

User Acceptance of Business Information Systems and their Influence on Organizational Performance

An agent-based model

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Abstract. In the past, great efforts have been made in the field of business information systems acceptance and usage to better understand, which parameters influence the acceptance and use. However, often those studies remain on the individual level of analysis. In the paper at hand, we extend existing research to the organizational level and allow for an analysis over time employing data from an agent-based simulation model. We find that the environmental complexity negatively affects acceptance and usage of business information systems, which eventually leads to a decreased organizational performance. This has implications for the management of business information systems in changing environments.

Keywords: agent-based model, simulation experiment, business information systems, technology acceptance, IS success, complex systems

1 Introduction

Today data is omnipresent, and its volume is ever-increasing. In 2012, 2.5 exabytes of data were created every day and it was assumed that this number will double every 40 months [1]. Others predicted that the total volume of data will reach 40 zettabytes by 2020 [2]. This data, however, only becomes valuable if it is processed in a way so that meaningful information can be retrieved [3]. To master this enormous amount of data and to extract the needed information, business information systems (BIS) are used. They provide means to collect, process, store and distribute data and information [4].

BIS, aim at providing a comprehensive understanding of an organization's operations today and in the future [5]. This helps employees to access more suitable information that support their tasks [4]. Eventually, BIS support generating competitive advantages, help to innovate businesses, to enter new markets and to improve value chains by adapting processes, based on the gained insights [6-9].

Despite all the promises that come with the implementation of BIS, these systems can only deliver to their full potential if they are accepted and continuously used [10, 11]. However, acceptance and continuous usage are not guaranteed, given that BIS are

often used on a voluntary basis unlike, e.g., transactional information systems [10-12]. That is why acceptance and usage are among the major concerns when it comes to successful BIS implementation [13, 14].

Concerning the acceptance and usage of new information systems (IS), a lot of research has been conducted in the last decades given its importance in a progressively more digitalized world [15, 16]. Among the most prominent models to analyze IS acceptance and usage are DeLone and McLean's *IS success model*, the *technology acceptance model* (TAM), and the *unified theory of acceptance and use of technology* (UTAUT) [16].

This paper builds on this existing research and investigates whether employees will accept and use a BIS. Extending previous research that often relies on structural equation modeling (SEM) as a rather static perspective, this paper takes a bottom-up approach from individual employees, their behavior in an organization, and their relationships and interactions with each other over time, to the organization as a whole and its environment [17]. To conduct such analyses, we propose an agent-based model as an abstraction of the system. Subsequently, simulation experiments are conducted to investigate the inner workings of that system regarding the acceptance and usage of BIS, their contribution to organizational performance, and how the system changes over time in different environmental settings. This leads to the research questions we aim to answer here: *How does an organization's environmental complexity influence the acceptance and usage of BIS among its employees? And how do acceptance and usage of BIS influence organizational performance?*

2 Conceptual foundations

With respect to IS success, various theoretical models have been developed to identify and explain the factors that are essential for individuals to accept and joyfully use IS [16, 18]. Our conceptual model builds upon an integration of TAM and the IS success model that was proposed by Wixom and Todd [18]. The goal of combining TAM and the IS success model is to bring together two main research streams: First, there is the *technology acceptance* literature (TAM and UTAUT [15, 19]), which focuses on attitudes and beliefs to predict usage and acceptance [18]. Second, there is the *user satisfaction* literature with its object-based approach [18]. Models following this second stream (e.g., the IS success model [20]), measure user satisfaction by considering system and information characteristics [18].

Both research streams have strengths and weaknesses. One of the fundamental problems of the user satisfaction stream is the limited explanatory and predictive power, for predicting system usage [18, 21, 22]. The reason is that the *perceived system and information quality* of the IS (fig. 1), and the affected *user satisfaction* are not directly predictive for IS *usage* [18, 23]. Rather, user satisfaction is an object-based attitude, serving as an external variable that has an indirect influence on *intention to use* and the actual *usage* over *perceived ease of use* and *perceived usefulness* [18, 24]. User satisfaction itself is composed of *information satisfaction* and *system satisfaction*, which are determined by *information quality* and *system quality* [18]. In this

framework, information and system quality are considered object-based beliefs. The constructs behind information quality are *completeness*, *accuracy*, *format*, and *currency of information*. The constructs behind system quality are *reliability*, *flexibility*, *integration*, *accessibility*, and *timeliness of the system*. Building on these foundations, a model is proposed that integrates both, TAM and the IS success model (fig. 1) [18].

