used during network generation
β	Clustering exponent used during network generation
ε	Stochastic utility evaluation error term
Γ_p	Triangular distribution $\Gamma_p \sim \text{triang}(\gamma_p^{\text{min}}, \gamma_p^{\text{max}}, \gamma_p^{\text{mod}})$ used for determining the failure rate of a product p

IV Model variables

Variable	Explanation	Auxiliary variable
Attributes	Set of attributes k a sending consumer j is aware off	✓
$awareness^{attr}_{i,p,k}$	Awareness of consumer i regarding attribute k of product p	
$awareness^{prod}_{i,p}$	Awareness of consumer i regarding product p	
$belief^{attr}_{i,p,k}$	Belief of consumer i regarding attribute k of product p	
$connected_{i,j}$	Indicates whether consumer i and consumer j are directly linked in the social network	
$Consumer^{connectable}$	Set of connectable consumers	✓
$Consumer^{connected}$	Set of already added consumers to the network	✓
$Consumer^{init}$	Set of initially connected consumers	✓
$consumer^{edges}_{i}$	Number of edges of consumer i	
n^{edges}_{i}	Number of peers of consumer i	
$norm_{i,p}$	Normative social influence on consumer i concerning product p	
$own^{peers}_{i,p}$	Number of peers of consumer i owning product p	
$own^{prod}_{i,p}$	Indicates whether consumer i owns product p	
$prob^{consumer}_{i}$	Probability of connecting with consumer i	✓
$prob^{cutoffRW}$	Random cutoff value for the summarized probabilities during the roulette wheel procedure	✓
$prob^{sumRW}$	Sum of probabilities of connectable consumers considered so far in the roulette wheel procedure	✓
$prob^{sum}_{i}$	Sum of probabilities of all connectable consumers with consumer i	✓
Topics	Set of topics in a communication event between consumers	
$utility^{max}_{i}$	(Current) maximum utility of consumer i during the decision phase	✓
$utility^{prod}_{i,p}$	Expected utility of product p by consumer i	
value	Attribute's performance value of the received information (by marketing activities, word of mouth, or first-hand experience)	✓
weight	Weighting factor for the received information (by marketing activities, word of mouth, or first-hand experience)	✓
$weights_{i,p,k}$	Sum of weights for attribute k of product p obtained by consumer i	

V Functions

Functions	**Explanation**
connect(C_i, C_j)	Connects consumer i with consumer j
distance(c_i^{pos}, c_j^{pos})	Returns the geodesic distance between the geographical positions of consumers i and j
random$(\mathit{value1}, \mathit{value2})$	Returns a random number between *value1* and *value2* based on a continuous uniform distribution
randomAttribute$(\mathit{Attributes})$	Returns a random attribute index from a set of attributes
randomConsumer(C)	Returns a random consumer from a set of consumers C
$\mathrm{u}_{\mathrm{i,k}}^{\mathrm{attr}}(\mathit{value})$	Returns the part-worth utility of consumer i for attribute k and value *value*

VI Model indices

Index	**Explanation**
i, j	Index of consumer
k	Index of attribute
k^*	Index of selected attribute
p	Index of product
p^*	(Current) preferred product
q	Index of marketing activity

VII Structured process and sources utilized for parameterization

The parameterization of the agent-based simulation was based on (i) information provided by company representatives, (ii) the outcome of the scenario analysis, (iii) census data, and (iv) data retrieved from literature. The lion share of company information was gathered in the course of a structured process including three workshops with managers from engineering, innovation management, and marketing as well as several personal consultations, as described below in greater detail.

The **first workshop** started with a clarification of the project's goals before we engaged in a thorough discussion regarding the strategic positioning of the company, relevant markets and products, characteristics of (typical) consumers and possible future strategies. After this initial, rather unstructured, outline of the managerial challenges, in the second part of the workshop, a field manual was used to more systematically collect further information needed for modeling the market under consideration. Thus, the two perspectives—the company view as well as that from the modeling team—were equally considered. In the third part of the workshop, we explained the basics of an agent-based market simulation in order to establish a common understanding for the method and its possible gains and limitations. Based on the information retrieved from this initial workshop, a draft of the agent-based model was implemented in a first version of the simulation tool. Although several adaptations became necessary in the course of the project, having such a draft at hand turned out to be very helpful for channeling the discussion in the successive workshops.

While the first workshop aimed at facilitating an open discussion of potentially relevant aspects, the **second workshop** primarily targeted on determining the characteristics of consumer agents and parameterizing them. The company possessed rather detailed information regarding the targeted consumer groups ("personas"), which was presented and then jointly discussed with respect to a suitable parameterization process. Subsequently, any additional information that was not available during the workshop could be retrieved from the respective departments (e.g., more detailed marketing data from the marketing department).

