SimPLS – Model description

Article: *The PLS Agent: Predictive Modeling with Partial Least Squares and Agent-based Simulation*

Submission to JBR, SI on Prediction-oriented Modeling in Business Research by Means of Partial Least Squares Path Modeling.

Table of Content

Model description

According to the ODD Protocol (Grimm et al. 2006 and Grimm et al. 2010)

Purpose

The simulation model SimPLS shows an application of the PLS agent concept and its added value through its consideration in a dynamic context. The simulation model implements the PLS path model TAM about the decision of using innovative products. Simulation experiments analyze the diffusion of innovative products under demographically varying populations consisting of young and aged consumers.

State variables and scales

Table 1 provides an overview of the state variables and scales of the consumer agent.

Consumer

State variables	Default value	Description
aged	False	Indication whether the consumer agent is of type aged (true) or young (false).
early-adopter	False	Indication whether the consumer agent is an early adopter (true).
product-information	False	Indication whether the consumer agent has information about the innovative product (true or false).
links-to-neighbors	random	Random establishment of links to neighbor agents according to the probability value of link-chance.
adoption-intention	0	Calculation of the adoption intention value for each consumer type (young and aged) according to the total effects of the PLS path model and the given product attribute values (see 4. Submodels).
technology-use-intention	0	According to adoption-intention, for technology-use.
adopted	False	Indication whether the consumer agent adopted the innovative product (true or false).
use-technology	False	Indication whether the consumer agent uses the innovative product (true or false).

Table 1 State variables and scales - consumer agent

Process overview and scheduling

SETUP (Initialization)

For each simulation run, the simulation experiments have the following input parameters:

- number of agents
- percentage of aged consumers (other agents are young)
- perceived product attributes ease-of-use and relative-advantage
- link-chance
- amount of early adopters

The young and aged consumers as well as the early adopter agents spread randomly over the network. Initially, only the early adopter agents have information about the innovative product. Each agent establishes randomly a directed link to each neighbor, according to the probability value link-chance. Neighbors are all agents in the four cells within the Von Neumann neighborhood of the agents' patch.

GO (Simulation round)
In each step, the simulation follows this schedule:

1: CALL: update-intentions

2: ASK all consumer agents:

3: IF product-information AND not yet decided about adoption intention
4: CALL: decide-adoption-intention

5: IF adoption intended AND not yet decided to use technology
6: inform connected neighbors about product
7: CALL: decide-technology-use

8: CALL: update-globals

Submodels

UPDATE INTENTIONS
The calculation of the intention values for adoption-intention and technology-use-intention are based on (1) the perceived product attributes of ease-of-use and relative-advantage and the (2) the total effects of the PLS path model. The total effects of the PLS path model are the results of an empirical study for the groups young and aged consumers. The perceived product attributes are set as input parameter to explore the effect of different product characteristics. The maximum value of the product attributes (here: 10) is used to calculate a relative probability to adopt and use the product. The following describes the intention calculations.

Empirical basis: Total effects of the TAM PLS path model

Young consumers

	Adoption Intention	Ease of Use	Rel. Advantage	Technology Use
Adoption Intention	1.000			0.704
Ease of Use	0.434	1.000	0.463	0.306
Rel. Advantage	0.418		1.000	0.294
Technology Use				1.000

Aged consumers

	Adoption Intention	Ease of Use	Rel. Advantage	Technology Use
Adoption Intention	1.000			0.731
Ease of Use	0.709	1.000	0.552	0.518
Rel. Advantage	0.092		1.000	0.067
Technology Use				1.000

Adoption intention

The total effects of the PLS path model for **young consumers** on **adoption intention** are:

	Adoption Intention
Ease of Use	0.434
Rel. Advantage	0.418

The calculations within the program code are:
a. maximum possible adoption intention value (perceived product attribute 10):

set max-value-adoption-intention-young (**10 * 0.434** + **10 * 0.418**)

b. adoption-intention value for young consumers, given the value of perceived ease-of-use and relative-advantage (input parameters):

set adoption-intention-young ((**ease-of-use** * **0.434** + **relative-advantage** * **0.418**) / max-value-adoption-intention-young)

Total effects of the PLS path model for **aged consumers** on **adoption intention**:

	Adoption Intention
Ease of Use	0.709
Rel. Advantage	0.092

The calculations within the program code are accordingly:

set max-value-adoption-intention-aged (**10 * 0.709** + **10 * 0.092**)

set adoption-intention-aged ((**ease-of-use * 0.709** + **relative-advantage * 0.092**) / max-value-adoption-intention-aged)

Technology-use intention

Total effects of the PLS path model for **young consumers** on **technology-use** intention:

	Technology Use
Ease of Use	0.306
Rel. Advantage	0.294

The calculations within the program code are accordingly:

set max-value-technology-use-young (**10 * 0.306** + **10 * 0.294**)

set technology-use-young ((**ease-of-use * 0.306** + **relative-advantage * 0.294**) / max-value-technology-use-young)

Total effects of the PLS path model for **aged consumers** on **technology-use** intention:

	Technology Use
Ease of Use	0.518
Rel. Advantage	0.067

The calculations within the program code are accordingly:

set max-value-technology-use-aged (**10 * 0.518** + **10 * 0.067**)

set technology-use-aged ((**ease-of-use * 0.518** + **relative-advantage * 0.067**) / max-value-technology-use-aged)

DECIDE-ADOPTION-INTENTION

The consumer agent decides randomly about the intention to adopt the innovative technology, with a probability according to adoption-intention.