We do not consider UTAUT because. Despite the fact that it explains a reasonable amount of variance in the context of behavioral intention (*intention to use*) and actual usage behavior of IS [25], it is often also criticized for being too complex, with its at least 41 independent and 8 dependent variables, while some important variables and features are still neither considered nor included in the model [26]. The goal pursued with this decision, was keeping the model complexity at a manageable level. Furthermore, the IS success model and the TAM are still today by far the most used models in the discussed research context [16].

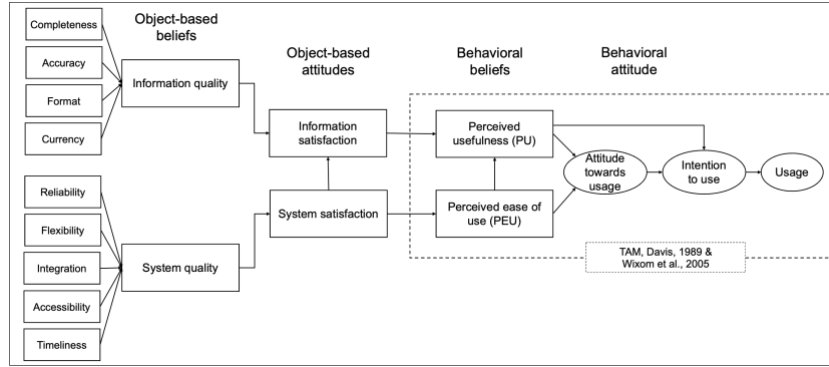


Fig. 1. Decision model with integrated TAM and IS success model (based on [18])

Our proposed conceptual model (fig. 2), which abstracts the reasoning process of individual employees on whether to accept and use a BIS, builds upon the work of Wixom et al. [18] who provided the foundation for linking TAM and the IS success model.

To keep complexity at a manageable level, not all constructs and antecedents introduced by Wixom et al. are included in our model. We consider only the statistically most significant ones [18]. Correspondingly, for information quality, *completeness* and *accuracy* are included, as well as in the case of system quality, *reliability*, *flexibility*, and *accessibility* are included in the model [18]. Of course, the assumption that the constructs that were the most significant ones in Wixom's analysis of the success of data warehousing, are significant in the context of BIS success as well, is a simplifying assumption. The included constructs might not be exhaustive. Yet, Wixom et al. assume that the results can be transferred to a certain extent to other contexts, too [18].

Beyond Wixom et al.'s work, additional factors that influence the dependent variables, *acceptance and usage of the BIS* as well as *organizational performance*, were considered for our conceptual model [8, 18]. First, we accounted for users' interactions by conceptualizing *social influence* and how it affects *intention and attitude to use* and

accept IS [25, 27]. Second, we included the facilitating organizational conditions, focusing on the *provided training* and the *quality and frequency* of it. Here, *managers* act on behalf of the organization offering those trainings [28].

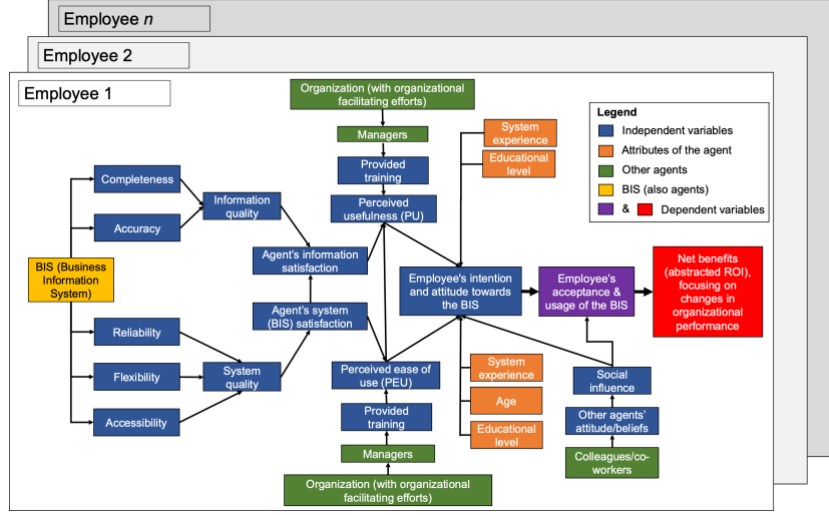


Fig. 2. Proposed model on acceptance and use of BIS in organizations (based on [18, 28, 29])

3 Research method and approach

3.1 Agent-based modelling and simulation

Agent-based modelling and simulation (ABMS) is an approach to model complex systems composed of distributed and interrelated parts that contain interacting autonomous agents [30, 31]. ABMS is well suited to model and analyze complex systems that may demonstrate non-linear behavior that *emerges bottom-up*, from individual *agents* to the entire organization, and *over time* [31-33]. Agents have specified *behavioral rules*, *attributes*, and *interactions* with other agents, situated in an *environment* [30, 34]. From those interactions the overall systems' behavior emerges. Due to these characteristics, ABMS are well suited to model organizations, or sociotechnical systems, and conduct experiments exploring underlying mechanisms and evolving dynamics [30, 35-38].