In the **third workshop**, the parameterization of agents was addressed again, but this time the discussion was led by exemplary results based on initial simulation runs (performed for a generic setting without taking into account future scenarios). Thus, it was possible to deepen the common understanding of the methodological approach and to fine-tune certain parameter settings. After this feedback loop, the remainder of the workshop was concerned with consequences of scenarios and respective (possible) management measures. As the company representatives were also involved in the creation of the scenarios, it was relatively straightforward for them to translate implications from the scenarios into the respective parameterization for the market simulation. Whenever necessary, we could crosscheck assumptions made in the model or for the parameterization with the corresponding departments (later-on) again. Regarding the strategy alternatives to be tested by means of the market simulation, we essentially followed the suggestions and requests made by the company managers, but still were able to propose strategy alternatives.

As already mentioned, multiple additional touch-points for **further callbacks** were possible. One such opportunity for information exchange led to conduct a historical validation for a previously introduced product from the same company. This step turned out to be important for trust building regarding the methodological approach.

A detailed list of the sources utilized for the parameter setting as well as the initial values or ranges are provided in the table below.

Parameter	Explanation	Source	(Initial) value / range
A	Set of attributes (indexed by k)	Scenario analysis / company	price, quality, smartness, smart-grid capability
$a_{p,k}^{\text{true}}$	True performance value of product p regarding attribute k	Scenario analysis / company	[0,1]
c_i^{pos}	(Geographical) position of consumer i	Census data	—
L^{fhx}	Continuous uniform distribution $L^{\text{fhx}} \sim \text{uniform}(l^{\text{fhx,min}}, l^{\text{fhx,max}})$ used for determining the time span between the product purchase and the first-hand experience	Company	$l^{\text{fhx,min}}$: [25] $l^{\text{fhx,max}}$: [35]
$L_{p,i}^{\text{life}}$	Triangular distribution $L_{p,i}^{\text{life}} \sim \text{triang}(l_{p,i}^{\text{life,min}}, l_{p,i}^{\text{life,max}}, l_{p,i}^{\text{life,mod}})$ used for determining the product lifetime of product p purchased by consumer i	Company	$l_{p,i}^{\text{life,min}}$: 365 $l_{p,i}^{\text{life,max}}$: 912 $l_{p,i}^{\text{life,mod}}$: 730
L_i^{wom}	Triangular distribution $L_i^{\text{wom}} \sim \text{triang}(l_i^{\text{wom,min}}, l_i^{\text{wom,max}}, l_i^{\text{wom,mod}})$ used for determining the length between two communication events of consumer i	Company	$l_i^{\text{wom,min}}$: [20,70] $l_i^{\text{wom,max}}$: [60,120] $l_i^{\text{wom,mod}}$: [30,90] (dependent on personas)
m_q^{attr}	Attribute targeted by marketing activity q	Company	smartness, smart-grid
m_q^{cont}	Content (performance level) communicated by marketing activity q	Company	See Section VIII
m_q^{prod}	Product targeted by marketing activity q	Company	smart-standard, smart-premium
m_q^{range}	Range of marketing activity q (probability that a consumer is exposed to marketing activity q)	Company	0.05
N	Number of consumer agents	Set after sensitivity analysis	1,000
n^{edges}	Number of edges set for each consumer during network generation	Company / literature	3

Parameter	Explanation	Source	(Initial) value / range
P	Set of products (indexed by p)	Company	discount, standard, premium, smart-standard, smart-premium
w_i^{fhx}	Weighting factor determining the impact of first-hand experience on consumer i	Company; validated using historical company data of a similar product (see Section 3.3.1 in the main paper)	1
w_i^{mark}	Weighting factor determining the impact of a marketing activity on consumer i	Company; validated using historical company data of a similar product (see Section 3.3.1 in the main paper)	0.5
$w_{i,j}^{\text{wom}}$	Weighting factor determining the impact of information received via word of mouth by consumer i from consumer j	Company; validated using historical company data of a similar product (see Section 3.3.1 in the main paper)	0.75
α	Spatial exponent used during network generation	Company; validated using historical company data of a similar product (see Section 3.3.1 in the main paper)	2
β	Clustering exponent used during network generation	Company; validated using historical company data of a similar product (see Section 3.3.1 in the main paper)	-2
ε	Stochastic utility evaluation error term	Not used in application case	0
Γ_p	Triangular distribution $\Gamma_p \sim \text{triang}(\gamma_p^{\text{min}}, \gamma_p^{\text{max}}, \gamma_p^{\text{mod}})$ used for determining the failure rate of a product p	Company	γ_p^{min}: [0.020,0.075] γ_p^{max}: [0.035,0.060] γ_p^{mod}: [0.025,0.050]

VIII Parameterization of products

Product	Price	Quality	Smartness	Smart-grid
discount	0.350	0.350	0.450	0.000
standard	0.450	0.450	0.550	0.000
premium	0.550	0.550	0.550	0.000
smart-standard	0.550	0.400	low: 0.605 high: 0.825	no: 0.000 yes: 1.000
smart-premium	0.750	0.550	low: 0.605 high: 0.825	no: 0.000 yes: 1.000

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