INFORM CONNECTED NEIGHBORS

The consumer agent informs all neighbors with a directed connection about the innovative product (set the attribute product-information of the connected neighbor agents to TRUE).

DECIDE-TECHNOLOGY-USE

The consumer agent decides randomly to use the technology, with a probability according to technology-use-intention.

UPDATE-GLOBALS

Updates global variable values.

Verification and Validation

According to the categories defined by Rand and Rust (2011).

Verification

PROGRAMMATIC TESTING

The simulation model is implemented in NetLogo (Wilensky, 1999). In the graphical user interface a visual representation of the model is included. Here, the young and aged agents are displayed in different colors (green and red), and the early adopters in a specific shape (big circle). The directed links between the agents are visible by arrows. Over the simulation process, shapes represent the states of the agents, which are: having no information (default shape small full circle), having information (big size full circle), intending to adopt (target symbol), and using the product (wheel). Based on this visualization, the state transitions of 10 single agents along simulation steps were verified in different settings. In addition, the graphical user interface comprises many monitors that allow the verification of the correct implementation of the PLS path model (e.g. by displaying values for adoption intention and technology use intention). Monitors and plots about the overall number of agents in the respective agent states allow the evaluation of the diffusion process.
The simulation model was tested under different settings (low, medium, and high values for the relevant input parameters).
In code walkthroughs, the program code was read and discussed with two colleagues who were not the programmer of the code.

TEST CASES AND SCENARIOS

A further verification step was the systematic design of experiments within the simulation model analysis, by which all input parameters of the simulation model were analyzed systematically, as described below. The simulation model exhibited a plausible overall behavior and the effects of the different variables appeared reasonable as well with respect to the conceptual model.

DOCUMENTATION

For verification purpose, a description of the model is provided (see Model description) that also allows the replication of the model.

Validation

MICRO-FACE VALIDATION

The validated micro-foundation of the agent behavior by PLS path models is the core motivation for this simulation model. This model shows how empirical data analyzed by PLS-SEM may serve as basis to specify agents. Therefore, the relationships between latent variables in the PLS path model serve as decision criteria for actions in the simulation model. Here, the TAM (Technology Acceptance Model) is the basis for the agent model and the results from an online survey about the intention and usage of e-book readers.
PLS-SEM results from multi-group analysis may define different agent types in the simulation model. To show the added value of this concept, the simulation model SimPLS comprises the interaction of agents by spreading information to neighbors. As there are no empirical results about the network formation of the given empirical data set, a simple data network structure is defined to include the conceptual element.

MACRO-FACE VALIDATION

The validation of the diffusion process on the macro level requires further data about the network structure that should then be included in the model. However, the diffusion process within the model has the typical s-shape (Rogers 1993) and varies in speed and level as expected under varying settings.

EMPIRICAL INPUT VALIDATION

For the analysis, the input parameters were set according to the empirical survey behind the PLS path model as follows: The number of agents was set according to the number of respondents in the data set. For reasons related to the graphical user interface in NetLogo, the number of agents is restricted. Here, each agent is set on one patch. With a grid size of 24 x 24 patches, we implemented the number of agents close to the number of participants (562 participants in the survey, 576 agents in the simulation model). Also, the amount of early adopters was set according to the empirical study (23.67%). The mixed population in the simulation model was set to 47% aged[1] consumer, which represents the amount of aged consumers in the study.

EMPIRICAL OUTPUT VALIDATION

The validation of the diffusion process with empirical data on the macro level requires further data about the network structure that should then be included in the model.

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[1] In the empirical study, the participants are divided by age <=49 for young consumers, and >=50 for aged consumers.

Design of experiments

The description of simulation experiments and analysis follows Lorscheid, Heine, and Meyer (2012) standardized procedure.

Purpose of Experiment

The simulation experiments investigate the effects of the observed differences between young and aged consumers in terms of diffusion on the population level. The investigation focuses on the interplay between population characteristics and product attributes regarding diffusion. This may extend the predictive capability of the PLS path model TAM from the individual level to the predictive capability of diffusion on the population level.

Classification of Variables

Table 2 reflects the purpose of the simulation experiments in terms of the independent, dependent, and control variables. The independent variables product attributes and population characteristics, as well as their influence (alone and together) on the dependent variable diffusion rate, are the focus on this study. The control variables are the population size, the design of the network to which the consumers are connected and in which they exchange information about innovative products, as well as the number of early adopters.

Independent Variables	Control Variables	Dependent Variables
Product attributes	Population size	Diffusion rate
Population characteristics	Network	
	Early adopters	

Table 2 Classification of Variables

Experimental Factors, Factor Levels, and Response Variables

The definition of experimental factors, control variables and response variables prepares the simulation experiments by transferring the model variables in simulation parameter values for the analysis.[2]

Here, the experimental factors are the representation of the independent variables product attributes and population characteristics in the simulation experiments (see Table 3). The product attributes are ease-of-use and relative-advantage, according to the exogenous variables of the PLS path model TAM. The value of these attributes determines the product characteristics. The characteristics may vary from low to high emphases of ease-of-use and relative-advantage. The length of scale of the product attributes pre-determines the distinctiveness of characteristics. Here, the scale is between 1 and 10. Gradations among these values allow the representation of diverse products in terms of their characteristics. The amount of aged consumers specifies the population characteristics in terms of age. Population of only young consumers (aged consumers = 0%) and population of only aged consumers (aged consumers = 100%) mark extreme points, and, thus, allow extreme scenarios. Increments between 0 and 1 allow the explicit consideration of demographic developments and their influence on diffusion.