This makes ABMS very attractive, since it relaxes many of the limitations of classical experiments and empirical research that can hardly study the effects of various manipulations in large organizations over time [36]. At the same time, ABMS provides challenges for researchers, too. It requires focus, complexity reduction, abstraction, and simplification, while not oversimplifying complex phenomena [32, 33]. An additional challenge encountered was the astonishing scarcity of precedent studies that use ABMS in a comparable context. While there is quite some research on using ABMS for *technology adoption*, in the IS success literature on BIS implementation, acceptance,

and usage, agent-based modelling and simulation seems to be a practically unexplored methodological approach with only a very recent paper in a somewhat different setting [51]. On the one hand, this underlines the relevance and novelty of our study but on the other hand, this also implies being particularly careful in the development of the simulations model and making sure that this paper is properly grounded in the existing theoretical foundations. Our approach to this matter is outlined in more detail below.

3.2 The Agent-based Model (ABM)

There are three main component types that form an ABM: *agents*, *interactions*, and *environments* [31].

Agents. ABMs comprise two types of agents. First, there are actors. They take decisions according to some decision rules, behave in a certain way, and communicate and interact with other agents. In return, agents interacting with one another may influence their decisions and behavior [34, 39]. In our simulation model *employees* are actors who act autonomously to achieve their objectives [34]. These employees have characteristics, such as *age*, *educational level*, and *system experience*, which are randomly assigned according to certain distributions. For instance, age ranges from 18 to 65 and is allocated following an equal distribution. The employees can be considered utility-based agents. They look for the optimal, potentially accessible BIS, and gain access to this BIS to solve tasks in the best possible way [40]. Thereby, the employees maximize their utility [40]. We operationalize utility by the ROI generated through solved tasks.

Another type of actor are *managers* acting on behalf of the organization (fig. 2). Their role is reduced to providing trainings for the employees to enhance their capabilities in dealing with the BIS.

Second, we consider the BIS themselves as material technology artifacts that are used by employees to solve tasks [41]. We model BIS as simple *reflex-based agents*. In the ABM, these BIS and their interactions are modeled using situation-action rules (if-then rules) [40]. For instance, with an increasing age, a BIS outdates, i.e., it becomes less suitable to solve current tasks.

Environment. Two environments need to be differentiated (fig. 3). First, there is an actor's working environment (office space, IT infrastructure, etc.) in which the actor is located. Second, there is the organization's environment (specific industry, legal framework, etc.). In our model the latter environment provides (business) opportunities to an organization. We abstract this environment as a complexity scale [42-44]. The more complex the environment is, the more components, relationships, and dynamics of those can be observed [42, 45]. Accordingly, interdependencies in complex systems may not be apparent, they may be unclear or ambiguous [46]. The growing amount of information and the increasing difficulties in correctly processing progressively more ambiguous and uncertain information [45, 47], make solving tasks harder.

Interactions and agent's behavior. Five basic classes of interaction can be distinguished in ABMs: *agent-self*, *environment-self*, *agent-agent*, *environment-environment* and *agent-environment* interactions [31]. These interactions can be modeled by connections and information flows [44, 48].

Agent-self interaction means that the interaction happens within the agent and among its parts (decision rules, attributes, etc.) [31]. This type of interaction plays a crucial role in our ABM considering that most of the cognition and reasoning (e.g., deciding whether to accept and use a certain BIS) of an agent involves interacting with itself [31]. In each tick of the simulation model, agents consider their current state and decide how to adjust and which action to take, based on the specified decision rules [31].

Two additional types of interactions need to be considered as well. First, the interaction between each employee and the BIS accessible to her. As part of this *agent-agent* interaction [31] each employee evaluates, which of the BIS at disposition is the optimal one to solve the assigned tasks. Among all accessible BIS an employee chooses the most suitable one. Second, there is the related *agent-environment* interaction, where the employees solve tasks to contribute to the exploitation of opportunities that arise from the environment [3, 4, 43].

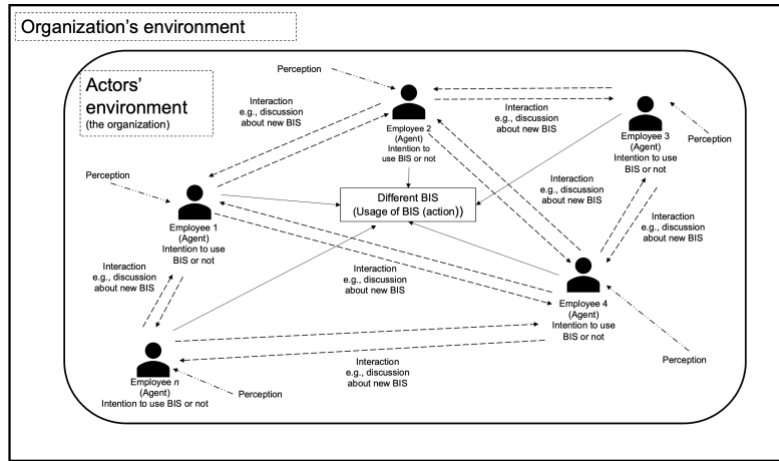


Fig. 3. Simplified representation of the ABM including the environments, the actors (employees) and their interaction (based on [49, 50])

3.3 Model Validation

Other studies often rely on simulation models that were validated in previous studies, by adapting or extending those models for their purposes [44, 52]. This was possible only to some extent in our research. This is due to the circumstance that only little research exists, relying on ABMS in the areas of IS success, acceptance and usage of BIS, and their influence on organizational performance. Yet, existing patterns were used whenever possible and reasonable. For instance, the *fitting score*, a measure describing how well a BIS is suited to solve a certain task, was calculated based on Haki et al.'s computation of the match between IT applications and opportunities [44].

We base the implementation of our ABM on well-established theoretical foundations such as the IS success model, the TAM, research about BIS, and the concepts of complex adaptive systems. We tested our model in various simulation runs for internal

validity, predominantly focusing on consistency across several runs. We tested the value ranges for the different independent variables for which the model is valid and works properly before degenerating beyond those value ranges.

In the last validation step, we tested whether the developed simulation model is able to reproduce well-established theoretical and empirical findings. This validation step aims for attesting that our simulation model is in line with its theoretical foundations.

In principle, our data support the findings from previous studies that better accessibility results in higher system quality and therefore in higher *acceptance and usage among employees* [18, 53]. Furthermore, the linear, as well as quadratic components, were found to be statistically highly significant. This means, an increase in *accessibility of BIS in the company* on a lower initial level has a bigger effect on *acceptance and usage*, than further enhancing the accessibility if the initial accessibility level was already high. Put differently, it can be stated that our data supports a diminishing marginal effect of *accessibility of BIS in the company* on *acceptance and usage* [54, 55].

In previous studies the provided training was found to have a significant effect on *perceived usefulness* (PU) and *perceived ease of use* (PEU) and therefore also on the *acceptance & usage of BIS* [28, 56]. Different studies in the field of BIS research, support unanimously that a higher *quality* of trainings as well as a higher *amount* of training have a positive impact on PU and PEU [28, 56]. In line with this, a positive effect on the *acceptance & usage of BIS among employees* is corroborated, too [28, 56].

In our ABM, training was operationalized, relying on two constructs that have been used in multiple previous studies to assess how PU and PEU are affected by training. First, the construct *quality of training* is employed [28]. Second, the *amount and frequency of training* was considered [56].

Examining the data generated during the simulation experiments regarding the relationship between *quality of training* and *acceptance and usage*, it can be observed that there is a positive relation between the two: if the quality of the training increases, the *level of acceptance & usage of BIS among employees* increases as well. This is consistent with the results of previous studies [28].

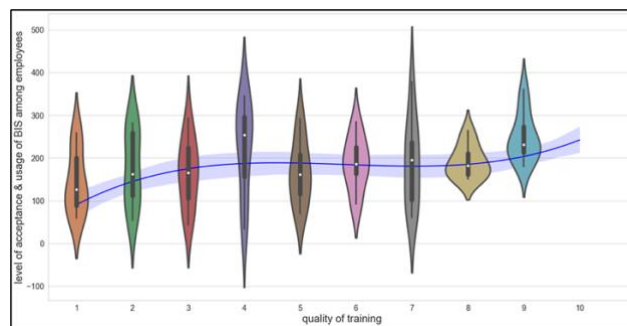


Fig. 4. Quality of training and its effect on acceptance and usage of BIS among employees

Having a closer look at fig. 4, it becomes apparent that the relation between *quality of training* and *acceptance and usage of BIS* is not just a positive linear relation but rather

a dependency with a quadratic and a strongly influential cubic component, too. This finding is supported by the fact that in a regression analysis with *quality of training* as independent variable and *acceptance and usage* as the dependent variable, all three components are found to be highly significant ($p < 0.02$).