The number of agents in the simulation experiments is close to the number of questionnaires (576 agents and 562 answers). The network characteristic determines the connections and, thus, the communication channels between consumers. In the simulation experiments, the control variable link-chance determines the probability for each consumer to establish a local connection to a neighbor. Each adjacent agent is a neighbor. With a link-chance of 100%, each agent has 4 connections to each neighbor. Results from pre-tests show, link-chance determines the scale of diffusion. Loosely connected consumers may only achieve lower levels of diffusion than strongly connected networks. For the simulation experiments, the network should not limit the diffusion process. At the same time, only a minimum number of connections allow the emergence of diffusion on distinguishable levels. To avoid extreme cases, the control variable link chance has random values for each run, based on a uniform

[2] Please note that we only use the terminology independent variable and dependent variable in the paper, also in the context of the simulation experiments, for reasons of clarity and simplification.

distribution between 30% and 70% link chance to each neighbor. Next to the network design, the number of early adopters is relevant for the diffusion process. The specification of the number of early adopters reflects the amount of early adopters as identified in the empirical data set (here 23.67%). The response variable measures the number of consumers using the innovative product. The endogenous variable technology use from the PLS path model TAM serves as basis. The number of consumer agents which adopted the innovative product and uses the product, is the basis for the diffusion rate for each run.

Parameters		Scales
Experimental factors		
Product attributes		
	ease-of-use	Є [1,…,10]
	relative-advantage	Є [1,…,10]
Population characteristics		
	% aged consumers	Є [0,…,1]
Control variables		
	number of agents	N
	link-chance	Є [0,…,1]
	% early adopters	Є [0,…,1]
Response variable		
	diffusion rate	Є [0,…,1]

Table 3 Experimental factors, control variables, and response variables

Factorial Design

Design of experiment techniques support a systematic analysis of simulation models (Law, 2015; Lorscheid et al., 2012). The simulation experiments apply a systematic 3k-factorial design (see Table 4). In a 3k-factorial design, k stands for the number of factors, and 3 for the number of values per factor. As required for this design, each experimental factor has one low, one medium, and one high value. The simulation experiments perform each possible parameter combination based on these parameter values. This systematic design may reveal interaction effects between experimental factors. By including a medium value, also non-linear effects are observable. Both product attributes have factor values of 2, 5, and 8 in the experiments for the representation of varying product characteristics. The population characteristics vary with 15%, 47%, and 85% aged consumers. The first value determines a young population; the third value defines a more aged population for the analysis. In addition, a mixed population is part of the experiments, with 47% aged consumers, which is exactly the population characteristic as identified in the empirical data set.
The simulation output reports the diffusion rate of each simulation run. The analysis considers the changing diffusion rates, caused by changes of the experimental factor values.

Parameters	Scales	Experimental design
Experimental factors		
Product attributes		
ease-of-use	Є [1,…,10]	(2, 5, 8)
relative-advantage	Є [1,…,10]	(2, 5, 8)
Population characteristics		
% aged consumers	Є [0,…,1]	(0.15, 0.5, 0.85)
Control variables		
number of agents	N	576
link-chance	Є [0,…,1]	random Є [0.3,…,0.7]
% early adopters	Є [0,…,1]	0.24
Response variable		
diffusion rate	Є [0,…,1]	

Table 4 Experimental design

As variation, simulation study B assumes different network designs for young and aged consumers. For this, the control variable network becomes an independent variable. The simulation experiments represent the experimental factors link-chance-young and link-change-aged as the network characteristics. The link-chance for young consumers is set on 0.6 and on 0.4 for aged consumers for the experimental design. Scenario I initializes the simulation as a network with 15% aged consumers, and scenario II uses a network with 85% aged consumers. Consequently, scenario I contains a loose network with a majority of young consumers, and scenario II a denser network with a majority of aged consumers. All other experimental factors, control variables, and response variables remain the same as in baseline study A.

Parameters	Scales	Experimental design
Experimental factors		
Product attributes		
ease-of-use	Є [1,…,10]	(2, 5, 8)
relative-advantage	Є [1,…,10]	(2, 5, 8)
Population characteristics		
% aged consumers	Є [0,…,1]	(0.15, 0.5, 0.85)
Network		
link-chance-young	Є [0,…,1]	0.3, 0.5, 0.7
link-chance-aged	Є [0,…,1]	0.3, 0.5, 0.7
Control variables		
number of agents	N	576
% early adopters	Є [0,…,1]	0.24
Response variable		
diffusion rate	Є [0,…,1]	

Table 5 Experimental design (Variation)

Error Variance Analysis

The experimental design defines the parameter combinations for the simulation experiments. For running the experiments, the number of repetitions per setting has to be defined. For this, Lorscheid et al. (2012) propose the analysis of variations over increasing number of runs as objective measure. For this pre-test, three design points (= parameter combinations) are chosen. A low design point, with low values for all experimental factors (ease-of-use = 2, relative advantage = 2, % aged-consumers = 0.15, link-chance= 0.3), a medium design point (ease-of-use = 5, relative advantage = 5, % aged-consumers = 0.5, link-chance= 0.5), and a high design point. (ease-of-use = 8, relative advantage = 8, % aged-consumers = 0.85, link-chance= 0.7). For these design points, simulation experiments with 1, 10, 50, 100, 250, and 500 runs are conducted, to learn about the variability of results (see Table 6).