Considering fig. 5, it can be stated that a higher amount of training and more frequent training sessions lead to a higher *level of acceptance & usage of BIS among employees*. This is consistent with the results and conclusions of previous studies [56]. So, with our ABM, the findings for *frequency & amount of training* and its impact on *acceptance and usage of BIS among employees* can be reproduced.

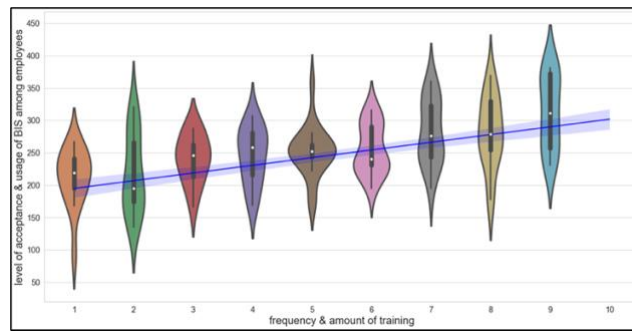


Fig. 5. *Frequency & amount of training and its effect on acceptance and usage of BIS among employees*

However, in our ABM, a higher amount of training (more frequent training) and training of higher quality, both lead to higher costs, too. These effects will be crucial, in assessing the impact of acceptance and usage of BIS as well as of other parameters on the organizational performance. This model design accounts for the fact that training also generates costs, which in return diminishes the profits in the short run but may increase organizational performance over time.

Not least, *completeness* and *accuracy*, two well-established and highly significant measures for *information quality* (figs. 1 & 2), as well as the *reliability* of a BIS, affecting *system quality* [18], were all three subsumed in the abstract independent variable *fitting score*. It describes how well-suited a certain BIS is to solve a certain task.

To investigate, how the *fitting score* influences the *acceptance & usage of BIS among employees*, we first uniformly manipulated the *fitting score* by an offset value. Second, we vary how impactful the fitting score is on the prospects of success that an employee solves a task, and she can retrieve the information desired with the help of a BIS. This independent variable is called *impact of fitting score on successfully solving tasks*. Investigating the data on how the two variables, *value of fitting score* and *impact of fitting score on successfully solving tasks*, affect the *level of acceptance & usage of BIS among employees*, we found that with increasing values for both variables, the *acceptance and usage of BIS* is positively affected (fig. 6).

By being able to reproduce results from previous studies, and by investigating these results in more detail, additional evidence could be collected that our ABM works as

intended. Accordingly, the validity claim for our model could be further strengthened. Therefore, we considered taking the next step of contributing insights to the IS success literature.

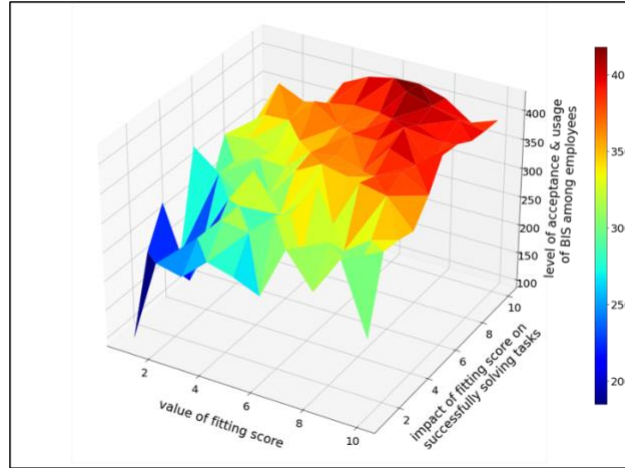


Fig. 6. Value of fitting score and impact of fitting score on successfully solving tasks and their impact on acceptance and usage of BIS among employees

4 Results

4.1 The effects of environmental complexity

The environment's complexity represents the complexity of a sector/industry/market an organization finds itself in. It conceptualizes diverse aspects such as the complexity of the interdependencies in this specific context, the complexity of the regulatory environment, speed, frequency, foreseeability of occurring changes, and so forth [42, 45, 46]. Employees can contribute to exploiting the opportunities arising in the environment, by successfully solving tasks. BIS are crucial for taking advantage of these opportunities and exploiting them.

Successfully solving tasks generates a positive contribution to an *abstracted ROI* (fig. 2). It is called *abstracted* because it is an abstraction of a multidimensional measure of *organizational performance* that includes monetary benefits but also non-monetary short- and long-term net benefits [57]. There are many discourses on how and what to measure for describing organizational performance [69]. While finance-oriented people may rather suggest different profitability measures, marketing researchers might propose customer satisfaction as a measure of organizational performance [70]. In recent research, multidimensional conceptualizations of organizational performance are usually relied upon [70, 71]. By taking into account monetary as well as non-monetary short- and long-term net benefits in our abstraction,

this practice of multidimensionality is reflected while keeping conceptual complexity at a low level.

If tasks are solved correctly, the ROI increases, while in case of not being able to solve the tasks, due to an increasingly complex environment or other factors, the ROI is reduced, given that costs are still incurred. Generally, it applies, the higher this *abstracted ROI*, the better the organizational performance in exploiting new opportunities that arise. If the environment becomes more complex, it becomes increasingly difficult to take advantage of arising opportunities and therefore it is also getting harder for employees to successfully solve the task presented to them. That is why the ROI, and thus the organizational performance in exploiting arising opportunities, is hypothesized to decrease with increasing *environmental complexity*.

Following this argumentation, the perceived *information quality* and *system quality* of the BIS among employees diminish in an increasingly complex environment. This is due to the fact that fewer tasks can be solved and the desired information can often not be retrieved or is less helpful. In other words, in more complex environments the completeness and accuracy of the information, which affect the information quality, the reliability of the BIS, and the system quality, diminish. Accordingly, the agents' satisfaction, PU, PEU, and hence also the *level of acceptance & usage of BIS among employees* decrease (fig. 2). We will further discuss these aspects in the following.

Environmental complexity and its influence on acceptance and usage. Analyzing the generated data with respect to the influence of *environmental complexity* on the *acceptance and usage of BIS among employees*, a decrease in *acceptance and usage of BIS among employees* with increasing *environmental complexity* was found, as hypothesized above (fig. 7). Examining this relation more closely, it becomes apparent that the way *environmental complexity* is affecting *acceptance and usage* is not simply linear or quadratic but rather cubic (fig. 7). This applies for the range of *environmental complexity*, in which the simulation model is considered to be valid. By adding a cubic component to the regression model, adj. R^2 is increased by 0.05. Furthermore, the coefficient of the cubic component is statistically highly significant ($p < 0.001$). In addition, the f-statistic is high and clearly above ten. In such a case, having a very small p-value and an f-statistic clearly above ten, it can be assumed that the cubic relation is valid [58, 59]. Moreover, the RMSE decreases from 66.5 to 61 when adding a cubic component to the regression.

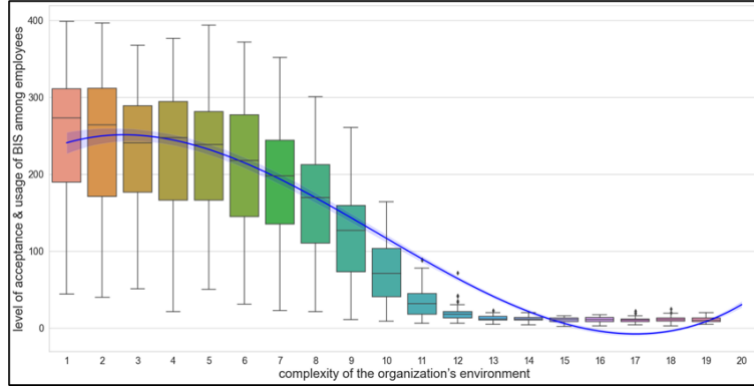


Fig. 7. Effect of *environmental complexity* on *level of acceptance & usage of BIS among employees*

This cubic relationship signifies, that if the complexity of the environment is varying on a modest level, there is hardly any impact on the *level of acceptance and usage of BIS* but from a certain threshold on, an increase in complexity immensely impacts the *acceptance and usage*. Further, if an organization already finds itself in a highly complex organizational environment, a further increase *environmental complexity* only affects the *acceptance & usage of BIS among employees* in a negligible way. We conclude that only if an organization finds itself in an environment of medium complexity, the organization's management has to anticipate a significant drop in *acceptance & usage of BIS among employees* in case the *environmental complexity* is further increasing, and appropriate measures should be taken.

Environmental complexity and its impact on organizational performance. Investigating the generated data concerning the effect of the *environmental complexity* on *organizational performance*, a decline in *organizational performance* with the increasing complexity of the environment was found (fig. 8), as hypothesized.