Table 6 Error variance analysis about the variation of diffusion rates for increasing number of runs (SD = standard deviation, CV = coefficient of variation).

Design point	**Diffusion rate** (% of agents using the technology)	**1 run**	**10 runs**	**50 runs**	**100 runs**	**250 runs**	**500 runs**
Low	*Mean*	0.05	0.060	0.056	0.056	0.054	0.054
	SD	-	0.010	0.008	0.008	0.009	0.009
	CV	-	0.17	0.14	0.14	0.17	0.17
Medium	*Mean*	0.202	0.196	0.200	0.198	0.198	0.197
	SD	-	0.016	0.019	0.019	0.018	0.017
	CV	-	0.08	0.10	0.10	0.09	0.09
High	*Mean*	0.526	0.556	0.540	0.543	0.543	0.545
	SD	-	0.025	0.028	0.030	0.030	0.029
	CV	-	0.04	0.05	0.06	0.06	0.05

Table 6 shows a stabilization of variance from 250 runs. From this point, the standard deviation (SD) as well as the coefficient of variation (CV) only changes by <= 0.001. Thus. the diffusion rates only vary by 0.1 %. Already with 100 runs a stabilization can be observed with an interval of <= 0.002 in comparison to results with more repetitions. Given the identified variations on such a small scale, 250 repetitions may be sufficient according this pre-test. However, more repetition leads to more accuracy of results. Also, the complexity of the model is low, which leads to fast simulation runs. Therefore, the number of repetition is set to 500 for the simulation experiments, which is still affordable in terms of computational time for the given simulation model.

Sensitivity Analysis Link-Chance

The network characteristic determines the connections and, thus, the communication channels between consumers. In the simulation experiments, the control variable link-chance determines the probability for each consumer to establish a local connection to a neighbor (Stonedahl & Wilensky, 2008). Each adjacent agent is a neighbor. With a link-chance of 100%, each agent has 4 connections to each neighbor.

According to DOE methodology the control variables can be set or randomly varied (Lorscheid et al., 2012). Varying the control variables has the advantage that the results obtained are more general, as a wider range of settings is explored. Nevertheless, as we ensure via our sensitivity analyses that the control variables do not have a high impact on simulation behavior both approaches are viable.

Results from pre-tests show (see Figure 1), link-chance determines the range of diffusion rates. Loosely connected consumers may only achieve lower levels of diffusion than strongly connected networks. For the simulation experiments, the network should not limit the diffusion process. At the same time, only a minimum number of connections allow the emergence of diffusion on distinguishable levels. To avoid extreme cases the range for random values of link-chance are set on a medium range between 30% and 70%.

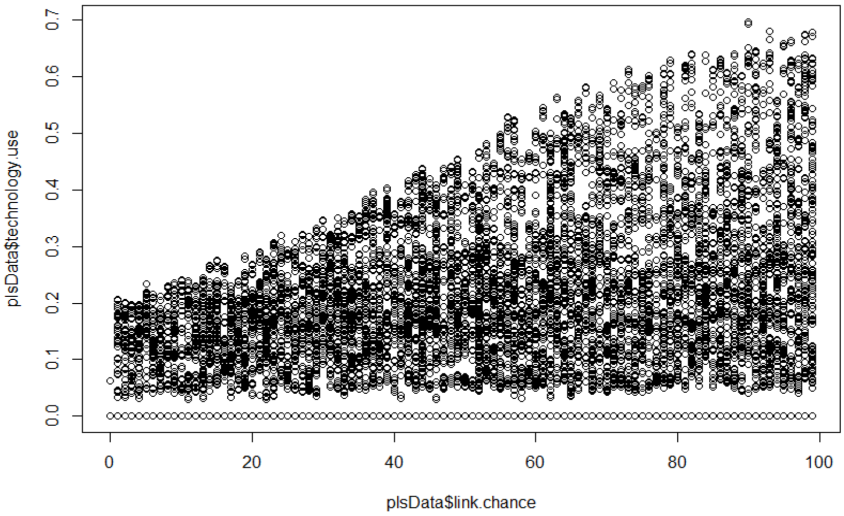
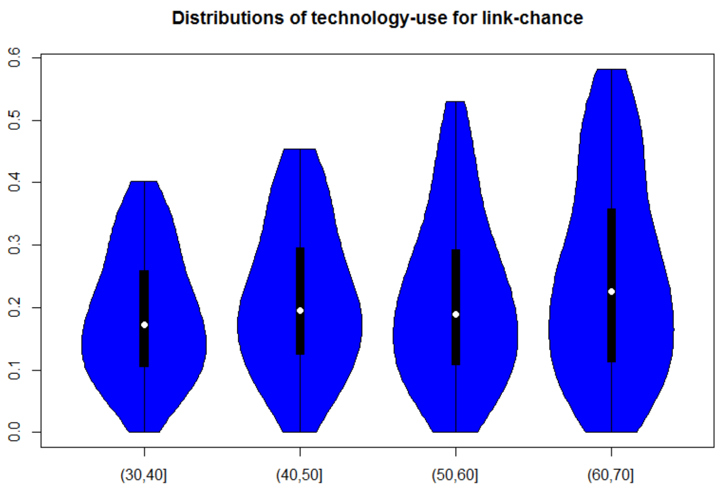


Figure 1 Sensitivity analysis - Link chance



Effect Analysis

Within the analysis, the interaction of the link chances with the other experimental factors on the diffusion rate is in focus. First, an overview of the factor effect sizes provides a condensed picture of the model behavior and, in particular, of the influence of product attributes and population characteristics on the innovation diffusion. Table 6 shows the effect matrix (Lorscheid et al., 2012) of all the experimental factors and their effect on the diffusion rate.

Response variable: diffusion rate	ease-of-use	relative advantage	% aged Population
ease-of-use	0.788	-	-
relative-advantage	0.052	0.423	-
% aged population	0.079	0.082	0.002

Table 7 Effect matrix

The results show ease-of-use (η^2=0.788) has the highest impact, followed by the big effect of relative-advantage (η^2=0.423). Given this result, ease-of-use seems to be more crucial and the more relevant product characteristic for the diffusion process than relative-advantage. The experimental factor aged population, on the other hand, has only a small effect (η^2=0.082). Examining aged population's interaction effects on the product characteristics, only small effect sizes are again observable, with η^2=0.079 between aged population and ease-of-use, and η^2=0.082 between aged population and relative-advantage. The PLS path model TAM shows that young and aged consumers have different product characteristic preferences. Given this knowledge, the effect sizes of aged population seem to be counterintuitive, due to the lack of a remarkable difference between aged and young consumers. Effect sizes provide an aggregated evaluation measure. The simulation model analysis is subject to a more detailed effect analysis by means of a graphical investigation.

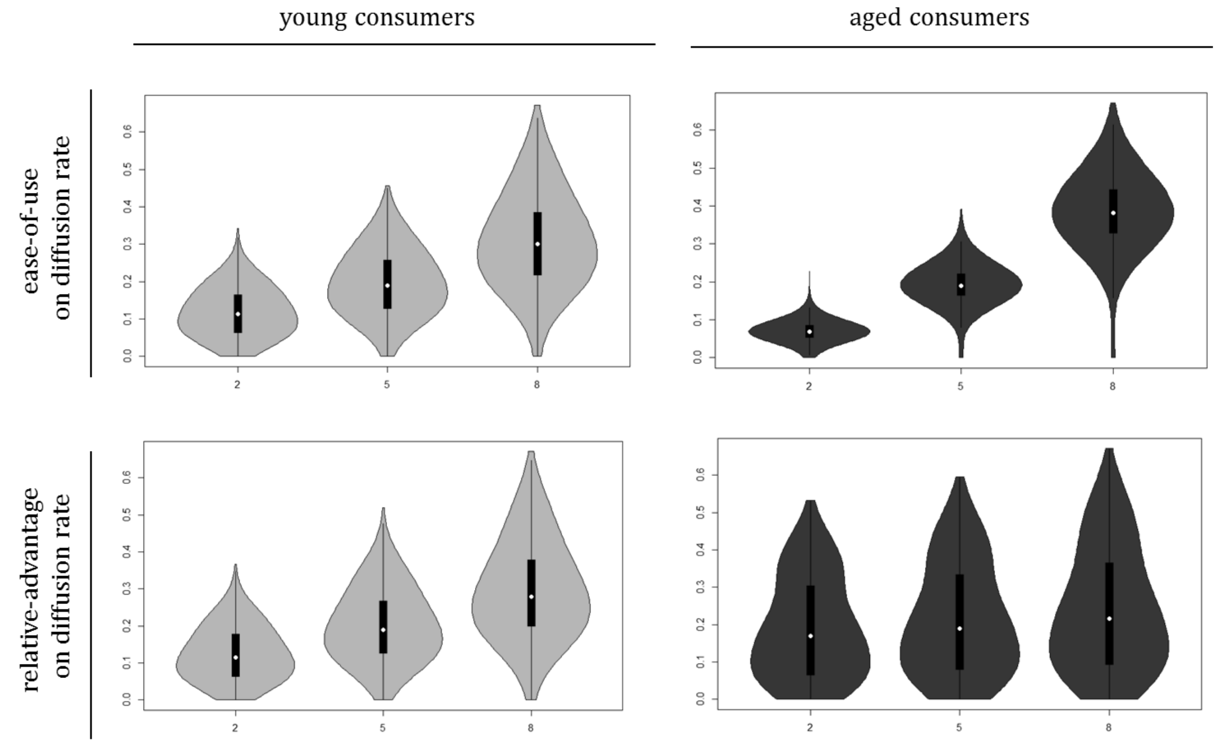


Figure 2 Diffusion rates for young and aged consumers

Figure 1 shows the distributions of the mean diffusion rates of varying product characteristics (upper part and lower part), divided into young and aged consumers (left and right part). Examining the distributions of the mean diffusion rates of varying values of ease-of-use for young and aged consumers, one identifies more overlap between the varying ease-of-use values and young consumers (upper left part) than between them and aged consumers (upper right part). This result is in line with the PLS path coefficients. For aged consumers, the total effect of ease-of-use is remarkably higher (0.518) than for young consumers (0.306). In addition, relative-advantage has a very small total effect on the technology use of aged consumers (0.067), while the determinant is comparably high for young consumers (0.294). Here, the diffusion rates regarding aged consumers are dependent on the product characteristic ease-of-use.