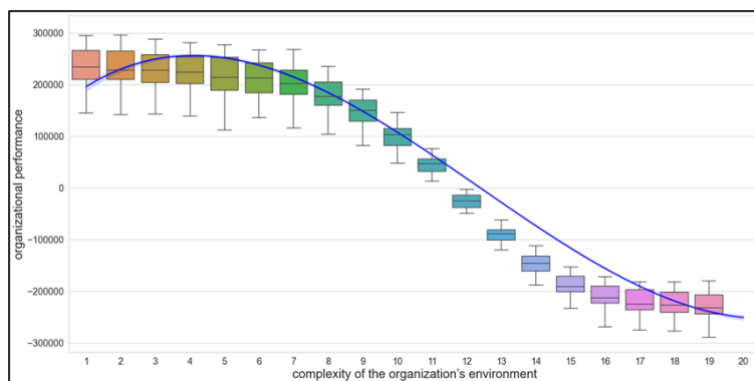


Fig. 8. Effect of *environmental complexity* on *organizational performance*

It can be stated, that the higher the complexity of the environment, the worse the *organizational performance*, respectively the lower the *abstracted ROI*. More precisely, this relationship can be described as a cubic one with statistically highly significant linear, quadratic, and cubic components.

4.2 The effect of acceptance & usage of BIS on organizational performance

In a final simulation experiment, the influence of *acceptance and usage of BIS among employees* on *organizational performance* was investigated. We controlled for other variables discussed before (fig. 9).

Analyzing the data generated through this rather comprehensive simulation experiment, a positive relationship between *acceptance and usage of BIS among employees* and *organizational performance* was found. While this finding is supported by a highly significant positive slope coefficient, found for *acceptance and usage of BIS* in relation to the impact on *organizational performance*, this finding is also consistent with the theoretical foundations and concepts previously introduced. If BIS are more often used in the right context due to high *acceptance and usage among employees*, relevant tasks are more often solved successfully. Therefore, a higher proportion of the successfully solved tasks contribute to profitably exploiting opportunities in the organization's environment. In line with our previous discussions, it also applies, that the more opportunities can be taken advantage of, the higher the increase in *organizational performance*, given that exploited opportunities contribute to an increase in *organizational performance*.

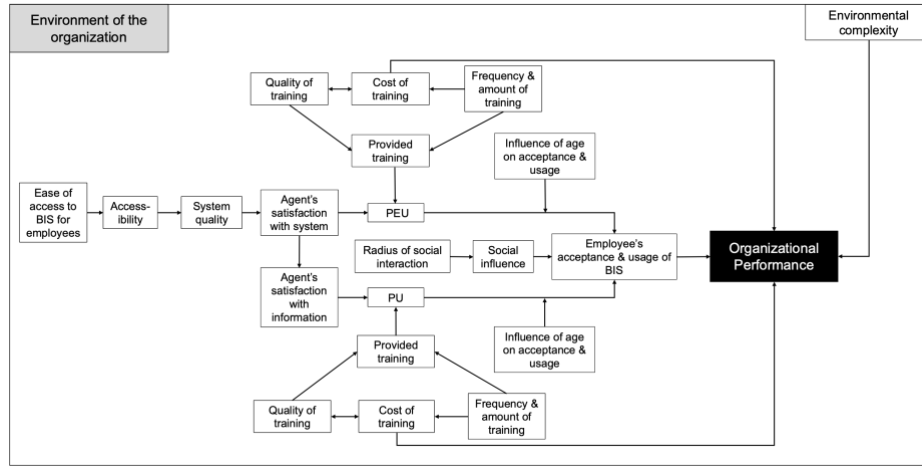


Fig. 9. Tested model in the simulation experiment

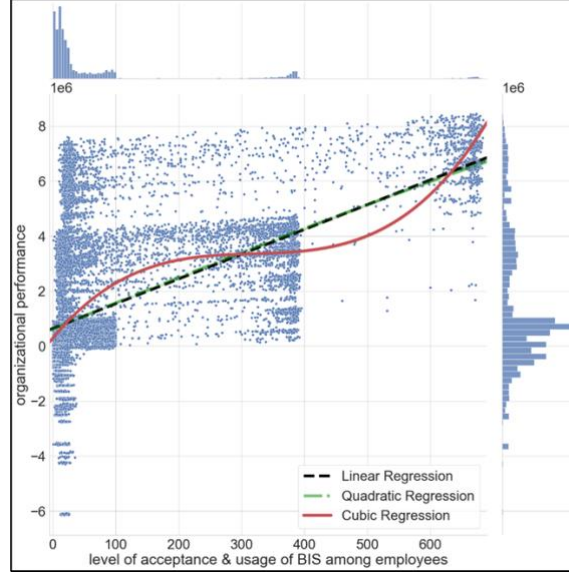


Fig. 10. Effect of *acceptance and usage of BIS among employees* on *organizational performance*

Following this argumentation, it becomes clear why this finding of a positive impact of an increasing *level of acceptance and usage of BIS among employees* on *organizational performance* (fig. 10) is supported by the theoretical foundations, too.