Consequently, the mean diffusion rates of the varying values of relative-advantage are similar for aged consumers (lower right part). The rate values increase only slightly with the higher values of relative-advantage. This result is due to the total effect of relative-advantage on the technology use of aged consumers, which is very small in the TAM. The distributions regarding young consumers, on the other hand, differ with the higher values of relative-advantage (lower left part). The shapes of the distributions are very similar to the distributions of the varying values of ease-of-use for young consumers. This result follows from the similar total effect sizes of relative-advantage and ease-of-use on technology use in the PLS path model TAM.

Overall, this graphical analysis shows higher diffusion rates of the high values of ease-of-use than the high values of relative-advantage. This supports the interpretation of the effect sizes that ease-of-use is more relevant for diffusion. Thus, high ease-of-use lead to both consumer types exhibiting more diffusion. On the other hand, the population characteristics have an impact on relative-advantage. For young consumer populations, relative-advantage is almost as important as ease-of-use, but is not important for aged consumer populations. While this interaction effect is only small, as reflected in the overall interaction effect value (see effect matrix), this result becomes obvious in a graphical representation (Figure 2).

The interaction graph shows that younger populations have higher rates of diffusion (15% aged population) than aged populations (85% aged population) and, thus, that age has an interaction effect on relative-advantage’s effect on diffusion. Hence, the high values of relative-advantage have an impact on young consumer populations, but a remarkable smaller impact on aged consumer populations.

Beside the individual priorities for product attributes, the network design is of relevance for the diffusion process. Depending on the behavior of other individuals in the network, individuals may be aware of innovative products or not.

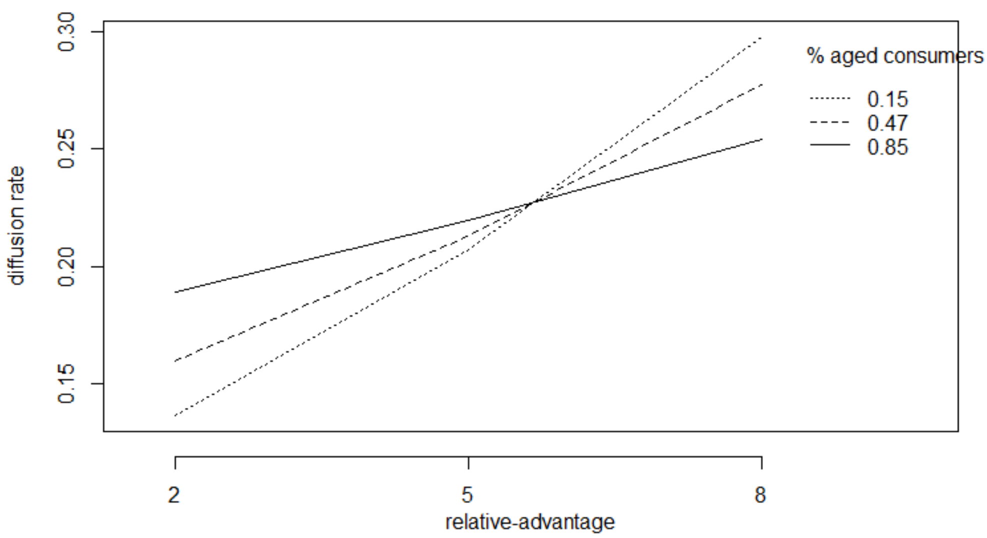
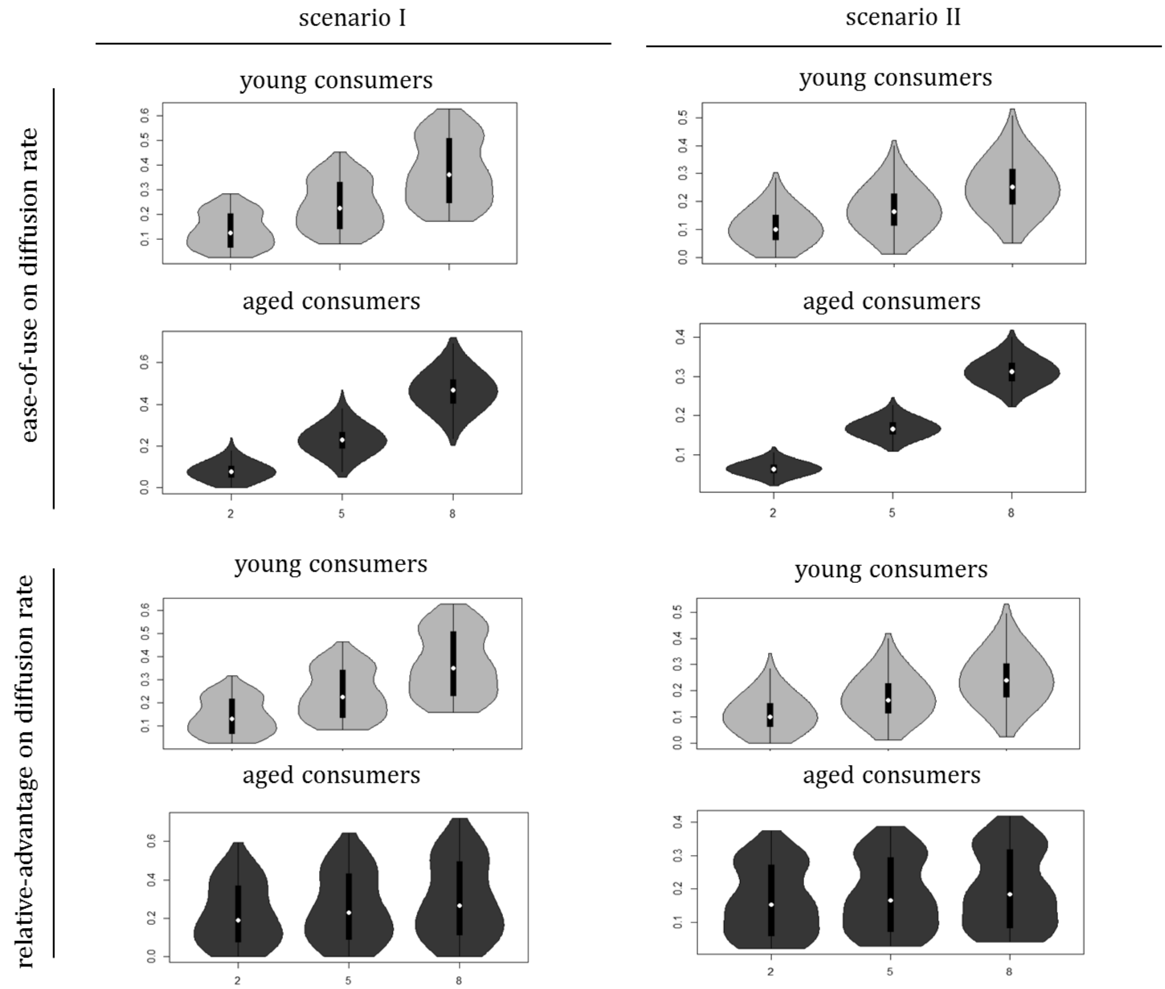


Figure 3 Interaction graph

The analysis continues with an adaptation of the simulation model in order to further analyze the role of network structure and neighborhood influence. This variation considers two population scenarios: Scenario I represents a population with a majority of young consumers and a dense network between the individuals; scenario II represents a majority of aged consumers and a loose network. The simulation analysis combines two dimensions of decision making: the individual preferences of the consumer types young and aged, as well

as the connection to and communication with other consumers (for more details about the design of the simulation experiment see Appendix).
The simulation model analysis reveals that the preferences in the network influence individual decisions about using the innovative product (see Figure 5).



Note: The figure displays the distributions of the mean diffusion rates of varying product characteristics of young and aged consumer types, divided into categories of two population scenarios (scenario I in left column, scenario II in right column).

Figure x shows the diffusion rates of young and aged consumers in population scenario I (left column) and scenario II (right column). The upper half shows the diffusion rates of varying values of product characteristic ease-of-use, the lower half the diffusion rates of varying product characteristic relative-advantage.
The population scenarios influence the individual diffusion rate distributions, although the individual decision models remain the same. In scenario I, mostly young consumers surround young consumers, while the majority of consumers in scenario II are aged consumers. The network scenarios influence the awareness of products by individual young consumers, and, thus, their decision to use a technology. Relative-advantage is important for aged consumers, which is why the information about products with this characteristic spreads less than about products with high ease-of-use, which is the most important factor for aged consumers. Young consumers, thus, receive more information about products with high ease-of-use than about products with high relative-advantage. Consequently, the diffusion rates of products with high relative-advantage among young consumers are lower in scenario II than in scenario I. The same phenomenon, only in a different direction, is obvious for aged consumers in population scenario I. With a majority of young consumers, more aged consumers decide to use products with high relative-advantage. Scenario I shows that the

consumers receive more information about this kind of innovative product than in aged societies, where products with high relative-advantage rarely spread.
These results show how context matters and shapes the individual decisions. Consequently, innovative products may be in use by individuals with sometimes even other priorities. This relevant aspect is not obvious by looking only at the PLS path model TAM, but becomes evident in a dynamic simulation-based analysis with varying populations and network characteristics.

Additional material

Scenario I

What are the average diffusion rates for inputs?			
	product attributes		
ease-of-use	*2*	*5*	*8*
mean diffusion rate	**9%**	**19%**	**35%**
relative advantage	*2*	*5*	*8*
mean diffusion rate	**15.76%**	**20.82%**	**26.96%**
% aged consumer	*15%*	*47%*	*85%*
mean diffusion rate	**20.91%**	**21.16%**	**21.47%**
	case study		