5 Discussion

Limitations. We have taken measures to assure model validity with regard to its content, to extant research, and to the methodological approach of ABMS. After the initial development, the ABM was revised, enhanced, tested, and validated in an iterative manner. The successful reproduction of findings from previous research in the same field of study, but with different methodological approaches, further supports the validity of the proposed ABM.

However, a limitation inherent to all simulation models is its abstraction and simplification of reality and real-world phenomena [32, 60]. Through simplification and abstraction these phenomena are “translated” into computational representations, which aim at representing complex systems like organizations, their environment as well as the humans (employees) within the organization [32, 60, 61]. The only solution to keep model complexity at a manageable level is to reduce and abstract. For instance, the organization’s environment and the different possibilities of either the organization or the employees to interact with the environment were reduced to the environment’s complexity and to opportunities that arise in the environment, exploitable by the organization and its employees. Not least, the human behavior and individuality of the employees, modeled as agents in the ABM, can only be simplified, reduced, and

abstracted, given that their multi-layered psychology, their subjective preferences, and their humane, potentially irrational choices can never be fully captured by a model with reasonable complexity [34, 62]. In return, such a highly complex model would lose explanatory power, since it would be difficult to understand [34, 62]. Still, the ABM approach does account for the diversity of agents and their interactions that emerge into a complex and non-linear behavior.

The way ABMS abstracts real-world phenomena makes it a powerful tool for exploring the underlying mechanisms of complex systems. Yet, (our) ABM is not well suited for predicting the behavior or outcomes of a specific system instance, that is of a specific organization, due to its high level of abstraction.

Not least, for the analyzed parameters only a certain range of values is evaluated in which the model is considered to be valid and is not degenerating. With regard to these limitations, the results presented in section 4 and the derived insights, theoretical and practical implications, should be critically examined in the following, and conclusions should be drawn carefully.

Implications for Research and Practice. At the beginning of research, it was not entirely clear whether the methodological approach, ABMS, as well as the developed model, are suitable to investigate the phenomenon of *BIS acceptance and usage* in an organizational context, the impact of *environmental complexity* on *acceptance and usage of BIS* as well as the impact of *acceptance and usage of BIS* and of *environmental complexity* on *organizational performance*. This ambiguity arose due to the very scarce number of precedent studies that use ABMS in a similar context. Furthermore, in the IS success literature and with regards to BIS acceptance and usage, agent-based modelling and simulation seems to be an entirely unexplored methodological approach. The successful development of an ABM and the fruitful reproduction of some results, effects, and dependencies, found in previous studies, applying this atypical methodological approach, strongly endorse ABMS as a promising methodological approach for further research in the field of BIS implementation, acceptance, and usage [63-65]. Further, ABMS could be presented in this paper as an auspicious approach to extend the established individual-level of analysis into true multilevel research [63-65]. Likewise, we offer an approach on extending the existing IS success literature or more precisely the streams focusing on BIS implementation, acceptance, and usage to an organizational level.

For organizations, our results highlight that acceptance & usage of BIS is not only related to individual users but entails dynamics in the social system of an organization that is not limited to an intra-organizational perspective but stretches beyond the “boundaries” of an organization. While this finding may be intuitive, it has implications for the evolution of BIS in organizations that may increasingly become part of digital platform ecosystems or even chose the role of platform owners. The aim of digital platform ecosystems to accommodate environmental complexity more effectively [66, 67] will increase the requirements for BIS in organizations.

Opportunities for Future Research. Admittedly, in this paper we only took a first step of extending IS success and acceptance research to the organizational level of analysis and to the analysis over time. There still are various opportunities for focus and extension such as modeling parameters of social networks in organizations and, for

example, observing the effects of increasingly omnipresent approaches in agile organizations.

However, another rather interesting path may be to deliberately move the level of analysis to the ecosystem level [68], including customers, partners, complementors, and their acceptance of BIS as well as the effects on organizational performance or even ecosystem performance.

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