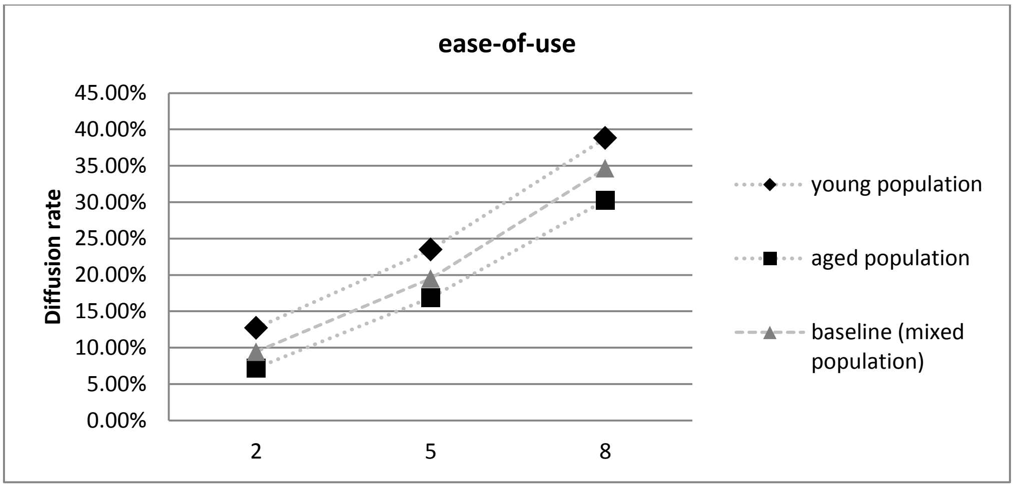
What are the resulting effects on diffusion?						
ease-of-use	*low_medium*	**10.06%**	*main effect*	**25.21%**	*eta-squared effect size*	**0.79**
	medium_low	**15.15%**				
relative advantage	*low_medium*	**5.07%**	*main effect*	**11.20%**	*eta-squared effect size*	**0.79**
	medium_low	**6.13%**				
% aged consumer	*low_medium*	**0.25%**	*main effect*	**0.56%**	*eta-squared effect size*	**0.52**
	medium_low	**0.32%**				

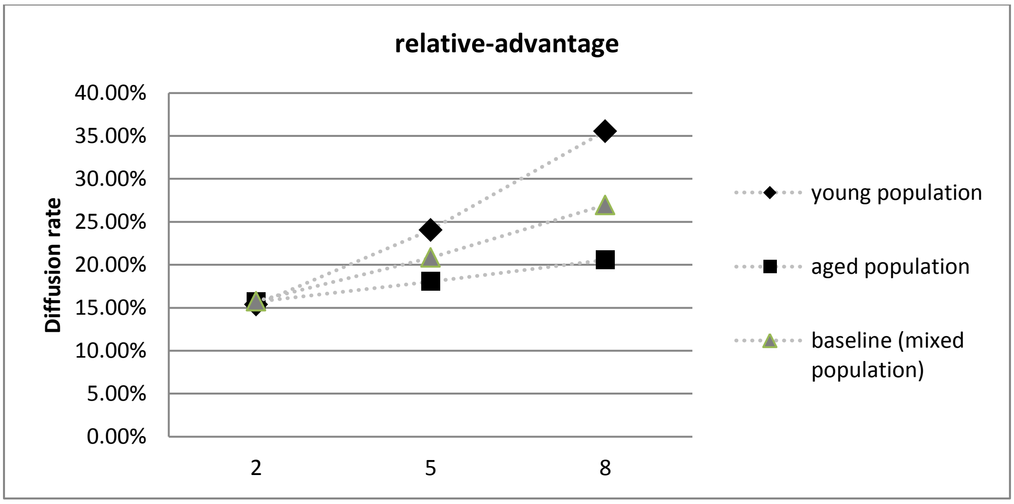
Scenario II

What are the average diffusion rates for inputs?			
	product attributes		
ease-of-use	*2*	*5*	*8*
mean diffusion rate	**9.64%**	**20.00%**	**35.41%**
relative advantage	*2*	*5*	*8*
mean diffusion rate	**16.15%**	**21.31%**	**27.64%**
% aged consumer	*15%*	*47%*	*85%*
mean diffusion rate	**21.38%**	**21.64%**	**22.07%**
link-chance-young	*30%*	*50%*	*70%*
mean diffusion rate	**19.49%**	**21.73%**	**23.88%**
link-chance-aged	*30%*	*50%*	*70%*
mean diffusion rate	**19.35%**	**21.72%**	**23.92%**

What are the resulting effects on diffusion?

ease-of-use	*low_medium* *medium_low*	**10.37%** **15.41%**	*main effect*	**25.77%**	*eta-squared effect size*	**0.85**
relative advantage	*low_medium* *medium_low*	**5.15%** **6.33%**	*main effect*	**11.49%**	*eta-squared effect size*	**0.53**
% aged consumer	*low_medium* *medium_low*	**0.26%** **0.43%**	*main effect*	**0.69%**	*eta-squared effect size*	**0.00**
link-chance-young	*low_medium* *medium_low*	**2.24%** **2.15%**	*main effect*	**4.39%**	*eta-squared effect size*	**0.14**
link-chance-aged	*low_medium* *medium_low*	**2.37%** **2.20%**	*main effect*	**4.57%**	*eta-squared effect size*	**0.14**





Summary			
ease-of-use	*2*	*5*	*8*
young population	12.70%	23.46%	38.79%
aged population	7.18%	16.86%	30.26%
baseline (mixed population)	9.43%	19.49%	34.63%
relative advantage	*2*	*5*	*8*
young population	15.36%	24.04%	35.55%
aged population	15.69%	18.05%	20.56%
baseline (mixed population)	15.76%	20.82%	26.96%

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